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SAND94-8451
Unlimited Release
Printed January 1994

A GLOBAL CONFORMANCE QUALITY MODEL*
**A NEW STRATEGIC TOOL FOR MINIMIZING DEFECTS CAUSED BY VARIATION,
ERROR, AND COMPLEXITY**

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Abstract

The performance of Japanese products in the marketplace points to the dominant role of quality in product competition [1][2]. Our focus is motivated by the tremendous pressure to improve conformance quality by reducing defects to previously unimaginable limits in the range of 1 to 10 parts per million. Toward this end, we have developed a new model of conformance quality that addresses each of the three principle defect sources: 1) Variation, 2) Human Error, and 3) Complexity.

Although the role of variation in conformance quality is well documented [3][4][5], errors occur so infrequently that their significance is not well known. We have shown that statistical methods are not useful in characterizing and controlling errors, the most common source of defects [6][7][8][9][10]. Excessive complexity is also a root source of defects, since it increases errors and variation defects.

A missing link in the defining a global model has been the lack of a sound correlation between complexity and defects. We have used Design for Assembly (DFA) methods to quantify assembly complexity and have shown that assembly times can be described in terms of the Pareto distribution in a clear exception to the Central Limit Theorem. Furthermore, within individual companies we have found defects to be highly correlated

* Based on a Ph.D. dissertation submitted to Stanford University

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with DFA measures of complexity in broad studies covering tens of millions of assembly operations.

Applying the global concepts, we predicted that Motorola's Six Sigma [5] method would only reduce defects by roughly a factor of two rather than orders of magnitude, a prediction confirmed by Motorola's data [11][12]. We have also shown that the potential defect rates of product concepts can be compared in the earliest stages of development.

The global Conformance Quality Model (CQM) has demonstrated that the best strategy for improvement depends upon the quality control strengths and weaknesses. Using this model, efficient improvement strategies can be defined that show: 1) *what to improve*, 2) *how much to improve*, and 3) *which quality tools to use*. The study reinforces the value of continuous effort to reduce complexity across a broad spectrum of production activity, pointing to the importance of global perspectives in design and development decisions.

Preface and Acknowledgements

Initially the proposed research objective was to establish a structured method for efficient development of world class product concepts. Two major barriers were encountered in this effort. First, there are so many confounding factors in design, such as team skill, management priority, and development time, that a study involving many design teams and control groups is required to verify that the source of improvement is the change in methodology. This poses many practical challenges. Even if such a study could be performed, it was soon recognized that the inability quantify global improvement presented a second major barrier.

This led to the study of Design for Assembly (DFA) as a method for measuring assembly complexity. While many studies have attempted to identify what makes assembly easier, this is the first known effort to quantify how easy assembly is. The result of this work suggests that there are many global product attributes which can be quantified. Hopefully this can lay a foundation for better qualification of proposed improvement to the design process.

Professor Philip Barkan, my advisor, has been particularly helpful in this effort. In addition to key insights and critical guidance, it has been through the work performed by students in his classes that assembly data on a wide spectrum of products has been obtained. He aided in identifying contacts within organizations who might have an interest in participating in this study. His reputation and prior cooperative efforts have opened doors and encouraged participation in this work. His kind patience and sustained support have been truly appreciated.

We are deeply indebted to many organizations and individuals that supplied data for this study. In particular, Dave Gebala at Motorola provided product complexity and defect data that played a key role in the development of this work. Kent Peterson at General Motors provided stop watch measurements of actual production assembly processes that helped to validate the Pareto distribution. We have promised confidentiality in many cases, and for that reason cannot mention every company or organization by name, but we are grateful for their assistance.

Both Larry Leifer, and Hau Lee, have been kind enough to serve on the Reading Committee at Stanford University and have offered valuable suggestions for improvement.

I am deeply indebted to Sandia National Laboratories and the Department of Energy for the financial support of this effort. Al West, my immediate manager at Sandia, has been very supportive and encouraging. In addition, Al West, Anton West, and Cliff Yokomizo have reviewed this work at Sandia and have had many helpful comments.

Although the help has not been technical in nature, my wife, Karen, has believed in me. Her cheerful attitude has lent a spirit of balance and hope. She has put up with the clutter,

and been patient with my frustrations. Our children have also helped in their own way, often by not interrupting when they wanted to do so.

Finally, I would like to give thanks to the source of all inspiration which led me in this path and for that portion of ideas within this work that is sound, useful, and worthwhile.

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Chapter 1

Thesis Overview and Summary

Introduction

Buzzell et al [1] proclaimed that "Quality is King," affirming its dominant role in market share and Return on Investment. The performance of Japanese products in the marketplace reinforces this conclusion [2]. Our focus is motivated by tremendous pressure to improve conformance quality by reducing product defect rates to previously unimaginable limits.

Illustrating the required level of performance, Toyota asserted in 1991 that their North American suppliers had defect rates that were two orders of magnitude higher than their Japanese suppliers [13]. Similarly, the goal of Motorola's 6 sigma [5] program has been to reduce defects by roughly 4 orders of magnitude. In both cases the new target for defects levels is in the range of 1 to 10 parts per million (ppm). By contrast, defects in the range of 20,000 ppm are perceived as normal using traditional Statistical Quality Control (SQC) [3].

The consequences of this trend are profound, pointing to the need for a new rigor in understanding defects as an essential element for improvement. It is not enough to confront defect issues on the factory floor. A means of addressing potential defect sources early in the design process is essential, requiring a comprehensive approach.

NRC Study

A recent NRC [14] study proposed a combinatorial model of defects which offers several insights useful in the development of a comprehensive approach. They gave the following equation for product yield or the probability of producing a defect free product (P) as:

$$P = \prod_{j=1}^n q_j \quad (1.1)$$

Where, n = total number of **parts and assembly** processes

q_j = the probability that the jth assembly process or part is acceptable (i.e. free of defects)

Equation 1.1 has the same general form that was first applied in the field of reliability [15], illustrating the combinatorial nature of defects. A parametric plot based on values used in the NRC paper of the yield versus the number of parts and assembly processes is given in Figure 1.1. For each of the curves in the figure, the yield of each part and assembly

process (Q) is held constant. The analysis clearly demonstrates that product yield is sensitive to complexity and to the part and operation defect probabilities.

Figure 1.1. Effect of Component and Assembly Quality on Yield [14].

The model offered in the NRC paper embodies three key factors necessary to correctly quantify product conformance quality:

- 1) A comprehensive classification of defect sources,
- 2) A model of product complexity, and
- 3) A combinatorial description of probabilistic phenomena.

Their model is of limited use, however, because it offers no insights into the means of improvement other than prescribing reductions in defects rate and the number of defect sources.

In this model offered in the NRC paper, **product yield** is defined in terms of **defects** generated during the *manufacturing process*. This is the principle measure of **conformance quality** for products described by Garvin [16]. Conformance quality defined by this measure provides a convenient bound for exploring and comparing several aspects of product complexity within a reasonable scope. Although reliability and durability may be improved by increased conformance quality, they will not be addressed in this study.

The purpose of our study is to examine the relationship between complexity and conformance quality, with the goal of developing a more global model useful in the earliest stages of product development.

Several concepts and methods have evolved which have the purpose of improving conformance quality. The focus of these methods often leads to strategies for defect reduction that are limited, particularly when the goal is to achieve defect rates below 10 ppm. We will first critically review several traditional methodologies and examine their limitations.

1.1 Existing Conformance Quality Methods

Statistical Quality Control

Statistical Quality Control (SQC) [3] was one of the earliest quality improvement methods to be developed. It has become the backbone of several other techniques. It is based on the fundamental principle that variation can be observed in all processes and that such variation can be described statistically. Building upon this concept, sampling has been used to characterize process dispersion and control processes. Figure 1.2, based on the work of Ishikawa [3], illustrates a sampling, measurement, and feedback cycle which is the basis for this method.

Figure 1.2. Population and Sample from Ishikawa [3].

This traditional Quality Control method has two major shortcomings:

1. Defects or deviations are detected *after* they are created as Figure 1.2 shows that the number of defects produced is very sensitive to the response time of the feedback cycle, which can have many delays when the point of detection is downstream from the defect source.
2. It focuses exclusively on the production process, accepting the design as given. Since many defects originate in design, a focus on eliminating defects in the production process is less effective.

In this sense, the two major shortcomings are related since they both center on a downstream process control. This represents a serious limitation that generally is too late for maximum effectiveness.

Taguchi's Robust Design

Taguchi's [17] robust design represents an important advance in this perspective. This method addresses defect problems during the design/development phase. This method considers defect issues relative to the product design as well as the production process. Taguchi robust design seeks defect reduction (and improved reliability) by reducing

sensitivity to variation. Largely an experimental procedure which comes late in the design process, it has relatively limited application in the earliest phases of design.

Motorola's 6 Sigma and the Process Capability Index

Motorola's 6 sigma [5] seeks to control defects caused by variation through assuring that design requirements have been correctly established in the design phase and that the production process capability matches these requirements. Like the Taguchi method it can influence the design as well as the production process. An important measure used by Motorola's 6 sigma method to identify appropriate production processes is the Process Capability Index (C_p) [5]. It provides a measure of how well variation is controlled relative to specified limits. For bilateral tolerances, this index (which has also been called the "standard capability ratio" [18]) is defined as:

$$C_p = \frac{|USL - LSL|}{6 \cdot \sigma} = \frac{\text{tolerance width}}{\text{process capability}} \quad (1.2)$$

Where, USL = Upper Specification Limit
LSL = Lower Specification Limit
 σ = the Standard Deviation of the production process

A related index (C_{pk}) [5] addresses "shifts and drifts" in the process mean. Motorola has based the 6 sigma method upon the likelihood of a mean shift that is estimated to be 1.5 standard deviations.

Process Capability - An Insufficient Measure for Predicting Defects

By way of illustration, the relationship of the process capability index to the probability distribution function for two hole forming processes is displayed in Figure 1.3. These distributions are based on published economical tolerance specifications for the processes indicated [19]. The specification limits and process control indices for these two cases are illustrated in the same figure.

The process capability index can be used to predict how frequently the outcome of a process will exceed specified limits. However, *the probability of a defect is significantly different from the probability of exceeding specification limits*. The difference can be illustrated by examining the interference between a cylinder and mating hole. The probability of an interference can only be determined by evaluating the joint probability distributions for the cylinder and hole diameters. Interference will only occur if the cylinder is large and the hole is small. This type of analysis reveals that there is a high probability with random assembly that an oversized cylinder can be correctly assembled with adequate clearance. In general, the probability of a defect caused by variation is lower than the probability of exceeding the specification limits (assuming the limits have been set correctly).

Figure 1.3. The probability distribution functions for a drilling and reaming operation. The vertical lines indicate the Lower Specification Limits (LSL) and the Upper Specification Limits (USL). The drilling operation has a mean diameter of 0.742 inches with a standard deviation of 0.0018 inches. The reaming distribution is based on a mean of 0.750 inches with a standard deviation of 0.00017

Harry [5] showed that the *dimension, tolerance, and process capability* for each related feature must be determined before a Root Sum of Squares (RSS) method can be used to predict the probability of assembly interference defects. More sophisticated three dimensional treatments of tolerance variations that depend of Monte Carlo simulations have shown that the RSS method is inaccurate for complex problems [20][21]. These types of evaluations are generally not practical until the detailed design has matured. Consequently, the Process Capability Index cannot be used without other measures to predict the rate of defect occurrences even though it is a useful tool in controlling variation.

Limitations of the Variation Paradigm

As generally applied, each of the methods that focus on variation are based on three fundamental assumptions:

- 1) The normal distribution describes variation,
- 2) Sampling can be used to identify all significant sources of variation, and
- 3) All defects are a result of variation.

Based on these assumptions, sample sizes are generally small and "odd-ball" readings are discarded or averaged in a manner that dilutes their significance. Such practices, while convenient, effectively preclude an accurate assessment of the "tails" of the distribution. Our work challenges each of the three underlying assumptions that lead to these practices. Understanding the nature of rare events and the limitations of statistical methods is particularly important when the goal is to achieve extremely low defect rates below 10 ppm.

Describing Rare Events Using a Combination of Probability and Variation

The limitations of describing defects in terms of variation can be demonstrated with a simple example for a reaming process. In preparation for reaming, a slightly smaller hole is first drilled into the part. The distribution of the diameters after drilling and reaming would be similar to those illustrated in Figure 1.3.

Failure to ream a hole after drilling will result in a defect that is not visually obvious. In a study of over 23,000 production defects, Rook [6] found that the probability of omitting an operation *and not detecting the omission* using traditional production practice was approximately 0.00003. In other words, roughly one operation in 33,000 will be omitted without detection. While reaming variations that exceed the specification limits may or may not cause a defect, virtually every reaming omission will cause a defect. Neglecting every other defect source, this will result in a defect rate of 30 ppm, several times greater than a goal of 10 ppm.

Figure 1.4 shows the probability distribution function for the hole diameter when one reaming operation in 33,000 is accidentally omitted. The distribution differs distinctly from a normal distribution. The frequency and magnitude of defects resulting from omitting a reaming step exceeds the variation of reamed hole diameters.

Figure 1.4. The probability distribution function (note the logarithmic scale) for a reaming process where one reaming operation in 33,000 is accidentally omitted after drilling. The quality control levels for traditional and 6 Sigma limits are also illustrated.

Based on the assumed rate of omission of the reaming operation, the minimum required sample size is 76,750 observations to have a 90 percent chance of observing at least one reaming omission! Given a sampling rate of one part in a hundred, over seven million parts would have to be produced to provide a sample of this size. When observed, the measurement of an unreamed hole would typically be discarded as an outlier because it grossly exceeds the observed process variation. Even if the observation of the unreamed hole was not discarded, it would change the mean only $2.4\text{e-}7$ inches, and the standard deviation would change less than 3.5 percent. *A normal distribution based on even this enormous sample size does not provide any real improvement in describing reaming omission errors.* Variation is an inadequate model for some types of defects.

Reducing the variation of reamed hole diameters has no influence on the probability that a reaming operation will be omitted. Similarly, checks that reduce the probability of omitting a reaming step do not alter the assessed variation or the process capability index. Thus, to achieve defect rates less than 10 ppm, *omitting a process step must be treated as a separate defect source from reaming variation.*

Probability-The Only Universal Method for Describing Error and Variation

In the previous example, the *result* of omitting a reaming operation was described as a distribution that could be easily distinguished from the principle reaming variation. However, there are many types of errors where the outcome can only be defined in terms of the probability of occurrence. One book edited by the Nikkan Kogyo Shimbun, Ltd. [22] identified the following types of error which they listed "in order of importance" as:

1. Omitted processing	6. Processing the wrong piece
2. Processing errors	7. Misoperation
3. Errors setting up workpieces	8. Adjustment error
4. Missing parts	9. Equipment not set up properly
5. Wrong parts	10. Tools and jigs improperly prepared

Missing parts, wrong parts, processing the wrong piece, and transposing wires are among the numerous types of error that can not be described as variation. These errors either occur or they do not. A part is either present in the product or missing. *Many errors and the resulting outcome can only be described in terms of probability.*

Moreover, errors are so rare that, even when possible, it is impractical to characterize them as distributions. It would typically take more than a million observations to have enough errors of one type to characterize it as a distribution.

While we can express every type of variation in terms of a probability of exceeding specification limits, a probability of interference, or a probability of a defect, all error probabilities can not be expressed as variation. *Consequently, the only universal method of describing both errors and variation is probability.*

Human Error-A Critical Factor in Defect Creation

Although some writers have alluded to a difference between mistakes [23], or human error, and variation, this distinction has not been accurately described in the literature. This is probably due to the fact that it is virtually impossible to accurately assess rare events using sampling methods. *As shown by our example, the assumption that variation alone can characterize all defects is flawed and often prevents identification of major defect sources.*

There are many types of error that can occur in an operation. While each of these are individually rare occurrences, collectively they can have a significant impact on conformance quality. Harris [7] concluded that 80 percent of the defects in complex systems could be attributed to human error. In an examination of 23,000 production defects, Rook [6] found that 82 percent of all defects were caused by human errors. His

tabulation revealed that most errors occurred during assembly. Voegtlen [8] reported that 60 percent of product failures could be traced to workmanship defects, pointing to assembly since defective parts were tabulated separately. A recent study [9] of front end automotive headlamps by a major manufacturer also showed that more the 70 percent of 6,600 observed defects were caused by assembly or handling errors. NASA [10] reported that most space shuttle mishaps are the result of human error based on a study of mishaps occurring since October 1990. These studies all point to human error as a key source of defects.

Self and Source Inspection

Shingo has introduced several quality concepts that overcome some of the limitations of other methods. Self inspection, and source inspection [24] have the goal of detecting and eliminating defects at their **production source**. Self inspection has the objective of detecting defects as close to the point of generation as possible to reduce or eliminate delays in the feedback. By gaging tools, materials and activities *upstream* of the process, it is possible to eliminate many defects *before* they are created using source inspection. However, these techniques, like Statistical Quality Control (SQC), do not address design as an important cause of defects.

Poka-Yoke and 100 Percent Inspection

Shingo [22][24] also makes an important distinction between human error and product defects. *While errors are inevitable, defects are not*. He has shown that, in many cases, simple methods can provide early error detection that assure correction before a defect is passed to the next stage in the production process. He stated:

"We should recognize that people are, after all, only human and as such, they will, on *rare occasions*, inadvertently forget things. It is more effective to incorporate a checklist-i.e., a poka-yoke-into the operation so that if a worker forgets something, the device will signal that fact, thereby preventing defects from occurring. This, I think, is the quickest road leading to attainment of zero defects." (italics added) [24]

This is consistent with observations made by Rasmussen [25], who concluded that the frequency of errors derived from incident reports (such as defects) is dependent on the opportunity for people to detect and correct the errors immediately. No amount of vigilance or training will assure that unintentional errors will be recognized. A core concept is that **poka-yoke**, in combination with **100 percent inspection**, can catch virtually every error.

Using these techniques, a washing machine drainpipe assembly line processing 30,000 units a month involving 23 workers achieved zero defects for six consecutive months [24]. This level of performance is orders of magnitude better than the lowest estimates of human error rates [26]. Using poka-yoke, defect probabilities will be less than error probabilities. Consequently, defects are more likely to be related to the level of quality

control than to the frequency of errors. As illustrated, centering attention on error prevention and intervention is more productive than prediction of error rates for production problems.

Poka-yoke can be incorporated in the product to assure that a part cannot be assembled in the wrong position or orientation [27]. In some instances it possible to design the product so that assembly cannot proceed if a part is missing or incorrectly positioned. In this sense, poka-yoke is an important design tool. *In practice, however, poka-yoke is not a full solution because it is largely limited to specific process steps with the design accepted as given.*

Conformance Quality - an Evolving Perspective

Collectively these conformance quality methods identify two distinctly different sources of defects, variation and human error. As illustrated in Figure 1.4, the role of human error only becomes apparent as the control of variation improves, explaining the chronological evolution of Statistical Quality Control (SQC) and poka-yoke. While process variation has been decreasing, product complexity generally tends to increase through the addition of features. For example, the airplanes and automobiles manufactured today are more complex than those built 60 years ago. These two trends will lead to a continued increase in the relative importance of human error in conformance quality.

Since parts are defined by features, dimensions, and material properties that must be controlled, control of variation is an important element of part fabrication. Variation also contributes to defects in *some* assembly processes such as aligning wheels, aiming head lamps, and torquing bolts. However, for many assembly operations involving the handling and insertion of parts, variation within the limits of proper fit is not a quality issue. Incorrect assembly is generally a result of an error rather than variation as observed by Rook [6]. From this, variation is likely to play a dominant role in part defects while error is a dominant factor in assembly defects.

None of the existing methods, by themselves, can provide a basis for a total strategy of defect elimination because none of them address problems in a global manner. They do not distinguish the multiple sources of defects, and the very different characteristic of the solutions which each source requires.

The most effective opportunities to undertake pro-active steps for defect prevention occur in the earlier stages of design, while the design of both the product and the production processes are still in the drawing stage. Yet the existing approaches to quality conformance have very little application at this stage of the design process. As noted, a serious deficiency that commonly occurs when applying any of the existing conformance quality methods is that the appropriateness of product design is accepted without question, resulting in a focus that is exclusively "after the fact." Many of the defects caused by variation and errors would be eliminated by simpler designs or processes and should be attributed to excessive complexity rather than errors.

1.2 A Global Classification of Defect Sources

Each of the approaches that have been reviewed have focused on a narrow aspect of product defects. Consequently none of these methods will independently support the development of a comprehensive conformance quality strategy. Collectively these methods have addressed three fundamentally different sources of product defects:

1. Excessive Variation:	Source:	control of production processes
2. Human Error:	Source:	human limitations
3. Complexity:	Source:	design of the product/process

The NCR model identifies another method of classifying defects according the phase of production where the defect is generated, rather than by the cause such as variation or human error. It distinguishes defects according to two types:

- a. defects in parts, and
- b. defects in assembly.

A global classification of defects must consider both the defect source and the phase of production when the defects are introduced. Table 1.1 summarizes the type of defect, source of defects, and potential metrics for assessing the relative importance of the defect source. Among the factors listed in this table, complexity is the least understood source of defects because of the difficulty of defining relative measures of complexity.

Table 1.1. Types of defects, the cause of defects, and their metrics.

Defect Source	Defect Type	
	Parts	Assembly
Variation: Naturally occurring process dispersion	Dispersions in Human Control; Wear; Material Properties; Temperature; Vibration; Operating speed; Measurement; Gage Reading; Power.... Metrics: $f(C_p, USL-LSL, Dim.)$	Dispersion in fine motor skills; Adjustment variations; Torque variations; Minor misalignment; Gage reading Metrics: $f(C_p, USL-LSL, Dim.)$
Human Error: Failure to perform a task, performance of a prohibited action, or a process deviation that exceeds the frequency and magnitude described by variation	Tolerances assignment error; Measurement error; Omission of process steps; Mishaps in handling, transport and storage; Gage reading error; Incorrect Metrics: Human Error Prob.	Gross misalignment; Omitted/incorrect parts; Transposed wires/parts; Handling, test, and transport mishaps; Omitted operation... Metrics: Human Error HEP
Complexity: The number of elements and difficulty of generating or executing the elements	Number of features; precision/size relative to process capability; Number of process steps; Material formability; difficulty of handling... Metrics: Number of Parts; Difficulty of Part formation	Jumbled part presentation; Reach distance; Selection Decisions; Positioning precision; Insertion resistance; Tools; Tangling; Visual/handling access; Size... Metrics: No. of operations; Predicted Assembly Time

Complexity - A Key Quality Element

As products become more complex, there is an increasing probability that an error will be made in defining feature dimensions or assigning tolerances. While gross errors will be discovered early in development and production, minor errors may be very difficult to detect. Consequently, increases in complexity can also lead to increases in defects resulting from variation. Task complexity has also been recognized by researchers [28][29] as an important factor influencing human error rates. We believe that complexity is a major causal factor.

Although many axioms espouse the importance of simplicity [30][31][32], or avoidance of complexity, there are only a few relative and no absolute measures of either "simplicity" or "complexity." Control of product complexity, a major source of defects, has thus far been hampered by this lack of a quantifiable basis of measurement.

We introduce a general perspective on complexity, proposing that a valid measure of this characteristic must have two essential elements:

- a) a **quantity measure** - identifying the number of elements which contribute to complexity
- b) a **difficulty measure** - a relative measure of the difficulty in generating or executing each of the elements.

It is generally easy to count the number of elements contributing to complexity, such as the number of assembly operations in a product. However, assessing the relative difficulty of the elements is challenging. A common weakness in efforts to understand the role of complexity has been the singular focus on number of elements.

According to the NRC model, defects originate in parts or assembly operations. For each category, we need to identify appropriate parameters which may can form the basis of quantifying complexity.

Part Complexity

Since the primary goal of our study relates to assembly complexity, it is beyond the scope of this work to develop detailed models of part complexity. We wish, however to briefly identify some reasonable measures that could constitute the basis of future effort.

Part Quantity Measures

There are many elements of part complexity that can be determined by simple enumeration. Minimizing some of these elements has become an important goal of Designing for Manufacturability. Important **quantity measures** of part complexity include:

- A. The number of parts per product or component,
- B. The number of features per part,
- C. The number of process set-ups,

- D. The number of process steps per part,
- E. The number of different processes, and
- F. The total number of parts to be produced.

The significance of such measures is evident in design rules which call for minimizing the number of parts in a product [30][31] or minimizing the number of processes per part. The General Electric Company [33] has employed a design constraint that parts must be manufacturable with no more than three processes. While such guides are useful, they are not infallible. Barkan and Hinckley [34] have shown that sometimes adding parts and processes permits reduction in complexity and improvement in quality. A limited focus on the quantity measures without consideration of the difficulty measures can lead to incorrect design decisions.

Part Difficulty Measures

For this application, our concept of "**difficulty**" must relate to the likelihood that part complexity will increase the probability of error and/or degrade the ability to control variation. Due to the distinctly different nature of these defects sources, there is no common measure that is consistently correlated with both error and variation in part fabrication. The process that minimizes variation may maximize errors! For example, a reaming operation requires more steps that are more difficult than required for a drilling operation. The reaming process provides an improvement in the ability to control hole variation but increases the probability of errors due to the increased process difficulty. *This points to an new concept in quality control, where a process could be selected on the basis of providing the minimum combination of variation defects and error defects.* The optimum solution is likely to fall between the extremes of minimizing either error or variation.

As previously discussed, the Process Capability Index (C_p), and the related index C_{pk} , merit particular consideration for this purpose as a measure of the control of variation. They provide a measure of **difficulty** that is related to likelihood that all critical features on a part can be produced consistently. Part quality involves meeting necessary tolerances on critical features. The difficulty of meeting these requirements must relate to the capability of the manufacturing system to produce each attribute of each part within the range of tolerance necessary to achieve the required level of product quality. To be useful measures of defects, a significant amount of detailed information regarding tolerances and production processes must also be available.

The Process Capability Index (C_p) measures control variation, which we have shown is not an adequate measure for controlling errors. Human error is driven by the performance limitations of human beings. There are a variety of factors that increase the probability of human error. Some of these factors may also influence the process capability. At least six difficulty measures in addition to the process capability index have been identified as follows:

- a) part material formability,
- b) features complexity (undercuts, internal cavities...),

- c) part size,
- d) difficulty of process set-ups,
- e) difficulty of the process,
- f) difficulty in transportation, handling, storage, and
- g) corporate experience and skill.

The breadth of the factors that must be addressed in a global definition of part complexity poses a formidable barrier. However, in circumstances where products are evolutionary, and considerable production experience is available for similar parts and processes, it may be possible to define part complexity with adequate accuracy.

It is well beyond the scope of this study to attempt to establish a perfectly general or global measure of part complexity or process difficulty. Consequently, we have chosen to structure our model of product defects in a manner which encompasses part complexity in a global sense while permitting refinement of the model as the understanding of part complexity improves.

Assembly Complexity

Every product with more than one part requires assembly. To quantify assembly complexity a measure is needed for the number of assembly operations and the difficulty of each operation. The time required for assembly as predicted by Design for Assembly (DFA) methodologies can provide a basis for both of these important aspects of assembly complexity. This measure provides an opportunity to create a new standard for assessing complexity.

Design for Assembly (DFA) methodologies were developed with the objective of helping designers identify opportunities for making assembly easier, thus providing guidelines for reducing the complexity of assembly. In every method, the number of parts, and assembly operations are counted. Virtually, all of these methodologies also translates handling, insertion, and securing actions into an estimate of the nominal time needed to perform an assembly process.

In general, for every factor that increases the difficulty of the action or the complexity of the assembly interface, there is an increase in the predicted time for execution. The total assembly time per operation provides an approximate relative comparison of the complexity of dissimilar assembly activities. This approach is an evolution of Time and Motion studies that substantiate the general trend of increased execution time for increases in the difficulty and complexity of the assembly task.

Assembly Complexity - A Key Factor in Conformance Quality

In late 1990 Brannan [35] at Motorola published the data shown in Figure 1.5 which demonstrated that the number of defects per million parts decreased dramatically for increases in the manual assembly efficiency, an arbitrary measure used in the Boothroyd Dewhurst® [36] Design for Assembly (DFA) method. In general, as the assembly

efficiency increases the number of assembly operations and the average time required to perform each operation decreases. Assuming a constant probability of human error per unit time, the defect rate should increase as the assembly time per operation or complexity increases. Thus, the relationship between defects and assembly efficiency observed by Motorola is intuitively sound. Motorola did not explain this relationship.

Figure 1.5. Observed Defects per Million Parts versus the Manual Assembly Efficiency published by Motorola [35]. The line drawn by Motorola is not the best fit.

The data provided by Motorola piqued our interest because it suggested that there may be a quantifiable link between a criterion describing assembly complexity and product defects. Such a theory could be used to evaluate the conformance quality potential of product concepts before tolerance studies are even initiated. In addition, the theory could provide important insights useful in defining quality improvement strategies.

1.3 Goals

A major shortcoming of the current conformance quality concepts is that their singular focus makes correct identification of the principle source of defects difficult. Without sound measures and a comprehensive model, a company may continue to pursue reductions in variation, when their principle weakness is assembly errors. A clear concept of complexity is a key element in unraveling the differences between the error sources.

For these reasons, this study entails three specific goals:

- 1) Measure and characterize assembly complexity,
- 2) Test the relationship between assembly complexity and production defects, and
- 3) Based on such a relationship define a comprehensive model of conformance quality.

The results of this study have a potentially broad application. In juxtaposition with most quality methodologies that have minimal application during the formative stages of product concepts, this work aids in setting quality improvement strategies, evaluating concepts, and guiding important design decisions. Following is a summary of the significant results of this study.

1.4 Overview of the Importance and Benefits of the Study

A new model for conformance quality has been defined which, for the first time, spans the three principle sources of product defects: complexity, variation, and human error. With minimum effort, this model can be used to identify the general strengths and weaknesses of current performance. Rather than a replacement for existing methods, it guides the establishment of improvement goals in specific areas, supporting the development of clearly defined quality strategies while identifying the techniques that will be most effective in meeting the goals. Rather than focusing on defect sources, its formulation draws attention to the opportunities for minimizing defects: a) minimize and simplify assembly operations, b) improve quality control of the assembly process, and c) minimize defects and variations in parts. It is based on a combinatorial relationship developed in Chapter 9 section 9.1 which is given as follows:

$$P_Y = \prod_{i=1}^{N_0} \{1 - c_k(t_i - t_0)^k\}(1 - d_i) \quad (1.3)$$

Here, P_Y = Probability that an assembly is defect free ($\equiv$ Yield), $0 \leq P_Y \leq 1$

c_k = A constant related to the quality control of assembly operations, $c_k \geq 0$

t_i = Predicted time for the i th assembly operation, $t_0 \leq t_i \leq \left(\frac{1}{c_k}\right)^{\frac{1}{k}} - t_0$

t_0 = threshold assembly time for least complex assembly operation

k = A constant reflecting the sensitivity of defects to assembly complexity, $k \geq 1$

N_0 = Number of assembly operations (Number of parts is a subset of this value)

d_i = Probability that the i th part contains a defect, $0 \leq d_i \leq 1$

Figure 1.6 illustrates the major elements of this model and their relationship with the sources of product defects. As illustrated in the figure, part defects originating from variation, human error and part complexity have been grouped into a single factor, since there is no current method of assessing relative part complexity, and data are generally insufficient to distinguish part defects caused by variation or human error. This approach permits refinement of the model as improvement in the understanding of part complexity and part defect sources are realized.

The probability of an assembly defect resulting from either error or variation is defined by a single probability for each assembly operation ($c_k(t_i - t_0)^k$). This approach is required since probability is the only universal method of modeling both variation and error. Using a combined probability for variation and error also allows us to address the relative control of these two defect sources as a separate issue, a useful approach because organizations differ significantly in the relative control of these factors. The quality control of each organization determines the probability of a defect occurring for a given operation (c_k), and the sensitivity of that defect probability to the task complexity (k).

Defect Source				
Stage	Variation	Human Error	Complexity	
			Difficulty	Quantity
Parts	Part/Material Defects (d_i)			Part Count (subset of N_i)
Assembly Operations	Assembly QC (c_k, k)		DFA Ass'y Time ($t_i \sim t_o$)	Operation Count (N_i)

Figure 1.6. Relationship between elements of the new conformance quality model and the sources of product defects.

Assembly complexity, based on Design for Assembly (DFA) predicted assembly time (t_i), plays a key role in the model of conformance quality. The time values used in Equation 1.3 may be determined either by DFA analysis directly or by prediction of the distribution of assembly time derived from the Pareto or zeta functions (see Section 4.1 and 5.4). The easiest method to use depends upon the complexity of the product which is being evaluated.

This model of conformance quality demonstrates that a sustained focus on any single source of defects will yield diminishing returns as illustrated in Section 9.2. As defects in one area are minimized, defects from other sources will tend to dominate. This points to the need for a continuing search for the current weakness and the importance of comprehensive goals.

A New Aid in Concept Evaluations

One of the most significant benefits of the model given by Equation 1.3 is that it permits a relative comparison of the conformance quality potential of product concepts in the earliest stages of design (See Section 9.2). This aids in the evaluation and selection of concepts at a point in the process when most methods for improving quality conformance are ineffective. To illustrate, Figure 1.7 shows three concepts with a curve representing a constant number of assembly defects passing through point "B." Any concept above this curve is likely to have more defects than a point on the curve, and concepts below the curve are likely to have fewer defects.

Even though concept "C" in the figure has the most assembly operations, it has the shortest assembly time. Of the three concepts, the average assembly time per operation is significantly shorter for this concept and the model predicts that this concept is most likely to have the fewest assembly defects.

Figure 1.7. Boothroyd Dewhurst predicted assembly time versus the number of assembly operations. Seventy five percent of the evaluations will fall in the heavily shaded region, and ninety percent of the observations will be within the limits of the lightly shaded region. Given a constant level of quality control, the number of assembly defects per unit (DPU) will be constant along a curve like the one labeled "Iso-DPU". Predicted points for three concepts are labeled A, B, and C.

The Impact of Variety and Automation

Equation 1.3 also provides new and important insights into broad range of production decisions described in Section 9.4. To illustrate, the model shows that each factor that increases assembly complexity will increase the number of defects (if assembly pace and the level of quality control remain constant). Variety will increase assembly complexity and must, therefore, lead to an increase in the frequency of defects. These trends have been substantiated in several studies. For example, Gatchell [37] observed that operators with 10 parts made 46 percent more errors and needed 13 percent more decision time than operators that could choose from only 4 parts. These impacts may be partially offset by Poka-Yoke [24][22] techniques, but they cannot be reversed.

Managers and designers must decide upon the level of automation for production early in the design process. The decision to automate is often partially justified on the basis of potential improvement in *product quality*. Our studies question this justification if total system quality as the criterion. Automation can only replace the simplest manual assembly operations. Since our model shows that the most time consuming operations are the most probable source of defects, automation will not result in a significant improvement in product conformance quality until the majority of assembly operations are automated. This insight is graphically illustrated in Figure 1.8. Unless the intent is large scale automation, similar levels of quality improvement can generally be obtained by poka-yoke techniques, improvement in the feed parts, and/or simplification of the assembly process at substantially lower cost with greater manufacturing flexibility.

Figure 1.8. Product Yield (Probability of a Defect Free Assembly) versus percent of automated operations for 3 ratios of automated to manual defects. Manual operations are replaced by automated operations in a sequence from least time consuming to most time consuming. Curves are based on automotive product with 198 assembly operations and 129 parts with a Boothroyd Dewhurst Predicted manual Assembly time of 1300 seconds. ($c_k=0.0001$, $d_i=0$)

There are many situations which require or justify automation of assembly. For example, harsh or intolerable environments, a demand for high precision, or the need for high levels of productivity may favor or require automation. However, where possible, manual assembly can reduce capital investment and the time to market, while increasing flexibility. The ability to automate assembly often depends upon design changes that would also improve the productivity and quality for manual assembly. Consequently, the decision to automate assembly should only be made within the global context of other opportunities to improve design and production.

The Relative Control of Variation and Error

We have used an event tree to create a simple representation of manufacturing processes that is useful in evaluating the relative control of variation and error for each organization. Using the event tree described in Chapter 8, we have shown that each of the existing methodologies address distinctly different factors that influence defect rates. The event tree consistently predicts that each methodology will reduce defects. However, all improvements are not equally effective.

Using the event tree, we estimated that Motorola's Six Sigma [5] would only reduce defects by roughly a factor of two rather than several orders of magnitude because the Motorola approach did not address the control of errors. Our prediction is consistent with Motorola's own data. However, when Motorola recently added mistake-proofing (poka-yoke) they achieved defect rates in the tens of parts per million [12], a result that is consistently predicted by our event tree model.

Based on an evaluation of each organizations quality control philosophy, the event tree can be used in conjunction with sensitivity analysis to identify the quality control changes

that will be most effective for that organization. The level of improvement required in specific areas can be targeted to define a strategy consistent with defect rate goals.

Predicted Assembly Time-A New Measure of Complexity

The Design for Assembly (DFA) methodologies predict assembly complexity using time as a standard. We have shown that these predicted times are superior to simplistic measures but are imperfect gages of assembly complexity (see Sections 4.3-4.4). They are strongly correlated with production defects [34].

Reducing assembly complexity will reduce the defects and increase productivity. However, attempting to accelerate the pace without simplifying the design or operations can lead to disastrous increases in human error rates, injury producing accidents, and a net decline in productivity (See Section 3.4). Assembly pace is a quality control factor that is distinctly different than complexity, an important distinction that is sometimes confused because they are both measured in the same units.

In a broader sense, the implications of these observations is that improvements that reduce the complexity of every type of operation, including transportation, inspection, and part fabrication, will also reduce defects. The highest levels of productivity *achieved through reduction of complexity* are consistent with the highest levels of quality. This does not mean that satisfactory operations should be replaced with unsatisfactory operations on the basis of reducing complexity, but points to the need for a continuing search for the "one best way" [38] to achieve satisfactory results.

Defects Are Strongly Correlated with Design for Assembly Predictions

In a study spanning more than 30 products, three manufacturers, and hundreds of millions of assembly operations, we have demonstrated that defects are strongly correlated with predicted Design for Assembly (DFA) total assembly time and the number of assembly operations. A simple power model provided the strongest correlation for both two manufacturers who supplied Design for Assembly data (see Section 7.5).

The study clearly revealed differences in the quality control between manufacturers, explaining the reason that industry wide studies of the relationship between complexity and defects have generally resulted in poor correlations. This comparison has also demonstrated that the conformance quality performance of manufacturers can be benchmarked even in the case where they are producing dissimilar products.

The Zeta Function and Manufacturing Processes

To our knowledge, no one has ever previously studied the *distribution* of the complexity of assembly processes within products or across a broad spectrum of products. Knowing how to make assembly less complex is different than understanding how complex

assemblies are. A global perspective of assembly complexity is a key element in defining its relationship to product defects.

Pareto charts [3][4] have been frequently used with nearly every Design for Assembly methodology to identify assembly operations that are the "trivial many" or "important few [39]." The fact that a few operations consistently constitute a major fraction of the total assembly time suggested that the zeta [40] function used by Pareto [41] may be an important tool in understanding and bounding assembly complexity (see Sections 3.2 and 5.3). In the process of this study, we have found that the zeta function has potentially broad application for manufacturing operations. The zeta function should also be useful in establishing stable metrics of product complexity across a broad spectrum of design factors.

The zeta function provides a description of predicted and observed assembly times that is superior to other common statistical models such as the Normal, lognormal, binomial and geometric distributions (see Section 5.3). This is the first known application of this function to manufacturing processes. Expressed as a probability function, the zeta distribution used by Pareto [42], can be written as:

$$P\{X = x\} = \frac{C}{x^{\alpha_d + 1}} \quad \text{for } x = 1, 2, 3, \dots \quad (1.4)$$

In this equation, α_d and C are constants.

Benefits of the Zeta Function

The zeta distribution is shown in this work to accurately characterize the distribution of predicted Design for Assembly (DFA) times in a product. We have also found that the zeta distribution which models an existing product is very similar to the optimum model for a redesign of the same product (see Section 5.4). The similarity in the distributions before and after redesign allow us to use the zeta distribution as a powerful predictive tool and provides a good estimate of design changes with a minimum amount of detailed DFA analysis. In particular, the impact of redesign can be approximated with a minimum effort. This suggests that the zeta distribution can be used as a predictive tool in many manufacturing applications.

We have found that the Normal distribution does not provide a good model for numerous sets of actual assembly data including that shown in Figure 1.9 (see also Section 6.3). This result is clearly inconsistent with the central limit theorem but fully explained by the properties of the zeta function. Rejecting the Normal distribution in a case where it has been traditionally assumed has potentially broad implications for many manufacturing processes which can be described by a Pareto distribution as described in Section 6.6. In particular, the frequency and magnitude of rare events may be significantly underestimated by current statistical methods. Traditional sampling procedures are not adequate for characterizing the tails of a distribution. The limitations of statistical methods identified in

this study are critical when the objective is to predict rare events, such as defects, and demonstrate that different techniques are required to control error and variation.

Figure 1.9. Cumulative Distribution Function (CDF) of assembly times per unit for a worker repetitively performing a self paced "light" assembly task [44]. The "optimized" zeta distribution based on 38 convolutions is an excellent fit to the observations. The best fit normal distribution for the worker is also shown, and illustrates the superior match of the zeta function.

The total assembly time for a product is the sum of the time required to complete many independent assembly steps, with the variation in the time to complete each step described by a zeta distribution. The distribution of the total assembly time is a convolution [43] of these zeta functions (see Section 6.1). Our study is the first known study of zeta convolutions, and has produced results that are remarkably consistent with the *observed* assembly times as illustrated in Figure 1.9 which shows the distribution of times for repetitive operations performed by one worker. The zeta function clarifies changes in the distribution of assembly time resulting from changes in pace and complexity that heretofore have not been understood.

Improved Understanding of Assembly Complexity

Many Design for Assembly (DFA) methodologies have been developed. Since their databases were independently derived, it is not surprising that predicted assembly times for *individual* operations as determined by different DFA methodologies are highly inconsistent (See Section 4.3). Further, the actual time required to perform assembly of identical parts often varies substantially at different stages of production [45]. This large variance in assembly time is accurately described by the zeta distribution. The large variance suggests assembly is so complex that a highly accurate method of predicting assembly time for individual operations would become so cumbersome that it is probably impractical.

However, we have observed that the *distribution* of predicted assembly times for activities comprised of many assembly operations is virtually identical using any DFA method except for a scaling factor and can be described by a common zeta distribution! Thus, the zeta distribution is a more fundamental and consistent measure of complexity than any

individual methodology. The zeta function can account for the general consistency in predicting total assembly time using any of the various DFA methods.

The attempts to bound assembly complexity using the zeta function have led us to challenge one of the most commonly accepted rules of modern design: "**minimize part counts.**" Our studies show that a superior design rule, which reduces assembly complexity while tending to reduce part count and product defects, is to: "**simplify and minimize assembly operations.**" One benefit of this rule can be seen in the comparison Figures 1.10 and 1.11 (see Section 5.6). On the vertical scale in Figure 1.10 the Assembly Efficiency is shown to increase as the number of *operations* approach "Theoretical Minimum Number of Parts" (NM) as defined by Boothroyd Dewhurst. The "theoretical" minimum quantity of parts is determined for each assembly by those parts essential to the product function that 1) must be separate to allow movement, 2) must be made of different materials, or 3) must be separate to permit assembly and disassembly.

Figure 1.10. Boothroyd Dewhurst Assembly Efficiency versus the Operation Count Ratio (Number of Operations per Theoretical Minimum Number of parts). The upper and lower bounds are derived from the zeta distribution, and the heavy line is the least squares fit.

Figure 1.11. Boothroyd Dewhurst Assembly Efficiency versus the Part Count Ratio (Number of Operations divided by the Theoretical Minimum Number of parts). The upper and lower bounds are limits from Figure 1.10, and the heavy line is the least squares fit.

Figure 1.11 shows a similar trend as the number of *parts* approaches the "Theoretical Minimum." However, compared to Figure 1.10, there is greater scatter, particularly in the lower left corner. Thus low part count does not assure high assembly efficiency. This demonstrates that minimizing part counts without simplifying assembly can lead to unnecessarily complex and difficult assembly. By contrast, minimizing and simplifying assembly operations will tend to reduce part counts, but also assures easier and less complex assembly operations.

In summary, the results of this analysis have provided many insights into the design and development process. In particular it has led to an improved understanding of assembly complexity and conformance quality. In addition, the applicability of the zeta distribution

to manufacturing process has been clearly demonstrated in the first known application of this type.

1.5 Overview of Remaining Chapters

The purpose of this study is to examine the relationship between complexity and conformance quality. Chapter 2 provides the definitions and nomenclature used in this work. This is followed in Chapter 3 by a review and analysis of the literature relevant to this topic. Chapters 4 through 6 explore the suitability of using Design for Assembly (DFA) methods as a measure of product complexity. In the first of these chapters, we examine the accuracy and consistency of Design for Assembly (DFA) methods as a measure of complexity. In Chapter 5 the Design for Assembly methods are used to determine the distributions of predicted assembly times. Chapter 6 examines the actual distribution of assembly time observed in research and production environments.

In Chapter 7, the correlations between measures of complexity and the product defects are examined. In Chapters 8 and 9 we present the development of the global conformance Quality Model, which is the foundation for comparing product concepts and defining conformance quality Strategies. The last two chapters (10 and 11) summarize the key findings, and discuss the implications with suggestions for further research.

Chapter 2

Definitions and Nomenclature

Definitions of the terms used in the dissertation:

Assembly Action: An assembly activity performed by man or machine. An action generally consists of a cognition phase (or sensor equivalent for machines), a motion phase and an alignment/insertion phase. By this definition, fastening would be considered a separate action. This definition is only one of many possible ways of subdividing assembly activities [36][46]. Generally, each major change in the direction of motion requires a distinctly different observation, analysis, movement and alignment/insertion.

Assembly Defect: A defect caused by an assembly error such as: 1) a missing or incorrect part or subassembly, 2) an incorrectly positioned or oriented part or subassembly, 3) loose connections, 4) damage due to mishandling, insertion or joining, or 5) an inadequate joining processes. Assembly errors detected and corrected before sending the part to the next assembly station are not counted as defects. In recording defect data, each company may have used different criteria than given here.

Assembly Efficiency (EM): An arbitrary method of comparing the estimated total manual assembly time (TM) to the assembly time of an imaginary product containing the Theoretical Minimum Number of Parts (NM) (see definition in this section) each of which can be assembled in an "ideal" time of three seconds for the Boothroyd Dewhurst® DFA methodology [36]. The assembly efficiency [36] is computed according to the following equation:

$$EM = \frac{3 \text{ seconds} \times NM}{TM} \quad (2.1)$$

Assembly Operation, Simple: A simple assembly operation is comprised of a sequence or series of assembly actions which produce a single, complete change in the state of an assembly necessary for the function of the product or subsequent assembly operations. Adding and securing a single part (bolts, nuts, screws, etc. counted separately), performing a single spot weld, an adjustment or alignment that changes the position of a single part that is already a part of the assembly, or a single reorientation of a partially completed subassembly are examples of single, complete changes. This definition is similar to the definition of an "operation" used by groups performing Time and Motion studies. (see Barnes [46]). It is consistent with Shingo's [24] definition of operations that may be described as actions used by the agents of production to create products. Complex assembly operations consist of a sequence of simple assembly operations. Note that this definition excludes transportation and inspection, and storage actions.

Assembly Pace: The relative rate at which assembly proceeds. There is no simple method of defining assembly pace [46]. It is a relative description of how rapidly operations are performed.

Complexity: A relative state characterized by a) the number of elements, and b) the relative difficulty of generating or executing each element comprising an article or operation.

Class I Assembly Operation: An assembly operation that can be performed using a consistent number of assembly actions. Example: unobstructed insertion of parts that are easy to handle and insert.

Class II Assembly Operation: An assembly operation that cannot be repeated in a consistent pattern. This type of operation generally requires repeated assessment of the level of completion. Examples: Grinding a braze to an appearance finish, adjustment, and handling tangled parts.

Design for Assembly (DFA): Any methodology which aids in evaluating the complexity of assembly processes and the identification of opportunities for less complex assembly alternatives, including the reduction in the number of parts or assembly processes.

Human Error: A failure to perform a prescribed task, the performance of a prohibited action, or the misinterpretation of information essential to correct task execution which could result in damage to equipment and property, or the disruption of scheduled processes. This definition is similar to one attributed to Hagen [48], and preserves the important distinction between variation and error. Other proposed definitions can confuse these distinctions. For example, Meister defined a workmanship error as a discrepancy between a standard and the hardware produced by a worker during the production process [49]. This definition encompasses both out of limit variations and human errors. It is important to recognize that variation can lead to defects even when an error has not occurred. Errors are typically rare events.

Inspection: The examination of the quality or condition of material, part, feature, product, or performance parameter for the purpose of determining acceptability relative to defined standards.

Material Defect: A defect or imperfection in material of sufficient size or magnitude to degrade the function or appearance of the material which is caused by impurity or processing and which is present before assembly begins. Some examples are: inclusions, incorrect material, or failure to heat treat.

Part Defect: A defect in a part, excluding material defects, caused by processing which is present before assembly begins. Examples include a mislocated feature, out of tolerance feature, or damage caused by handling prior to assembly.

Productivity: A measure of the effectiveness of production, especially the effectiveness of assembly measured in terms of time required per product. This is consistent with Stalk

[50] who measured productivity in terms of man hours per unit. It is not the same as units produced per hour which is sometimes used as a measure of productivity.

Simplicity: A relative state or quality of having less complexity characterized by fewer elements, or elements that are less difficult to generate or execute.

Task: The objective or purpose of an intentional change in an object of production. Each operation intended to change a part or product may be composed of some actions or motions that are excessively fatiguing, unnecessarily difficult or time consuming, or unessential. Thus, the complexity or difficulty of the operation is always greater or equal the complexity required by the task. This definition of task is similar to Shingo's [24] definition of a process, which he defines as, "how objects of production change according to methods, space, and time." While we concur with Shingo's distinctions, his definition is not consistent with the stereotype used by most individuals, and can lead to significant confusion without lengthy explanation.

Theoretical Minimum Number of Parts (NM): An arbitrary number of parts for an assembly determined in the Boothroyd Dewhurst ® [36] method by identifying those parts which must be separate according to at least one of the three following criteria:

1. Does the part move relative to all other parts already assembled during operation?
2. Must the part be made of a different material or does it require isolation?
3. Must the part be separate to make assembly and disassembly possible?

Product Yield: The probability of producing a defect free product. For the purpose of this paper, a product is free of defects if it does not contain material defects, part defects, or assembly defects. Yield may be measured at different points in production, such as shipment, or the end of the assembly line. Here, yield is at the end of the production line before corrective measures are taken to repair defects identified by inspection. This definition of yield is consistent with the NRC [14] formulation given in Equation 0.1 in Chapter 1, but is not consistent with definitions of yield that focus on productivity [2].

Variation: The naturally occurring process dispersion resulting in divergence of the characteristics of a part, operation, product or any of their elements from the nominal.

Chapter 3

Literature Analysis - Complexity and Defects

The traditional conformance quality methods described in Chapter 1 independently focus on singular defect sources, either variation or human error. The critical missing element needed for developing a comprehensive conformance quality model has been the characterization of complexity and its influence on defect probabilities. This chapter will focus on the evolution of the ability to measure assembly complexity and an analysis of the literature that has related task complexity to human error and defects.

3.1 Measuring Assembly Complexity

It is a relatively simple matter to count the number of assembly operations in an assembly. However, the *difficulty* of individual operations varies widely, even within a single product. There is no single method of characterizing and subdividing assembly operations that is agreeable to everyone. While these issues cannot be entirely resolved, it is possible, through comparison, to identify the strengths and weaknesses of our current measures and within these limitations establish a basis for quantification of global assembly complexity.

Any comparison of dissimilar characteristics or activities requires a metric. For assembly activities, time has been the most frequent basis of comparison [36]. As a metric it has the advantage of being stable, familiar, and having a common international value.

Development of Time as a Measure of Complexity

The first efforts to measure work using time as a standard can be traced to Taylor, who is generally credited with the development of "Time Study" which was first applied at the Midvale Steel Plant in 1881 [46]. Due to the importance of productivity, time is a natural measure of work. Assembly processes require the skills of sensory perception, decision, and coordinated motion per Park [51]. As the difficulty in exercising any of these skills increases, the time required to perform a task can be expected to increase. For individuals, increasing task complexity tends to increase the *mean* time of execution. For example, in studies of visual search Bloomfield [52] found that the mean time to find a target among similar objects increased when the target size decreased. The increased search time was found to be inversely proportional to the target area.

Evolution of "Standard" Time

The development of Predetermined Motion Time Systems (PMTS) laid the foundation for the methods of measuring complexity that are essential to this study. Classification of human motion was a natural evolution of the efforts to identify changes in movement that

would improve the efficiency of work. By 1924, A. B. Segur [53], who worked with Gilbreth during World War I, had perfected a system of predicting assembly times which provided accurate and consistent results. By 1952, nine different Predetermined Motion Time Systems (PMTS) for predicting the time required for human actions had been defined in the United States [46].

These systems aided industrial engineers in planning production activities prior to the fabrication of hardware. They improved assembly, fabrication and production planning, and provided a check on efficiency of production work. Since 1952 most of the Predetermined Motion Time Systems (PMTS) have been adapted, improved, abbreviated and/or expanded. For example, there are at least six forms of the "Work-Factor" system and eight versions of the "Methods-Time Measurement" [46] system, two of the more well known approaches.

Fitts' Law

Perhaps the strongest evidence for the relationship between the task complexity and time of execution comes from Fitts' law [54]. Fitts had subjects tap an object back and forth between two targets. He found that the mean time (MT) to move to a target of width W which lies at a distance (or amplitude) A is:

$$MT = a + b \cdot \log_2 \left(\frac{2A}{W} \right) \quad (3.1)$$

In this equation "a" and "b" are empirical constants found through linear regression. This equation shows that the time to perform tasks described as "target acquisition" is logarithmically related to the distance between targets divided by the target width. In 1989 MacKenzie [55] developed a more theoretically sound model which also provided a better fit with empirical data which is given as follows:

$$MT = a + b \cdot \log_2 \left(\frac{2A}{W} + 1 \right) \quad (3.2)$$

The log term as been described as an index of the task difficulty, and demonstrates that the time of execution must increase as the difficulty increases. The general relationship has been tested for a wide variety of tasks and has been found to be a generally robust model of human motion [56].

Evolution of Design for Assembly (DFA) Methods

When the process of performing a task is inefficient, significant improvements may be made without changing the task. However, as a process approaches the "one best way," [38] it becomes more apparent that continued improvement in the operation can only be achieved by reducing the complexity of the objective task. The emphasis of the Design for Assembly methodologies shifted the basis of predicting assembly time from human motion to the assembly task as dictated by the part or operation characteristics. Thus the Design

for Assembly methodologies are a natural evolution of continued improvement of the manufacturing process.

Among the more well known DFA methodologies are the Boothroyd Dewhurst® [36] method, and the Hitachi Ltd. [57] method. Assembly View™ [58] uses the Westinghouse Database which based its index of difficulty on the information theory developed by Fitts [54]. The Xerox Corporation [59] has developed their own method, and AT&T [60] has adapted procedures from other methodologies. IBM [61] and General Electric [62] have also published design guides for assembly. In the methods, a penalty is assigned to an operation based on the factors that make the operation more difficult. *In every case, these penalties are associated with an increase in the assembly time for the added complexity.*

In Table 3.1 the major factors in the predicting operation time are listed for well known Predetermined Motion Time Systems (PMTS) and Design for Assembly techniques. The factors identified in the early PMTS methods have had a clear influence on the Design for Assembly methodologies, but new factors, particularly joining processes have been added, while the role of discrete motions have been de-emphasized.

A review of Table 3.1 reveals that each methodology has gaps in the factors that they address. Most of the methodologies recommend correction of some assembly deficiencies for which they do not assign assembly time penalties. For example, the Hitachi approach recommends control or elimination of part tangling but does not assign time penalties if such problems exist.

Parallel Observations in the Field of Robotics

The repetitive nature of assembly tasks fostered the development of automated assembly. The evolution of automation is moving toward robots that are capable of autonomously planning and executing specified tasks, including assembly. This has required a more rigorous examination of motion planning and assembly analysis. Latombe [63] has pointed out that the most important measure of computational complexity in robot motion planning is the execution time for the algorithms. He observed that,

"The complexity results surveyed...give strong evidence that the time required to solve a motion problem increases quickly with the dimension of the configuration space, the number of polynomial constraints on the robot's motion, and the degree of these constraints." [63]

These observations reinforce the relationship between task complexity and execution time. Wilson and Latombe [64] have also proposed additional measures of complexity for assembly including:

- 1) The number of "hands" required to move parts and subassemblies during assembly
- 2) The ability to position parts without intermediate positions or regrasping
- 3) The nature and number of degrees of freedom required to perform the motions
- 4) The ability to use linear versus non-linear algorithms
- 5) The number of "fingers" required to grasp parts and subassemblies
- 6) Uncertainties requiring sensors

Table 3.1. Comparison of factors which increase the predicted process time for several methods.

Action	PMTS Methods		Design for Assembly Methods		
	Work Factor [46]	Methods-Time Measurement[46]	Boothroyd & Dewhurst [36]	Assembly View [58]	Hitachi [57]
Grasp					
Presentation of Parts	X	X			
Size/thickness/diameter	X	X	X	X	
Entangled/nested	X		X	X	
Slippery	X		X		
Distance	Pt.-Pt. Line	True Path Length		X	
Walking	X	X			
Body Motions(hand, feet,leg)	X	X			
Swivels/Rotations/Stooping	X	X			
Manual Control	X				
Part weight/worker sex	Wght/Sex	Weight	Weight	Weight	
Handling Ease			X	X	
Grasping Aid/Two Hands			X	X	
Reach	X				
Destination Nature		X			
Type of Reach		X			
Move	X				
Destination Nature		X			
Type of Move		X			
Assemble	X				
Alignment ease	X		X	X	X
Orientation - End-End/Rotat.		X	X	X	X
Fit/pressure/resistance		X	X	X	
Access-visual/mechanical	Visual		X	Mechanical	
Holding Down Req'd		X	X	X	X
Insertion direction				X	X
Rotation of base part			X	X	X
Mental Processes	X				
Eye Motion/Focus		X			
Release/Disengage		X			
Joining Processes					
Snap/press Fit		X	X	X	X
Bending/crimping/Riveting			X	X	X
Screw/screwing/nuts			X	X	X
Weld/solder/braze			X	X	X
Heating/Machining					X
Adhesive Bonding			X	X	X

Although these factors are related to the difficulty of both manual and automated assembly, their relative importance and impact on assembly performance has not yet been quantified. Their work suggests that our ability to quantify assembly complexity will continue to improve.

Competing Objectives - Ease of Use versus Completeness

In developing methodologies for measuring assembly complexity, researchers face competing objectives. For ease of use and practicality in development, the methodology may only address a limited number of factors. However, for the greatest generality, as many factors as possible covering the broadest spectrum of issues is desired. The current methodologies represent a compromise between these competing goals. Their ease of use in assessing assembly complexity is offset by the gaps in the factors which they are able to address. The most significant gaps are likely to involve the most time consuming assembly activities since such activities will be less common and more difficult to describe in general terms.

Exceptions in Relating Assembly Time to Complexity

There are exceptions to the trend relating assembly complexity to assembly time. Barnes [46] and Weschler [65] found measurable differences in human skills. Gilbreth [66] showed that individuals may use different motions to perform the same complex task, a factor that can have a major impact on the time required to complete a task. Measurement of the total assembly time for products also includes delays [24], which typically can be in the range of 95 to 99.5 percent of the time the parts are in the system [50]. Hancock et al [67] demonstrated that the cycle time per task decreases as experience, measured by the number of repeated cycles (x), increases. They described this phenomenon as the "Learning Curve" which has the form:

$$Y_x = \frac{K}{x^{\alpha_L}} \quad (3.3)$$

Here, Y_x = cycle time per task for the xth cycle

K = the time for the first cycle, and

α_L = a constant determined by the learning rate (typically about 0.80)

There are also many additional factors which can produce apparent exceptions to the trend of increasing assembly time for increasing difficulty such as differences in pace, or changes in the environment or personal condition. Because of these factors, observations of actual assembly time are not sound measures of the assembly complexity. This may partially explain the reason that strong correlations between actual assembly time and defect rates have not been consistently demonstrated. In an international study of automotive assembly plants Krafcik [68][69] showed that the number of assembly defects per hundred vehicles was weakly correlated (correlation coefficient (r) = 0.15) with the assembly time

per vehicle. Such weak correlations demonstrate the need for a better measure of assembly complexity that is less sensitive to variations in local or time varying conditions.

A Standard for Comparison is Required

Womack et al [2] recognized that a "tear-down" analysis of competing products may provide a better assessment of assembly complexity than provided by the actual assembly time. In a tear-down analysis, the products are disassembled, the parts are counted, the difficulty of the assembly processes are compared. Although they anticipated better correlation using this approach, prohibitive expense prevented their evaluation.

Because different teams may not consistently interpret the results of a tear-down analysis, correlations developed using this method may not be useful in other applications. Without a standard for analyzing complexity, the value of the effort could be significantly limited.

Design for Assembly - The Best Current Standard

Similar to a tear-down analysis, each Design for Assembly (DFA) Methodology identifies the sequence of assembly, and part counts. However, as a method of comparing assembly complexity, DFA methodologies have several advantages compared to tear-down analysis. First, in each methodology the time penalties for individual operations are selected from a database based on the characteristics of the assembly operation. The databases and rules of use encourage a more consistent interpretation than can be achieved in a tear-down analysis. Thus, the DFA methodologies provide a standard for comparison that is not available from other methods.

Design for Assembly (DFA) methods are better than Predetermined Motion Time Systems (PMTS) for assessing assembly complexity because they are more directly related to product characteristics than production planning. In addition, a DFA analysis can be performed using drawings, without having to physically disassemble products or define each assembly motion. The DFA methods can also be used to evaluate concepts before products are even fabricated. Consequently, the DFA methods are less time consuming, and less expensive than a tear-down or Predetermined Motion Time Systems analysis. As a standard, the Design for Assembly (DFA) methods are also more readily available than Wilson's [64] proposed measures of complexity.

Typically, the DFA methodologies have been used to evaluate specific products and modifications of those products. They have not been used to assess the distribution of the complexity of assembly operations, or to assess assembly complexity across a wide spectrum of design, one of the major objectives of this study. Such an understanding is essential for comparison of dissimilar products and concepts and for estimating complexity where very little information is available.

Pareto Charts Identify Opportunities for Making Assembly Easier

Pareto charts are frequently used in Design for Assembly (DFA) analysis to identify the assembly processes that offer the greatest opportunity for improving ease of assembly. As illustrated in Figure 3.1, a few assembly operations typically require most of the assembly time. The consistency of shape observed in numerous Pareto charts prepared on several projects suggested that it may be possible to bound assembly complexity using a Pareto distribution.

Figure 3.1. Pareto Chart for a series of assembly operations. The data is from a study of thermal conductivity test equipment. Individual assembly operation times represented by bars are plotted with the scale on the left. The scale on the right is for the cumulative assembly time shown as a line Barkan et al [34].

3.2 The Pareto Distribution - A Model of Complexity

The first version of Pareto's Law was published in November of 1895. This was followed by a paper entitled *La courbe de la répartition de la richesse* published in 1896 [41]. In these papers, Vilfredo Pareto examined the income distributions for eleven groups or populations from several countries. The minimum sample size was 17,000 observations. For each group he listed a sequence of increasing annual incomes (x) and tabulated the number individuals (N) receiving an income equal to or greater than the listed value. Table 3.2 is taken from the work he published in 1896.

Pareto plotted the logarithm of the number of individuals (N) having an annual income greater or equal to a specified value (x) versus the logarithm of the annual income (x) and observed that the result was essentially a straight line. The "Pareto curve" shown in Figure 3.2 is a plot of the data of Table 3.2. He identified the equation of a line matching this data using two constants, A and α , as:

$$\text{Log}(N) = \text{Log}(A) - \alpha \text{Log}(x) \quad \text{or} \quad N = \frac{A}{x^\alpha} \quad (3.4)$$

Comparing Equations 3.3 and 3.4 we observe that the Learning curve has the same basic form as a Pareto distribution!

Table 3.2. Pareto's table for the number of people (N) in England (Angleterre) having an income as great or greater than the value (x) in the first column. The dates indicate the time of the census. [41]

ANGLETERRE				
x £	N		Log N	
	1843	1879-80	1843	1879
150	106,637	320,162	5.02791	5.50537
200	67,271	190,061	4.82783	5.27889
300	38,901	101,616	4.58996	5.00696
400	25,472	61,720	4.40606	4.79043
500	18,691	45,219	4.27163	4.65532
600	13,911	33,902	4.14336	5.53023
700	11,239	27,008	4.05073	4.43149
800	9,365	22,954	3.097151	4.36086
900	7,923	19,359	3.89889	4.28688
1,000	7,029	17,963	3.94689	4.25438
2,000	2,801	7,611	3.44731	3.88144
3,000	1,566	4,480	3.19479	3.65128
4,000	1,040	3,050	3.01703	3.48430
5,000	701	2,292	2.84572	3.36021
10,000	208	853	2.31206	2.93095
50,000	8	68	0.90309	1.83251

Pareto noted that the slope of the curves and the minimum income remained nearly constant within a population. Although there is a 36 year interval between the two census figures plotted in Figure 3.2, the curves are essentially parallel. Olkin et al [70] noted, "Even after the progressive tax legislation adopted in almost every socialized country in the present century, the probability law (used by Pareto) provides a reasonably good fit to personal income data." The remarkable invariance to intentional efforts to modify the distribution as well invariance to time pose one of the most significant and unexploited potential features of this probability law.

In 1905 Lorenz [71] plotted incomes based on Pareto distributions as cumulative distribution functions, but he did not extend the application beyond economics. A Lorenz curve based on the 1843 census data given in Table 3.2 is plotted in Figure 3.3. Note that Pareto listed income in non-uniform "bin" widths. The plot in Figure 3.3 is based on the best zeta function fit to Pareto's data with uniform income increments of 150 £. Lorenz curves are more widely known as Pareto charts today.

Figure 3.2. *Pareto curve* of "N" versus 1843 and 1879 English income in a log log plot per Pareto [41] (Table 3.2). "N" is the number of people having an income greater or equal to a specified value.

Figure 3.3. *Lorenz curve or Pareto Chart* showing the number of individuals in each income group for column three of Table 3.2. The maximum income in the chart is limited to show more detail in the figure.

In 1975 Juran published an article in *Quality Progress* on the history of the "Pareto Principle." [39] stating that he (Juran) appeared to be the first to identify the phenomenon of the vital few and trivial many as a 'universal.' He applied the name 'The Pareto Principle' to this universal and coined the phrase "vital few and trivial many." He used the Lorenz curves, like the one shown in Figure 3.3, to depict this principle in graphic form.

Although Juran's "Pareto Principle" has broad application, he did not use the mathematical underpinning provided by Pareto. The Lorenz curves used by Juran have become a popular technique for evaluating processes. They are easy to use and are powerful tools for in identifying the "vital few." Unfortunately the simplicity of Pareto charts has probably contributed to the limited interest in understanding the underlying mathematical concept. The significance of Pareto's law seems to be virtually unknown or ignored in design [72] [73].

The original form of plotting the data proposed by Pareto is considerably more powerful than the Lorenz curves used by Juran for several reasons.

1. It is equally effective in identifying the "vital few."
2. Linearity of the plot provides a criterion for rapid qualitative assessment of applicability of the Pareto distribution.
3. The slope and minimum value of the Pareto *curve* define the mathematical characteristics of the distribution which cannot be readily obtained from Pareto charts.
4. The predictive potential is more readily apparent as observed in Figure 3.2.

The Pareto Distribution

The distribution used by Pareto has been expressed in both a discrete and continuous form. The term "Pareto" distribution is generally used to refer only to the continuous form as given in Equation 3.4. Expressed as a density function, the Pareto distribution may be written as [42]:

$$p_X(x) = \frac{\alpha_c k^{\alpha_c}}{x^{\alpha_c + 1}} \quad \text{for } x \geq k \geq 0 \quad (3.5)$$

In this equation, α_c and k are constants, with k being the minimum value in the population ($k^{\alpha_c} = A/N_{\max}$ from Equation 3.4). The accepted notation for the continuous Pareto distribution is $P(\alpha_c, k)$.

The Zeta or Zipf Function-A discrete form

G. K. Zipf is credited [74][75] with demonstrating that the discrete form of the Pareto distribution could be applied to a broad variety of problems. Popularizing its use, he used this function to describe the population of cities, frequency of word usage, and sizes of library books. The Zipf function can be written in the following form:

$$P\{X = x\} = \frac{1}{\zeta(\alpha_d + 1) \cdot x^{\alpha_d + 1}} \quad \text{for } x = 1, 2, 3, \dots \quad (3.6)$$

Where, ζ represents the Riemann zeta function [43]. The Zipf distribution given in Equation 3.6 is also called the zeta distribution due to its relationship with the Riemann zeta function. The solution of the Riemann zeta function for a value of $\alpha_d + 1$ is a constant which is defined as follows:

$$\zeta(\alpha_d + 1) = \sum_{k=1}^{\infty} \frac{1}{k^{\alpha_d + 1}} \quad \text{for } \alpha_d \geq 0 \quad (3.7)$$

Although the discrete and continuous form are similar, a common value of α in both forms does not result in the same distribution. The subscript indicates a discrete (d) or continuous (c) function. For distributions such as assembly time, "x" can represent "bins" of any uniform size. For example, with $\alpha_d = 1.225$ ($\zeta(\alpha_d + 1) \approx 1.4751$), the probability that an observation would fall in the first bin is 0.6779, in the second bin would be 0.1450, and so forth. The following shorthand notation will be used for the zeta or Zipf distribution: $Z(\alpha_d, 1/\zeta(\alpha_d + 1))$.

The Riemann function given by Equation 3.7 must be evaluated to determine the mean, and variance of the zeta or Zipf function in Equation 3.6. In this sense, these functions are intimately related. The Riemann zeta function is peculiar in the sense that it can be expressed as an arithmetic series, a continuous function, or a product of a function of all prime numbers. It has properties of both discrete and continuous functions.

The Pareto or Zipf function has also been used to describe the capacity of steel producers [70], occurrence of natural resources, and stock price fluctuations [42]. In one particularly interesting application, error clustering in telephone circuits has been modeled. Berger and Mandelbrot [76] showed that bit errors in digital transmissions tended to appear in clusters of varying size. They showed that the time interval between individual

errors as well as error clusters could be described by the Pareto distribution. An interesting potential application is that defect clustering in production may also follow a Pareto distribution.

The Riemann zeta function has been one of the most widely studied mathematical functions [77] with many articles on this subject appearing in the mathematics and physics literature each year. However, virtually none of the research is relevant to our problem. Most research has focused on the form based on the product of primes and values of α between 0 and 1. This is termed the "critical strip" because of its important role in number theory. However, in this range ($0 < \alpha < 1$) the mean value of the function is infinite. This contrasts with common natural processes which have finite mean values.

Violation of Fundamental Statistical Theorems

In order for the zeta or Pareto function to converge in either the discrete or continuous form, the constant α must be greater than zero. ***For the mean to converge, α must be greater than one. In addition, the variance will not converge unless α is greater than two!*** This results in a number of interesting problems since the best fit distribution for the data we examined often has a value of α less than two. In such situations samples will have a finite variance but the implied population variance is infinite.

Fundamental statistical theorems such as the Central Limit Theorem and the Strong Law of Large Numbers are based on the assumptions of finite variance and/or upper limits for the value of a single observation [43]. The zeta and Pareto distributions can violate the underlying assumptions upon which these fundamental principles of statistics are based. Pareto was the first to recognize this problem [40].

Mandelbrot [76] addressed this important issue and pointed out that the variance of some types of data does not converge as the sample size increases. He stated, "From the erratic behavior of sample moments, it follows that a substantial portion of the usual methods of statistics should be expected to fail, except if extreme care is exerted. *This failure has of course often been observed empirically*, and has perhaps contributed to the disrepute in which many writers hold the law of Pareto; but it is clearly unfair to blame a formal expression for complications made inevitable by the data." He also noted that the moments, such as the variance, will be finite for any finite sample, but approach infinity only as sample size approaches infinity.

Lack of familiarity with these limitations of the zeta function can lead to significant errors. Most importantly, when dealing with data that follows a Pareto distribution, the sum of a large number of independent random variables *will not* be normally distributed. We shall subsequently demonstrate that this is more than a mere theoretical issue which has potentially broad implications.

Shewhart's Grouped Observations

Juran stated, "The Pareto principle would lead us to expect that *most distributions of quality characteristics* would not quite be normal. Both Shewhart's and the authors' experience confirm this [4]." (Italics added) The implication of these observations with regards to manufacturing activities is that the normal distribution should be used with caution. Rather than characterizing and using the appropriate distribution, Shewhart organized the data in subgroups of four to five observations, and determined the average value of each subgroup. Shewhart concluded that the distribution of these averages was "close to normal" with virtually all averages falling within ± 3 standard deviations of the mean for sample sizes of 25 subgroups. The bounds of modern control charts are based on this technique.

Shewhart's [4] justification for this approach is based upon the following equation which is an immediate consequence of the central limit theorem:

$$\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}} \quad (3.8)$$

Where, $\sigma_{\bar{x}}$ = The standard deviation of the distribution of averages
 σ = The standard deviation of the population
 n = The number of observations

This relationship does not hold for the Pareto or zeta distributions where sample variances do not estimate the population variance. Using Monte Carlo methods to simulate random trials from a Pareto distribution, we found that the "averages" may appear to be normally distributed if a single outlier in as many as 1000 observations is discarded, or if the sample size is small (<100 subgroups). The consequence of Shewhart's approach is that the frequency of rare events (more than three standard deviations from the mean) can be underestimated by several orders of magnitude in many situations.

3.3 The Link Between Defects and Assembly Complexity

Thus far we have identified a potential method of measuring assembly complexity as well as a potential model that may be useful in describing the distribution of assembly complexity. Our goal is to relate the assembly complexity to conformance quality. This requires a better understanding of the impact of complexity on error rates and defects.

Measuring Human Error Probabilities

Human Error Probabilities (HEP) [78], or the number of errors divided by the number of opportunities for error, have been determined for a number of discrete tasks. By nature, errors for skilled operators are generally rare events. Large samples are required to assess the Human Error Probabilities of a single operator, for a single task, under a single set of conditions. Swain [78] observed that the typical laboratory experiment is made deliberately difficult so that a high Human Error Probability can be obtained for statistical

convenience. He noted that studies of skilled persons tended toward lower error probabilities. This observation supports the thesis that increases in assembly complexity will tend to increase the number of errors and defects.

Because errors occur infrequently, the distribution of Human Error Probability over a population of people has not been established in the literature, although a log-normal distribution is typically assumed [78][51]. In a study of individual differences, Rook [78] found that the maximum rate of defects generated per individual was approximately twice as great as the minimum rate of defects generated per individual. This is consistent with Wechsler's Ratio [46], a pattern of proportional performance observed in many human activities.

Table 3.3 contains a summary of some of the error rates that have been observed. As this table demonstrates, error rates tend to be significantly higher in inspection than assembly. Although the sample sizes for assessing assembly errors seem quite large, they are actually too small for the intended objective. To accurately assess the probability of one error in 10,000 (95% confidence interval with an error of less than 10 percent) requires a samples size approaching 4,000,000 observations based on a Poisson approximation to the binomial. From this we can infer that the frequency of human error in production is not accurately known.

Table 3.3. Error rates observed in assembly and inspection tasks. Note the Assembly errors are based on those that are made and not caught by the assembly operator.

Example	Number of Observations	Error Rate	Human Reliability
Errors in assembly [6]			
Insufficient solder	47,075	0.002	0.998
Component wired backwards	2,610	0.001	0.999
Transposition of 2 wires	13,083	0.0006	0.9994
Component (small) Omitted	10,388	0.0003	0.9997
Wrong value component used	13,880	0.0002	0.9998
Solder Joint Omitted	47,075	0.00005	0.99995
Operation Omitted	59,435	0.00003	0.99997
Errors in Inspection [29]			
Centerline Location		0.0417	0.9583
Algebraic Sign		0.0250	0.975
Measurement Reading		0.0083	0.9917
Copy Errors		0.0043	0.9957

Evidence of the Links Between Complexity, Errors, and Defects

There is substantial evidence in the literature pointing to the relationship between error rates and complexity. Seidenstein [29] stated that the systems which produce high error rates are characterized by:

- Complexity
- Requiring many operations
- Poor man machine interfaces
- Psychological stress

Seidenstein [29] also identified 11 factors that increase stress and error rates. Table 3.4 demonstrates that there is a remarkable consistency between these factors that are known to increase errors and the factors that increase assembly time.

Table 3.4. Factors identified by Seidenstein as increasing stress and the probability of error are shown in the first column. In the second column are related factors identified in the Design for Assembly and Predetermined Motion Time Systems Methodologies as factors that increase assembly time.

High Stress Factors Increasing Errors	Factors Increasing Assembly Time
Individual steps must be coordinated	Two hands or holding down required
Difficult discrimination (of Displays)	Subtle alignment features
Feedback is inadequate	Obstructed access or restricted vision
Long task sequence	Complex assembly process
Comparison of Displays required	Alignment/orientation (Feature Comparison)
Decisions based on several inputs	Mental processes, adjustments
Nature & Timing of inputs unanticipated	Jumbled part presentation

Meister [79] prepared a list of some causes of human errors that has been cited frequently. His list included: 1) Inadequate lighting in the work area, 2) Inadequate training or skill of the concerned manpower, 3) Poor equipment design, 4) High temperature in the work area, 5) High noise level, 6) Inadequate work layout, 7) Crowded work space, 8) Poor motivation, 9) Improper tools, 10) Poorly written equipment maintenance and operating procedures 11) Inadequate handling of equipment, 12) Poor management, 13) *Task complexity*, and 14) Poor verbal communication.

Many of the factors identified by Meister are related to environmental and factory conditions which, within the context of an entire assembly plant, are likely to change gradually. The design complexity also remains nearly constant between design cycles. This may explain why defect rates are fairly stable following the production start up transition, a phenomenon that has been frequently observed [80][81].

While defect rates change somewhat gradually within a single facility, they can differ by orders of magnitude between manufacturers of similar products as discussed previously in the first chapter [13]. The differences between producers must be traced to general conditions in the work environment and the levels of quality control rather than variation in human capability. Since the general level of control differs significantly from one organization to another, industry wide comparisons of defect rates and complexity are likely to produce scatter plots reflecting weak correlations as already observed. A superior approach would be to compare the changes in defect rates versus assembly complexity in environments where the level of "quality control" remained as uniform as possible, namely within a single company or factory.

Studies Relating Defects to Complexity

Several studies clearly reveal that task complexity impacts both process time and error rates. Park [51] presented data on the operation of aircraft joysticks. The joystick length, angle of movement, resistance force, and response time lag were varied. Every change that increased the time required to perform an operation also increased the error rate and decreased the reliability. Card et al [82] compared the speed and error rate for using different pointing devices to select items on a Cathode Ray Tube (CRT). Their results are shown in Figure 3.4 and again show the trend that the lowest error rate is for the shortest duration process. MacKenzie et al [56] performed a similar experiment comparing input devices for *pointing* and *dragging*, using a mouse, a trackball, and a stylus with a tablet. He also found that the more difficult task (dragging) increased the mean time of execution and the error rate. Comparing the different devices, the mean time and error rates were highest for trackballs which were described as requiring the highest muscle and limb interaction.

Figure 3.4. Percent error versus process time for 4 computer input devices. Card [82]

Figure 3.5. Defects per hundred machines versus "complexity" per Xerox [81]. (Complexity not defined)

Ekins [81] published the plot reproduced in Figure 3.5 which was prepared by Xerox as part of their competitive benchmarking. This figure reveals a clear trend of increasing defects for increases in complexity. The figure does not contain any dimensions and the method of determining product complexity is not discussed in his report.

Variety

Variety has been shown to be a particularly important factor in error frequency. Gatchell [37] observed that operators with a choice of 10 parts made 46 percent more errors and needed 13 percent more decision time than operators who could choose from only 4 parts.

Stalk and Hout [50] studied a train wheel factory spanning a twenty four year period. Initially the factory produced only two products. Faced with excess capacity, the company introduced new products, increasing the variety of offerings (decreasing the focus) as well as the complexity of factory operation. Productivity and yield declined dramatically. When the company decided to change its strategy and re-focus efforts on

train wheel production in 1982, productivity rebounded (no data on yield was provided for this period). These trends are illustrated in Figures 3.6 and 3.7. In these figures, the maximum variety corresponds with the minimum focus.

Figure 3.6. Productivity versus product focus for train wheel production 1971-1988 [50]. Focus is defined as the percent of the production accounted for by the top two products. The correlation coefficient (r) for a power fit is 0.763. Variety increases to the left.

Figure 3.7. First pass casting yield versus focus for train wheel production 1971-1979 [50]. Focus is defined as the percent of the production accounted for by the top two products. The correlation coefficient (r) for a linear fit is 0.852. Variety increases to the left.

Stalk et al [50] also provided numerous additional examples demonstrating that variety and complexity increase overhead cost while reducing productivity. They also pointed out that converting to a "flexible" factory by improving the flow of material and reducing the complexity and cost of setups permits rapid changes in the product mix while reducing the batch sizes. The flexible factory reduces risk in the market place caused by delays, increases profit, and reduces lead time. These changes allow increased variety while minimizing the productivity and quality penalties commonly encountered.

Inspection

Several studies of inspection activities further substantiate the role of complexity in increasing human error. Error rates for vigilance tasks have received particular attention since they are related to such activities as air traffic controller errors or the ability of a driver to control lane position. Most of these studies have focused on simple tasks of unchanging complexity.

Jerison [83] set up a clock-like apparatus where the hand would advance in single jumps with intermittent double jumps. The task of the operator was to detect the double jumps. The task complexity was increased by repeating the test with two "clocks" and three "clocks." The percentage of double jumps detected for 2 clocks was about 10 percent lower than for one clock. When the third clock was added, the number of double jumps detected dropped another 20 percent. Most tasks are more complex than the simple

monitoring of a single device. Jerison concluded that common inspection tasks are more complex and intellectually demanding than tasks studied by vigilance research and recommended care in applying conclusions from such research to industrial settings. This research suggests that inspection may not be as effective in detecting defects as predicted based on laboratory research.

Harris [84] had ten electronic items inspected by 62 experienced inspectors. Eight or more inspectors examined each item and inspectors were allowed an unlimited amount of time to identify defects. The complexity of the items, measured by counting the number of major parts, varied from 6 to 100. For the minimum complexity products, an average of 75 percent of the defects were detected. The detection rate decreased in a nearly linear fashion to 15 percent as the equipment complexity increased to 100. The author concluded that significant improvement in performance could only be achieved by reducing the complexity of the task.

This pattern of performance has particularly significant implications for products. Individual parts are the simplest whole elements that products can be divided into. Therefore, part defects are more likely to be detected than assembly defects since an assembly must always be more complex than the parts it contains. Given that assembly defects and part defects have approximately equal probability, inspection will tend to reduce part defects more than assembly defects.

3.4 Complexity Versus Assembly Pace

Design for Assembly (DFA) databases give a fixed assembly time for a defined operation. This measure of assembly complexity has a constant value for a defined task. By contrast, the actual time required to perform such a task can vary due to pace, automation, environmental conditions, and material flow delays. For example, a surge or drop in demand can alter the pace of assembly.

Both the predicted Design for Assembly (DFA) time and assembly pace, can be stated in terms of the time required to complete an operation. *Even though assembly pace has the same dimensions as predicted Design for Assembly (DFA) assembly time (time per unit) they cannot be equated.* This can lead to a situation that is very confusing. Accelerating the assembly pace will reduce the actual assembly time per operation but it does not change the complexity of the objective which is independent and constant for a given design.

If assembly pace is accelerated, the difficulty of performing a task of constant complexity may increase beyond the performance capability of the operators. There have been a number of humorous television and motion pictures based on this situation. Data taken from the study of inspection tasks provides significant insights into the influence of pace. Chapman et al [85] conducted a study of inspection of chicken carcasses where the speed of the belt carrying the birds past inspectors was varied. Plotting the percentage of below

grade birds detected as a function of belt speed they found that a viewing time of 0.94 seconds per bird maximized performance. At higher speeds it was postulated that the inspector missed birds that should be rejected as a result of the time he looked away from the belt to remove defective carcasses. This had been anticipated. However, as the belt speed decreased below the optimum, performance was also degraded. At the slower pace, it appears that the inspectors became less attentive.

Buck [86] provided a review of results on dynamic inspection and concluded that the percentage of errors decreased as exposure time increased. The observed improvement is consistent with Chapman's observations, but the degradation in performance for times longer than the optimum could not be observed because the studies he examined did not extend into this region.

Based on these observations we anticipate that there is an assembly pace which will minimize errors and defects. When this pace is exceeded, errors and defects will rapidly increase. Below the optimum pace, the error rate may be slightly higher than the optimum. Of course, the optimum pace must decrease as the complexity of assembly operations increase. These relationships are illustrated in Figure 3.8. At the present, the optimum assembly pace that will minimize defects is not known.

The operations used to complete assemblies may contain unessential actions or motions that are more fatiguing than necessary. In this sense, the complexity of assembly operations will be greater or equal to the complexity of the assembly task. Simplifying the operations or the task will reduce the defects and accelerate the rate of assembly. However, attempting to increase productivity without simplifying the task or operations can lead to disastrous increases in human error rates, injury producing accidents, and a net decline in productivity. In this sense, assembly pace is a quality control factor, rather than a complexity factor. The difference between complexity and pace can be observed in the production environment.

Changing Pace Versus Complexity - Results at Mazda and NUMMI

At the Mazda Flat Rock plant in Michigan [87], a second shift was added to double production in the summer of 1988. However, the size of the work force did not change proportionally. Although the task and operation complexity remained essentially constant, the expected output per worker was increased. During this period, the defect rate jumped dramatically, reaching as high as 70 percent with an annual average of one in four cars shipped having at least minor defects. During the same period, incidents resulting in lost work time also jumped sharply and were 54 percent higher than the average of other auto plants in the same state. These problems persisted for at least a year indicating that the difficulties were not transient anomalies.

Mazda's experience contrasts sharply with the success achieved in the NUMMI plant in Fremont California. Both plants use Just-In-Time (JIT) assembly methods, and *kaizen* or continuous improvement programs. At both plants, workers are occupied about 57 seconds out of 60. In August of 1991, NUMMI started producing Toyota trucks for the

first time, adding a new production line. In the first year of this production they achieved the highest quality ratings in their class according to J.D. Powers [88]. NUMMI's productivity is nearly as high as the Toyota's Takaoka plant, a global standard, even though its work force is older and less experienced [89].

Figure 3.8. Influence of Assembly Pace and Complexity on the Defect rate. A diagonal band indicates the assembly pace that will minimize defects. Above the optimum assembly pace, defects will increase rapidly. Below the optimum pace, the defect rate may increase moderately due to worker inattention. Two arrows show different methods for improving productivity that are consistent with observed performance in production.

Different philosophies for improving productivity, namely changing complexity versus changing pace, are at the heart of these differences. This is illustrated conceptually in Figure 3.8. At the Mazda plant, team sizes were reduced to *force* improvement in the operations. Workers at Mazda felt that management decisions were passed off with little input even though procedures gave the appearance of consensus building [87].

By contrast at NUMMI, workers on the production floor are trained and viewed as the experts of production. Adler and Cole [90] stated, "NUMMI's methods and standards are not designed to squeeze more work out of employees that management assumes are recalcitrant and irresponsible. Instead, these methods and standards are determined by the work teams themselves." Outstanding production workers do the prototype assembly, plan the production sequence, and have significant input to the design. Team members time each other, "looking for the safest, most efficient way to do each task at a sustainable pace. . . Safety improves and injuries decline because *workers* get a chance to examine all possible sources of strain and danger systematically. [89]"

Comparing working conditions at NUMMI today with the previous GM Fremont plant, one team leader commented, "Being consistently busy without being hassled and *without being overworked* takes a lot of the pain out of the job. You work harder at NUMMI, but I swear it, you go home at the end of the day feeling less tired and feeling a hell of a lot better about yourself. [89]"

A Continuing Search for the "One Best Way"

The approach at NUMMI is remarkably similar to the Gilbreths' continuing search for the "one best way." Barnes [46] wrote, "The Gilbreths made little use of time study. In fact, concentrating on finding the best way for doing work, they wished to determine the shortest possible time in which the work could be performed." Similarly, the NUMMI method may be described as choreographing the "one best way" as identified by the most experienced team.

By organizing work in short 60 second work cycles [90], NUMMI fosters improved industrial learning in several ways. In a 60 second work cycle, a worker will repeat the operations twice as many times as a worker on a 120 second work cycle. The experience level for the worker on the short cycle will always be twice as great as the worker on the longer cycle. Based on the learning curve [67] and typically observed learning rates, the time required for the short cycle worker to perform his task should be about 60 percent of the time required by the other worker to perform a similar task! The short cycle time, in addition to improving productivity, is probably an important factor in the ability of Japanese manufacturers to rapidly ramp up production [80].

The leverage of the short cycle time in achieving higher levels of productivity is substantiated in production performance. At Uddevalla, a Volvo automobile plant that was recently closed, the cycle time was around two hours [90]. In that facility it took 50 hours to assemble a vehicle compared to 20.8 hours at NUMMI. Some of these differences may be attributed to the ease of assembly of the NUMMI products, but the difference in assembly time is substantial, and must be partially attributed to the much shorter cycle time.

The short cycle times also promote better task documentation and standardization [90] of the "one best way." At the Uddevalla plant the long cycle times made it virtually impossible to standardize performance or track it at a detailed level.

The short cycle time also contributes to improved quality. As Seidenstein [29] noted increases in cycle times increased the probability of errors. As product variety increases, it is also more difficult for workers to recall correct procedures for longer cycle times as observed by Adler and Cole [90]. Clearly the short cycle time contributes to the superior standard of productivity and quality set by NUMMI which is based on the Toyota production system used.

Thus far our attention has focused on assembly operations. However, these principles should be equally valid for every production activity, including inspection, transportation, and any production activity. Reducing complexity will improve productivity and quality conformance, while changing the pace may not achieve either goal. This does not mean that satisfactory operations should be replaced by unsatisfactory operations simply for the sake of simplicity. Rather, unnecessary tasks and operations should be eliminated. Every operation and process should be continuously improved.

Defects Rates as a Function of Assembly Time

The distinction between *pace* and *complexity* is particularly significant in defining a relationship with defects. Park [51] noted that the *distribution* of actual assembly times represents a random time to successful completion. From this he concluded that: "the frequency distribution of performance times cannot be directly fused into the concept of human error distribution function in the same sense that one derives the hardware failure distribution function, $F(t)$, for a failure density function, $f(t)$, which represents the random time to failure."

The Design for Assembly (DFA) methods give a single value of time for each operation, which is related to a mean value of the operation time. In this sense, predicted times are not a distribution of the random time to success. Also, we are not attempting to relate predicted time or complexity to a failure distribution function. We simply assume that over *long* periods of production, variations in human error rates may be averaged out. In this case, we would expect a larger number of defects for more complex and time consuming assembly operations given that pace, working conditions, and quality control are essentially the same in either case.

3.5 Summary of Literature Analysis

In this chapter we have shown that every known method of measuring assembly task complexity has been based on assembly time as the standard. Design for Assembly (DFA) methodologies estimate assembly time determined by operation complexities.

Pareto Charts have suggested that the distribution of assembly process times may follow a Pareto or zeta distribution. Although Pareto provided a mathematical description of this distribution nearly 100 years ago, it has been virtually ignored in Engineering sciences.

It has also been shown that human errors during assembly are among the most prominent source of product defects. Current models of human error do not adequately address the variation in task complexity, assembly conditions and the quality control of the assembly process.

Finally, assembly complexity for a given design is a constant that is independent of assembly pace even though these may both be characterized in the same units of assembly time per unit.

Chapter 4

Testing Design for Assembly as a Standard of Complexity

In this chapter our goal is to assess the adequacy of using Design for Assembly (DFA) analysis as a metric of assembly complexity. An ideal standard should be accessible [91], and should also have cause and effect link between measured and correlated values. For example, depth below a free surface in a liquid is a good measure for predicting pressure since the pressure is caused by the weight of the supported liquid. In this chapter we will investigate the cause and effect link between the computed DFA assembly time prediction and defect probabilities.

In addition, an ideal standard must be unbiased, consistently interpreted, accurate and precise. In the following sections, our selected standard is evaluated by comparison to this ideal. As is often the case in the real world, we shall demonstrate that Design for Assembly methods, while imperfect, are still useful measures.

4.1 Description of the Boothroyd Dewhurst Method

As previously mentioned, accessibility is one of the characteristics of an ideal standard. The Boothroyd Dewhurst® [36] method has been selected as the basis for comparing complexity because it is the most widely known of the Design for Assembly (DFA) methodologies in this country and is the most accessible standard. The procedures for using the Boothroyd Dewhurst® [36] method will first be briefly described.

A Boothroyd Dewhurst® [36] analysis is executed in five steps as follows:

- Step 1. Obtain information, such as drawings or hardware, for the product being analyzed.
- Step 2. Each unique part is numbered in sequence based on a conceptual or physical disassembly of the product
- Step 3. Perform a conceptual sequential reassembly. Based on the characteristics of the part, a manual handling code relating to the difficulty of picking up, and handling the part are identified. For these characteristics there is an associated time extracted from the database. A manual insertion code and insertion time are determined in a similar manner. The combined handling and insertion times are multiplied by the number of times that the operation is repeated. For each part, three questions are addressed to determine if the part is essential:
 - 1) must the part be separate to allow motion,
 - 2) must the part be made of a different material, and
 - 3) must the part be separate to allow assembly, disassembly or service.

Step 4. A cumulative value for the assembly time (TM) and essential parts is determined. This cumulative number of essential parts is called the "theoretical minimum number of parts (NM)."

Step 5. The assembly efficiency (EM) is determined by comparing the "ideal" assembly time, found by multiplying the theoretical minimum number of parts by 3 seconds, to the total predicted assembly time using the following equation:

$$EM = \frac{3 \text{ seconds} \times NM}{TM} \quad (4.1)$$

A simple Design for Assembly analysis using this method is illustrated in Figure 4.1 and Table 4.1.

Figure 4.1. Assembly proposed by Olivera [92] for the study of variation. This figure is used in association with Table 4.1 to illustrate the Boothroyd Dewhurst [36] Method. To assemble the product, the base (3) is put in place (note unsymmetrical bosses), the lid (2) set on the box, and the two screws (1) are installed.

Table 4.1. Sample Boothroyd & Dewhurst worksheet completed for the part shown in Figure 4.1.

1	2	3	4	5	6	7	8	9	Name of Assembly	
Part ID No.	No. of times the operation is carried out consec.	two-digit manual handling code	manual handling time per part (sec)	two-digit manual insertion code	manual insertion time per part (seconds)	Operation time 2*[4+6] (seconds)	Operation cost (cents) 0.4 * (7)	Figures for estimation of theoretical minimum parts	Box	
3	1	30	1.95	00	1.5	3.45	1.4	1	Base (Unsym. Bosses)	
2	1	30	1.95	02	2.5	4.45	1.8	1	Lid	
1	2	10	1.50	38	6.0	15.0	6.0	0	Screws	
						22.9	9.2	2	EM = $\frac{3 \cdot NM}{TM}$ = 0.26	
						TM	CM	NM		

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4.2 The Link Between DFA Assembly Time and Defects

The value of using Design for Assembly (DFA) analysis to compare and predict defect rates is strengthened if it can be shown that there is a cause and effect relationship between predicted DFA assembly time and defect rates. The literature review in Chapter 3 showed that increasing task duration and complexity will result in more errors and defects given a constant level of conformance quality control. This provides an intuitive link between predicted DFA assembly time and *error* rates. Our goal in this section is to demonstrate that increases in DFA assembly time also results in higher defect rates caused by *variation*. We will show that the probability of interference resulting from tolerance variation is related to the DFA predictions, demonstrating that predicted DFA times are a causal factor that increases defects resulting from both error and variation.

Tolerance Studies - A Method of Predicting Interference Probabilities

Assembly problems can occur if variation in an interface dimension results in excessive interference or improper alignment. Tolerances studies are performed to minimize these problems. The standard practice of worst case tolerance analysis does not accurately estimate interference probabilities. In 1988 an international committee of The American Society of Mechanical Engineers was convened to examine research needs in the area of mechanical tolerancing. They stated,

"The current methods for analysis and synthesis consider only discrete tolerance evaluations of one-dimensional linear or non-linear assemblies. These methods involve "worst-case" scenarios, which invariably lead to tighter than necessary part tolerances and more expensive manufacturing. The statistical methods of tolerancing, if perfected, could provide more realistic and, hence, cost effective tolerances on parts and assemblies."[93]

Statistical Methods - One-Dimensional Tolerance Studies

The application of statistical methods to tolerance studies will typically allow tolerances to be relaxed considerably relative to worst-case studies. Generally part feature variations are assumed to follow a Normal distribution, and the probability of interference is computed using a root sum of squares method [94]. This is the basis of Motorola's Six Sigma [5] approach to mechanical tolerancing for predicting the probability of assembly interference based on the process capability.

While such statistical methods have important applications they commonly overlook feature interactions in multiple dimensions and are based on simplifying assumptions that are not conservative. ***As a result, the probability of interference can be significantly underestimated.*** There are three factors contributing to the limited accuracy of these statistical methods:

- 1) Variation is generally applied to a *one*-dimensional stack up of tolerances,
- 2) Real variations in features often can not be described by a Normal distribution, and
- 3) Statistical methods do not address the ability to search for a fit if an interference is encountered [95].

The first two factors contribute toward an unconservative estimate of the probability of interference while the third factor mitigates some of the lack of conservatism. Since the first factor also applies to worst case evaluations, there are situations where this type of analysis may also be unconservative.

Limitations of One-Dimensional Analysis

To illustrate these weaknesses, consider the case first introduced by Olivera [92] and examined by Harry and Stewart [5] as illustrated in Figure 4.2. They studied one-dimensional variations for a simple product to define tolerances with the goal of supporting Motorola's performance standards of a probability of nonassembly of 3.4 ppm. It was assumed that each dimension followed a Normal distribution.

Figure 4.2. "Product," consisting of a lid, base and two screws, studied by Harry and Stewart [5] to demonstrate optimization of tolerances. The cutout is for clarity. Tolerances were defined in only one plane illustrated on the right.

Many dimensions which influence the probability of successful assembly for this simple product were not considered in their analysis, with the consequence that the probability of nonassembly is underestimated. Among the factors that they did not examine which will degrade the probability of assembly are:

- 1) Dimensional tolerances in the transverse direction illustrated in Figure 4.3.
- 2) Inner wall feature control on the base.
- 3) Lid lip feature control.

Tolerance variations in the transverse direction alone will approximately double the probability of nonassembly computed by Harry and Stewart when considered as independent variables. Since the lid must have some clearance in the transverse direction for assembly, the clearance holes for the screws can be offset in the transverse direction as well as in the plane that Harry and Stewart analyzed. This will reduce the clearance for inserting the screws resulting in additional degradation of the assembly probability.

Section B-B

Figure 4.3. Transverse dimensions which increases probability of nonassembly. Misalignment in orthogonal directions influences total hole/screw alignment errors not considered by Harry and Stewart.

Limitations of the Assumption of Normal Dimension Variations

The impact of non-Normal distributions on assembly can be illustrated by examining the clearance for inserting the lid of Figure 4.2 into the base. The lid has a lip that must fit within the walls of the base for successful assembly. Regardless of the method for dimensioning this lip, a perpendicularity tolerance is required to establish the lip feature. Figure 4.4 shows a view of the lid on the base with an exaggerated non-perpendicularity in the lip feature. As shown in Figure 4.5, every deviation from perpendicularity reduces the clearance for the lid. Even if the perpendicularity follows a Normal distribution, the gap does not. Since, both the base and lid can be non-perpendicular, small variations in perpendicularity have a large impact on the probability of assembly that is often neglected.

Figure 4.4. Top view of lid on base studied by Harry and Stewart. Exaggerated non-perpendicularity of the lip on the lid can significantly increase probability of nonassembly.

Figure 4.5. Any deviation from perpendicularity results in a decrease in the assembly gap. The gap distribution is not a Normal distribution, even when the perpendicularity variation is Normally distributed.

Because of the non-Normal characteristic of many feature interactions, interference in three dimensions requires Monte Carlo simulations [20][96]. Such studies have demonstrated that assembly clearances are often highly skewed distributions and that the traditional root sum of squares approach is not a valid way of combining variation in multi-dimensional problems [20].

Move to Fit-A Human Capability Not Modeled by Statistics

During assembly, if an interference is encountered, the operator will generally translate and rotate the part to find a position of acceptable assembly [95]. Although Monte Carlo methods can simulate the feature variation, the ability to search for an acceptable fit can not be represented by a statistical process. Search to fit routines are the most difficult part of accurate three dimensional tolerance studies and must be tailored to each problem. Without them, interference probabilities are overestimated. Since this gives a conservative estimate of defect rates, tolerance studies are generally performed without this refinement.

A Monte Carlo Study of Assembly Interference

Our goal in assessing tolerance variation is to understand how the probability of interference is related to assembly complexity and length of assembly time. For this purpose, several simple "products" having a range of complexity and assembly time were postulated. An accurate assessment of assembly interference for these "products" was performed using a multi-dimensional Monte Carlo technique.

The simple dimensions in these examples were treated as Normally distributed, although this approach would be inappropriate for other types of dimensions such as parallelism and flatness [20]. The resulting clearances did not always follow a Normal distribution. In each case, a drift in the mean of 1.5 standard deviations, similar to Motorola's [5] "Static Root Sum of Squares" analysis, has been incorporated in the simulated variations. A routine was written for each case, when required, to search for an alignment that would allow fit if an interference was encountered in the initial positioning.

The "products" examined in this study are illustrated in Table 4.2. The simplest design is a straight cylinder which is inserted in a round hole with tolerances established to just meet the guidelines used by Motorola (probability of nonassembly equal to 3.4 ppm).

Assembly of a Rectangular Prism

The second "product" examined, consists of a simple rectangular prism assembled into a rectangular hole. It illustrates the impact of transverse interfaces. Initially, the sides are considered to be flat and straight (no axial taper), opposite faces are assumed to be parallel, and adjacent faces are assumed to be perpendicular. Given the same basic dimensions and variation as applied to the cylinder, the probability of nonassembly based on a one-dimensional analysis would be 3.4 ppm, the same as the probability of nonassembly for the cylinder. Consideration of the transverse direction doubles the probability of nonassembly for the cube to 6.8 ppm, since fits in orthogonal directions are independent probability distributions.

The definition and production of rectangular prisms requires perpendicularity tolerances. Variations in perpendicularity must be allowed for both the plug and the hole, as illustrated in Figure 4.6. Given that the perpendicularity tolerance between adjacent faces is a third of the basic dimension tolerance, the probability of nonassembly increases by a factor of five to 34.7 ppm. *A one-dimensional analysis underestimates the probability of interference by an order of magnitude.*

Table 4.2. Influence of Complexity on Assembly Time and Interference Probabilities

Item	Cylinder			Cube			2 Plug Bar		4 Plug Bar
	Basic Cyl	W/Key	Key+Axial	Perpendicular	Non-Perp.	&Key	Basic	w/Key	Basic
Plug Dimension	99.214	9.214	9.214	99.214	On 2 edges	9.214	99.214	9.214	99.214
Tolerance +/-	0.3	0.3	0.3	0.3	(1 edge on	0.3	0.3	0.3	0.3
Cp	1	1	1	1	the hole,	1	1	1	1
Cpk	0.75	0.75	0.75	0.75	1 edge on	0.75	0.75	0.75	0.75
Cavity Dimension	100	10	10	100	the plug)	10	100	100	100
Tolerance +/-	0.3	0.3	0.3	0.3		0.3	0.3	0.3	0.3
Cp	1	1	1	1		1	1	1	1
Cpk	0.75	0.75	0.75	0.75		0.75	0.75	0.75	0.75
Other Dimension		key & slot width	key & slot depth	Trnsvrs Prism 109.214	Perpendicularity		CL Dist. 400	key & slot width	TP Hole & Plug CL Dist. between plugs 400
Tolerance +/-				0.3	0.1		0.15		0.15
Cp				1	1		1		1 (radial dimension)
Cpk				0.75	0.75		0.75		0.75
P(nonassembly) (ppm)	3.4	6.8	10.2	6.8	34.7	38.1	10	13	102
Deg of Freedom (min)	2	4	6	4	6	8	6	8	24
DFA Analysis									
Alpha	180	360	360	180	180	360	360	360	360
Beta	0	360	360	180	180	360	180	360	360
Handling (sec)	1.13	1.95	1.95	1.5	1.5	1.95	1.8	1.95	1.95
Insertion (sec)	1.5	1.5	1.5	1.5	1.5	1.5	2.5	2.5	2.5
Total time (sec)	2.63	3.45	3.45	3	3	3.45	4.3	4.45	4.45

Figure 4.6. Interface dimensions for a rectangular prism and a hole for the prism in a block. Dimensions are in millimeters.

Assembly Interference for Multi-Plug Bars

Although the last part, a four plug bar as shown in Table 4.2, appears to be fairly simple, there are 24 degrees of freedom in the simplest assembly analysis (8 diameters, and 8 positions in the x and y direction). The position of each hole and plug is assumed to be Normally distributed in the x and y direction about the true position.

The probability of nonassembly for the 4 plug bar is eight times as great as for a 2 plug bar, also shown in Table 4.2, which has the same basic tolerances. Given that designers base the tolerancing of the four plug bar on a one-dimensional analysis of a two plug bar they will underestimate the probability of interference by nearly an order of magnitude.

One-Dimensional Analysis Can Significantly Underestimate Interference

Designers compensate for complex interfaces by tightening specified tolerances to reduce the probability of assembly interference. However, we have shown in three separate cases that statistical one-dimensional tolerance studies, a common basis for specifying tolerances, can significantly underestimate the probability of interference. The inadequacy of the oversimplified approach is overlooked because the impact multi-dimensional interactions and feature control, such as perpendicularity, are not generally understood.

For the "products" examined in this study, an error in using one-dimensional analysis is the root cause for defect rates exceeding the intended frequency. Failing to recognize this error, the resulting defects might be attributed to variation in production, demonstrating the difficulty in identifying the root cause of defects. Furthermore, sampling inspection and Statistical Quality Control (SQC) are not likely to reveal the difference between the goal and true rate of interference because interference is such a rare event in these cases.

Complexity Increases the Likelihood of Defects

In this study of assembly interference, there are several important trends that are relevant to understanding the relationship between complexity and defects. First, given the same basic level of tolerance control for each feature, the probability of interference increases as

the number of constraints in the interface grow. Each interface feature represents a constraint which may vary in size or position. All of the possible variations in these features or *degrees of freedom* (DOF) must be specified in design and controlled in production to assure proper assembly. This is illustrated in Figure 4.7 which plots the probability of nonassembly versus the dimension degrees of freedom for the products from Table 4.2. Each increase in the number of interface constraints increases the probability of nonassembly.

Figure 4.7. Probability of nonassembly versus the number of degrees of freedom for "products" illustrated in Table 4.2. Items below the dashed line have been evaluated using one-dimensional analysis, and items above the line have been evaluated using multi-dimensional analysis. Arrows indicate the impact of multi-dimensional analysis on specific concepts.

A second trend is that the more complex an interface becomes, the more likely it is that it will be analyzed *incorrectly*. This is reflected in Figure 4.7 by the arrows which show the difference between one-dimensional evaluations and multi-dimensional analysis. Tolerances established using widely accepted one-dimensional methods will typically result in significantly higher rates of interference than anticipated.

Using the best process control, some parts with excessive variation will be used in the assembly process, and can result in damage and defects. Defects originating from this source will occur more frequently as the probability of interference grows. Since increasing interface complexity leads to increased interference, it will also result in higher defect rates.

When process control techniques are guided by tolerance specifications that are not correct, the degraded assembly reliability may never be detected or corrected. This points to one advantage of functional inspection fixtures over computer controlled measurement techniques that can only qualify a part to standards that may not have been set correctly.

Assembly Time Is an Indicator of Interface Complexity

The dimension degrees of freedom for the "products" from Table 4.2 are plotted versus the Design for Assembly (DFA) predicted assembly time in Figure 4.8. This figure shows that there is a general increase in the interface complexity as the DFA assembly time increases.

Figure 4.8. Degrees of Freedom versus DFA assembly time for "products" illustrated in Table 4.2. The solid line is a power curve fit to the data (correlation coefficient (r) = 0.764).

The number of cases examined is not sufficient to accurately characterize the relationship between DFA assembly time the number of interface degrees of freedom, however the trend in Figure 4.8 suggests that the DFA assembly time is an *indicator* of the interface complexity. This trend is consistent with the observation that many of the factors relating to increased assembly time in the DFA tables are associated with orientation and alignment control that become more difficult as the number of constraints increase.

Since DFA predicted assembly time is an indicator of multiple interface dimensions or constraints, it is also an indicator of an increased likelihood of inadequate tolerance analysis leading to higher defect rates. Thus we have established a sound link between Design for Assembly (DFA) time and defect probabilities.

4.3 Bias of the Boothroyd Dewhurst Method

While most designers can easily obtain access to the Boothroyd Dewhurst methodology, using it involves many subjective interpretations. Consequently the results are not invariable measures. In addition, this methodology may be biased in comparison with other methods for predicting assembly times. In this section, the biases of the Boothroyd Dewhurst method are examined.

Bias Relative to Other DFA Methods

Several Design for Assembly (DFA) methodologies have been developed, including an AT&T [60] method, the Hitachi [57] method, and Assembly View [58] which is based on a Westinghouse database. There is an substantial overlap in the basic method of describing assembly times using different DFA methodologies. For example, to predict "Manual Handling" times the Boothroyd Dewhurst method uses factors for axial and rotational orientation control that are very similar to the guidelines used several other approaches. This can be used to compare the bias between the methodologies by

identifying simple geometries, evaluating the "Manual Handling" time by both methods, and comparing the results. Figure 4.9 and 4.10 compare the "Handling" and "Insertion" times for two methodologies labeled "A" and "B." In this comparison, only the part and operation characteristic that are common to both databases have been considered.

Figures 4.10 and 4.11 demonstrate that the trend in "handling" time and "insertion" time for the two methods are similar. If the methods had no relative bias, the assembly time for each assembly action would be the same by either method. This is represented by the "ideal unbiased fit" line shown in both figures. The predicted handling times for method "B" are slightly less than for method "A." This bias is reversed for insertion times where the predictions for "A" are nearly 2 seconds less than method "B." In either case, the greatest consistency is for the least time consuming assembly actions. Brisley et al [97] noted as similar trend in the study of Predetermined Motion Time Systems (PMTS). They stated, "the shorter time values of single-motion elements have much smaller SDs (standard deviations) than those of the longer elements."

Figure 4.9. Handling time by method "A" versus handling time for method "B" for 71 "parts." The correlation coefficient (r) is equal to 0.888 for a power fit.

Figure 4.10. Insertion times for method "B" versus insertion times for method "A" for 61 "parts." The correlation coefficient (r) is equal to 0.818 for a power fit. Note the strong bias.

The scatter in these figures show that the predicted times for individual operations may differ by more than a factor of two. Using the "T" test for the mean of paired observations, we can conclude that the two methods are biased and do not predict the same mean assembly time at the 0.01 level of significance for both "handling" and "insertion."

Each database provides a single time value for a given assembly condition. For example, in Figure 4.9 a square marks the handling time for a part which is predicted to take 4 seconds by one method and 8 seconds by the other. However, the actual handling time for this part is not a single value as either database implies. In a production setting the handling time for such a part varies and is properly described by a distribution rather than

a single value. For this part the difference in the database values suggests that the mean assembly time by the two approaches differs by roughly a factor of two.

This does not mean that one database is correct and the other is in error. Rather, it suggests that there are real differences in the assembly setup, parts, and/or the assembly tasks that have led to different estimates of the average assembly time by the two methods. These inconsistencies are particularly significant. It indicates that the global distribution of assembly times for commonly described operations must be much broader than observed in any single setting and must span the database values!

Even though each method may address more than 14 independent handling variables, they do not capture all of the important subtleties necessary to assure accurate prediction of the time required to perform a single assembly operations. Hence an endless effort to refine these models will be a wasted effort. *None of the methodologies are ideal models of the true complexity of the individual assembly operations.* A method that captures all of the factors necessary to accurately predict the time required to perform a single operation of moderate complexity is likely to be so cumbersome that it will not be a practical analytical tool.

Bias Relative to "Time and Motion" Based Methods

"Standard" times derived from Predetermined Motion Times Systems (PMTS) and the Boothroyd Dewhurst Design for Assembly (DFA) predictions have also been compared in a similar fashion [98]. As in the previous study, only operations that are common to both methods were studied. This analysis was performed for assembly of three separate components consisting of 62 parts. The results for this analysis are shown in Figure 4.11. Where operations were repeated consecutively, the tabulated values plotted in the figure reflect the total execution time for that operation.

Figure 4.11. Boothroyd Dewhurst predicted assembly times versus Predetermined Motion Time System "standard" times for 62 parts on three components [98]. The correlation coefficient (r) is equal to 0.789 for a linear fit. (To show more detail, one point is off the scale)

From Figure 4.11 we can observe that the "standard" time is roughly two thirds the Boothroyd and Dewhurst predicted assembly time. Again we see a wide scatter in the results. Based on the "T" test of the mean for paired observations, we again conclude that the two approaches do not predict the same mean assembly time at the 0.01 level of significance.

The student report [98] noted one important factor that has not been addressed by any of the DFA methodologies: sequentially repeated identical operations can be completed faster than the same operations performed independently. For example, installing five identical bolts in consecutive order takes less time than installing the same five bolts when there are intervening assembly operations. Repetition reduces the cognitive task, and often allows one hand to feed the parts to the other in a manner that substantially reduces the cycle time between insertion activities. Modifying the Design for Assembly methods, particularly the computerized versions, to reflect the reduced assembly time achieved by repetition would be extremely simple. Since repetition is frequently encountered, this would improve correlations with the actual assembly time.

The Distribution of Assembly Times - A Better Measure of Complexity

Although the predicted times for individual operations are not same by different methods, it is fortunate that the *cumulative* distribution of all assembly times follows a relatively consistent pattern. Figures 4.12 and 4.13 are Pareto charts of the predicted assembly times using the Predetermined Motion Time System (PMTS) standard and the Boothroyd Dewhurst method. This is the same data as plotted in Figure 4.11. To prepare a Pareto chart, the assembly operations were first ordered from the most time consuming to the least. The two figures show the relative position of the same two operations in each distribution and illustrate that their positions in the distributions change dramatically. This reflects the large variance predicting the assembly time for specific operations. Comparing the two sets of ordering shown in Figure 4.12 and 4.13, the average difference in the order for a single operation is greater than 10. In spite of this, the shapes of the distributions are virtually identical.

Note that the vertical scales are different in Figures 4.12 and 4.13. Because the shape of the distributions are essentially the same, simply multiplying the Predetermined Motion Time System standard times by 1.82 will approximate the distribution of the Boothroyd Dewhurst assembly times. After rescaling, the remarkable consistency of the two distributions is illustrated in a cumulative distribution function in Figure 4.14 and in a Pareto curve in Figure 4.15.

Due to the rescaling, a comparative test of the means is not meaningful. These two distributions can be described by a mathematical equation based on the zeta function as used by Pareto. The optimum zeta value of α is identical for both distributions ($\alpha_d = 1.15$). A Kolmogorov-Smirnov goodness of fit test will accept the zeta distribution at the 0.20 level of significance while rejecting the normal distribution at the 0.05 level for both sets of data. *From this it follows that the predicted distribution of assembly time is a*

better measure of assembly complexity than the assembly time predicted for individual operations using any method.

Figure 4.12. Pareto chart of PMTS standard times for 62 assembly operations shown in Figure 4.11.

Figure 4.13. Pareto chart of Boothroyd Dewhurst predicted assembly times for the same 62 assembly operations in Figure 4.11 and 4.12.

Figure 4.14. Cumulative distribution of Boothroyd Dewhurst and rescaled standard times for 62 assembly operations compared [98].

Figure 4.15. Pareto curve of Boothroyd Dewhurst and rescaled standard times compared [98]. Dashed line is least square fit to Boothroyd Dewhurst data ($r=.930$). "N" is the number of operations having a greater or equal assembly time.

Bias Due to the Randomness of Classification

Noting that the factors used to identify the assembly time are similar for the various DFA methodologies, it is possible that they could share a common weakness that would not be revealed by mutual comparison. In particular, all of the DFA methods depend upon subjective assessments to appropriately classify each assembly operation. In these cases, there is a possibility that the results may be strongly biased by the randomness of classification process. One of our goals is to test the effectiveness of the classification process.

Classification - A Sorting Problem

An illustrative example of a similar task that shares this problem is a sorting operation such as separating apples into "good" and "bad" bins. The effectiveness of the sorting process could be evaluated by determining the fraction of Type I errors (good apples in the "bad" bin) and Type II errors (bad apples in the "good" bin) that are present after a large sample of apples had been sorted. However, without a standard for "good" and "bad" apples, this type of test cannot be performed. This is the situation that is faced in evaluating the effectiveness of classifying assembly operations.

Using Decision Analysis [99] it can be shown that strong inferences regarding the accuracy of sorting or classification processes can be made even in the absence of absolute standards if three things are known:

1. The "prior" or expected distribution of outcomes can be anticipated,
2. The distribution of the possible outcomes is known, and
3. The observed distribution resulting from sorting is measured.

In the apple sorting example, a farmer watching the harvest may estimate that about 90% of his apples appear to be "good." This represents his "prior" for apple goodness. Where the apples may only be sorted into two bins, a random process will result in 50% of the apples in each of the two bins, representing the distribution of possible outcomes. After the apples have been sorted, the farmer learns that 93% of the apples were put in the "good" bin, providing the observed distribution after sorting. *A key observation from Decision Analysis is that most sorting or classification actions must be correct if the outcome of sorting is skewed in the same direction as the "prior" relative to a random process.*

Economics Favors Efficient Assembly - The "Prior" for Assembly Time

The sorting example illustrates the technique that can be used to assess the accuracy of classifying assembly operations. Productivity is an important element of success in the market place. Inefficient manufacturers will eventually lose market share and will go out of business. As a result, simple assembly operations should be more common than complex assembly operations. Thus, the distribution of assembly times must be skewed to the right.

The Distribution of a Random Sorting Process

If the classification of assembly operations were perfectly random, each handling outcome and each insertion outcome would have exactly the same probability of occurrence. There are 100 possible handling codes or outcomes in the Boothroyd Dewhurst method, and 54 possible insertion outcomes (excluding operations where all solid parts are in place). Together, there are 5400 possible combinations of handling and insertion. Each outcome would be equally likely if handling and insertion codes were randomly determined for each part. The distribution of these outcomes is plotted as a histogram in Figure 4.16.

Figure 4.16. Histogram of observed assembly times for 3782 assembly operations. Also shown is a histogram predicted for random selections of Boothroyd Dewhurst handling and insertion times.

The Measured Distribution after Classification of Assembly Operations

Detailed Design for Assembly data was obtained from 3,782 assembly operations spanning a wide variety of electro-mechanical devices as will be described in the Chapter 5. A histogram of these observations is also plotted in Figure 4.16.

As shown in Figure 4.16, the measured distribution of assembly times is not symmetric and has a long tail on the right hand side of the figure (skewed right), a characteristic that is distinctly different than the distribution that would be obtained with a random classification of assembly time. Because of the large sample size, and marked differences in the shapes of the histograms, we can conclude that classification of assembly operations is not a random process at highly significant levels without resorting to any statistical tests. The "prior" of assembly time is consistent with the *measured* distribution, that is, they are both skewed to the right. Since these distributions are consistent and distinctly different than a random distribution of outcomes, we can conclude that the classification process, is generally correct at least in global terms. This indicates that the predicted assembly times reflect a real link with assembly complexity.

Bias Due to Factors Not Addressed by the Methodology

Thus far we have examined bias measured using factors that are common between the methodologies. As study [98] noted, each of the methods addresses some factors that are unique. For example, the Predetermined Motion Times Systems consider walking time.

Some Design for Assembly methods address the distance between the part pick up point and insertion point.

If picking up part does not require walking, and the methodology used to assess assembly complexity does not address walking, the bias in the results may be minimal. However, if walking is required but is not addressed by the methodology, the bias could be substantial. As illustrated the bias resulting from omitted factors can vary considerably depending upon the specific operation(s) being analyzed. For this reason, an attempt to make a quantitative comparison would not yield useful information. It is more productive to identify the opportunities for improving the methods.

Although a practical method that comprehensively describes assembly may never be defined, we should seek to capture as many of the **major** elements as possible. We have identified four significant factors that deserve added attention in developing better DFA models for assessing of assembly complexity, 1) distance from pick up to insertion point, 2) part presentation, 3) mental processes, 4) and task consistency.

Distance

As previously mentioned, the distance between the part pick up point and insertion point may vary. In particular, large or heavy parts often must be moved a greater distance because they cannot be easily placed at the point of insertion. The partially completed subassembly may also increase the insertion distance. For example, the distance between the pick up point and insertion point on an automobile may be greater, requiring a longer reach, than for a similar part installed in a small appliance like a hand mixer. This factor is addressed by some Design for Assembly methodologies, but not all. It clearly can increase the assembly time and difficulty of the task.

Part Presentation

Gilbreth [100] demonstrated that bricks could be laid at a faster pace with fewer motions if the bricks were arranged in a specific orientation rather than heaped in a jumbled pile. As this illustrates, part presentation can significantly impact the complexity of assembly operations and the "handling" time. Parts should be pre-positioned in the optimum orientation to minimize motions during assembly. Dispensing devices can also simplify handling. For example, picking up small flat items from a flat surface can be difficult and time consuming, but a simple device that presents one flat item at a time with an exposed edge will minimize the handling difficulty and time.

The penalties for handling complexity should be reduced in the DFA methodologies when part presentation is optimized. Such an approach would also foster improved assembly planning in the earliest stages of design. It is remarkable that this is not specifically addressed by any of the DFA methodologies.

Mental Processes

Mental processes, a factor addressed by Predetermined Motion Time Systems (PMTS), are not incorporated in the Design for Assembly (DFA) Methodologies. This factor is

particularly important in assessing the impact of variety, and could be added with minimum difficulty. Variety increases assembly complexity by requiring selection decisions, or decision to include or not include a part. The benefit of Poka-yoke techniques in simplifying these decisions could also be reflected in the database. This approach would permit a clearer assessment of the impact of variety on productivity and quality at the earliest stages of product design.

Task Consistency

Kent Peterson [101] of General Motors provided stopwatch readings for 15 assembly operations observed in a production setting. This data revealed two distinctly different classes of assembly activities which we refer to as Class I and Class II assembly operations. In Class I operations, comprising the majority of cases, assembly activities can be completed in a discrete number of motions which remain fairly constant. Examples of this type of activity are installing light bulbs, purse clips, and prop rods. The distribution of assembly times for this type of operation typically has a single mode.

In the second class of operations, the number of motions required to complete the process is not consistent. For Class II operations, the operator must examine the work in progress and determine if additional action is required. For example, in grinding a braze to an appearance finish, the operator must stop the work in progress, examine the surface conditions, and decide to continue grinding or pass the work to the next assembly station. The distribution of assembly times for these operations are clearly multi-modal as illustrated in Figures 4.17 and 4.18. This class of operations also has larger ratio of variance relative to the mean than Class I operations.

Figure 4.17. Histograms of the time to remove tape during assembly per GM [101]. The operation is described as requiring 1 to 4 "regrasps.

Figure 4.18. Histogram of the time to insert a foam pad per GM [101]. Note Bi-modal distribution.

The Design for Assembly Methodologies do not adequately consider Class II assembly operations. As a consequence, the time to complete the most time consuming assembly operations is generally underestimated. The maximum assembly time in the Boothroyd

Dewhurst database is only 24 seconds. By contrast, the data supplied by GM included operations that took more than 30 seconds to complete, and students identified some assembly operations that they estimated took at least 300 seconds. If Class II operations were incorporated in the DFA methodologies, an increase in the number of operations in the tail of the distribution would be expected.

There may be significant advantage in converting Class II operations to Class I operations. For example, the tape removal illustrated in Figure 4.17 is described as requiring 1 to 4 "regrasps." Increasing the size of grip tabs, or changing the adhesive pattern or strength may increase the probability that the tape will be removed on the first attempt without degrading its function.

4.4 Precision

Subjective standards such as a DFA methodology may have wide variations in interpretation which limit the precision of the standard. To be useful, interpretive variations (noise) must be small relative to the general predictions (signal). As one of the homework assignments in the ME217 [102] graduate class in Design for Manufacturability, students were asked to perform a DFA analysis of a common home Video Cassette Recorder (VCR) tape using the Boothroyd Dewhurst method. Each team of students received a cassette and the same instructions. The consistency of interpreting the assembly complexity was accomplished by comparing the responses for 26 design teams.

Each cassette has 25 parts, of which 21 are unique. The reels and tape were considered as a single part by all of the design teams. As shown in the Table 4.3 teams were most consistent at counting the number of assembly operations based on the ratio of the standard deviation to the mean. Teams were also moderately consistent at counting the number of unique assembly operations and predicting the total Manual Assembly time.

On the other hand, estimates of the Theoretical Minimum Number of Parts were not consistent. Just prior to the evaluation, students were introduced to the concept of "living hinges" where thin sections molded in plastic parts permit large relative motion. The hinge on the cap of plastic shampoo bottles illustrates this type of feature. This undoubtedly contributed to the wide variation in this interpretation, as different teams perceived distinctly different opportunities for eliminating parts through the use of living hinges. The large variability of all of the other assembly parameters can be directly traced to this source.

The consistency of estimating the Theoretical Minimum Number of Parts is likely to be better in products made of metal which cannot have living hinges compared to products made of plastic. It is also probable that a random sample of designers would show less variability than a group that has just been introduced to the concept of living hinges.

However, we would still anticipate that the total assembly time and number of assembly operations would be the most consistently predicted values.

Table 4.3: Statistical summary of the results obtained by 26 teams analyzing a Video Cassette Recorder (VCR) tape using the Boothroyd Dewhurst DFA method. The number of parts in the assembly (N_p) is 25.

	Mean	Sample Standard Deviation	Ratio (std dev/mean)
Number of Unique Operations	20.54	3.02	0.15
Total Number of Operations (N_a)	26.65	2.26	0.08
Manual Ass'y Time (TM) (sec)	191.48	30.88	0.16
Theo. Min. No. of Parts (NM)	11.85	4.09	0.34
Part Count Ratio (N_p /NM)	2.42	1.03	0.43
Op Count Ratio (N_a /NM)	2.57	1.12	0.44
Ass'y Efficiency (EM)	0.185	0.058	0.31

4.5 Improvement Achieved by Using DFA Methods

An important question that is often asked is, "How much improvement is achieved by using Design for Assembly (DFA) methods?" While this does not have a direct bearing on the qualities of the DFA methods that determine their utility as a standard, it does relate to the value in using the methods.

For 27 of the projects studied, Design for Assembly data was available on existing products as well as preferred design concepts. A comparison of these values indicates the level of improvement. The results for this study as well as similar published results are given in Table 4.4.

Table 4.4. Summary of Improvements obtained through the application of Design for Assembly Methodologies.

Data Summary 27 Studies	This Study			Booth. Dew. Improvement (%) [103]	AT&T DFS Improvement (%) [60]
	Average Before DFA	After DFA	% Improvement		
Part Count (N)	43.04	20.52	52.3	51.4	25-45
Theo. Min No. of Parts (NM)	12.41	10.41	16.1		65
N/NM Ratio	4.13	1.98	52.0		
Average Assembly Time	491.9	208.7	57.6	62.3	40-60
Average Efficiency	0.117	0.274	234		

The studies show an average of 57% reduction in total assembly time. In general, the different studies showed similar levels of improvement in reducing the part count, ranging for 25 to 52 percent. The AT&T [60] study showed a significant reduction in the theoretical minimum number of parts not observed in our study.

4.6 DFA as a Measure of Complexity - A Summary

In the engineering sciences, designers have become accustomed to refined standards of high precision and accuracy such as the measurement of length or energy. However, the names for some units, like the foot, remind engineers that these standards were once immature and inconsistent. Although we have shown that our ability to measure product complexity is immature it is a useful relative gage of complexity. From these comparisons, the following conclusion have been drawn:

1. Traditional one-dimensional tolerance studies are not adequate for setting tolerance limits. Although worst case evaluations will tend to be overconservative, one-dimensional statistical methods are generally unconservative.
2. Complex feature interactions often result in non-Normal distributions of clearance. Consequently, predicting the probability of rare interference based on the normal distribution can lead to significant errors.
3. The Design for Assembly (DFA) time is an indicator of the number of interface feature degrees of freedom. Thus, DFA time is linked to part complexity as well as the difficulty of the assembly operation.
4. The probability of interference and defects increases with the complexity of the interface. From this, there is a cause and effect link between Design for Assembly (DFA) time and defect rates.
5. A comparison of the methodologies has demonstrated a consistent trend of increasing assembly time for factors that increase the difficulty of assembly.
6. Each of the investigated methods is biased compared to other methodologies.
7. Assembly time is sensitive to test conditions as reflected in the differences and inconsistencies between database values for individual operations.
8. Since the Design for Assembly database values are derived from an average of several observations, the actual variation in assembly time will be **greater** than the differences between the databases.
9. Due to the range of human performance and conditions of assembly, it is unlikely that any database will ever be able to accurately predict the assembly times of individual operations for a wide variety of industrial settings.
10. The distribution of assembly time predicted by any method is a better measure of assembly complexity than predictions for any individual operation by any method.
11. The predicted assembly times using the Boothroyd Dewhurst method are clearly not a random process. This suggests that the predicted assembly times are in fact related to the complexity of assembly.
12. The DFA methods would be a better measure of assembly complexity if they
 - a) Addressed the decrease in assembly time achieved by sequentially repeated

operations.

- b) Addressed the improvement in assembly achieved by part presentation.
- c) Incorporated factors for the time required for decision processes.
- d) Addressed Class II assembly operations where the number of assembly motions vary from one operation cycle to the next.

13. Designers are most consistent in assessing the number of assembly operation. Using the Design for Assembly methodology, they are less consistent in predicting the total assembly time. Predictions for the Theoretical Minimum Number of parts, an arbitrary measure of the Boothroyd Dewhurst Method, are highly inconsistent.

Chapter 5

Measuring Assembly Complexity

Although we have demonstrated that our ability to measure assembly complexity using Design for Assembly (DFA) methods is immature, the DFA methods are the best available tools for assessing assembly complexity. In this chapter, the Boothroyd Dewhurst method will be applied to assess the complexity of products.

The function and constraints of a design may dictate assembly solutions that are not optimal from an assembly viewpoint alone. Thus, assessments of assembly complexity must be based on the difficulty of assembling real products rather than an assessment of DFA rules or guidelines. The assembly complexity of products may differ substantially from one industry to another and from one company to another. Consequently, data from a large number of projects taken from many different industries has been sought to assure that the conclusions may have the broadest possible application.

To characterize the distribution of observations, a mathematical model is selected and a null hypothesis is formulated that the model describes the data. The experimenter then attempts to reject the null hypothesis using analysis-of-variance test, a Chi-square or Kolmogorov-Smirnov goodness of fit test [104][105]. Traditionally, such an evaluation is performed for a single set of observations, and then assumed to apply to a broad class of similar problems. This practice of characterizing only one or two distributions can lead to serious errors as we shall show.

Following a description of the data sources for this study, the relationship between the simplest measures of product complexity, namely the number of parts and operations, will be examined. In the following sections, the distribution of assembly times and the relationship between total assembly time and the number of assembly operations will be presented. Building upon this relationship, the usefulness of using the arbitrary Boothroyd Dewhurst assembly efficiency as a measure of complexity will be investigated. Finally, the powerful potential for using the Pareto distribution as a predictive tool will be described.

5.1 Source of Design For Assembly Data

Design For Assembly (DFA) evaluations of existing products were performed by students participating in the Mechanical Engineering course on Design for Manufacturability (ME217) taught by Professor Phil Barkan at Stanford University. Their evaluations have been used to quantify the complexity of assembly. Students in the class are organized into groups of two to four students. Each group evaluated an existing product, defined several

alternatives, and evaluated the new concepts to identify a preferred product concept. Among other activities, the Boothroyd Dewhurst® Design for Assembly methodology was used to evaluate the existing products and new concepts.

Although the methodology is relatively easy to learn, the majority of students are novices in its application. Off-campus students participate in the class at several companies throughout the United States. Most of students are majoring in Mechanical Engineering.

Fifty projects have been studied covering a broad class of electro-mechanical products. Since design groups frequently evaluated competitor's products, the study spans an even broader experience base. Over 240 assemblies and subassemblies were investigated by the design teams. A partial list of the companies providing projects included in this study illustrates the breadth of industries covered as follows:

Ford, General Motors, Boeing, Hewlett Packard, Quantum, Sandia National Laboratories, NASA, Toyota, NUMMI, Apple, Silicon Graphics, Hughes, IBM, Raychem, Varion, Cardiac-Mariner, Dionex, FMC, Applied Materials,

Limitations

Although the assembly complexity was assessed for a broad class of products, the study was limited to projects used in Stanford's ME217 class, which may not be representative of global assembly complexity.

In a following section in this chapter, we shall show that assembly complexity can be described by the Pareto distribution. One of the characteristics of this distribution is that it can have an extremely large variance, a consideration that led to the examination of many assemblies in this study. Because of this characteristic, it should not be surprising to find some products that are exceptions to the observed trends. For example, the assembly complexity of one medical component submitted for the class was so difficult that most of the operations could not be described by the Boothroyd Dewhurst method. Failing to recognize these limitations of the Pareto distribution, other researchers could evaluate a single product and conclude that assembly time is normally distributed or follows another distribution.

It is also possible that experienced users of the Boothroyd Dewhurst method may categorize the assembly operations differently than novices. If such differences do exist, it is expected that they would be minor.

5.2 The Relationship Between Part and Operation Quantities

One of the goals of this study is to develop models of complexity that can be used to approximate the impact of design changes without requiring lengthy analysis. For example, it may be helpful to estimate how many assembly operations are required for a competitor's product if only the number of parts are known.

At least one assembly operation is required for each part inserted into a product. However, there may be assembly operations such a spot welding, soldering, or reorientation required that do not add a part to the product. As a result, the number of assembly operations will always equal or exceed the number of parts per product or subassembly. The relationship between the number of assembly operations and the number of parts can be tested as shown in Figure 5.1.

Figure 5.1. The Number of Assembly Operations per subassembly versus the number of parts per subassembly for 240 observations. It is impossible to have valid observations in the shaded area. The solid line, which has the equation shown in the figure, is a linear least square fit and has a correlation coefficient (r) = 0.977.

The equation given in the figure shows that there is an average of five assembly operations for every four parts in a product. An *analysis-of-variance* test rejects the null hypothesis that the slope of the data is zero, demonstrating that the linear model is a reasonable description of the relationship between the number of parts and assembly operations at a highly significant level (0.01).

Better Estimates of the Operation Count for Redesigned Products

A better estimate of the number of assembly operations can be obtained for a redesigned product. We examined 17 cases where we had the number of parts and operations for a product before and after redesign. The ratio of operations to parts was generally about the same before and after redesign. Multiplying the number of parts after redesign by the ratio of operations to parts in the original concept predicts the number of operations in the new concept. We found that these predictions were better in 14 of 17 cases than obtained using the equation in Figure 5.1. The average error in predicting the number of assembly operations by this method was less than a third of the average error by the previously described approach.

5.3 The Distribution of Assembly Time in a Product

One of the primary objectives of this study has been to characterize the distribution of assembly times for a variety of assemblies. Defining such a relationship is a key element in understanding assembly complexity, providing a critical link that enables comparison of the complexity of dissimilar products and concepts.

The distribution of Boothroyd Dewhurst predicted assembly times for 18 assemblies have been studied in detail. A histogram and Pareto chart for the assembly times per operation for a product are shown in Figures 5.2 and 5.3. These distributions are typical of the general pattern that has been repeatedly observed for hundreds of products. The histogram clearly indicates that assembly times are strongly skewed to the right. The Pareto chart of the same data substantiates the relationship of the trivial many and important few observed by Juran [39]. The consistency of these patterns suggested that the complexity of assembly could be described by a distribution which was non-normal.

Figure 5.2. Histogram of Boothroyd Dewhurst predicted assembly time per assembly operation for an instrument panel (Case 3). Data is sorted into 1.7 second time bins.

Figure 5.3. Pareto chart plotting the Boothroyd Dewhurst predicted assembly time per operation sorted in descending order for an instrument panel (Case 3).

Figure 5.4 is a Pareto *curve* of the assembly time per operation for the same product examined in Figures 5.2 and 5.3. The pattern of the data reflects a remarkably linear trend when plotted on this log-log scale.

Figure 5.4. Pareto curve plotting the number of assembly operations having an assembly time greater or equal to the value on the x-axis for an instrument panel (Case 3). The points reflect the Boothroyd Dewhurst predictions. The solid line is the least squared linear fit to the log-log data, and the dashed lines represent the Maximum Likelihood Estimator.

Comparing the Least Squares Fit and MLE

Figure 5.4 also illustrates the differences between the least squares linear fits to the log-log values and the Maximum Likelihood Estimator (MLE) for Pareto distributions described by Johnson and Kotz [42]. The MLE value of the slope ($\alpha_{c(MLE)}$) may be determined by the following equation:

$$\alpha_{c(MLE)} = \frac{n}{\sum_{i=1}^n \ln(x_i / x_{min})} \quad (5.1)$$

Where, n = the number of observation
 i = counter for the observations
 x_{min} = minimum observation
 x_i = i th observation
 $\ln$ = the natural logarithm

The line based on the Maximum Likelihood Estimator (MLE) must pass through the observation with the minimum assembly time. By contrast, the least square fit is not constrained to pass through any point. As illustrated, the linear fit generally has slightly steeper slope.

The shape observed in Figure 5.4 is typical of many Pareto distributions. Berger and Mandelbrot [76] noted that the linear form reflected in this figure is sufficient to reject the normal distribution and as well as geometric distributions. Deviations from linearity at the extreme ends of the curves are commonly encountered [74][76]. Palgrave [106] noted that Pareto's "law does not and cannot be expected to hold good at the two extremities ... As the law relates to averages it is not be expected that it should be verified at the higher extremities where only one or two observations occur..."

Table 5.1 summarizes the important statistical properties of the 18 distributions studied. Based on the data listed in this table, the normal distribution can be rejected for three specific reasons. First, the normal distribution predicts that a significant fraction of assembly operation will take *less than zero seconds*, an outcome that is clearly impossible. Secondly, the distributions of assembly time are clearly skewed to the right, a property that is not consistent with the normal distribution. Finally, in six of the eighteen cases, the null hypothesis that assembly time is normally distributed is rejected at the 0.01 level of significance using the Kolmogorov Smirnov goodness of fit test.

In contrast, the null hypothesis that the distribution can be described by the zeta or Zipf distribution cannot be rejected at the 0.20 level of significance in 17 of the eighteen cases using the Kolmogorov Smirnov goodness of fit test. Thus, the zeta distribution is a clearly superior fit to the data than the normal distribution.

In Figure 5.5 the level of acceptance for the normal distribution and the zeta distribution is plotted as function of the number of operations in the assembly. As shown in this figure, the ability to reject the normal distribution is very sensitive to the size of the sample. Furthermore, serious errors could be made in incorrectly accepting the a null hypothesis if the experimenter depended upon a single set of data to characterize a distribution. Note that the normal distribution is accepted at the 0.15 level of significance for a sample containing 80 data points. This points to an important weakness in current statistical practice.

Figure 5.5. The level of acceptance using the Kolmogorov Smirnov goodness of fit test versus the sample size for a test of two null hypothesis: A) the distribution of assembly time can be described by the normal distribution, and B) the distribution of assembly time can be described by a zeta distribution.

Table 5.1 shows that the time step increments for the optimum zeta distributions are very large, revealing a potential weakness in accepting the zeta or Zipf function. As a consequence of the large time step increments all of the data falls within the first 3 or 4 bins resulting in a poor level of resolution for testing the goodness of fit. This has led to a more thorough investigation of the distribution of assembly time.

**Table 5.1. Summary of Statistical Evaluations for Boothroyd Dewhurst Predicted
Assembly Times for 18 Assemblies**

Case	Description	# of Ops (N)	Mean	Std Dev	Skew- ness	Std Dev/ Mean	Normal		Discrete zeta or Zipf			LstSqr-loglog		Converted Distribution				
							Max	Accept	α	Time Step	Accept Level	raw data		α (c)	Min Time	Accept Level	r(neg)	MLE α
							S(n)-Fx(n)	Level				α	r(neg)					
1	Panel A	198	6.567	3.165	1.18	0.48	0.281	<0.01	1.60	5.00	0.20	2.12	0.937	1.58	2.90	0.20	0.965	1.58
2	Panel B	136	7.108	3.380	0.80	0.48	0.214	<0.01	1.73	5.94	0.20	1.91	0.905	1.45	2.95	0.20	0.946	1.45
3	Panel C	125	6.054	2.758	1.62	0.46	0.267	<0.01	1.73	5.06	0.20	2.45	0.966	1.77	2.95	0.20	0.982	1.77
4	Sub Ass'y A	31	6.377	3.157	1.54	0.50	0.397	<0.01	1.73	5.33	0.20	2.03	0.941	1.87	2.70	0.20	0.991	1.87
5	Sub Ass'y B	10	4.790	1.348	0.82	0.28	0.279	0.20	1.73	4.00	0.20	2.72	0.956	3.02	2.70	0.20	0.977	3.02
6	Panel D	129	5.598	1.632	0.56	0.29	0.16	<0.01	1.73	4.68	0.20	2.96	0.903	2.07	3.45	0.20	0.966	2.07
7	Panel E	133	6.223	2.31	0.14	0.37	0.124	0.01	1.73	5.20	0.20	1.95	0.834	1.59	3.50	0.05	0.921	1.51
8	Heater	17	7.319	3.308	-0.13	0.45	0.243	0.20	1.73	6.12	0.20	1.22	0.820	1.44	3.20	0.20	0.897	1.44
9	Heater	13	7.343	3.620	0.21	0.49	0.194	0.20	1.73	6.22	0.20	1.18	0.846	1.33	3.30	0.20	0.919	1.33
10	Door	35	5.120	1.323	1.38	0.26	0.329	<0.01	1.75	3.50	0.20	3.27	0.893	2.18	3.10	0.20	0.970	2.18
11	Pulley Old	148	7.100	3.204	0.55	0.45	0.167	<0.01	1.75	5.75	0.20	1.72	0.859	1.44	3.70	0.05	0.938	1.44
12	Pulley New	62	8.606	3.328	-0.20	0.39	0.155	0.10	1.60	5.90	0.20	1.49	0.769	1.25	3.70	0.20	0.885	1.05
13	Sensor Old	136	7.146	2.211	0.45	0.31	0.140	0.01	1.75	5.75	0.20	2.61	0.874	1.62	3.30	0.20	0.951	1.49
14	Sensor New	20	6.665	3.152	0.41	0.47	0.226	0.20	1.50	5.75	0.20	1.51	0.895	1.64	3.00	0.20	0.949	1.64
15	Switch	84	7.071	2.033	0.01	0.29	0.119	0.15	1.75	5.50	0.20	2.32	0.809	1.85	4.20	0.20	0.931	1.66
16	Window	204	6.943	3.038	0.20	0.44	0.086	0.05	1.70	5.90	0.05	3.18	0.828	1.40	3.40	0.01	0.925	1.38
17	Headlamp-A	53	6.342	2.437	0.84	0.38	0.217	0.01	1.80	5.25	0.20	2.78	0.827	1.57	3.00	0.20	0.947	1.57
18	Headlamp-B	30	6.037	2.901	1.22	0.48	0.193	0.15	1.75	4.75	0.20	2.43	0.939	1.72	2.80	0.20	0.978	1.72
Mean			6.58	2.684	0.64	0.40	0.211	0.07	1.71	5.31	0.19	2.21	0.878	1.71	3.21	0.17	0.947	1.68

Notes Acceptance levels are for Kolmogorov-Smirnov "Goodness of Fit" Test
Max |S(n)-Fx(n)| is the Kolmogorov Smirnov Test Statistic

α = Riemann zeta coefficient
r = Correlation Coefficient
MLE= Maximum Likelihood Estimator

$$\text{Skewness} = \frac{\sum (x - \bar{X})^3}{N \times \sigma^3}$$

Two Opportunities for Improving the Data

We have obtained the predicted assembly times for 3,782 individual operations. A cumulative distribution function for this data is plotted in Figure 5.6. There are two remarkably sharp steps in this distribution, which contribute to the difficulty of fitting any function to the data. The first and largest step begins near an assembly time of 5 seconds.

Figure 5.6. The cumulative distribution function for the Assembly time per operation for 3782 operations. Although the data extends to 300 seconds per operation, the horizontal axis has been limited to 24 seconds to show greater detail for bulk of the data. Note the vertical and horizontal steps in the data.

This step is almost horizontal. There can only be two causes for such a sharp step in the data: 1) there are virtually no assembly operations that take between 5 to 6.3 seconds, or 2) there is an error in the data base that causes the step.

A Boothroyd Dewhurst Database Deficiency

There are several reasons for suspecting that the horizontal step is caused by a problem with the database. First, there is no intuitive reason to suspect that there can be a real gap in assembly complexity. Figure 5.6 shows that the slopes before, and after the step are virtually identical, suggesting that there is a simple offset in the predicted assembly time. The cumulative distribution reveals that roughly 35% of all assembly operations take less than 6 seconds. For these operations, insertion times must be less than 4.9 seconds, yet this group of insertion times constitutes only 14% of the insertion alternatives. In this critical group there is a significant gap in the Boothroyd Dewhurst insertion times at 3 seconds. Since the operation time must be split between "handling" and "insertion" times, this gap is roughly consistent with the observed step. Comparison with other databases indicates that the Boothroyd Dewhurst insertion times are generally 1.5 seconds greater, which is roughly consistent with the 1.3 second discontinuity.

To obtain any acceptable fit with a function having reasonable continuity, this horizontal step must be eliminated. The simplest method that is consistent with the shortcomings observed in the Boothroyd Dewhurst database is to subtract 1.3 seconds whenever the predicted operation time equals or exceeds 6.3 seconds.

Converting Discrete Database Values to Distributions

There are also several vertical steps in the cumulative distribution function for assembly time as may be seen in Figure 5.6. The most notable of these occurs at an assembly time of 12 seconds, near the top of the curve. This particular step appears to be due to the frequent use of self tapping screws. These vertical steps can be eliminated by converting the DFA predicted assembly times from discrete values to distributions.

In the production environment, the time required to perform any operation will vary and will not be a single precise value as predicted by the Design for Assembly (DFA) Methods. While these methods use discrete database values for assembly time because of the importance of computational ease, a distribution is a better representation of the time required to complete each assembly operation. The database values should be viewed as the average time required to complete an assembly task.

The study of actual assembly operations has provided a foundation for estimating the assembly time distribution when the average assembly time of an operation is known. In Chapter 6, we shall describe convolutions of the zeta or Zipf function and demonstrate that these convolutions provide an excellent model for assembly performance. Based on a zeta distribution with $\alpha_d=2.0$ and a time step increment of 0.5 seconds, nominal values derived from the evaluation of more than twenty assembly processes, a series of distributions with a sequentially increasing average assembly time were created. Now for each Boothroyd Dewhurst predicted assembly time a search was made to identify the distribution with the mean assembly having the closest match to the DFA prediction. The selected distribution times were then scaled by a constant to precisely match the DFA prediction.

This process was repeated for each operation in the product. The probability distributions for the individual operations were accumulated in a vector for the entire product, producing a distribution of assembly times for the entire product that is likely to be more consistent with production performance than the DFA predictions. Converting discrete predictions of assembly time to distributions tends to smooth the distributions, which improves the ability to find a suitable fit for the data. When a single item such a screw, was used with unusual frequency in a product, this approach would tend to minimize the apparent discontinuities. This tendency to smooth the data is consistent with the observation that the time required to perform assembly of identical parts at different stages in the production process can vary substantially [45].

Converting the Distributions

Each of the distributions studied has been "converted" by eliminating the gap in assembly complexity and by converting the predicted time for each operation from a discrete value to a distribution. As shown in Table 5.1, these conversions improve the linearity of the data. The average correlation coefficient (r) for a linear least squares fit to the logarithm of "N" versus the logarithm of assembly time is -0.878 for the raw data. After the conversion, the average correlation coefficient (r) has increased to -0.946, indicating a

very strong linear trend when plotting the data as a Pareto curve. In every case an *analysis-of-variance* test also rejects the null hypothesis that the slope is equal to zero at the 0.01 level of significance, reinforcing the selection of a zeta or Pareto model.

The difference between the raw data and the "converted" distribution is illustrated for Case 3 in Figure 5.7. Note that the converted distribution has a flatter slope than the raw data. Since assembly times follow a distribution, the shortest assembly times in production

Figure 5.7. Pareto curve of the Boothroyd Dewhurst assembly times and a "converted" distribution obtained by eliminating a gap in complexity and treating each operation time as a distribution rather than a single discrete value for Case 3.

must be shorter than the minimum Boothroyd Dewhurst prediction and longer than the maximum Boothroyd Dewhurst prediction. Thus, the reduction in slope is logically consistent with the observed change.

Using the Kolmogorov-Smirnov Test to Find a Better "Fit"

While the data demonstrates a strong linear tendency in every case, we have been able to define a Pareto distribution which provides a better "fit" to the data based on the Kolmogorov-Smirnov goodness of fit criteria than can be determined using either a linear least squares fit or the Maximum Likelihood Estimator. To illustrate the method for finding a better fit, we will start with a brief description of the Kolmogorov-Smirnov "goodness of fit" method which is given for Case 1 in Table 5.2.

As shown in Table 5.2, the Kolmogorov-Smirnov "goodness of fit" test is based on a comparison of the cumulative distribution of the data to the cumulative distribution of the hypothesized model. As long as the absolute difference between cumulative distribution of the data and the model is less than the Kolmogorov-Smirnov test criteria, the model is accepted at the defined level of significance.

Table 5.2. Kolmogorov-Smirnov "Goodness of Fit" test for the null hypothesis that the zeta distribution ($\alpha_d = 1.6$, time step increment = 5 seconds) fits the Case 1 data. Columns 2 through 4 are based on the data. Column 5 is the cumulative distribution predicted by the assumed model for the data. Since the maximum value in the last column (.069) is less than the Kolmogorov-Smirnov criteria for a level of significance equal to 0.20 ($D(0.20)=0.76$), the zeta function is accepted.

Step	Observed Frequency (Operations per Time Step)	Observed Cumulative Frequency	Relative Cumulative Frequency $S_n(x)$	Expected Relative Cumulative Frequency $F(x)$	$ F(x)-S_n(x) $
0	0	0	0.000	0.000	0.000
1	138	138	0.697	0.766	0.069
2	52	190	0.960	0.892	0.067
3	7	197	0.995	0.936	0.059
4	1	198	1.000	0.957	0.043
Max =					0.069
D(0.2)					0.076
Accept					Ho

The Kolmogorov-Smirnov criteria can be converted into limits about the hypothesized Pareto distribution. To accept an assumed Pareto distribution defined by N_0 , α_c , and t_{min} , it can be shown the number of operations (N) having an assembly time greater or equal to time "t" must fall within the following limits to satisfy the Kolmogorov-Smirnov criteria:

$$N_0 \cdot \left[\left(\frac{t_{min}}{t} \right)^{\alpha_c} - D(\beta) \right] \leq N \leq N_0 \cdot \left[\left(\frac{t_{min}}{t} \right)^{\alpha_c} + D(\beta) \right] \quad (5.2)$$

Where, $D(\beta)$ = Kolmogorov-Smirnov Test Criteria for a level of significance = β

The value of "N" is further constrained by the fact that it cannot exceed the total number of assembly operations (N_0) or be less than zero.

Plotted in Figure 5.8 is a proposed Pareto distribution to be evaluated for as a model of the assembly time for Case 3. The Kolmogorov-Smirnov criteria limits for accepting the Pareto distribution at the 0.20 level of significance are plotted in the same figure. Note that *every* point on the "converted" distribution falls within these limits, indicating that the Pareto distribution can be accepted as a model of assembly time for this product at the 0.20 level of significance. Since the entire curve falls within the limits, this represents a very rigorous test for the goodness of fit of the Pareto distribution.

Currently, we do not have a method that will fit a Pareto distribution to the data in a manner that will maximize the level of acceptance by the Kolmogorov-Smirnov criteria. For each distribution, we have arbitrarily adjusted the minimum assembly time (t_{min}) and

slope (α_c) of the Pareto "fit" line with the goal of accepting the Pareto distribution at the highest possible level of significance. In general, an acceptable fit can be obtained using the MLE slope calculated for the converted distribution, however, the value of $t_{\min}$ must be adjusted. The Pareto distribution can be accepted in every one of the 18 cases studied as shown in Table 5.1. For 15 of these cases, the Pareto distribution is accepted at the 0.20 level of significance, in 2 cases it was accepted at the 0.05 level of significance, and in one case it was accepted at the 0.01 level of significance.

Figure 5.8. The Kolmogorov-Smirnov (K-S) limits for a 0.20 level of significance are plotted as dashed lines on either side of a proposed Pareto curve ($\alpha_c = 1.77$, $t_{\min} = 2.95$ sec) to be tested by the Kolmogorov-Smirnov criteria as a model for the Case 3 data (solid line). Note that the data falls within the Kolmogorov-Smirnov limits, indicating that the hypothesized distribution is accepted.

Consideration for Other Distributions

Other common distributions have also been examined as models of assembly time, including the binomial, poisson, geometric, and exponential distributions. The binomial is not acceptable because it limits the maximum assembly time to a value less than many observations. The geometric distribution does not provide as good a fit as the Pareto distribution. The exponential is related to the Pareto distribution by a simple logarithmic transformation [107]. Such a transformation would degrade the quality of the correlation.

Shown in Figure 5.9 is the Pareto curve for 3,782 assembly operations that we have studied from a variety of products. The general linear trend substantiates the assumption of the Pareto distribution. Note that there are many operations that are predicted to take longer than the maximum possible value (24 seconds) that can be obtained from the Boothroyd Dewhurst database. The long assembly times were reported for assembly operations such as sewing and electrical wiring connections made in the field.

The shortest assembly operation in each product varied from 2.6 to 7.0 seconds. This variation contributes to the distinct curvature in the upper portion of both curves, making it impossible to fit the distribution with a single Pareto curve. We have been able to generate similar distributions using Monte Carlo simulations of Pareto distributions that

vary in the slope, minimum assembly time, and number of operations per assembly. This figure clearly demonstrates that the combination of many Pareto distributions cannot be described by a normal distribution, a geometric distribution or a Pareto distribution!

Figure 5.9. Pareto curve for the assembly time per operation for 3782 assembly operations from a variety of electro-mechanical products.

Although this sample is very large compared to traditional statistical methods, based on the Pareto distribution we would not expect the shape of the distribution to be the same for a different sample of the same size! To provide an accurate assessment of global complexity, the desired sample size must be orders of magnitude larger than this sample, since characterizing the tail of the distribution is critical. The Design for Assembly methodologies are not useful for estimating the time required to perform rare and difficult assembly operations. In fact, the DFA categories may encourage classifying unusual operations as less difficult than they are. For these reasons, we have chosen to focus on the fact that the distribution of assembly times for individual products can be described by a Pareto distribution, a conclusion that is not invalidated by the larger sample.

The Pareto Curve - A Model of Assembly Complexity

This analysis demonstrates that assembly complexity can be completely characterized by three constants which define a point-slope relationship:

- 1) The number of assembly operations (N_0)
- 2) The minimum assembly time for the Pareto curve ($t_{\min}$)
(This time corresponds to the maximum ordinate on the Pareto curve and may differ from the minimum Boothroyd Dewhurst prediction for the product due to the non-linear extremities)
- 3) The slope of the Pareto distribution (α_c).

In most situation, a precise characterization of the distribution is not required. However, due to the range of assembly complexity that can exist, a simple approximation for each product would be extremely helpful. *Since the Pareto curve is a straight line in the log-*

2 of 3

log plot, the assembly complexity can be estimated by performing a Boothroyd Dewhurst analysis of only 2 assembly operations per product! A simple procedures for estimating assembly complexity is given as follows:

- Step 1. Count the number of assembly operation for the product or subassembly (N_0).
- Step 2. Sort the assembly operations according to difficulty using judgement.
- Step 3. Select two of the operations (A and B) for the product and perform a Design for Assembly (DFA) analysis to determine their predicted assembly time (t_A and t_B). To avoid the non-linear extremities, we recommend selecting one operation near the top quartile and one near the bottom quartile for the DFA evaluation. For these two operations, count the number of operations of greater or equal complexity (N_A and N_B)
- Step 4. Calculate the Pareto constant α_c , and t_{min} using the following equations:

$$\alpha_c = \frac{\log(N_A) - \log(N_B)}{\log(t_B) - \log(t_A)} \quad (5.3)$$

$$t_{min} = t_A \cdot \left(\frac{N_A}{N_0} \right)^{\frac{1}{\alpha_c}} \quad (5.4)$$

- Step 5. If desired, the assembly time for i th assembly operation may be estimated using Pareto's law as follows:

$$t_i = t_{min} \cdot \left(\frac{N_0}{N_i} \right)^{\frac{1}{\alpha_c}} \quad (5.5)$$

Where, N_i = the number of operations of greater or equal complexity for the i th operation. If the operations have been sorted from least complexity to greatest complexity, $N_i = N_0 + 1 - i$

- Step 6. Finally, the total assembly time (TM) may be estimated by summing the predicted assembly time for each operation given in Equation 5.5.

$$TM = t_{min} \cdot \sum_{i=1}^{N_0} \left(\frac{N_0}{N_i} \right)^{\frac{1}{\alpha_c}} \quad (5.6)$$

This procedure for predicting the assembly complexity is illustrated in a graphical form in Figure 5.10 for a product having 120 assembly operations. Given $N_A = 90$, $N_B = 30$, $t_A = 5$ seconds and $t_B = 9$ seconds, we would estimate $\alpha_c = 1.87$, $t_{min} = 4.29$ sec, and the total assembly time (TM) would be 1019 seconds.

Figure 5.10. Graphical illustration of the steps (circled numbers) for estimating assembly complexity: 1) determine number of operations, 2) sort operations by difficulty, 3) find assembly time for quartile points, 4) calculate Pareto constants α_c and $t_{\min}$, and 5) estimate assembly times for each operation.

5.4 Using the Pareto Distribution as a Predictive Tool

In the previous sections we have illustrated the ease of estimating the properties of a Pareto distribution when it is used as an analytical tool. In this section we will demonstrate that the measures of complexity can be used as powerful predictive tools that are particularly useful in rapidly estimating the impact of design changes in the concept phase.

We will begin with Case 1 as a baseline design. This product has 198 assembly operations (N_0) with 129 parts. The ratio of operations to parts for this product is $198/129 = 1.53$. Now, for the redesigned product (Case 2) we simply count the number of parts (88) and determine the theoretical minimum number of parts (20). Following a linear trend, for the redesigned product we anticipate 135 assembly operation (88 parts times 1.53 operations per part).

The Pareto parameters defining assembly complexity for the original product are: $\alpha_c = 1.58$ (dimensionless); $t_{\min} = 2.90$ seconds. Although the slope and minimum time can vary from one product to another, we have generally observed that the slope and minimum assembly time of the Pareto curve for a redesigned product is very similar to the Pareto curve of the original product. Thus we anticipate the same slope ($\alpha_c = 1.58$) and the same minimum assembly time ($t_{\min} = 2.90$) for the improved product. The distribution of assembly times and the total assembly time (TM) can now be approximated for the redesigned product based on $N_0 = 135$, $\alpha_c = 1.58$, $t_{\min} = 2.90$ using Equations 5.5 and 5.6 given in the previous section. The total assembly time based on Equation 5.6 for the

redesigned product is 927 seconds which agrees well with the total assembly time of 966 seconds determined by a detailed Boothroyd Dewhurst evaluation.

Figure 5.11 plots the straight line Kolmogorov-Smirnov fit to the Case 1 distribution. The Kolmogorov-Smirnov fit for the redesigned product is plotted as a straight line in Figure 5.12, and in the same figure is the predicted distribution of assembly times based on the Pareto constants determined for the original product.

Figure 5.11. Kolmogorov-Smirnov Fit Pareto curve for the assembly time for Case 1.

Figure 5.12. The line is the Kolmogorov-Smirnov fit Pareto curve for the assembly time for Case 2, a redesign of Case 1. The points are the Pareto based predicted assembly times derived from the slope and minimum assembly time of Case 1.

The Pareto based assembly efficiency using a total assembly time of 927 seconds and a theoretical minimum number of parts equal to 20 is equal to 0.065. Again this is very close to the assembly efficiency of 0.062 determined by a detailed Boothroyd Dewhurst analysis but requires a fraction of the time to resolve. Table 5.3 provides a summary comparing the Boothroyd Dewhurst analysis of the redesigned product and the predictions based on the Pareto properties of the original product, demonstrating remarkable consistency between the two methods.

Table 5.3. A comparison of a Boothroyd Dewhurst analysis of a redesigned product and the predictions derived using a Pareto distribution based on the original product. The slope and minimum assembly time from the original product, Case 1, and the part count and theoretical minimum number of parts from the redesigned product, Case 2, have been used to make the predictions that are highly consistent with the Boothroyd Dewhurst analysis.

	Case 1 Original Design	Prediction for Redesign	Case 2 Redesigned Product B&D Analysis	% Difference Prediction vs Redesign
Parts (N_p)	129	88	<-----88	
Ass'y Operations (N_a)	198	135	136	0.7
Min. Ass'y Time (t_{min})	2.9 -->	2.9	2.95	1.7
Pareto Slope (α_c)	1.58 -->	1.58	1.45	9.0
Total Ass'y Time (sec)	1300	927	966	4.0
Theo. Min. No. of Parts	27	20	<-----20	
Assembly Efficiency (EM)	0.062	0.065	0.062	4.2

5.5 Wide Potential Application of Pareto's Law

The Pareto and zeta distribution may have potentially wide application. To illustrate, we have also found that the distribution of parts and assembly operations per product follow Pareto's law. In addition, ME217 [102] students submitted a breakdown of the cost per part for some of the products which they examined. Five Pareto curves of part cost from the student reports are plotted in Figure 5.13. While we have not studied these distributions in detail, the highly linear nature of the curves, suggests that this is another suitable application of Pareto's law.

Figure 5.13. Pareto curve of Part Cost for five products (Stanford ME217 data [102]).

From an even broader perspective, we have tabulated the cost per unit volume and annual United States production for several common engineering materials in the period between 1990 and 1992 [108][109][110]. The data, covering a range from polypropylene to continuous cast steel, is plotted in Figure 5.14 and appears to follow Pareto's law.

Collectively these examples suggest that Pareto's law has broad application in understanding product complexity, and may be of particular benefit in defining part complexity.

Figure 5.14. Pareto curve of Material Value in thousands of dollars per cubic meter based on values from Rauch [108], Predicast's Forecasts [109], and Metal Statistics [110]. The ordinate is equal to the total number of cubic meters of material produced. The solid line is the linear least squares fit to the log-log values of the data.

5.6 Total Assembly Time Versus the Operation Count

Some data supplied for this study included the total DFA predicted assembly time without a breakdown of the time distribution for the individual assembly operations. In these cases, the relationship between the total predicted assembly time and the number of assembly operations provides another useful, though less accurate, assessment of assembly complexity. The total assembly time for a product provides a composite view of the cumulative impact of the individual operations. Figure 5.15 is a plot of the total assembly time versus the number of assembly operations for 240 assemblies and subassemblies.

While the figure shows that there is a strong linear trend relating the total assembly time to the number of assembly operations, the spread in the distribution about the trend line is significantly larger than would be anticipated if individual operations times were normally distributed. Assuming that assembly operation times for each product follow a Zipf (or Pareto) distribution, each assembly operation can be thought of as a random "trial" or draw from an infinite Zipf distribution. For example, in a product with 40 operations, we can think of the distribution of assembly times as 40 random draws from a Zipf distribution. The cumulative time of the 40 random trials has a distribution that can be

described by 39 convolutions (trials-1) of the Zipf function. The method for computing convolutions of the Zipf function is described in detail in Chapter 6.

Figure 5.15. Total Manual Assembly Time versus the Number of Assembly operations for 240 assemblies and subassemblies. The bounds in the figure are based on a Zipf distribution with $\alpha_d = 1.55$, and a time step scale factor of 4.40 seconds.

The bounds illustrated in Figure 5.15 have been determined using convolutions of the Zipf function. Note that the distribution is not symmetric about the median value indicated by the solid line, a characteristic that is also reflected by the data. Lines representing the 50% and 90% confidence interval based on the Zipf distribution are also shown in the figure. The number of observations falling in each confidence band is consistent with these defined probabilistic limits. There is no simple equation that describes the shape of these curves, although they appear to be nearly linear. Using curve fitting techniques the shape of these curves may be approximated. This has been the basis for bounding assembly efficiency which is described in the following section.

Assembly Efficiency

According to the Boothroyd Dewhurst Design for Assembly (DFA) Method, the most important measure of ease of assembly is the assembly efficiency (EM). This relationship has become a relatively common measure of assembly ease and is given by the following equation [36].

$$EM = \frac{3 \text{ seconds} \times NM}{TM} \quad (5.7)$$

Where, NM = Boothroyd Dewhurst Theoretical Minimum number of Parts

TM = Boothroyd Dewhurst predicted Total Manual assembly time

3 seconds = Boothroyd Dewhurst ideal assembly time per part of

One of our objectives has been to evaluate assembly efficiency (EM) as a measure of complexity. This requires comparison of assembly efficiency for a wide variety of products which differ in the number of parts, assembly operations, and theoretical minimum number of parts (NM). A common basis is needed to make meaningful comparison. Eventually this led to a dimensionless measure, the Operation Count Ratio,

which is simply the total number of assembly operations divided by the theoretical minimum number of parts for each product.

Figure 5.16 plots the assembly efficiency versus the operation count ratio for the 240 assemblies evaluated. Several points are off the scale to the right, but fall within the same general pattern. One of the striking features of the data shown in this figure is the distinct band where the observations are clustered.

Figure 5.16. The Boothroyd Dewhurst Manual Assembly Efficiency (EM) versus the Operation Count Ratio which is the number of operations divided by the theoretical minimum number of parts (NM). The data is for 228 assemblies and subassemblies. Another 12 observations fall within the same pattern but are off the scale to the right.

The assembly efficiency has a relatively constant value when the operation count ratio is large (>5). *In this region, assembly efficiency is not very descriptive of the differences in the ease of assembly.* When the assembly efficiency is very low, small changes in efficiency reflect large differences in the predicted assembly time. For example, the predicted assembly time for an assembly having a 2% assembly efficiency will be five times as great as a product with an assembly efficiency of 10% for the same theoretical minimum number of parts. A better comparative measure of ease of assembly would be the inverse of assembly efficiency. This "inefficiency" ratio has no upper bound, and is descriptive of the potential level of improvement.

Over a broad range of values, the difference between the upper and lower range of observations is very narrow, suggesting that the assembly efficiency can be estimated with very little effort, and without dependence upon a database or detailed analysis. The limits for these bands have been determined from the relationship of the total assembly time to the number of assembly operations. The limits for assembly efficiency actually become more restrictive as the theoretical minimum number of parts increase. This change is illustrated in Figures 5.17 and 5.18.

Figure 5.17. The Manual Assembly efficiency versus the operation count ratio (Operations per Theoretical Minimum Number of Parts) for assemblies where $NM=2$.

Figure 5.18. The Manual Assembly efficiency versus the operation count ratio (Operations per Theoretical Minimum Number of Parts) for assemblies where $NM=7$. Note the change of the confidence interval compared to Fig. 5.17.

Estimating Assembly Efficiency

When there is a desire to estimate the assembly efficiency without performing a detailed analysis, the following approximate formula has been developed based on fitting curves to the zeta convolutions of total assembly time for a given number of assembly operations:

$$EM_{\beta} = \frac{NM}{A + B \cdot N_A + C \cdot \sqrt{N_A}} \quad (5.8)$$

Here, β = The probability that Assembly Efficiency is less the calculated value

$$P\{EM < EM_{\beta}\} = \beta$$

N_A = The number of assembly operations, Note $N_A \geq NM$

A, B, C = Constants as given in Table 5.4.

Table 5.4. Constants for estimating the confidence intervals for the assembly efficiency when the number of operations (N_A) and Theoretical Minimum Number of Parts (NM) are known. The Constants A, B and C are used in Equation 5.8.

β	$1 < N_a < 40$			$N_a \geq 40$		
	A	B	C	A	B	C
0.05	44.1486	7.6092	-20.3941	4.4772	6.6093	-8.1133
0.25	25.2788	7.8462	-13.881	5.0710	7.3638	-7.7868
0.50	9.3976	8.0344	-7.2839	5.0516	8.0473	-6.6851
0.75	-9.0395	8.2818	2.2564	3.0079	8.8594	-3.0387
0.95	-12.9088	9.5547	22.1557	-12.8047	9.8475	20.1984

To illustrate the utility of these equations, we will apply them in predicting the assembly efficiency for Case 2 which has 136 parts with a theoretical minimum number of parts equal to 20. Entering these values into Equation 5.8, we predict that there is a 90% confidence that the assembly efficiency will be between 0.039 and 0.072 with an expected median value of 0.059. The result of a detailed Boothroyd Dewhurst analysis gives an assembly efficiency of 0.062 for Case 2 which is well within the predicted range and close to the median prediction for assembly efficiency. While the Boothroyd Dewhurst analysis would require several hours, our predictions can be made almost as quickly as the number of assembly operations can be counted.

5.7 Using Complexity to Guide Design

The study of assembly complexity has led us to challenge one of the most widely accepted rules of Design for Manufacturability: minimize the number of parts [30][31]. Whenever the goal of design focuses on a quantity measure, as this rule does, there is significant risk that the *difficulty* of the elements of design may be increased unnecessarily with a net increase in complexity rather than a reduction. A global perspective is essential if the hazards of overly simplified rules are to be avoided. This has been demonstrated by the characterization of assembly efficiency.

The assembly efficiency versus the operation count ratio is plotted on a log-log scale in Figure 5.19. This is the same data plotted in Figure 5.16 using a different scale. Adjacent to Figure 5.19, the assembly efficiency versus the part count ratio, or the number of parts (N_p) per the theoretical minimum number of parts (NM), is shown for the same projects. The least squares fit for the log-log values is shown by a heavy solid line in both figures, which clearly shows a strong linear trend in either cases. However, the data in Figure 5.20 has shifted downward compared to Figure 5.19.

Figure 5.19. Assembly Efficiency versus the operation count ratio (Operations per Theoretical Minimum Number of Parts (NM)). The upper and lower lines reflect the 90% confidence limits based on $NM = 4$. The heavy Solid line is a least squares fit.

Figure 5.20. Assembly Efficiency versus the part count ratio (Parts per Theoretical Minimum number of parts (NM)). The upper and lower lines reflect the confidence limits from Figure 5.19. The heavy Solid line is a least squares fit.

A Superior Design Rule

The most important difference in these two figures can be observed in the lower left hand quadrant of the respective figures. Along the vertical axis in Figure 5.20 there are three products which having assembly efficiencies below 0.10. In addition, there are nearly four times as many points below the lower bound in Figure 5.20 compared to Figure 5.19. *This shows that products can have extremely low assembly efficiencies even though the number of parts in the assembly have been minimized!* Minimizing the part count may contribute to difficult assembly. By contrast, reducing the number of assembly operations tends to reduce the part count but also assures that assembly efficiency improves as demonstrated by the sparsity of points below the boundary in Figure 5.19. Consequently, a superior design rule is: *Simplify and Minimize assembly operations*. This rule describes two different methods of improving assembly. Simplifying assembly involves reducing the difficulty of each assembly operation, which is the equivalent of reducing the time required to perform the operation. Minimizing assembly operations requires elimination of unnecessary operations.

The difference between simplifying and minimizing assembly operations is illustrated in Figure 5.21 using the assembly proposed by Olivera [92]. The DFA predicted assembly time for the original product (assuming the box is not square) is 22.5 seconds. Eliminating one fastener, which is illustrated in the top right corner of Figure 5.21, *minimizes* the number of assembly operations and reduces the assembly time by 7.8 seconds to 14.7 seconds, but does not change the difficulty of any of the remaining tasks.

After this change, the lid still has one subtle feature, the uncentered hole, that makes alignment difficult. In the second change, the single remaining fastener location is moved to the center of the box, and the box is squared so that the lid can fit in two orientations.

In this case, the number of assembly operations have not changed, but the lid is easier to orient, representing a *simplification* of the assembly process. The assembly time is reduced another seconds to 13.8 seconds.

In the last change, the lid is changed to a snap cover. In this case, an assembly operation (screw insertion) has been eliminated and the snap fit is easier than a screwing operation. Thus, this change both *simplifies and minimizes* the assembly operations. The predicted assembly time is 7 seconds, or a third of the time required for the original product.

Figure 5.21. Design changes that illustrate the design goal of "Simplifying and Minimizing" assembly operations. Beginning with the original design (Olivera [92]) in the top left corner, the assembly is first improved by: 1) eliminating a fastening operation (minimize), 2) centering the fastener (simplify), and 3) Changing the fastener to a snap cover (simplify and minimize).

Caveat in Applying the New Design Axiom

While the axiom of simplifying and minimizing assembly operations is superior to minimizing the number of parts, it must also be applied with discretion. We have shown in three separate cases involving printer and automotive products that a focus on simplifying assembly has lead to unnecessary part complexity [34]. In a study of Polaroid products and coffemakers, Ulrich et al [111] also observed that simplifying assembly could lead to increased part complexity. This in turn increases the cost of development and time needed to acquire tooling for parts on the critical path. A relationship between part complexity and mold fabrication time for plastic parts was presented by Ulrich et al as shown in Figure 5.22.

These observations reinforce the importance of global rather than local optimization. The optimum product has the minimum combination of *part and assembly complexity*.

Figure 5.22. Estimated Mold Lead Time versus Part complexity for 136 injection Molded Parts in 19 consumer coffeemakers from Ulrich [108]. They defined part complexity as "the sum of the complexities of the regions of the part corresponding to the mold cavity and to each of the mold actions. The complexity of the region of the part is in turn the product of the size of the region and a subjective 1 to 4 rating of feature complexity."

5.8 Summary of Observations on Assembly Complexity

In this Chapter, we have shown that there is a strong linear correlation between the number of parts and number of assembly operations in a product. As illustrated in Figure 5.1, there is an average of five assembly operations for every four parts in assemblies.

We have also shown that the distribution of assembly time follows a zeta or Pareto distribution, while rejecting at highly significant levels the possibility that assembly times are normally distributed. Assembly complexity can be completely defined by a point slope formula in the log-log space of a Pareto curve. As illustrated the Pareto curve for any assembly time of any product can be rapidly estimated without having to perform a complete Design for Assembly analysis.

We have demonstrated that the measures of complexity can be used in conjunction with the Pareto distribution to provide accurate assessments of the impact of design changes without the need to resort to detailed Design for Assembly (DFA) analysis. Thus, in addition to being an important analytical model, Pareto's law can be used as a powerful predictive tool.

We have also shown that the total assembly time can be bounded as a function of the number of assembly operations using convolutions of the Zipf function. These bounds lead to a technique for estimating the assembly efficiency that is highly accurate over a wide range of conditions.

The study of assembly complexity has led us to challenge one of the most fundamental axioms of Design for Manufacturability (DFM): minimize the number of parts. We have demonstrated that this can lead to inefficient assembly. A superior design rule is to simplify and minimize assembly operations. However, even this rule has limited value unless applied with discernment because it can lead to increased part complexity.

Chapter 6

The Distribution of Actual Assembly Time

The time required to perform an assembly operation will vary depending upon the assembler and the assembly conditions. Thus the assembly time for each operation will follow a distribution. The total assembly time for a product or subassembly is the sum of the times required to perform many individual assembly operations and is also subject to variation that can be described by a distribution.

Based on the central limit theorem, the normal distribution should accurately describe the cumulative assembly time for multiple assembly operations. However, we have shown that the *predicted* assembly times for individual operations follow a Pareto or zeta distribution which deviates from the assumptions of the central limit theorem. The two alternatives are mutually exclusive. Since a sound model of assembly complexity should be consistent with both the predicted and observed distributions of assembly time, assessing the real distribution of assembly time provides a critical test for our model.

In spite of the enormous importance of assembly time in production, more than 60 years after the first "Time Study," Applewhite [112] noted that there had been no effort to study the *distribution* of assembly time. He stated that researchers were preoccupied with the influence of time, social and metabolic effects, and that the advent of electronic equipment led to emphasis on the micro-components of assembly rather than the total performance. Consequently, the publication of observed assembly time distributions is relatively rare, typically reflecting the cumulative time of several assembly operations without rigorous evaluation. This focus in the literature on the total assembly time per product proved to be invaluable for us, since it led to a study of convolutions of the zeta distribution.

6.1 Convolutions of the Zeta Distribution

In many cases, such as the total assembly time of a product, the observations reflect the sum of a sequence of trials or activities. Each activity can be characterized by a distribution. The cumulative distribution for the sum of two independent random variables is called the *convolution* of distributions of the two variables. Figure 6.1 illustrates two Pareto distributions labeled "X" and "Y" plotted as probability density functions. In the same figure is plotted the distribution for the sum of "X" plus "Y," or the convolution of "X" and "Y." Note that the convolution no longer has the same shape as the Pareto distributions. The minimum value of the convolution is equal to the minimum value of the "X" distribution plus the minimum value of the "Y" distribution.

Figure 6.1. Probability distribution functions (PDF) versus time for two Pareto distributions "X" and "Y" and their convolution "X+Y." Note that the convolution does not have the same general shape as the Pareto distributions.

Convolutions Can Be Represented By A Markov Chain

In the case of assembly, there can be many independent actions requiring compound convolutions. In the continuous case, the convolution of two zeta distributions does not have a solution which can be readily calculated. Consequently, the more complex case requiring multiple levels of convolution is intractable. Fortunately, a solution for the discrete case exists. The outcome of a sequence of trials involving a zeta distribution may be represented by a Markov chain [43][113]. The state (S) after any number of trials is defined as the sum of the outcome for all preceding trials. To illustrate, if the steps in the chain represents assembly time and the first selected part required 2 time steps to assemble, the state after the first trial would be 2. If the next operation required 3 time steps to complete, the state after two "trials" would be 5.

Figure 6.2 shows the first five states of a Markov chain that will describe any zeta sequence of trials. The values in the circles indicate the state where "n" is the number of trials. The number of convolutions is equal to the number of trials minus one (n-1). The arrows indicate the transitions that may occur from any given state. Since every trial must increase assembly time, it is impossible to transition to a lower state. The probability that a transition will occur is indicated adjacent to the arrows. The probability that the next trial will add "i" steps to the total is given by:

$$p_i = P(X = i) = \frac{C}{i^{\alpha_d + 1}} \quad (6.1)$$

In terms of assembly time, p1 would be the probability that the next assembly operation takes one time step to complete and p3 would be the probability that the next assembly operation takes three time steps to complete.

Figure 6.2. Markov chain for state after n trials. This form of the Markov chain results in a constant transition probability matrix. Only the first five states and transitions to these states of this infinitely long series are shown for simplicity.

Using the form of the Markov Chain in Figure 6.2 allows the application of the Chapman-Kolmogorov theorem [43]. This can be used to provide the following equation for calculating the probability distribution for the cumulative value after any number of n trials or assembly actions:

$$\underline{\pi}(n) = \underline{\pi}(0) P^n \quad (6.2)$$

Here, $\underline{\pi}(n) = [\pi_1(n), \pi_2(n), \pi_3(n), \dots]$

A row vector, where elements of the vector ($\pi_j(n)$) are the probabilities that the system is in the j th state after n transitions. The j th state after n transitions is defined as: $S_j(n) = n + j - 1$

$$\underline{\pi}(0) = [1, 0, 0, 0, \dots]$$

A row vector showing the probability that the system is in the j th state before any trials occur: $P(Y=0 | 0 \text{ trials}) = 1$, and $P(Y>0 | 0 \text{ trials}) = 0$.

P = Transition probability matrix, which is formed as follows:

$$P = \begin{bmatrix} p1 & p2 & p3 & \dots \\ 0 & p1 & p2 & \dots \\ 0 & 0 & p1 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

Because the zeta distribution is an infinite series, the matrix and vectors also have infinite dimension. However, since all of the elements of the P matrix below the diagonal are zero, subsets of the matrices can be used to determine the outcome for a limited number of trials. For " m " trials the vectors must each have " m " columns, and the P matrix must have " m " rows and " m " columns.

These simple matrices allow us to compute the cumulative distribution for any number of trials, or assembly actions, in a direct manner without having to resort to complex conditional probability evaluations. Noting that the state represents a "bin" of outcomes, we can multiply the all of the states by a constant to reflect any desired time increment (t_{step}). In this manner the distribution of the total assembly time involving many assembly actions may be rapidly determined when the number of actions (n), the slope of the zeta curve (α_d), and the time step increment (t_{step}) are known.

While calculating the distribution is straightforward if the appropriate constants are known, the values of the constants are unknown and currently cannot be estimated when attempting to fit an existing distribution. To fit existing data, we have used a routine similar to a "Golden Section Search" [114] to find the value of the three constants which minimizes the Kolmogorov-Smirnov test statistic. In the following sections we apply these concepts to observed assembly times in research and production environments.

6.2 Assembly Time Distribution for Repeated Operations

A 1986 book on ergonomics published by a group at Eastman Kodak Company contained a section on the variability of work pace [44]. Included in this section was a figure reflecting the time to perform a self-paced light assembly task adapted from a 1929 study. The figure showed the time required to complete each of more than 260 sequential assemblies for two operators. One operator described himself a feeling "bored" and the other operator felt "fatigued."

The figure was enlarged and digitized. From the digitized figure, the assembly time for each unit was determined. Using this data, the average assembly time per unit was 41.8 seconds for the bored worker and 47.5 seconds for the fatigued worker.

The Kolmogorov Smirnov "goodness of fit" test was used to test the suitability of describing the assembly time as normal distributions. The normal distribution was rejected at the 0.01 level of significance for both the "fatigued" and "bored" worker.

A MATLAB® [115] program was written to search for the optimum time step and number of convolutions providing the best fit for any data given a value for the zeta constant α_d . This program has been provided on a disk. A list of available data and programs is given in Appendix A. For each set of data, the value of α_d was adjusted until the difference between the data and zeta function was approximately minimized. The Kolmogorov Smirnov "Goodness of fit" test was then used to test the suitability of the using the "optimized" zeta distribution to describe the observed assembly times.

Convolutions of the zeta distribution were accepted at the 0.20 level of acceptance for both the "fatigued" and "bored" worker. Figure 6.3 shows the cumulative distribution

functions (CDF) for the assembly times for the two workers and the optimized zeta distributions.

Figure 6.3. Cumulative distribution of assembly times per unit for two workers performing the same self paced "light" assembly task [44]. The "optimized" zeta distributions show excellent fit to the observations. The best fit for the "bored" worker is based on 38 assembly actions fitting the $Z(2.05, 0.8255)$ distribution and for the "fatigued" worker the best fit is based on 110 assembly actions with a distribution of $Z(2.05, 0.3237)$. The best fit normal distribution for the bored worker is also shown, and illustrates the superior match of the zeta function.

It is likely that the two operators had not been trained in performing the assembly in the same "one best way." Unless trained, Gilbreth and Barnes noted that no two people performed their work in exactly the same way [46]. They also noted that workers that could perform their tasks most rapidly used fewer motions that were shorter and less fatiguing. The best fit zeta distributions suggests that the fatigued worker was using about 110 assembly actions each lasting 0.43 seconds and that the bored worker was using only 38 assembly actions each lasting 0.91 seconds to complete the same task. *Thus, the difference in the number of convolutions for the two workers is consistent with the fact that the fatigued worker was probably using more motions in the assembly process.* This is also the first time that the distribution of total assembly time has been accurately defined in terms of the distribution of the time to complete discrete actions.

6.3 Assembly Time Distribution for Different Operators

The data reproduced in the Kodak document demonstrates that the variation of assembly time for each individual performing identical operations in a sequential pattern follows a zeta distribution. However, the same distribution may not apply to samples where many different operators perform the same operation. This type of situation frequently occurs where the volume of production requires many assemblers to perform the same task, where assemblers work in shifts, or where assemblers trade tasks to increase the variety in the job.

Turnball's Block Tossing Experiment

T. R. Turnball [46] had 500 employees in a factory toss 32 blocks measuring $\frac{3}{8}$ inch by $\frac{3}{8}$ inch by 2 inches into a 2 inch by 4 inch hole 4 $\frac{1}{2}$ inches from the edge of the table. At the start of the task the blocks were prepositioned in 4 rows on a work table. The method of performing the task was first explained to each operator. The operator watched the person ahead of him perform the task, and then he tossed the blocks into the hole as fast as he could. An observer recorded the time taken by each person to perform the operation.

Using a random sample of 500 people, each having the same level of training in performing the operation, it would seem natural to assume that the normal distribution would apply to the results based on the central limit theorem. Thus, Barnes overlaid a normal curve on a histogram of the operation times. We analyzed the data using the Kolmogorov-Smirnov goodness of fit test and determined that the normal distribution is rejected at the 0.01 level of significance!

In contrast, convolutions of the zeta distribution can be accepted at the 0.20 level of significance using the Kolmogorov Smirnov test. The best fit for the zeta distribution was found to be the equivalent of 64 assembly actions where each action follows a distribution define by $Z(1.95, .2694)$. The normal and zeta distributions are plotted in Figure 6.4.

Figure 6.4. Cumulative Distribution Function (CDF) for Turnball's [46] block tossing experiment versus the time to move the blocks. The best fit normal and zeta distributions are shown. The vertical distance between the data and the theoretical curves are plotted using a separate scale on the right and demonstrate that the Pareto Distribution is a better match with the data.

The reason that the distribution does not follow the normal is explained by the fact that the value of α_d is less than 2, where the zeta function violates the assumptions required for the central limit theorem to apply.

Sensitivity to Sample Size

While the zeta convolutions shown in Figure 6.4 provide an excellent match for the bulk of the data, the normal distribution appears to provide a better match for the extreme values. The inconsistency between the data and the zeta convolutions is due to the sensitivity of the zeta function to sample size. Illustrated in Figure 6.5 are three Pareto curves having the same slope and minimum assembly time for three different sample sizes.

Figure 6.5. Pareto curves based on $t_{\min} = 3$ seconds and $\alpha_c = 1.75$. The three curves are for three sample sizes: $N_0 = 10, 25$, and 1000. Data must reflect observations for $N \geq 1$.

Figure 6.6. Cumulative Distribution Functions for the data from three Pareto curves shown in Figure 6.5. The three curves are for three sample sizes: $N_0 = 10, 25$, and 1000. Note the differences in curves.

Although Pareto curves are theoretically infinite, the minimum number of assembly operations in a Pareto curve is equal to 1 which is represented by the horizontal line in Figure 6.5. It is unlikely that the data will contain an observation with an assembly time greater the intersection of the Pareto curves with this horizontal line. *Thus, the data is a subset of an infinite Pareto distribution.* Consequently, the cumulative distribution for the data will change with the sample size as illustrated in Figure 6.6.

Truncating the Zeta Distribution

To match the cumulative distribution of a set of data, the infinite zeta distribution must be truncated in a manner that is consistent with the sample size. Using Pareto's law, we first note that the maximum assembly time ($t_{\max}$) in a sample will be equal to:

$$t_{\max} = t_{\min} \cdot \left(\frac{N_0}{N_{\min}} \right)^{\frac{1}{\alpha_c}} \quad (6.3)$$

Where, $N_{\min}$ = The minimum value of "N," ($N_{\min} = 1$ for any finite sample).

This equation can be rearranged to give:

$$\frac{1}{N_0} = \frac{N_{\min}}{N_0} = \left(\frac{t_{\min}}{t_{\max}} \right)^{\alpha_c} \quad (6.4)$$

We can use this relationship to determine the fraction of an infinite population that has assembly times less than the maximum observation in a sample. The cumulative distribution for assembly times that follow Pareto's law can be written [42] as:

$$F_t(t) = 1 - \left(\frac{t_{\min}}{t} \right)^{\alpha_c} \quad (6.5)$$

Where, t is the assembly time per operation in seconds.

The desired fraction of the population can be determined by solving Equation 6.5 using the maximum observed assembly time ($t_{\max}$) in place of " t ". We can then substitute Equation 6.4 into this relationship and simplify to give the following equation:

$$F_t(t_{\max}) = 1 - \left(\frac{t_{\min}}{t_{\max}} \right)^{\alpha_c} = 1 - \frac{1}{N_0} \quad (6.6)$$

Returning to the block tossing experiment of Turnbull, every person performed 32 operations tossing the blocks into the hole. The cumulative fraction of an infinite population represented by 32 operations using Equation 6.6 is equal to 0.96875, which is the basis of truncating the Pareto distribution to model the smaller sample. This is accomplished in two simple steps: 1) the probability distribution (Equation 3.6 in Chapter 3) is divided by the value obtained from Equation 6.6, and 2) this modified distribution is truncated at the point where the cumulative probability reaches a value of unity. This change is made to each row of the "P" matrix in Equation 6.2.

The Truncated Zeta Distribution - A Superior Fit

Based on the truncated zeta distribution, we again searched for the zeta function and number of convolutions which would minimize the Kolmogorov-Smirnov goodness of fit matching Turnbull's data. The results, plotted in Figure 6.7, model that data so accurately that we were surprised by the results. The hypothesized distribution based on 30 trials (29 convolutions) is superior to the normal distribution across the entire span of data and is easily accepted by the Kolmogorov-Smirnov test at the 0.20 level of significance.

Figure 6.7. Cumulative Distribution Function (CDF) for Turnbull's [46] block tossing experiment versus the time to move the blocks. The best fit **truncated** zeta distribution based on 29 convolutions is shown. The vertical distance between the data and the theoretical curve is plotted using a separate scale on the right.

The optimum fit based on an infinite zeta distribution and a truncated zeta distribution are significantly different. In both cases, the optimum number of convolutions is approximately equal to an integral number of assembly actions required to throw each block into the hole, suggesting an important fundamental relationship that may exist between the zeta distribution and actual assembly performance. In addition to providing a superior fit to the data, the zeta function clarifies deviations from the normal and provides deeper insight into the structure of the assembly activities.

Predicting Extreme Values

As the number of operations in a product increases, the shape of the distribution of the total assembly time may appear to be nearly bell shaped. Consequently, the normal distribution is generally assumed without testing even when it is clearly an incorrect choice. Such an error is particularly critical when the goal is to predict the frequency and magnitude of rare events.

Turnball's experiment provides a basis for comparing predictions of rare events using the normal distribution and convolutions of the Zipf distribution. Plotted in Figure 6.8 is the predicted fraction of the distribution in the tails versus the deviation from the mean assembly time measured in standard deviations for Turnbull's experiment. In the region close to the mean, the zeta convolution predictions are very similar to the normal distribution. However, when the distance from the mean exceeds three standard deviations, the predictions of the two functions diverge dramatically.

Figure 6.8. The fraction of the distribution in the tail(s) as a function of the distance from the mean in standard deviations for a normal distribution and 29 convolutions of the zeta distribution ($Z(1.40, .5471)$). Note the divergence above 3 standard deviations from the mean shown by the ratio of the zeta fraction to the normal fraction.

At six standard deviations from the mean, the fraction of the distribution in the tail of the zeta convolutions is nearly three orders of magnitude greater than would be predicted by a normal distribution. Note that the region of divergence between the two functions, 3σ to 6σ , is precisely the range of transition between traditional Statistical Quality Control (SQC) [3] and Motorola's Six Sigma [5]. This demonstrates that the normal distribution should not be assumed without extensive testing when variation must be controlled at the highest levels.

Zeta Convolutions Do Not Tend Toward a Normal Distribution

Since convolutions of the zeta function *appear* to become more like a normal distribution as the size of the sample increases, some may argue that the deviation from normal behavior is only due to small sample sizes. They may suppose that the zeta function just requires more samples than average to approximate the normal. Consequently they may assume that these arguments may be dismissed and the traditional dependence on the normal distribution may be maintained.

Barnes [46] published a distribution of the performance index for a company having some 9000 employees on a wage incentive program based on work rate. The performance index is a measure of relative output of each worker. The distribution covered a 10 year span, and the average performance index of each person was computed every three months. In a ten year period, this represents about 360,000 observations. The data published by Barnes is shown in Figure 6.9.

Figure 6.9. "A distribution curve of the 10-year performance index of all workers (about 9000) in a plant on incentive." per Barnes [46].

By multiplying a constant by the inverse of the performance index, the output of a worker can be converted to a relative measure of the time required to perform a "standard" task. For example, a worker with a performance index of 182 has 1.82 times the output of a worker with a performance index of 100. To achieve the higher output, the worker with the high performance index of 182 must perform the same task in 54.9 % of the time required for the worker with the performance index of 100. Using this approach, the performance index distribution was digitized and converted to a time per standard task. While the performance index is skewed to the left, the time per task is skewed to the right. We have then fit the distribution of the time per standard task with zeta convolutions as shown in Figure 6.10.

Because the number of operations examined per worker in a ten year period is very large (estimated to be about 1600 per worker), it is inappropriate to truncate the zeta distribution which is the basis for computing the convolutions. However, not every person is suited for production activities. Many who lack this aptitude may not even apply for production positions. Others who lack the necessary skills to meet a minimum level of performance may be quickly released or retrained for other positions by the company. In this sense, there is a literal discarding of "outliers" in the population. To model this

influence, the *convoluted* function is truncated. To do this the $\pi(n)$ vector in Equation 6.2 is rescaled and truncated at the point that the modified cumulative distribution reaches unity. The infinite and truncated distribution based on removing the poorest performing 3.3% of the population are plotted in Figure 6.10.

Figure 6.10. Cumulative distribution function (CDF) of the time required to complete a "standard" task for 9000 operators over a ten year period based on data from Barnes [46]. The dashed line is the fit obtained from the zeta function ($Z(1.5,0.0042)$) 105 convolutions, and the solid line is a truncated version of the same distribution with 3.3 percent of the longest times removed. The truncated distribution is accepted at the 0.20 level of significance by the Kolmogorov-Smirnov test.

The truncated convolution of the zeta distribution ($Z(1.5,0.00418)$) using 105 convolutions is accepted at the 0.20 level of significance using the Kolmogorov-Smirnov goodness of fit test. By comparison, the normal distribution is rejected at the 0.01 level of significance. No matter how large the sample becomes, the normal distribution will not be an appropriate model of assembly performance.

6.4 Assembly Time Distribution as a Function of Work Pace

The pace of performing similar tasks may differ from one location or organization to another. Changes in the work pace could possibly impact the distribution of the assembly time. In reviewing the literature, Applewhite [112] noted that the change in the variance of assembly times appeared to be related to the output. He also noted that, prior to his work, none of the research was specifically designed to determine the relationship between output and frequency distribution, but that these relationships were mentioned incidentally as part of previous studies. This is remarkable, particularly in view of the fact that the Predetermined Motion Time Systems (PMTS) had been developed decades earlier.

To determine the distributions of assembly time, Applewhite had 52 college students perform the task of assembling a cable clamp for 15 minute periods. The desired performance levels were explained to the students, who were then asked to perform at four specified levels. The four levels were: a) a "bad day" when no one is watching, b) a "comfortable" work pace level, c) a work rate under an incentive system, and d) the fastest possible level of performance. Conscious work errors were to be corrected at any pace. The part layout was changed to accommodate differences between right and left handed

participants. Applewhite used the data from only 40 of the participants because the work pace of some subjects did not show any distinction consistent with the defined work rate.

The pace of assembly was timed electronically. Whenever a part was removed from a bin or placed in a bin, an electrical pulse passed through a grounding strap worn by the assembler resulting in a computer recorded timing mark. The cable clamp, similar to those found in household control panels, consisted of five parts as illustrated in Figure 6.11. A plot reproducing Applewhite's raw data is given in Figure 6.12.

Our Boothroyd Dewhurst analysis predicted that the assembly time for these 5 parts is 32.7 seconds, or 50 percent greater than the average time for the slow assembly pace. We estimate that the "Theoretical Minimum number of parts" for the clamp is 3, and the assembly efficiency is 28 percent. Counting the manual handling and insertion as separate actions with one reorientation to assemble the nut, there are eleven assembly actions. Using the "Methods Time Measurement" system by Karger and Bayha [116], Applewhite identified twelve assembly operations and predicted a "standard" time of 14.7 seconds which is consistent with the "incentive" pace.

Figure 6.11. Sketch of Cable Clamp assembly studied by Applewhite. Product consists of 2 screws, a nut, a clamp and the clamp body.

Figure 6.12. Frequency distribution of average assembly time for cable clamp for 4 different assembly paces per Applewhite [112]. (Histograms with 2 second time bins would be a more appropriate method of presenting this data)

Again we have tested the data to find the most appropriate fit and have found that zeta convolutions are a superior description of assembly time than the Normal distribution. However, the sample size is so small, that both distributions may be accepted at the 0.20 level of significance by the Kolmogorov Smirnov test. Figure 6.13 illustrates zeta convolutions that match the observed distributions of cycle time.

Figure 6.13. The cumulative distribution (CDF) of cycle time to assemble cable clamps at 4 different paces for 40 students [112]. The curves are based on 26 convolutions of a zeta distribution ($\alpha_d=2.25$), except the slow pace where the number of convolutions was 10.

Every one of the observed distributions are clearly skewed to the right so significantly that the Normal distribution was rejected by Applewhite on the basis of skewness ($\alpha > .09$) and kurtosis ($\alpha > 0.38$). The number of convolutions (=27) for the best fit of a zeta distribution is larger than the number of assembly actions (=12) based on the Methods Time Measurement system or the number of operations (=11) determined using a Boothroyd Dewhurst DFA analysis. In part, this may be explained by the fact that screws and nut were each turned five times to loosely attach these parts to the clamp body. These "actions" may play a real role in describing the distribution of the assembly times even though they are not identified as distinct actions by either of the assembly time assessment methodologies.

Changes in Pace Modeled by a Single Constant

The fit of the convoluted Pareto distribution to this data is remarkable in several respects. Unlike the normal distribution, it reflects the proper tendency for skewness. More importantly, a common number of convolutions (27) and a common value of α_d (2.25) optimize the fit for the three most rapid rates of assembly. The only difference in these three distributions is the scaling factor for the zeta time step increment, which changes in proportion to the mean assembly time as shown in Figure 6.14. *By changing a single constant it is possible to correctly modify the mean, the variance and skewness in a pattern consistent with changing assembly pace.*

Table 6.1 contains a summary of the statistics for the Applewhite data and the predictions based on the zeta distribution. The statistics for zeta function have been based on a truncated zeta distribution. Except for the standard deviation of the Slow assembly pace, the predictions in this table show remarkable consistency with the Applewhite data.

Figure 6.14. Change in the Optimum zeta time step factor as a function of the mean assembly time for optimum fit to the Applewhite cycle times for changing work pace. The number of zeta "trials" (27) and α_d (2.25) are the same for all cases. The line is a linear least square fit through the origin (correlation coefficient, $r = 0.998$). The value represented by the diamond for the slow work pace results in a zeta fit which can be accepted at the 0.20 level of significance but is not the optimum fit to the data.

Table 6.1. Comparison of the statistics for the Applewhite [112] data and the best fit zeta distribution for the fast, incentive and comfortable pace ($\alpha_d=2.25$, 26 convolutions).

Pace	Source	Time Step	Mean	Standard Deviation	Skewness
Fast	Aplwht Data		13.7	1.50	0.63
	zeta	0.4262	14.1	1.61	0.72
Incentive	Aplwht Data		15.0	1.80	0.66
	zeta	0.4675	15.5	1.77	0.72
Comfortable	Aplwht Data		17.2	2.30	0.46
	zeta	0.5408	17.9	2.05	0.72
Slow	Aplwht Data		21.0	3.70	0.56
	zeta	0.6394	21.2	2.42	0.72

The zeta distribution, using a single linear variable, can account for all of the changes in the shape of the distribution resulting from differences in assembly pace. The setup Applewhite used provided timing for each of 12 separate assembly operations necessary to complete each assembly. Plotted in the form of a Pareto charts as shown in Figure 6.15, the assembly operations clearly follow a Pareto distribution (The sample is too small to provide any meaningful statistical test). When the operations are sorted in order of the most time consuming to the least, the order of the operations change for different assembly paces. However, in spite of significant changes in pace and changes in the rank of the operations, the distribution remains virtually unchanged, substantiating the fundamental basis for the zeta distribution.

Figure 6.15. Percentage of cycle time per "action" for four assembly paces in assembly of a cable clamp [112]. Note that the distribution is independent of assembly pace. The order of the operations changes as follows: Slow pace = (1,2,3...12); Comfortable pace = (1,2,3...8,9,11,12,10); Incentive pace = (1,2,3...8,9,12,11,10), and Fast pace = (1,2,3,4,5,7,6,8,9,12,11,10).

6.5 Assembly Time Distribution in Production

While the data provided by the research community is invaluable in understanding assembly, the validity of the theories is strengthened by demonstrating that they apply to a production setting. At our request, Kent Peterson at General Motors was kind enough to provide stop watch readings of 15 assembly operations [101] which they sampled from their files accumulated over a 25 year period. We requested data that provided the largest possible number of observations per operation. In addition, we asked that the selected operations cover a range of average assembly times.

Steve DeLaet, a contract employee working for Kent Peterson, stated in a telephone conversation that their stopwatch readings are taken by trained industrial engineers in production facilities on mature production lines. From this, it can be inferred that the assemblers are skilled and that they are familiar with the assembly operations being performed.

The greatest weakness of the General Motors data for the purpose of this study is the small size of the samples which ranged from 15 to 31 observations. These sizes prevent conclusively distinction between the appropriateness of the normal and zeta distribution. In one of the 15 GM cases the normal distribution could be rejected at the 0.01 level of significance. In two other cases the normal distribution could only be accepted at reduced levels, namely the 0.10 and 0.15 level of significance. Without a single exception, an "optimized" zeta distribution will fit the data better than any normal distribution. On the average, the value for the Kolmogorov-Smirnov test statistic for the zeta distribution is a factor of three better than for the normal distribution. In every case, the zeta distribution could be accepted at the 0.20 level of significance.

Perhaps the strongest evidence supporting the zeta model is the changing pattern of distributions as the mean time for the assembly operations increase. The distributions for

short assembly operations are strongly skewed to the right as illustrated for Case 2 in Figure 6.16, a pattern consistent with a minimum number of convolutions. As the assembly time per operation increases, the distribution spreads, and there is an increasing fraction of values left of the mode as shown for Case 15 in Figure 6.16. More complex operation are comprised of a larger number of separate motions or actions, explaining why more convolutions are required to fit the distribution. This change is intuitively sound and provides a better fundamental explanation for the shape of the distribution than achieved by any other approach.

Figure 6.16. Histograms and Cumulative distribution functions for assembly times of three General Motors stopwatch records of assembly operations. In the histograms, the solid line is the shape of the "optimized" zeta distribution. In the cumulative distribution function plots, the solid line is the best fit zeta distribution, the dashed line is the best fit normal distribution, and the circles are the cumulative distributions of the data. Note the superior fit of the zeta distribution.

6.6 A Global Perspective of Total Assembly Time

We have shown that convolutions of the zeta function have proven to be superior to the normal distribution in describing assembly operations. In addition, the zeta function provides fundamental insights that account for the impact of assembly pace, as well as pointing to relationships to model human variability.

Additional insights can also be derived from the zeta function representations of the skewness of assembly time. Table 6.2 provides a summary of the evaluations performed in this analysis. Of the twenty three distributions studied, all but two were positively skewed! The probability of this occurring in random sample of a distribution that is not

Table 6.2. Summary of Statistical Evaluations for 23 Assembly Distributions

Case	Description	# of Obs. (N)	Variables	Mean $\bar{X}$	Std Dev σ	Skewness	Std Dev/ Mean	Normal		Discrete Riemann zeta					
								Max S(n)-Fx(n)	Accept Level	a alpha	Time Step	"Trials" (Conv.)	Max S(n)-Fx(n)	Accept Level	
CLASS I Consistent Number of Ass'y Operations															
Kodak	Light Ass'y-Bored	267	Consistency	41.77	6.849	1.854	0.16	0.157	<0.01	2.05	0.826	38	0.019	0.2	
Kodak	Light Ass'y-Fatigued	267	Consistency	47.50	4.285	0.595	0.09	0.113	<0.01	2.05	0.324	110	0.037	0.2	
Barnes	Block Toss	500	Operator	23.67	2.915	0.548	0.12	0.083	<0.01	1.95	0.269	64	0.048	0.2	
Barnes	Performance Index	9000	Operator	0.799	0.139	0.978	0.17	0.121	<0.01	1.50	0.004	106	0.011	0.2	
Aplwht	Cable Clamp-Slow	40	Pace & Operator	21.0	3.7	0.56	0.18	0.066	0.2	2.25	1.671	11	0.052	0.2	
Apiwht	Cbl Clmp-Comfort.	40		17.2	2.3	0.46	0.13	0.09	0.2	2.25	0.541	27	0.055	0.2	
Aplwht	Cbl Clmp-Incentive	40		15.0	1.8	0.66	0.12	0.077	0.2	2.25	0.468	27	0.029	0.2	
Aplwht	Cbl Clmp-Fast Pace	40		13.7	1.5	0.63	0.11	0.087	0.2	2.25	0.426	27	0.035	0.2	
GM-1	Scan Bar Code	20	Operator, Task, & Operation Time	2.90	0.912	0.578	0.31	0.238	0.15	1.925	0.404	5	0.044	0.2	
GM-2	O-ring Stretch	30		3.40	0.621	1.120	0.18	0.407	<0.01	2.500	0.236	11	0.014	0.2	
GM-4	Insert Bulb	25		7.60	1.500	0.241	0.20	0.175	0.2	1.875	0.214	24	0.067	0.2	
GM-5	Install Purse Clip	25		8.36	1.411	0.830	0.17	0.201	0.2	2.000	0.285	21	0.039	0.2	
GM-6	Inst. Retainer Clip	20		11.55	1.820	0.197	0.16	0.253	0.1	2.000	0.502	17	0.083	0.2	
GM-9	Install 3 Clips	15		15.67	1.496	-0.779	0.10	0.145	0.2	2.250	0.184	68	0.082	0.2	
GM-10	Wrap Belt	21		19.00	3.162	0.289	0.17	0.121	0.2	1.650	0.195	60	0.076	0.2	
GM-11	Inst. Prop Rod	20		23.75	2.693	0.130	0.11	0.160	0.2	1.975	0.199	87	0.062	0.2	
GM-12	Insert Foam Pad	15		27.40	2.063	0.315	0.08	0.151	0.2	2.250	0.294	74	0.084	0.2	
GM-14	Transfer Engine	20		36.10	6.520	0.735	0.18	0.185	0.2	1.700	0.760	31	0.103	0.2	
GM-15	Fit Carpet	25		45.76	8.171	1.141	0.18	0.137	0.2	1.900	0.852	38	0.027	0.2	
GM-Average							0.17	0.198		2.002	0.375	40	0.062		
Combined Average							0.15	0.158		2.029	0.389	44	0.051		
CLASS II Variable number of Ass'y Actions															
GM-3	Remove Tape	31	Operator, Task, & Operation Time	7.13	3.905	0.478	0.55	0.176	0.2	1.175	1.167	3	0.111	0.2	
GM-7	Brush on Sealer	20		12.05	1.504	-0.875	0.12	0.163	0.2	1.875	0.189	42	0.094	0.2	
GM-8	Epoxy Repair	19		14.26	4.318	0.328	0.30	0.207	0.2	1.350	0.571	17	0.122	0.2	
GM-13	Disc Grind Braze	20		31.95	5.826	0.006	0.18	0.152	0.2	1.750	0.553	38	0.108	0.2	
Average							0.29	0.1744		1.538			0.109		

Notes: GM Data=0.01 Min; Barnes-Index=Fractions; Other =sec
 Max $|S(n)-F_x(n)|$ is the Kolmogorov Smirnov Test Statistic

Acceptance levels are for Kolmogorov-Smirnov
 "Goodness of Fit" Test

$$\text{Skewness} = \frac{\sum (x - \bar{X})^3}{N \times \sigma^3}$$

skewed is incredibly remote. Let "p" be the probability that the distribution is skewed to the right. Given that we have no prior information on p, we will assume that it is equally as likely that p is skewed left, skewed right, or neutrally skewed ($P\{p=0\} = P\{p=1\} = P\{p=0.5\}$). These conditions would be satisfied if p had a uniform probability distribution function. Based on this assumption, we can use the binomial theorem to determine the probability of a left skewed or neutrally skewed distribution using the following relationship:

$$P\{p \leq 0.5 \mid 21 \text{ of } 23 \text{ dist. skewed right}\} = \frac{\int_0^{0.5} p^{21} (1-p)^2 dp}{\int_0^1 p^{21} (1-p)^2 dp} \quad (6.7)$$

The solution to this simple equation shows that the probability that the true distribution is neutrally skewed or that it is skewed to the left is about 18 parts per million.

Consequently, given a uniform probability of skewness it can be stated with a confidence of 0.999982 that assembly operation times cannot be described by the normal distribution or any other distribution that is not positively skewed.

Significance of Rejecting the Normal Distribution

It is difficult to imagine a process involving more random variables than assembly. There can be a large number of different kinds of parts, part presentations, grasping motions, reach distances, and insertion operations required to assemble even simple products, each requiring a different amount of time for execution. Production requires many repetitions of these motions and many different operators can be involved. Based on the central limit theorem, it is anticipated that the cumulative distribution based on independent random variables will approach a normal distribution as the number of random variables approach infinity [43]. On this basis, the total assembly time for products should be approximately normally distributed. This assumption has frequently been made, and is the basis for current methods of establishing "standard" times in Time Studies [46].

In a clear exception to the central limit theorem, we have rejected the normal distribution as a model of the total assembly time at the 0.01 level of significance in several cases based on the Kolmogorov-Smirnov "goodness of fit" test. This conclusion reinforces acceptance of the Pareto and zeta distributions, since they are peculiar in their deviation from the conditions of the central limit theorem. Thus, assembly time is a clear exception to this fundamental principle of modern statistics.

It is important to recognize that we have demonstrated exceptions to the central limit theorem, but have not invalidated it. The Pareto distribution and zeta convolutions do not have universal application. For the Pareto distribution to be a valid description of a population, all of the data must lie within the first quadrant. For example, in the Pareto curve of assembly time we cannot have negative assembly times or a negative number of assembly operations. Consequently, the Pareto distribution, or convolutions of the Pareto

distribution should never be considered if there can be negative values in the data. In some situations, this can be a simple matter of an appropriate definition of the parameters.

The traditional acceptance of the normal distribution as a model of assembly performance suggests that there may be a large variety of phenomena that are not normally distributed, even where tests have concluded that this is the case. This insight points to the importance of caution in using statistical methods to predict the probability of rare events.

One potential benefit of zeta function is that the number of convolutions appear to be related to the number of assembly actions that characterize each assembly procedure. This has provided important insights in the structure of the assembly activity that are not available when a distribution is fit to the data based only on a sense of similarity in shape. Although there is no *a priori* reason to assume human response should follow any particular distribution, in stark contrast to alternative models, the zeta function explains both the fine structure of activity (zeta distribution) and the distribution of the sum of many activities (convolutions).

The Impact of Outliers

We have found that rejecting as few as one observation in 1000 is sufficient to obscure the difference between zeta convolutions and the normal distribution, yet the practice of discarding outliers in data is common [45][112]. This may be one of the strongest indications that zeta convolutions have wide application. While this level of discarding outliers may not seem significant, it is a **critical** factor in predicting the frequency and magnitude of rare events as required when the goal is to achieve very low defect rates.

We are not suggesting that data should never be rejected. There are situations where the data has been incorrectly recorded and an outcome is simply impossible, such as negative assembly time. Although this type of data should be removed, it is inappropriate to remove data simply because it appears to be somewhat inconsistent with the general trend. Such data can be the most valuable information in predicting the distribution of the tails.

The Need for Large Sample Sizes

It is important to note that the standard statistical test was not able to reject the normal distribution when sample sizes were small. As shown in Figure 6.17, Pareto convolutions and the Normal distribution appear to be equal acceptable models of assembly in most cases when the sample size was less than 100 observations. Although the Pareto convolutions could be accepted in every case, large samples showed that the Normal distribution was clearly unacceptable. This figure suggests that the normal distribution may incorrectly be assumed in many situations where it is not appropriate. This is particularly important when the objective is to assess the distribution in the tails, such as defect probabilities. It clearly points to the need for large sample sizes in statistical analysis.

Figure 6.17. The Kolmogorov-Smirnov Goodness of Fit acceptance level versus the number of observations in the sample for the study of 22 distributions of assembly time. Note that the rejection of the normal distribution is stronger as the sample size increases. Shaded areas indicate the general regions where alternative models are accepted as descriptions of the data.

Acceptance of the Pareto distribution has two important implications. First, small samples will underestimate the population variance, a result of inadequately representing the distribution in the tail. Second, small samples will tend to underestimate the true value of the mean. Small samples will rarely contain observations from the tail, and when observed they will typically be discarded. Consequently, the population mean will generally be greater than the sample mean. For the fast paced assembly of the cable clamp, the sample mean was 13.7 seconds. The best fit zeta distribution suggests the population mean is 14.5 seconds, or 5.8 percent higher. The error will decrease as the sample size increases.

Assembly Time-On the Border Between Order and Chaos

The parameters of the zeta distribution which provided the best match with the data suggest that assembly operations are on the border between order and chaos. This suggests that efforts to standardize assembly actions may shift assembly into a ordered state, while uncontrolled assembly activities may result in chaos. The differences in the mean and variance of the two states can be profound even though the changes may appear to be relatively insignificant.

Rejection of the Lognormal Distribution

Many researchers have observed that assembly time or human response follows a distribution that is skewed to the right. Applewhite [112] cited three researchers who observed that output for high production rates is skewed negatively, and concluded from this that the time per task would be skewed positively. His own research reinforced these observations. Swain et al [78] cited five studies in which researchers concluded that human response followed a lognormal distribution that is a positively skewed function.

However, we reject the lognormal distribution for several important reasons. First, if human response per operation followed a lognormal distribution, then the total assembly time involving many operations must follow a normal distribution according to the central

limit theorem. Using the data published by Kodak, we have shown that the normal distribution can be rejected as a model of the total assembly time in two cases at the 0.01 level of significance. Consequently, it must follow that the time to perform each discrete assembly action cannot be described by a lognormal distribution, or any function consistent with the central limit theorem.

We have also tested the lognormal distribution as a model of Barnes [46] data for the performance of 9000 employees over a ten year period. Although the lognormal distribution is a better model than the normal distribution, the truncated zeta convolutions are clearly superior as shown in Figure 6.18. The lognormal distribution is rejected by the Kolmogorov-Smirnov goodness of fit test at the 0.01 level of significance.

Figure 6.18. Cumulative Distribution function of the time required to complete a "standard" task for 9000 operators over a ten year period based on data supplied by Barnes [46]. The truncated zeta convolutions are accepted at the 0.20 level of significance while the normal and lognormal distribution are rejected at the 0.01 level of significance by the Kolmogorov-Smirnov goodness of fit test.

A lognormal fit for the Kodak and Turnball data was also investigated. In two of the four cases studied the lognormal was rejected at the 0.01 level. In the remaining two cases, the lognormal distribution was rejected at the 0.10 level of significance. In contrast, the zeta convolutions can be accepted at the 0.20 level of significance. This demonstrates that the two most commonly accepted models of human response can be rejected at highly significant levels.

Additional Lognormal Applications Reinforce Limitations of the Normal Distribution

The lognormal distribution has been used for modeling quality data in other applications. Albin [117] found that the concentration of aluminum in recycled PET plastics was highly skewed. Like assembly time, the aluminum concentration can not have negative values and as a consequence, the distribution did not have a left tail leading to their use of the lognormal distribution (a zeta distribution will also fits the data). An interesting consequence of their study is that large sample sizes were required to control process

variation. This result supports our observation that large samples are required whenever the distribution has or may have long tails. This work also illustrates the fact that there are many situations where Normal distribution is an inappropriate model.

Zeta Convolutions-A Potential Model of Many Processes

Convolutions of the zeta distribution provide a new model that having potentially broad applications in situations where the lognormal distribution has been assumed. Johnson et al [42] noted:

"Many ...naturally occurring quantities are distributed according to certain statistical distributions with very long right tails... Many distributions have been developed in an attempt to explain these empirical data.

"The Pareto and lognormal distributions have played a major part in these investigations. It has been observed that while the fit of the Pareto curve may be rather good in the extremities of the income range, the fit over the whole range is often poor. On the other hand, the lognormal distribution fits well over a large part of the income range but diverges markedly at the extremities."

In this study we have shown that convolutions of the zeta function have provided a superior fit over the *entire range* of data in situations where the lognormal distribution has been previously assumed. This suggests that convolutions of the zeta function should be considered whenever a distribution appears to have an approximately lognormal shape and has a long right tail.

6.7 Key Findings from the Study of Actual Assembly Time

Following is a summary of the conclusions regarding the distribution of actual assembly times observed in research and production environments:

1. The distribution of observed assembly times does not follow either the normal or lognormal distribution. Our study has confirmed this fact at the highest levels of significance. This represents a clear contradiction of the central limit theorem.
2. While the normal distribution was rejected, convolutions of the zeta distribution were accepted at the 0.20 level of significance as a model of the total assembly time in every one of the 23 distributions examined.
3. The number of zeta convolutions required to match an observed distribution of assembly time is consistent with the number of simple changes in motion.
4. For the same task, the productivity will be lower and/or the stress level will be higher for individuals who use more motions. More convolutions of the zeta function are required to match the performance of individuals who employ a larger number of motions in executing a specific task. This insight reinforces the advantage of standardizing assembly using the "one best way."
5. The change in the mean, variance, and skewness of the assembly times that results from changes in assembly pace can be described by changing a single constant in

the zeta function. This constant, a time step increment, has a linear relationship with the mean assembly time, demonstrating the robust nature of the zeta model.

6. The shape of the distribution of assembly times changes as the complexity of the task increases. This change in shape is accurately modeled by convolutions of the zeta distribution. An increase in assembly complexity requires an increase in the number of convolutions required to match the distribution.
7. The likelihood of extreme values is underestimated by orders of magnitude when the normal distribution is inappropriately used to describe data that follows convolutions of the zeta distribution. This is an extremely important factor when the objective is to control variation to minimize the probability of exceeding defined limits as is often the case in quality conformance programs.

Chapter 7

Testing the Relationship Between Defects and Complexity

The second major objective of this study and the focus of this chapter is to test the relationship between the measures of complexity and production defect rates. Although strong correlations between many measures of complexity and conformance quality may exist, our goal is to determine specifically which of the complexity measures has the highest correlation with conformance quality based on actual production experience.

Producers of similar products can realize defect rates that differ by orders of magnitude [13]. Differences in the effectiveness of quality control can contribute to these differences in defect rates, obscuring the role of complexity. To minimize the confounding influence of different effectiveness levels of quality control between companies, we begin by comparing the defect rates of products within individual companies.

The source and limitations of the complexity and defect data will first be discussed. The results obtained from the analysis of data provided by three companies will be presented. We shall show that there is a remarkably strong correlation between Design for Assembly (DFA) predicted assembly time and the number of defects per unit. The consistency of this correlation is validated by comparing the predicted and observed defects per part.

7.1 Sources of Complexity and Defect Data

To test the desired relationships, data on complexity and defects must be available for several products or subassemblies within each company. Roughly 25 companies producing a variety of electro-mechanical products were approached by telephone or other personal contact to explore the opportunity of a cooperative effort in this study. Detailed written requests were sent to 18 of these companies offering the highest potential for useful data. A sample of the requests for data is included in Appendix B.

Although there appeared to be a keen general interest in this topic, in the majority of cases the desired data could not be obtained for several reasons, including:

- a) Lack of Design for Assembly (DFA) evaluations on projects in production,
- b) Unwillingness to release drawings for others to perform DFA analysis,
- c) Unwillingness to release defect data,
- c) Insufficient number of projects within a single organization, and
- d) Existing work loads which prevented participation in the study.

In several instances where Design for Assembly (DFA) analysis had been performed, it had only been applied to new products which had not reached the production stage. Consequently, the companies often had DFA data without defect rates for products in development or defect rates without DFA data for products in production. In several other instances, companies simply felt that the data was too sensitive to release.

Three companies provided data for this study. Since participation in the study required a substantial effort on the part of the participants, this level of response (17%) is relatively high.

Limitations of the Complexity and Defect Data

Our ability to characterize the relationship between complexity and defect rates has been limited by the response of organizations that elected to participate. This limitation is beyond the writer's control. It is possible that the relationships between defects and complexity for organizations that did not choose to participate could differ. The level of interaction with the companies also varied according to proximity. Differential responses cannot be tested adequately due to the limited number of responses.

Even when data was obtained, the criteria of product defects are subject to interpretation which may differ with each company. The build quantity, and maturity of the products may also vary, posing confounding factors in interpretation of the results.

A final limitation of the study has been the method of identifying the companies and individuals within the companies invited to provide defect data. Generally, defect information is only available through specific channels and organizations within a company. As outsiders, our ability to identify the appropriate organization and individuals was extremely limited, particularly in the many cases where a contact within the company was not known.

7.2 Automotive Manufacturer's Data

One of the companies providing data for this study is a major automotive manufacturer. Each of their products contain more than 9,000 parts. This company provided data for fifteen related products assembled at a variety of locations. Products assembled in a single facility of this company are generally very similar. One of the factories that is an exception to this rule produces three different products having a range of complexity.

This company did not have Design For Assembly (DFA) data for their products, and, owing to the complexity of the products, could not generate such information. The data which they provided included three measures of complexity for the fifteen products, namely:

- 1) Number of assembly operations per unit in the final assembly plant,

- 2) Number of parts per unit, and
- 3) The production rate (Number of units produced per hour)

The automotive manufacturer also provided the number of defects per thousand units for each of the fifteen products. In this application we define a unit as an assembly, subassembly, or product for which we have received complexity and defect data. In the case of the automotive manufacturer, each unit is a vehicle.

We have tried to test every possible relationship between defect rates and measures of product complexity based on the data that has been supplied. For example, defects can be expressed as defects per part, defects per operation, defects per unit or defects per hour. However, we cannot evaluate such factors as defects per worker since no information has been supplied on the number of operators. Similarly several measures of product complexity can be defined including number of parts per unit, the number of final assembly operations per unit, and the estimated assembly time. Although several relationships have been investigated, the following study will focus on the most significant relationships identified.

Quantity Measures Are Not Correlated with Defect Rates

Applying the concept of Statistical Quality Control [3] that is based on Normally distributed process variation, and given a uniform quality conformance objective for each feature, the probability of a defective part should be a function of the number of features in a part. Combining part defects, the total number of defects in a product should be related to the total number of features in the product. Since these products are closely related, the products with more parts should generally have more dimensional features leading to higher defect rates.

More than 250 million parts are produced annually for each product. In such large samples, the local defect variations should be averaged out. From this we would expect that there should be a clear trend of increasing defects as the number of parts in product increases. Such a correlation does not exist as illustrated in Figure 7.1. In fact, *the relationship between product defects and number of parts per product was the weakest of any relationship examined.*

The inability to demonstrate a strong correlation between the number of parts per unit and the defects per unit highlights the weakness of focusing only on quantity as the measures of complexity. There are three reasons that the defects per unit may not be related to the number of parts in these products:

- a) Part quality control is not consistent between products,
- b) Part defects are not the most important source of product defects, or
- c) There are wide differences in part complexity for each product.

Since automotive products share many similarities, it is unlikely that the weak association between part count and defect rates can be attributed to differences in part complexity. From this, the lack of correlation between part counts and defect rates is most likely to be

due to inconsistency in quality control, and may suggest that defective parts are not the dominant source of defects for these products.

Figure 7.1. Defects per unit versus the number of parts per unit for an assembler. The correlation coefficient (r) for this relationship is -0.05 . Data for three products from a common factory are shown as overlapping squares.

Figure 7.2. Defects per unit versus the number of final assembly operations per unit. The correlation coefficient (r) for this relationship is -0.20 . Data for three products from a common factory are shown as squares.

There is a weak trend shown in Figure 7.2 suggesting that the number of defects per unit *decreases* as the number of final assembly operations increase. At first glance, this trend is confusing and counter-intuitive. Without further investigation, we would be left to conclude that there is no link between the measures of complexity and defect rates. Additional analysis will, however, clarify the reasons that the simplistic quantity measures of complexity are inadequate.

Assessing the Complexity of Assembly Operations

A comparison of the horizontal axes of Figure 7.1 and 7.2 reveals that there are more parts than *final* assembly operations for each automotive product. This occurs because components and completed subassemblies are being installed in the assembly plant. For example, a final assembly operation could involve the installation of a car seat, or a transmission, each containing many parts. Figure 7.3 is a plot of the average number of parts added per assembly operation versus the number of final assembly operations per automobile. It reveals that the most complex components and subassemblies are being assembled in products with the minimum number of assembly operations. The differences in average component complexity are dramatic, varying by nearly a factor of two.

Complex subassemblies or components will generally require more electrical and/or mechanical connections than simpler subassemblies. For example, installing a transmission is more difficult than assembling a tire or cigarette lighter. Thus, the average assembly time per operation should be greatest for the products where average component

complexity is greatest. This assumption can be tested. By multiplying the number of operations per unit by the production rate, the number of operations performed per hour was determined for each product. Figure 7.4 demonstrates that productivity measured by the number of assembly operations completed per hour decreases as assembly complexity increases.

Figure 7.3. Average number of parts added per assembly operation versus the number of final assembly operations per unit (vehicle). The equation is a power fit that relates parts per assembly operation (N_p/N_a) to the number of assembly operations (N_a) with a correlation coefficient (r) equal to -0.811. Data for three products assembled in the same factory are shown as squares. Numbers indicate quantity of overlapping data points.

Figure 7.4. The operations performed per hour versus the average number of parts in a subassembly installed per operation. The line represents a linear least squares fit. The correlation coefficient (r) for this relationship is -0.773. Data for three products from a common factory are shown as squares.

Assembly Complexity - A Key Factor Related to Defects

Since the defects per operation should increase with the difficulty of assembly, a higher defect rate is anticipated as the average complexity of assembled components increases. A plot of these factors reveals a trend consistent with this prediction as shown in Figure 7.5.

Although the correlation between the number of parts per operation and the defects per operation is weak, it is *many* times better than any other relationship examined for this data.

Figure 7.5. Defects per operation (DPO) versus the average number of parts added per assembly operation (N_p/N_a). The correlation coefficient (r) for a power fit given by the equation is 0.367. Note, a linear fit for three products from a common factory shown as squares also has a positive slope consistent with the general trend.

Together the data shown in Figures 7.4 and 7.5 clarify the observed trend in Figure 7.2 which shows that the product defects are decreasing as the number of assembly operations increases. They show that the assembly operations are, on the average, considerably simpler in products having a large number of assembly operations. *The simpler assembly processes contribute to a lower defect rate per operation.* Consequently the defects per product are higher for products having the fewest assembly operations! This can be quantified by combining the regression fits from Figure 7.3 and 7.5, yielding:

$$\text{DPU}_{\text{auto}} = 261.08 \cdot N_a^{-0.8825} \quad (7.1)$$

Where, DPU_{auto} = The Defects per Unit (vehicle) for the automotive manufacturer
 N_a = The number of final assembly operations for the automotive manufacturer

Equation 7.1 has a slope which virtually matches the slope of the linear regression fit to the defects per unit versus number of assembly operations from Figure 7.2. The stronger correlations of the defects per unit with assembly complexity compared to part count suggests that assembly errors are a more dominant defect source than part defects.

In this case, the "difficulty" of assembly operations shows an intuitively sound correlation with defect rates, while the simple quantity measures of complexity do not. This clearly demonstrates the importance of understanding the difficulty of the elements of complexity and the hazards of focusing solely on quantity measure of complexity.

Lacking Design for Assembly (DFA) evaluations for these products, weak correlations were anticipated. In this respect, the results are not surprising. Although they are weak, they identified relationship is several times better than observed in industry wide studies of automotive manufacturers [68]. While we recognize that performing Design for Assembly analysis of 15 products of such complexity is impractical at this point, we believe that the correlation between the assembly complexity and defect rates may be stronger if such data were available.

Confounding Factors in Comparing Defects

Among the other confounding factors, variation in the level of quality control between facilities can be substantial. For this reason we requested an identification of products built in common facilities. For such products, we would expect higher consistency in the level of quality control. As shown in Figures 7.3 through 7.5, in every case the trends observed for three products produced in a common facility were consistent with the general trend observed for the entire sample. In addition, the correlations obtained for these three products were always significantly better than for the all of the data considered as a group. For example, the correlation coefficients (r) for a linear fit to the data for these three products in Figures 7.3, 7.4, and 7.5 were -0.9997, -0.997, and 0.683 respectively. Because of the limited size of this group, we recommend caution in attributing too much significance to the improved correlations. It is, however, reassuring that the correlations improved as the breadth of the sample decreased and that the trends were always consistent with the general trends observed in the larger samples.

Comparing the trends for defects per operation as a function of assembly complexity illustrated in Figure 7.5, the three products built in the same facility have a lower than expected defect rate. This suggests a more effective quality control in this facility. The linear regression for the products from the same facility also has a flatter slope than the general trend. As the effectiveness of the quality control increases, the sensitivity to complexity will decrease. However, independent of the level of quality control, reducing complexity will generally reduce the defect rate.

Production Rates - A Key Factor Influencing Defects

While production rates measured in units per hour are related to the production pace, these measures of productivity are not directly related to assembly complexity as described in Chapter 3. The production rates do provide one particularly useful comparison. In Figure 7.6, the production rate is plotted versus assembly complexity (parts added per assembly operation). The area of each data point is proportional to the defects per assembly operation. The maximum defects rates per assembly operation are for those products having a combination of both high assembly rates and high complexity. This relationship is intuitively sound.

Figure 7.6. Product assembly rate versus the average number of parts added per assembly operation. The area of each data point is proportional to the defects per assembly operation which ranges from 45 to 1250 defects per million assembly operations. Note that the products with the fewest defects per operation generally fall near a diagonal in the center of the plot.

Products with the minimum defect rates generally fall within a band between the two groups of data with the highest defect rates. Although there are exceptions, this pattern is remarkably consistent with the predicted pattern shown in Figure 3.7 of Chapter 3. This suggests that the pace of assembly can be a part of strategic quality planning. It also demonstrates that the optimum pace for productivity may be somewhat different than the pace which maximizes conformance quality.

For products that exceed the optimum assembly pace, defects could be reduced by slowing the assembly pace. This approach would result in an unbalanced line. The same reduction in defect rates could be achieved by simplifying the assembly operations, without suffering a loss in productivity.

Although there is no way to test the statistical significance of the pattern shown in Figure 7.6, the pattern is one of the strongest indicators that assembly complexity and assembly pace are dominant factors in product quality.

7.3 Motorola Data

Our work, combined with the potential of developing a method for defining a product quality strategy, motivated Motorola to participate in this study. David Gebala [11], in the Advanced Manufacturing Technologies division played a key role in accumulating and organizing their data for this purpose. They provided a summary of Boothroyd Dewhurst Design for Assembly evaluations for nine separate products. Their summaries included the number of parts, the number of assembly operations, the theoretical minimum number of parts (NM), the assembly efficiency (EM), and the total manual assembly time (TM)

(see definitions in Chapter 2) for each product. In addition they also provided the defects per unit for the nine products. These products are manufactured at different locations throughout the United States. One of the products, which was not identified, is manufactured overseas.

For one product having 258 assembly operations, the DFA average assembly time per operation was equal to the minimum possible DFA value. David Gebala noted that this was a particularly difficult product to manufacture, and that the values for this product may not have been reported to him correctly. However, he did not have sufficient information to verify or correct the DFA assembly time. Because the DFA assembly time was inconsistent with the perceived difficulty of fabricating the product, and since it is virtually impossible to have 258 assembly operations without requiring some operation more complex than the minimum difficulty, data for this product was not used.

Testing the Relationship Between Complexity and Defects

Our objective in evaluating the Motorola data has been to identify those product complexity factors that showed the strongest correlation with product defect rates. While we had postulated that the defect rates may be strongly related to a measure of assembly complexity based on the assembly time, it is clearly possible that other measures of complexity could have stronger correlations. From the data the following ten complexity measures having potentially strong correlations with defect rates were identified:

1. DFA Total assembly time (TM)	6. Average assembly time per part (TM/N_p)
2. Assembly Efficiency (EM)	7. Average assembly time per operation (TM/N_o)
3. Number of Parts (N_p)	8. Number of operations per part (N_o/N_p)
4. Number of Operation (N_o)	9. Parts per Theoretical Minimum (N_p/NM)
5. Theoretical Min. No. of Parts (NM)	10. Operations per Theoretical Min. (N_o/NM)

There are also many ways of expressing defects rates. For example, by dividing the defects per unit by the number of parts in a product, the average defect per part can be determined. Five measures of defect rates were identified for the Motorola data:

1. Defects per assembly operation
2. Defects per part
3. Defects per unit (Product)
4. Defects per theoretical minimum number of parts
5. Defects per second of assembly time

There are 50 different ways of comparing defect rates to possible measures of complexity. For each of the combinations of comparing defects to measures of complexity a linear regression was performed. The coefficient of determination (r^2) resulting from the regression analysis has been provided for each complexity-defect pair in Appendix C. Plots of the data were also examined to assess the possibility of non-linear correlations. There did not appear to be any distinct non-linear trends.

Assembly Time-The Strongest Relationship with Defects

Of the fifty paired comparisons, only three relationships had strong correlations ($|r| > .9$ where r is the correlation coefficient). *The DFA assembly time is a key measure of complexity in each of the three strongest correlations with product defects.* This evaluation demonstrates that DFA assembly time is a better method of predicting defect rates for the Motorola data than either the part or operation count.

The strongest linear relationship was for the defects per operation versus the assembly time per operation as shown in Figure 7.7. A plot of the defects per unit versus the total manual assembly time, the third strongest correlation, is given in Figure 7.8. In both figures, a line based on a fit using linear regression is also plotted.

Figure 7.7. Average number of defects per operation (DPO) plotted versus the average DFA assembly time per operation (TM/N_a) in seconds for Motorola data [11]. The line is the best fit curve based on a linear regression ($r = 0.94$).

Figure 7.8. Defects per unit (DPU) versus the DFA total assembly (TM) time in seconds for Motorola data [11]. The line is the best fit linear regression ($r = 0.870$) passing through the origin. The equation for the fit is $DPU = 6.83e-5 * TM$.

The strong correlations illustrated in Figures 7.7 and 7.8 suggest that the basic premise of relating assembly complexity to defects rates is sound. However, a linear model does have important limitations. We shall subsequently show in the last part of this chapter, that better correlations can be identified which also explain additional phenomena.

Factors Having a Weak Relationship with Defects

Several insights can be obtained from the factors that are poorly correlated with defect rates. Even though the theoretical minimum number of parts is a subset of the parts in a product, it cannot be directly related to the part count, the operation count, or the total assembly time for a product. Consequently, it is not surprising that this measure of complexity does not have any strong correlation with defects. This also explains the relatively weak relationship between defect rates and either assembly efficiency, or operations per theoretical minimum number of parts (N_a/NM).

Although DFA assembly time is strongly linked to defect rates, independently neither assembly count or part count is. This reinforces the concept that the difficulty measures, such as assembly time, provide a superior representation of complexity than quantity measures alone.

7.4 Disk Drive Data

The third set of data was provided by a computer disk drive manufacturer. Although their products have a high level of similarity, they were able to share information on the assembly complexity and defect rates of subassemblies as well as the finished product. By treating the subassemblies as "units," a greater range of complexity and defect rates could be addressed. Following a tour of their assembly facility where we had the opportunity of viewing the production assembly process, they gave us drawings which we used to perform Design for Assembly (DFA) evaluations. To avoid any conscious or unconscious effort to bias the DFA results, DFA evaluations were completed without subsequent modification prior to any comparison with defect data. A summary of the DFA and defect data is given in Table 7.1.

Table 7.1. Defect rates and DFA analysis summary of computer disk drive assemblies.

	Magnet Assembly	6 Head Ass'y	8 Head Ass'y	12 Head Ass'y	14 Head Ass'y	Complete Product A	Complete Product B
Parts (Np)	3	16	24	32	36	78	99
Operations (N _a)	5	37	47	63	71	108	138
Theo Min No Parts (NM)	3	9	11	15	17	32	41
Ass'y Efficiency (EM)	0.209	0.077	0.076	0.074	0.074	0.092	0.094
Ass'y Time (sec)	42.9	350.6	436.9	606.3	690.9	1044	1304
Defects/Unit (DPU)	0.00117	0.0929	0.127	0.148	0.211	0.344	0.608

The Head Assembly - A Test for the Role of Complexity

The head assemblies provided a unique opportunity to test the relationship between defects and assembly complexity. In each product a separate "head" is required to read and write to each face of a data storage disk. The number of disks in the products ranged from 3 to 7, requiring 6 to 14 heads. Since the assembly of each head is identical, the head defects and total head assembly time per unit should be proportional to the number of heads in the assembly. Head defect included bent heads, broken head wires, and failed gram loads. These defects constituted roughly 30 percent of the head assembly defects.

By contrast, there are many parts, and operations that are used only once in each unit and are independent of the number of heads in the assembly. For example, there is one pivot bearing in each assembly. The pivot bearing assembly time and defect rates should be independent of the number of heads in a unit. Defects that relate only to the entire unit constituted roughly 20% of the defect data.

The head defect rates, and "unit" defect rates are plotted versus the number of heads in Figure 7.9. As illustrated in this figure, the head defects per assembly have a strong correlation with the number of heads in each assembly (correlation coefficient (r) = 0.973). Although the number of data points is small, the linear model can be accepted in this case at the 0.05 level of significance using an analysis of variance. By contrast, the defects that are unique to each assembly are not consistently related to the number of heads in each unit. A linear model is rejected at the 0.05 level of significance based on an analysis of variance for this relationship.

Figure 7.9. Defects per head assembly versus the number of heads in the assembly. The head defects are strongly correlated ($r = .973$) with the number of heads in the assembly. In contrast, the defects that are related to the entire assembly, such as pivot bearing problems are not related to the heads per assembly.

The comparison of head and "unit" defects reinforces the relationship between complexity and defects. Head defects increased in direct proportion to the number of heads in each unit. However, defect rates of tasks and parts that are unique to each assembly are uncorrelated with the number of heads. This suggests that complexity is a causal factor in defect rates, rather than a coincidental relationship. Although only four points are plotted, these four points represent the assembly of over a half a million drive heads involving more than 2 million assembly operations.

Relating Complexity to Disk Drive Defects

Based on the results obtained with the Motorola data, our goal was to determine whether or not the same relationships applied to the data for the disk drive. The coefficients of determination for comparisons of complexity and of disk drive defects is also contained in Appendix C. The correlations between complexity measures and defect rates for the disk drives are generally stronger than observed for the Motorola data. This may be due to the fact that the disk drives are manufactured in a single facility, reflecting a narrower breadth than the Motorola products which were produced in various locations. As previously noted, correlations tend to improve as the breadth of the sample decreases, an observation that this data reinforces. Defects rates also had high correlations with the part counts,

operation counts and total assembly times in the disk drive assemblies since the part count and operation counts were nearly proportional with the assembly time in these products.

Assembly Time - The Key Element in Describing Defects

A single relationship had strong correlations for both the Motorola data and the disk drive data: the defects per unit (DPU) versus the total manual assembly time (TM). This relationship for the disk drive data is plotted in Figure 7.10. For both the Motorola and disk drive cases, we have found that measures of complexity based on the DFA assembly times provide stronger correlations with defect rates than part counts, assembly efficiency, or the average assembly time per part.

Figure 7.10. Defects per Unit versus DFA assembly time for disk drive data. The correlation coefficient (r) for a linear fit represented by the straight line passing through the origin is 0.935. The equation for this fit is $DPU=0.000373*TM$.

Multiple Linear Regression

The best linear model for the defects per unit for both the disk drive data and Motorola data was also determined using multiple linear regression. For consistency, the most appropriate model must have the same form for both sets of data. There were two common factors among the "strong" variables defining defects per unit by this approach: 1) the DFA predicted assembly time (TM), and 2) the DFA average assembly time per operation. With these basic variables, the only other factor having a consistent correlation with both sets of data was number of assembly operations.

In these multivariate models the number of assembly operations (N_a) have a *negative* correlation with the defects per unit (DPU), a trend that is consistent with the automotive data. This trend may be explained by the fact that the minimum assembly time per operation must be greater than zero seconds. Operations taking less time than this minimum cannot exist, and cannot contribute defects to the products. Hence, there is a threshold time per operation that must be subtracted to improve the correlation.

Additional detail on the multivariate models will not be discussed, because simpler non-linear models yielded better results.

7.5 Comparison of Defect Data

Thus far, we have focused on comparisons of defect rates and assembly complexity within individual companies. Additional insights into the validity and accuracy of the identified correlations can be obtained by collectively examining the data from the different manufacturers. Plotted in Figure 7.11 is the defects per part versus assembly efficiency from the original Motorola work [35] that prompted this study. In the same figure, the new Motorola data [11] and disk drive data has also been plotted. As this figure shows, there is a consistent trend of decreasing defect rates for increasing assembly efficiency.

Figure 7.11. The defects per part versus the DFA manual assembly efficiency for data supplied by Motorola and a computer disk drive manufacturer [35][11]. The correlation coefficient for the logarithm of defects per part versus assembly efficiency is 0.867.

Relative to other correlations, the relationship between defects per part and assembly efficiency is not the strongest. For any given assembly efficiency, the number of defects per part can differ by more than an order of magnitude. Our interest in this data is that it can be used to improve of our primary model relating defects per unit to the total assembly time.

A sound correlation between defects and assembly complexity should also be consistent with the data plotted in Figure 7.11. This provides a check on the best correlation between defect rates and assembly time. For each Motorola and disk drive product, the predicted number of defects can be estimated from the total assembly time using the equation for the linear fits from Figures 7.8 and 7.10. The estimated defects per unit can then be divided by the number of parts in the product to predict the average number of defects per part. The predicted and observed part defect rates versus assembly efficiency are plotted in Figures 7.12 and 7.13. The agreement between the predicted and observed part defect rates illustrated in these figures is disappointing. In particular, the slope of the line of fit for the predictions is much flatter than the observed trend in the data.

Figure 7.12. Measured and Predicted defects per part versus manual assembly efficiency for the Motorola data [11]. Predictions are based on a linear relation of defects per unit to total assembly time. Lines are least square fit of the log(DPP) versus assembly efficiency.

Figure 7.13. Measured and Predicted defects per part versus manual assembly efficiency for the disk drive data. Predictions are based on a linear relation of defects per unit to total assembly time. Lines are a least square fit of the log(DPP) versus assembly efficiency.

The Power Curve - A Superior Correlation

Our efforts to understand the differences in the predicted and measured defect rates per part when plotted against assembly efficiency led us to suspect that the problem stemmed from using a linear model to relate defects per unit to the total assembly time. A power fit for **defects per unit (DPU) versus DFA assembly time (TM)** resulted in a remarkable improvement in the correlation obtained for the Motorola data compared to the linear model (correlation coefficient $r_{\text{power}} = 0.966 > r_{\text{linear}} = 0.870$). A similar power fit also improved the correlation with the disk drive data ($r_{\text{power}} = 0.989 > r_{\text{linear}} = 0.956$). Note that these correlations are much stronger than that observed for the relationship between defects per part and assembly efficiency ($r = 0.867$). The key relationships between defects per unit and DFA assembly time are plotted with the best fit power curves for the Motorola and disk drive data in Figure 7.14.

The excellent correlations between defects and total assembly time for two distinctly different sets of data reinforce the validity of this model. The equation providing the best model of defects per unit (DPU) based on the DFA assembly time (TM) and number of assembly operations is as follows for Motorola:

$$\text{DPU}_{\text{Motorola}} = \frac{(\text{TM} - 1.68 \cdot N_a)^{1.316}}{112,370} \quad (7.2)$$

Similarly, for the disk drive manufacturer, the defects per unit can be estimated by:

$$\text{DPU}_{\text{disk drive}} = \frac{(\text{TM} - 3.00 \cdot N_a)^{1.765}}{248,489} \quad (7.3)$$

Figure 7.14. Defects per unit versus DFA assembly time for Motorola [11] and disk drive data. The solid lines represent power curve fits to the data. The correlation coefficient (r) for the Motorola data is 0.966, and for the disk drive data is 0.989, indicating excellent correlations.

Although the average assembly time per operation (TM/N_a) was a strong factor in multiple linear regressions, it did not have a consistent correlation using a power fit, and was consequently not incorporated in the model. However, reducing the DFA assembly time by a fraction times the number of assembly operations consistently improved the correlation and is therefore reflected in these equations. The power fit also assures that the defects per unit will approach zero as the total assembly time per unit approaches zero, an intuitively sound relationship for assembly defects.

A Check on the Power Model

The power fit to the Motorola and disk drive data can also be tested using analysis of variance. To perform such a test, a linear regression is performed using the $\log(TM \cdot c \cdot N_a)$ as the independent variable and $\log(DPU)$ as the dependent variable. The analysis of variance for the Motorola and disk drive data is summarized in Tables 7.2 and 7.3. The null hypothesis in both cases is that the slope of $\log(DPU)$ versus $\log(TM \cdot c \cdot N_a)$ is zero. The null hypothesis is rejected at the 0.01 level of significance in both cases, meaning that the power curve fit is accepted at a highly significant level.

Table 7.2. Analysis of Variance for the Null Hypothesis that the slope of logarithm of defects per unit ($\log(DPU)$) versus the logarithm of the DFA assembly time ($\log(TM)$) is zero for the Motorola data [11]. Since the computed f (=83.8) is greater than $f_{0.01}(1,6)=13.75$, the null hypothesis is rejected and we accept the power fit.

Source of Variation	Sum of squares	Degrees of freedom	Mean square	Computed f
Regression	SSR = 1.508	1	SSR = 1.508	SSR/ s^2 = 83.8
Error	SSE = 0.108	6	s^2 = 0.0180	
Total	SST = 1.616	7		

Table 7.3. Analysis of Variance for the Null Hypothesis that the slope of logarithm of defects per unit ($\log(\text{DPU})$) versus the logarithm of the DFA assembly time ($\log(\text{TM})$) is zero for the disk drive. Since the computed f ($= 223.1$) is greater than $f_{0.01}(1,5)=16.26$, the null hypothesis is rejected and we accept the power fit.

Source of Variation	Sum of squares	Degrees of freedom	Mean square	Computed f
Regression	SSR = 4.679	1	SSR = 4.679	SSR/ s^2 = 223.1
Error	SSE = 0.105	$n - 2 = 5$	$s^2 = 0.0210$	
Total	SST = 4.784	$n - 1 = 6$		

Improved Predictions of Defects per Part

We again predicted the defects per unit for the Motorola and disk drive products using the new power curve relationships from Equations 7.2 and 7.3. The estimated defects per unit were then divided by the number of parts in each unit to predict the average defects per part. These new estimates of defects per part are plotted against the assembly efficiency as shown in Figures 7.15 and 7.16. The power fit provides a significant improvement in

Figure 7.15. Measured and Predicted defects per part (DPP) versus manual assembly efficiency for the Motorola data [11]. Predictions are based on a power fit for defects per unit to total assembly time. Lines are least square fit of the $\log(\text{DPP})$ versus assembly efficiency.

Figure 7.16. Measured and Predicted defects per part (DPP) versus manual assembly efficiency for the disk drive data. Predictions are based on a power fit of defects per unit to total assembly time. Lines are least square fit of the $\log(\text{DPP})$ versus assembly efficiency.

the consistency between the predictions and the observed defects per part. Although individual points are not predicted precisely, the least squared fit to the data and the predictions match extremely well for both the Motorola and the disk drive data.

It is important to note that the improved prediction of defects per part versus assembly efficiency (DPP vs EM) has been obtained through a better model relating defects per

unit to DFA assembly time (DPU vs TM). The refinement in the model improved prediction of both the defects per unit and the defects per part, reinforcing the validity of the selected approach.

Comparing the Quality Performance of Manufacturers

One of the most useful benefits of this model of defect rates is that it permits inter-company comparisons of conformance quality control, even for organizations that are producing dissimilar products. Differences in conformance quality performance are clearly illustrated in Figure 7.14. For any given total assembly time and operation count, the ratio of disk drive defects to Motorola defects can be approximated by dividing Equation 7.3 by Equation 7.2, which produces:

$$\frac{\text{DPU}_{\text{disk drive}}}{\text{DPU}_{\text{Motorola}}} = 0.452 \cdot \frac{(\text{TM} - 3.00 \cdot N_a)^{1.765}}{(\text{TM} - 1.68 \cdot N_a)^{1.316}} \approx 0.452 \cdot (\text{TM} - 2.34 \cdot N_a)^{0.449} \quad (7.4)$$

Equation 7.4 illustrates a powerful but simple method of comparing the conformance quality performance ratio of any two organizations. It transcends differences in product complexity and removes many of the confounding influences that make conformance quality comparisons difficult.

7.5 The Pareto Distribution-The Basis of Correlation

We have observed that the DFA assembly times follow a Pareto distribution, which has the characteristic that longer assembly operations occur with lower frequency. DFA assembly time distributions also have large variances. Given these properties, a link between assembly time and defect rates is surprising. A key to understanding this relationship can be found in the distribution of defects. Plotted in Figure 7.17 is a Pareto curve for the number of defects in a specified category versus the number of categories having a greater or equal number of defects supplied by the disk drive manufacturer. As the figure clearly shows, the distribution of defects clearly follows a Pareto distribution. The Kolmogorov Smirnov "goodness of fit" limits for the 0.20 level of significance are also plotted in Figure 7.17. Since the data falls entirely within the limits, the Pareto distribution is accepted at the 0.20 level of significance.

Figure 7.17. Pareto curve of the defects per category for defect classification for disk drive data. The dashed lines are the Kolmogorov Smirnov "goodness of fit" limits for the 0.20 level of significance about the solid line estimate of the distribution. Since all the data falls within the bounds, the Pareto distribution is accepted.

The reason that assembly time and defect rates can be related derives from the fact that both can be described by Pareto distributions. As noted in Chapter 4, similarity in the distributions does not imply a one to one correlation between elements of the distribution. Thus, the defect rates per individual operation are not precisely proportional to the assembly time of that specific operation. The distributions can be similar, even when the sorted order of defect sources and assembly times are different. The correlation does suggest that there will be a trend of increasing defect rates for increasing assembly time for each operation, but there may be substantial scatter in the trend.

7.6 Key Findings in Relating Defects to Complexity

The relationship between assembly efficiency and the average number of defects per part identified by Motorola is not the best method of relating complexity to defect rates. However, this relationship has provided an important check on the predictions derived from a link between defects per unit and the DFA total assembly time. This check on predicted defect rates led to the identification of a power model which has proven to be superior to a linear and multivariate correlations between defect rates and assembly complexity.

We have shown that defects per unit (DPU) are strongly correlated with a combination of the DFA manual assembly time (TM) and operation count (N_a) for individual companies. A power fit, provided excellent correlations with two distinctly different sets of data. This model is intuitively sound as it assures that the defect rate will approach zero as the assembly time approaches zero. The general form of this relationship involving three constants, c_1 , c_2 , and c_3 , is:

$$DPU = \frac{(TM - c_1 \cdot N_a)^{c_2}}{c_3} \quad (7.5)$$

This model predicts that reductions in DFA assembly time will generally reduce the number of defects per unit, a trend consistent with a Boothroyd Dewhurst [103] publication showing that quality and reliability improved an average of 68 percent when assembly time was reduced by an average of 62.3 percent.

Independently, the simple quantity measures of complexity, such a part count and operation count are not consistently related to defect rates. This reinforces the critical role of the measure of difficulty in understanding complexity.

The conformance quality capability of a company can be compared with other companies using a simple method developed in this study, even if the companies produce dissimilar products. Differences between manufacturers can be easily discerned, explaining the weak correlations generally observed in inter-company comparisons of defect rates and complexity measures.

As anticipated, we have observed a general trend of improved correlations between the measures of complexity and defect rates as the span of the study decreased. For one set of automotive data, correlations were stronger for products produced within the same facility than obtained for company wide comparisons. Comparisons within a company produced better correlations than inter-company comparisons. The relationship of defects to assembly complexity was more strongly related for the disk drive manufacturer than for Motorola. This is consistent with the fact that the disk drives products were all produced in a single facility, while Motorola's products were produced in several locations.

The automotive data showed that products having the highest combination of complexity and production rates also had the highest defect rates. This suggests that complexity and production pace are both important elements of a quality improvement strategy.

The distribution of defects per category has been shown to follow a Pareto distribution at the 0.20 level of significance based on the Kolmogorov Smirnov "goodness of fit" test. This explains the correlation between defects and assembly time, since DFA assembly time also follows a Pareto distribution. However, this correlation should not be construed to imply a one to one link between operation time and defect rates for individual operations.

Chapter 8

Control of Variation and Error

The strong correlations between complexity and defects revealed in Chapter 7 show that we can predict the defect probability given the level of quality control and product complexity. The quality control level is a global measure of the defect probability resulting from both variation and error. Each manufacturer's ability to control error and variation can differ. For example, 80 percent of the defects may be the result of errors in one facility, while only 40 percent of the defects may be caused by error in another. In spite of such differences, the two facilities could have the same global level of quality control. The global correlation between defects and complexity is not effective in identifying the relative importance of error and variation for each manufacturer.

This points to the need for a separate tool useful in characterizing the quality control process. In this chapter we will introduce an event tree based on the principles of Decision Analysis [98] which aids in identifying the general strengths and weaknesses of the quality control methods used in production. We shall show that this method is consistent with production experience and superior to commonly accepted procedures for predicting defect rates.

8.1 A Simple Model of a Manufacturing Process

For this purpose, we introduce a model to represent a manufacturing step involving a single process, which has elements of input, process, inspection, and accepted output as illustrated in Figure 8.1. Materials, parts, equipment, and fixtures are typical of some physical inputs required to execute a process. Tool sharpness, feed rates, tool path definitions, and temperature control illustrate another class of inputs that is required. When all of the inputs are available, the process that alters physical elements from an initial state to a more desired state can be executed. Stamping, casting, molding, transportation, and assembly processes are examples of typical processes. The output, represented by the transformed state of the input elements after the process, is accepted if neither the inputs nor process are rejected by inspection.

Figure 8.1. A simplified representation of a manufacturing process. The dashed box surrounding inspections indicates they may or may not be used

A Quality Control Tree (QCT) Model of a Process

An event tree describing the possible input states, inspections, decisions, process, and output states has been developed using the methods of Decision Analysis [98] and is shown in Figure 8.2. The horizontal lines in the tree denote events, and the alphanumeric values by the connecting diagonals represent the probability that an event will occur. The probability of arriving at any event is equal to the cumulative product of the probabilities along all preceding paths leading to the event.

Imperfections and errors in the inputs and variation or errors in the process cause defects in the outputs. Inclusions in metals, voids in castings, and excessive variation in feature dimension illustrate types of input imperfections. Incorrect temperature settings, pressure settings, feed rates, or selection of the wrong process cycle represent typical input errors. Similar errors and variations during the execution of the process also lead to defects. The frequency of error states and excessive variation, denoted as error and bad states respectively in the event tree, can be described in terms of a probability of occurrence.

An inspection is a determination of acceptability based on an examination of the quality or condition of the input or output relative to defined standards. The result of an inspection is a report which indicates that the input or output is "good" or "bad." Since inspection is imperfect, the report, which is enclosed in parenthesis for distinction, may differ from the true state. When inspection results in a "bad" report, a decision must be made involving three possible actions according to Shingo [22], namely: 1) shutdown, 2) control, or 3) warning.

Predicting Conformance Quality Control Using the Quality Control Tree

The Quality Control Tree (QCT) in Figure 8.2 provides a means of combining the outcome of the independent events and estimating the significance of each quality control factor. Toward this goal, we can calculate several important characteristics of conformance quality from the "Accepted Output" probabilities. First, the probability of executing a process without interruption due to an a "bad" inspection report is equal to:

$$P\{\text{Accepted Output}\} = O_{\text{Total}} = \sum_{j=1}^8 O_j \quad (8.1)$$

Figure 8.2. Quality Control Tree (QCT) for predicting the impact of quality control factors

Where, O_j = The probability of reaching the j th accepted output from Figure 8.2.

From this, the proportion of defects in the output is:

$$D_{\text{Process}} = \frac{O_3 + O_5 + O_6 + O_7}{O_{\text{Total}}} \quad (8.2)$$

From Equation 8.2 and the probabilities in Figure 8.2 it can be shown that defect rates are a complex function of many quality control factors. Consequently, the quality improvement methods that focus on only a few factors can not achieve the highest levels of conformance quality demanded in today's competitive environment. Equation 8.2 can also be used to estimate the output or process yield (O_Y), which is one minus the fraction of output containing defects ($1 - D_{\text{Process}}$) for low defect rates.

From the Quality Control Tree, the ratio of defects caused by error to defects resulting from excessive variation (EV_{ratio}) can be approximated. Subsequently it shall be shown that this parameter is useful in setting quality control strategies, and is given by:

$$EV_{\text{Ratio}} = \frac{O_5 + O_6}{O_3 + O_7} \quad (8.3)$$

The great value of the Quality Control Tree is that it can aid in identifying the current conformance quality strengths, weaknesses and opportunities for each organization by estimating the probabilities for independent events in Figure 8.2. This benefit will be demonstrated by describing the event probabilities for some common quality methods, and comparing the predicted impact of these methods with results obtained in production.

8.2 Assessment of Independent Quality Control Probabilities

The performance of each organization in specific quality control areas can differ significantly. As a result, meaningful assessments of quality control must be performed for each organization or facility based on its quality control philosophy and production data. To illustrate, typical values for the independent event probabilities have been estimated for several well known quality control methods as listed in Table 8.1. Blank portions of the table reflect quality improvement areas where the methods have little or no influence.

Table 8.1. Table illustrating the probabilities for the event tree shown in Figure 8.2 for several common quality improvement methods. The Six Sigma column for zeta convolutions is based on 15 percent of the factors following a zeta distribution ($Z(1.40,1)$ @29convolutions).

Parameter	Traditional Manufact. & SQC [3]	Six Sigma Normal dist. [5]	Six sigma 15% zeta conv.	Poka-yoke [24][22]	Source Inspection [24]	100% Inspection [24]
$a_0 = a_i^{(1)}$	> 0.99995	> 0.99997	> 0.99996			
α_e				$< 0.001^{(2)}$		
$\alpha_i = \alpha_o$	$0.15-0.20^{(3)}$			$< 0.001^{(2)}$	$< 0.001^{(2)}$	$< 0.001^{(2)}$
b_i	$\leq D_{\text{Process}}^{(4)}$					
b_o	$0.002^{(5)}$	$3.4e-6^{(6)}$	$0.00016^{(7)}$			
$d^{(8)}$	0.3					
$e_i = e_o^{(9)}$	$0.0002-0.0005$			$0.00002-0.00005$		
$i_e = i_k$				$1^{(10)}$		
i_i	$< 0.01^{(5)}$				$1^{(10)}$	
i_o	$< 0.01^{(5)}$					$1^{(10)}$

- Notes: 1. $P\{\text{"good"}|\text{good}\} \geq 1 - P\{\text{"bad"}\} = \text{Output}$.
2. Shingo's "inspection" methods have high reliability due to 1) autonomous execution, 2) proximity to process, and 3) concept simplicity. However, there is no data on reliability.
3. $P\{\text{"good"}|\text{bad}\}$ is sensitive to complexity [7], number of repetitions [7], and inspection pace [85]. Values between 0.01 to 0.80 are reported, but values in table are typical [12][118].
4. $P\{\text{input exceeds variation limit}\} \leq D_{\text{Process}}$ (Note this requirement leads to iterative solution).
5. Assumed typical value based on sampling inspection for process control.
6. Target rate of defects from variation using Normal distribution per Motorola's Six Sigma [5].
7. Based on 15% of data following zeta convolutions ($Z(1.40,1)$ @29 conv.) not Normal dist..
8. Assumed value held constant for all cases examined - No known general data.
9. Rook [26] estimated error frequency to be about 0.0001 to 0.00001 per the "smallest behavior perceived as a unit." Processes typically require multiple behaviors with many failure modes leading to higher process error rates. Poka-yoke reduces errors an unknown amount.
10. 100% inspection ($P\{\text{inspection}\}=1$) may apply to a fraction of the inputs, outputs or features.

Six Sigma Reduces Variation in the Output

As illustrated in Table 8.1, the focus of quality control methods can differ significantly, each targeting specific improvement opportunities. For example, Motorola's Six Sigma [5] concept does not control errors since it depends on the sampling methods of Statistical Quality Control (SQC) [3]. Neither does the Six Sigma approach address inspection frequency or reliability. The objective of the Six Sigma concept is to optimize and set specification limits and select manufacturing processes to reduce assembly defects caused

by variation to a level of 3.4 ppm [5]. This goal can be modeled by setting the probability that output exceeds the variation limit (b_o) at 3.4 ppm.

Impact of non-Normal Distribution on Six Sigma

The Six Sigma method is based on the assumption that all feature variation can be described by the Normal distribution, an assumption that we have shown is not well founded. We can model the degradation in product quality when the true variation deviates from an assumed Normal distribution. To illustrate, we will assume that zeta convolutions are the best description of some variations. The assumed variation is based on one fit to real data for assembly time ($Z(1.40,1)$ @29convolutions) from Chapter 6 Figure 6.8. For this case, the defect rate would actually be 1050 ppm if a normal distribution had been inappropriately assumed and the Six Sigma criteria applied in setting specification limits. Given that zeta convolutions describe fifteen percent of the types of variation that occur, and that the Normal distribution describes the remainder, the actual defect rate due to variation (b_o) would be 160 ppm ($0.15*(1050\text{ppm})+.85*(3.4\text{ppm})$). This case is represented as the third column in Table 8.1.

Poka-yoke Reduces Defects Caused by Errors

The Poka-yoke [24] method, represented by the probabilities in column 4 of Table 8.1, is particularly effective in reducing defects caused by error. It can reduce the probability of errors by preventing operators from performing unacceptable actions. In other cases, it may warn an operator when an error could result in a defect such as the failure to drill the right number of holes. Although poka-yoke techniques can be applied to controlling variation, the probabilities in Table 8.1 are based on applying these techniques strictly to error control. Due to the rare nature of errors, poka-yoke inspections must be performed on 100 percent of the processes for the specific errors it is used to control. However, poka-yoke techniques often can not be applied to every feature or action. Thus, the error inspection probability (e_i and e_o) describes the fraction of actions controlled by poka-yoke.

Bounds on Several Event Probabilities Can Be Inferred

In establishing event probabilities, useful bounds on several parameters can be inferred without requiring extensive evaluation. For example, it can be shown in most cases that the probability of a "good" report given good inputs or processes must be greater than one minus the probability of a "bad" report which is very small in high quality production. As a result, a_i and a_o will be very close to a value of unity for most manufacturing processes.

Since the output represents a more complex state than the input, the proportion of defects in the output will generally exceed the input imperfections ($D_{\text{Process}} \geq b_i$). The probability of input imperfections can be iteratively updated until the output converges, a process requiring only a few cycles of iteration.

Setting Event Probabilities Using Production Data

Some event probabilities reflecting current quality control performance may be estimated using production data. For example, the probability that the output is reported as "good" when it is actually defective (a_0) can be estimated by dividing the number of customer reported defects by the total defects detected in the factory and by the customer. Another method of setting the probability that input exceeds the variation limits (b_1) could be based on the inspection reports of incoming supplies.

These examples illustrate how the event probabilities describing the quality control performance of each organization can be estimated based on their current quality control philosophy, inferences, and production data. As shown in Table 8.1, the methodologies applied by each organization as well as their level of skill and effectiveness can influence the event probabilities in specific areas, suggesting the opportunity for defining quality improvement strategies.

8.3 Using the Tree to Assess Quality Performance

The independent event probabilities from Table 8.1 may be substituted into the equations of Figure 8.2 and Equations 8.1 through 8.3 to develop an assessment of the current level of production quality control. Modification to the current performance can also be evaluated by changing the event probabilities according proposed improvements. For example, based on a "traditional" manufacturing philosophy and Statistical Quality Control (SQC) represented by the probabilities from the first column of Table 8.1, a defect rate of 1975 ppm would be predicted as shown in the first column of Table 8.2. This predicted defect rate is consistent with the traditional SQC quality objective of 0.002 (2000 ppm) defects per process.

Table 8.2. An illustration of the influence of several quality control methods on quality performance using the event tree model shown in Figure 8.2. The second thru fourth column are for Motorola's Six Sigma method, in the first case variation is assumed to follow a Normal distribution, and in the second case 15% of the variation is based on zeta convolutions ($Z(1.40,1)$ @29 convolutions).

	Traditional SQC	Six Sigma "Normal" dist.	Six sigma 15% zeta conv.	Six sigma 15% zeta & Poka-yoke	SQC & Poka-yoke	SQC & 100% Inspection	Poka-yoke, 100%, Cnt. Imp.
Parameter							
$a_o = a_i$	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
$\alpha_i = \alpha_o$	0.15	0.15	0.15	0.15	0.15	0.05	0.01
α_e				0.001	0.001	0.05	0.001
b_i	.001975	.001135	.001381	.000024	.000874	.000684	8.13e-6
b_o	0.002	3.40E-6	0.00016	0.00016	0.002	0.002	0.0002
d	0.3	0.3	0.3	0.3	0.3	0.3	0.3
$e_i = e_o$	0.0004	0.0004	0.0004	0.00004	0.00004	0.0004	0.00004
$i_e = i_k$	0	0	0	0.80	0.80	0.50	0.93
i_i	0.01	0.01	0.01	0.01	0.01	0.10	0.01
i_o	0.01	0.01	0.01	0.01	0.01	0.70	0.97
y_i	0.99762	0.99847	0.99840	0.99987	0.99909	0.99892	0.99995
y_o	0.99760	0.99960	0.99944	0.99980	0.99796	0.99760	0.99976
Result							
O_T	0.99996	0.99999	0.99998	0.99993	0.99991	0.99775	0.99963
EV_{Ratio}	0.68	2.38	1.98	0.22	.02	0.80	2.28
O_Y	0.99802	0.99886	0.99880	0.99991	0.99913	0.99468	0.99603
$D_{Process}$	0.00198	0.00114	0.00120	0.00009	0.00087	0.00068	8.13e-6
defect-ppm	1975	1135	1201	90	868	684	8

Defects are Underestimated by the Six Sigma Method

By replacing Statistical Quality Control (SQC) event probabilities with the appropriate Six Sigma event probabilities from Table 8.1 (b_o changes from 0.002 to 3.4 ppm), the impact of adding Motorola's Six Sigma method to the "baseline" SQC approach can be approximated. This change reduces the defect rate from 1975 ppm to 1135 ppm as shown in Table 8.2. Although the predicted improvement achieved by Six Sigma is substantial, this result is far less impressive than a defect rate of 3.4 ppm projected by the Six Sigma philosophy. The difference in the two predictions is greater than two orders of magnitude which we attribute primarily to the influence of errors, a factor not addressed by Six Sigma.

If production variation is partly described by zeta convolutions, Six Sigma tolerancing benefits would be even less impressive with a predicted defect rate of 1201 ppm as shown in the third column of Table 8.2.

The Quality Control Tree-A Superior Model of Quality Control

Given the large differences in the predicted defect rates, the Six Sigma method and our proposed event tree model can not be equally valid descriptions of quality control. The data supplied by Motorola can be used to identify which approach most accurately represents production experience. For the Motorola products included in this study, the average defect rate per part is 810 ppm and the average defect rate per process is 490 ppm. The Quality Control Tree predictions are 1.4 to 2.45 times the observed defect rates, depending on the factors that are being compared. This range of error is reasonable given our ability to estimate the event probabilities. By contrast, Motorola's observed defect rate is nearly 144 times the Six Sigma predictions.

Some may argue that Motorola has simply not achieved their Six Sigma goal. However, evidence that this is not the case can again be obtained from information published by Motorola. Smith [12] stated,

"Motorola elected to enter this market (electronic ballast) and set a quality goal of 6 sigma for initial delivery. This required a very strict TDU (total number of defects per unit) budget. But it became evident early in the project that achieving a C_p greater than 2 would go only part of the way. Mistake-proofing the design would also be required...Mistake-proofing the design is an essential factor in achieving the TDU goal. The design team is forced to investigate any opportunities for errors during manufacture and assembly, and to eliminate them." [12] (italics added)

Motorola's own experience clearly demonstrates that mistake-proofing (the English translation of poka-yoke [24]) must be applied in conjunction with control of variation. Table 8.2 contains a predicted defect rate of 90 ppm using the event tree when poka-yoke techniques are combined with Six Sigma (15% zeta convolutions), a prediction that is consistent with Motorola's observed return rates in the tens of parts per million [12] attained when these two concepts are both applied. Thus, the Quality Control Tree provides a clearly superior description of quality control than the Six Sigma method.

Poka-yoke the Best Independent Method of Reducing Defects

Also shown in Table 8.2 is the impact of adding poka-yoke methods to traditional production practice based on Statistical Quality Control. The improvement achieved by poka-yoke was greater than for any other quality concept considered independently, an observation consistent with Shingo's [24] view that poka-yoke techniques are, in his opinion, the quickest methods for reducing defects. It is also consistent with several studies which have identified human error as the principle source of defects [6][7][8][9][10].

Many Combinations of Methods will Achieve Low Defect Rates

The last column of Table 8.2 illustrates a combination of poka-yoke, Shingo's [24] 100% inspection, and continuous improvement. Here, we have interpreted continuous improvement as reduced output variation ($b_0 = 0.0002$). This case illustrates that there is more than one technique or combination of methods that will achieve low defects rates. One of the interesting characteristics of this example is that it requires minimal inspection of input other than for input errors. This is consistent with the experience at NUMMI which uses the Toyota production system that Shingo helped to develop. At NUMMI incoming parts and subassemblies are inspected by sampling during production start up until the quality is deemed acceptable [88]. Thereafter, parts are only inspected occasionally, or whenever problems are observed in incoming product.

Again our model predicts that poka-yoke must be combined with source inspection and 100 percent inspection [24][22] to achieve the lowest defect rates. It clearly shows that none of these methods are independently successful in achieving the highest levels of conformance quality, a result consistent with Shingo's Zero Quality Control concepts [24].

The Error to Variation Ratio Can Guide Quality Control Strategy

For each of the cases given in Table 8.3, the ratio of defects caused by errors to defects caused by variation has been provided based on Equation 8.3. This ratio is useful in selecting an improvement strategy. When the ratio is close to one ($.5 < EV_{\text{Ratio}} < 2$) defects from both variation and error must be reduced to realize the greatest conformance quality improvement. However, if the error to variation ratio is very low (a rare case) quality improvement methods should put increased focus on reducing variation. On the other hand, a high error to variation ratio points to the need to reduce error using methods like poka-yoke.

The Quality Control Tree-A Key to Understanding Quality Control

The event tree introduced in this chapter can be used to identify the relative strengths and weaknesses of conformance quality control programs. However, it is not a comprehensive model of defect rates. Quality control is a subset of the broader issue of conformance quality which must also incorporate the concepts of product complexity. Although the Quality Control Tree is generally consistent in estimating the *average* defect rates and trends for a broad spectrum of products and quality methods, it can be very inaccurate in predicting defect rates for specific products. The Quality Control Tree should be used in conjunction with the global conformance quality model that will be introduced in Chapter 9 to define quality strategies.

The event tree has demonstrated that there is no single quality tool which will assure the highest levels of quality performance, and that there are many different ways for improving product quality. It has proven to be consistent with general trends observed in

production, and provides useful distinctions in identifying the strengths and weaknesses of quality improvement methods.

8.4 Identifying Improvement Opportunities

One of the potentially important values of the event tree is that it can also be used to identify the changes that will maximize improvement in the next product cycle. This can be achieved by performing a sensitivity analysis. To illustrate, we will use as a baseline the case for traditional manufacturing and Statistical Quality Control from Table 8.2. Each of the independent parameters can be varied to test the sensitivity of the defect rate to improvement in specific areas. The range of variation selected for our example is plus and minus one tenth the difference between its current value and the ideal. The nominal, minimum, and maximum value of the independent parameters examined in this sensitivity analysis are given in Table 8.3.

Table 8.3. Minimum, nominal, and maximum parameter probabilities used in a sensitivity study of defect rates. The nominal values are based on the "Statistical Quality Control" values from first column of Table 8.2. The nominal defect rate is 1975 ppm. The range of variation is $\pm$ one tenth the difference between the nominal value and the ideal (where possible).

Variable	Minimum Value	Nominal Value	Maximum Value	Defects min (ppm)	Defects max (ppm)
$a_i = a_o$	0.99989	0.9999	0.99991	1975	1975
$\alpha_i = \alpha_o$	0.135	0.15	0.165	1975	1975
α_e	0.045	0.05	0.055	1975	1975
b_o	0.0018	0.002	0.0022	1892	2059
$e_i = e_o$	0.00036	0.0004	0.00044	1863	2087
$i_e = i_k$	0	0	0.1	1864	1975
i_i	0.00	0.01	.11	1907	1982
i_o	0.001	0.01	0.109	1839	1989

The data in Table 8.3 can be sorted according to the variables that result in the greatest changes in the defect rate, and plotted in a "tornado" diagram as shown in Figure 8.3. Together this table and figure show that the defect rate is most sensitive to the probability of an error. This suggests that control of errors is extremely important, particularly since the assumed error probabilities are among the event probabilities with the largest uncertainty.

The bars extending furthest to the left in Figure 8.3 represents the changes that will produce the greatest reduction in defect rates. From this, increasing the inspection rate of the output (i_o) should be one of the top priorities pointing to Shingo's [24] 100%

inspection concepts. Collectively, inspection of errors (i_e & i_k) and error probabilities (e_i & e_o) are likely to be even more significant, again pointing to the importance of poka-yoke.

The Quality Control Tree and sensitivity analysis aids in identifying the best course for improving quality control given the current levels of performance. Heretofore, such comparisons and insights have not been possible.

Figure 8.3. Tornado diagram illustrating the sensitivity of defect rate to changes in the probabilities for independent parameters from Table 8.3. The range of variation for each parameter is $\pm$ one tenth the difference between the nominal value and the ideal (where possible).

8.5 Summary of Key Findings

The global assessment of quality control based on the correlations between complexity and defects identified in Chapter 7 is not able to distinguish between the relative role of error and variation. In order to develop a sound strategy for improving product quality, a method is needed to identify the strengths and weakness in conformance quality control. For this purpose a Quality Control Tree based on the principles of Decision Analysis [98] has been defined. The results obtained using this model are consistent with the view Shingo [24] and several studies that have shown that human error is a dominant factor in product defects [6][7][8][9][10]. However, the Quality Control Tree has shown that source inspection and 100 percent inspection must be combined with poka-yoke techniques to achieve the highest levels of quality control, a conclusion consistent with Shingo's Zero Quality Control Concepts [24]. The Quality Control Tree has also clarified the limitation of Motorola's Six Sigma [5] method, providing estimates that are substantially more consistent with Motorola's own production experience.

The Quality Control Tree demonstrates that defect rates are a complex function related to the control of variation and error, as well as the type, timing, and reliability of inspection. It shows that control and reduction of human error is the most important means for

improving quality beyond the level achieved through the use of traditional Statistical Quality Control [3] methods.

Using this model, the current strengths and weaknesses of the quality control programs for any production line can be quantified in relative terms. A sensitivity study can be performed with minimum effort which aids in identifying the quality focus which will maximize the reduction in defects. The best method for reducing defects depends entirely on the current strengths and weaknesses. Thus there is no common strategy that will be universally successful for each organization.

Chapter 9

A Global Conformance Quality Model

The correlations between assembly complexity, defect rates, and the probability of interference described in previous chapters has laid a foundation for the development of a global Conformance Quality Model (CQM). The third and final goal of this work, and subject of this chapter, is to build upon these observations to define a combinatorial model of defect probabilities that spans errors, variation and product complexity. We will demonstrate that the model is consistent with the observed trends in relating product yield to complexity.

This model provides important insights essential to the formulation of a sound conformance quality improvement strategy, which will be illustrated in this chapter. One of the greatest potential benefits of this model is that it provides a method for comparing the conformance quality potential of dissimilar product concepts in the *earliest* stages of product development. It also provides a basis for assessing the impact of variety and automation on conformance quality.

9.1 Development of the Global Conformance Quality Model

The NRC [14] study presented on the first page of the first chapter introduced a combinatorial model of defects. This method of combining the probability of many independent events is the basis for all modern reliability evaluations and an essential element of a sound defect model. We will build upon this principle and adopt two useful defect categories used in the NRC study, namely: 1) part defects and, 2) assembly defects.

The Part Defect Model

As previously noted, a part may contain material defects, or be unacceptable due to variation or errors in processing and handling. Dispersion in temperature, vibration, operating speed, power fluctuations, tool wear, and gage response reflect only a few of the ways that variation can contribute to part defects. Operators can contribute to defective parts by omitting process steps, misreading gages or specifications, and making dimension measurement errors. Handling errors, such as dropping a part, may result in appearance defects like scratches or dings, as well as more serious damage that impairs function.

In defining part defects, we exclude variation in the interface dimensions, because problems with these features are revealed during assembly, and are related to assembly complexity and assembly time.

As shown in Chapter 7, defect rates have a weak correlation with part count, suggesting that: a) part defects are not the most dominant defect source in complex products and/or, b) part conformance quality is not uniformly distributed among the parts in a product. The large variation in part complexity contributes to the poor correlation between defect rates and part count. In addition, since parts are always less complex than a completed assembly made from the parts, traditional inspection methods are more likely to detect and remove part defects than assembly defects [82]. In consequence of these limitations and the weak correlation with part count, we will define the probability of a part defect in the simplest terms consistent with the NRC model - the probability that the i th part in a product contains a defect is:

$$P\{\text{ith part is defective}\} = d_i \quad (9.1)$$

This formulation will permit refinement as the ability to measure assembly complexity evolves and correlations with defect rates are refined. We note that the probability that the i th part is defective must be constrained to be greater or equal to zero and less than or equal to one.

The Assembly Defect Model

Errors, such as omitting a part, installing the wrong part, or putting a part in the wrong position or orientation will result in defects. In Chapter 3, several studies were cited which correlated an increasing probability of an error with the difficulty and time required to execute a task [37][50][51][55][78][81][82][83][84]. We have also observed that assembly pace can influence the probability that errors are detected and corrected [85].

In addition to errors, excessive variation in the interface dimensions which results in interference during assembly can lead to defects. In Chapter 8 we demonstrated that the probability of interference increases with the complexity of the interface which is related to assembly time.

The predicted increases in error rates and interference probabilities are consistent with the observed correlations between defect rates and assembly time observed in Chapter 7. Since errors and interference both increase with assembly complexity, it is not surprising that observed defects rates are not a linear function of assembly time.

A Global Model Must Reflect Differences in Quality Control Levels

Although defect probabilities increase with complexity, the control of errors, and variation can differ by orders of magnitude between organizations [13]. A comparison of the performance of Motorola and a disk drive manufacturer in Chapter 7 supports this conclusion. Furthermore, some organizations may be better at controlling errors while

other may be better at controlling variation. Consequently, a global model relating defects to complexity must span all of the defect sources without treating variation and errors separately. Separate methods, such as the event tree in Chapter 8, can be used to determine relative dominance of variation and errors once the global performance has been characterized, without reducing the value and effectiveness of the global link between defects and complexity.

There Are No Assembly Defects Below a Threshold Assembly Time

The least complex assembly operations require a finite time for execution. Below a threshold of assembly time, neither assembly operations nor assembly defects exist. Consequently, assembly errors must approach zero at the threshold of the minimum possible assembly time.

Modeling Assembly Defects

Based on these observations, a simple theoretical model describing the probability of a defect for an assembly operation was defined as follows:

$$P\{\text{defect from } i\text{th assembly operation}\} = a_i = c_k (t_i - t_0)^k \quad (9.2)$$

Here, c_k = A variable relating to the quality control of assembly operations, $c_k > 0$

t_i = Predicted time for the i th assembly operation, $t_0 \leq t_i \leq \left(\frac{1}{c_k}\right)^{\frac{1}{k}} - t_0$

t_0 = threshold assembly time for least complex assembly operation, $t_0 \leq 3$ sec/op

k = Constant for the sensitivity of defects to assembly complexity ($\equiv$ time) ($k \geq 1$)

The constraints in this model assure that the probability of a defect will be greater or equal to zero and less than or equal to one. This theoretical model reflects five essential elements for a comprehensive description of assembly defects:

1. Defects should be expressed in terms of the probability of occurrence (c_k) to span both error and variation, with separate methods for identifying the relative dominance of error and variation.
2. The probability of a defect is a function of assembly complexity measured by assembly time ($a_i = f(t_i)$).
3. The relationship between defects and assembly complexity is non-linear (k).
4. The model must be capable of reflecting differences in the level of quality control among organizations (c_k and k reflect organizations quality control capability).
5. Assembly operations, and defects are not defined below some threshold assembly time (t_0).

Yield is Easier to Predict than Defect Rates

Given that an assembly operation involves the addition of a part, the part could contain a defect, the assembly operation could cause a defect, or both the part and assembly operation could result in defects. Thus, there are three separate ways of introducing one or two defects into a product when assembling a part. By contrast, there is only one way of having a defect free assembly - the part must be defect free and the assembly operation

must not result in a defect. As a result, calculating the probability that an operation does not introduce a defect is much easier than calculating the probability it will cause a defect. The probability that a part does not contain a defect is:

$$P\{\text{ith Part is defect free}\} = 1 - d_i \quad (9.3)$$

Similarly, the probability that an operation does not introduce a defect is:

$$P\{\text{ith assembly operation does not result in a defect}\} = 1 - c_k (t_i - t_0)^k \quad (9.4)$$

Note, it is possible to have assembly operations so complex or so poorly controlled that an operation will invariably result in a defect. The number of defects per part could also be greater than one. However, the probability that a product is defect free can not be less than zero. Consequently, equations 9.3 and 9.4 are constrained so that they must be greater or equal to zero.

Describing Product Yield in Terms of Complexity

The joint probability that the ith part and ith assembly operation is free of defects is a product of the probabilities that neither introduces a defect as determined by Equations 9.3 and 9.4. For an assembly, we take the product of defect free probabilities for all assembly operations and parts to determine the probability that the assembly is defect free. This is equivalent to the production yield and is given by the following formula:

$$P_Y = \prod_{i=1}^{N_a} \{1 - c_k (t_i - t_0)^k\} (1 - d_i) \quad (9.5)$$

Where, P_Y = Probability that an assembly is defect free (Yield) ($0 \leq P_Y \leq 1$)

N_a = Number of assembly operations (Number of parts is a subset of this value)

In Equation 9.5, the time for the ith assembly operation (t_i) may be obtained from a detailed Design for Assembly (DFA) evaluation of a product or from a predicted distribution based on the Pareto function. **Equation 9.5 represents the most general form of the global Conformance Quality Model (CQM).** In the following section, we shall show how the equation can be modified to use a Pareto distribution rather than DFA predicted assembly time.

Describing Assembly Times as a Pareto Distribution

Given that assembly times follow a Pareto distribution, from Equation 5.5 the assembly time for the ith operation can be estimated as:

$$t_i = t_{\min} \cdot \left(\frac{N_a}{N_i} \right)^{\frac{1}{\alpha_c}} \quad (9.6)$$

Here, α_c = The power coefficient of the Pareto distribution (continuous form)

N_i = The number of operations have a greater or equal assembly time than t_i

$t_{\min}$ = The minimum assembly time for the Pareto Distribution.

We can replace N_i with "i" and substitute equation 9.6 into Equation 9.5 giving:

$$P_Y = \prod_{i=1}^{N_a} \left\{ 1 - c_k \left(t_{\min} \cdot \left(\frac{N_a}{i} \right)^{\frac{1}{\alpha_c}} - t_0 \right)^k \right\} (1 - d_i) \quad (9.7)$$

Equation 9.7 embodies the most important observations of this work. It links a description of assembly complexity based on the Pareto distribution, with a model that relates the defect rates to assembly complexity. It brings together in a single equation fundamental insights regarding assembly complexity and conformance quality. In the following sections, we will show that this form and related forms of this model can provide profoundly useful information in product development and concept selection.

Comparing the Theoretical Model to Observed Correlations

A sound model relating product yield to complexity should also be consistent with the observed correlations between production defect rates and assembly time from Chapter 7. To make such a comparison, it is necessary to understand how the defects per unit are related to the product yield. The product yield is equal to one minus the fraction of defective units (DU). However, each defective unit may contain more than one defect. As a result, the fraction of defective units is not equal to the defects per unit.

Using an average defect per operation (p), the product yield can be approximated using the binomial formula [43] as follows:

$$P_Y = (1 - DU) = \binom{N_a}{0} \cdot p^0 \cdot (1-p)^{N_a-0} \quad (9.8)$$

Relating Yield to Defects per Unit

The average defects per operation (p) is equal to the number of defects per unit (DPU) divided by the number of assembly operations (N_a). This can be substituted into Equation 9.8, and recognizing that the first two terms in this binomial formula of Equation 9.8 are equal to one, results in the following relationship.

$$P_Y = (1-p)^{N_a} = \left(1 - \frac{DPU}{N_a} \right)^{N_a} \quad (9.9)$$

This equation is very powerful because it permits estimation of the defects per unit if the product yield is known, or yield if the number of defects per unit is known. An alternate formulation of Equation 9.9 could be defined by substituting the part count for the operation count. From either equation it can be shown that the Defects per Unit (DPU)

always equal or exceeds the fraction of defective units (DU). Equation 9.9 can also be written as a product of probabilities as follows:

$$P_Y = \left(1 - \frac{\text{DPU}}{N_a}\right)^{N_a} = \prod_{i=1}^{N_a} \left(1 - \frac{\text{DPU}}{N_a}\right) \quad (9.10)$$

To assure that the yield probability does not go below zero, in this equation we must constrain the Defects per Unit to be less than or equal to the number of assembly operations ($\text{DPU} \leq N_a$), although greater defect rates can occur in practice. Since the defects per unit (DPU) must be greater or equal to zero, the yield is constrained by $0 \leq P_Y \leq 1$. In Chapter 7 (Equation 7.5) we demonstrated that the Defects per Unit (DPU) can be described in terms of the total DFA assembly time and number of assembly operations which can be substituted into equation 9.10 to give:

$$P_Y = \prod_{i=1}^{N_a} \left(1 - \frac{(\text{TM} - c_1 \cdot N_a)^{c_2}}{N_a \cdot c_3}\right) \quad (9.11)$$

Where, TM = The DFA predicted total manual assembly time in seconds
 c_1 , c_2 , and c_3 = constants.

Now, everything above and below the fraction bar can be multiplied by the number of assembly operations (N_a) raised to a constant (c_2) and rearranged to give:

$$P_Y = \prod_{i=1}^{N_a} \left(1 - \frac{N_a^{c_2}}{N_a \cdot c_3} \left(\frac{\text{TM} - c_1 \cdot N_a}{N_a}\right)^{c_2}\right) \quad (9.12)$$

We define a new variable as:

$$c_{\bar{k}} = \frac{N_a^{\bar{k}-1}}{c_3} \quad (9.13)$$

Now the DFA total assembly time (TM) divided by the number of assembly operations (N_a) is equal to the average assembly time per operation ($\bar{t}$). We can also define c_1 as a constant equal to the threshold assembly time t_0 , and rename the constant c_2 as $\bar{k}$. These relationships and Equation 9.13 can be substituted into Equation 9.12 to give:

$$P_Y = \prod_{i=1}^{N_a} \left(1 - c_{\bar{k}} \cdot (\bar{t} - t_0)^{\bar{k}}\right) \quad (9.14)$$

The Theoretical Model and Data Correlation Model Are Related

There are three minor differences between Equation 9.5 based on the theoretical development and Equation 9.14 derived from the correlations with observed defect rates. First, Equation 9.14 does not contain an expression for the probability that parts are defect free ($1-d_j$). This is equivalent to using a value of d_j equal to zero in equation 9.5. This should not be interpreted to mean that there are no part defects, but rather that part defects are more strongly correlated with assembly time than part count. Secondly, the yield in Equation 9.5 is based on the *distribution* of assembly time (t_i), while equation 9.14 relates yield to the *average* assembly time ($\bar{t}$). Finally, the value of c_k in equation 9.14 has been shown to be a function of the number of assembly operations. Initially, we assumed that c_k would be a constant in Equation 9.5. Based on these observations we redefine c_k in a manner consistent with Equation 9.13 as follows:

$$c_k = \frac{N_a^{k-1}}{c_3} \quad (9.15)$$

The similarity between Equation 9.5 and 9.14 is remarkable given that they were derived from two distinctly different approaches. Equation 9.5 was defined nearly a year before defect and complexity data was available. The relationship given in Equation 9.14 was only identified after a power fit was found to be most appropriate method for relating Defects per Unit (DPU) to DFA assembly time (TM). The fact that the same basic model has been identified using a theoretical and experimental approach, reinforces the validity of the general model.

Comparison of the Yield Using a Distribution versus Average Assembly Time

Although Equation 9.5 and 9.14 have virtually the same form, the predicted yield based on a distribution of assembly times can differ from the predictions based on the average assembly time as illustrated in Figures 9.1 and 9.2. The predicted and observed process yield for the disk drive data is plotted in both figures. As shown in Figure 9.1, which is based on a distribution of assembly time using Equation 9.7, the predicted yield is sensitive to the value of α_c and diverges as the number of assembly operations increase. By contrast, the predicted process yield is relatively insensitivity to α_c using Equation 9.14 as illustrated in Figure 9.2. Agreement between the two methods can be obtained if the value of k is not constrained to equal $\bar{k}$. In these comparison the value of $t_{\min}$ has been adjusted so that the total DFA assembly time (TM) is the same for a given number of assembly operations independent of the value of α_c .

In spite of the differences in Figures 9.1 and 9.2, the general pattern of the predicted process yield is the same using either a model based on a distribution or average assembly time. These figures also show that prediction of the yield based on either method will give similar results for products having a small number of assembly operations ($N_a \leq 50$). Of the 240 subassemblies we studied, 88 percent had fewer than 50 assembly operations, suggesting that the simpler equation (Equation 9.14) will be adequate in the majority of

cases. Where products are complex ($N_a > 50$), the distribution of assembly time can be used to predict changes in assembly complexity and provides a better estimate of yield using Equation 9.7. Thus, both forms of the model have important applications.

Figure 9.1. The predicted and observed process yield versus the number of assembly operations for the disk drive data. Predictions are based on equation 9.7 with $k = 1.65$, $c_3 = 248,489$, and $t_{\min} = 3.05, 3.94, 4.64$ for $\alpha_c = 1.25, 1.5$, and 1.75 respectively.

Figure 9.2. The predicted and observed process yield versus the number of assembly operations for the disk drive data. Predictions are based on equation 9.14 with $\bar{k} = 1.765$, $c_3 = 248,489$, and $t_{\min} = 3.05, 3.94, 4.64$ for $\alpha_c = 1.25, 1.5$, and 1.75 respectively.

In Chapter 7 and this chapter, we have demonstrated that the basic relationships defined in this work have provided a theoretically and intuitively sound description of defects per unit (DPU), defects per part (DPP) and process yield (P_Y) that is consistent with correlations observed in different production settings. We can use both forms of the defined models to provide new and useful insights into the role of design in conformance quality.

9.2 Insights From the Global Conformance Quality Model

Many Opportunities for Improving Conformance Quality

One of the most useful insights provided by the conformance quality model is that it identifies several different approaches for reducing defects. Equation 9.7 suggests five opportunities for reducing product defects as follows:

1. Reduce the number of assembly operations (N_a)
2. Reduce the difficulty (time) of assembly operations (t_i)
3. Improve the control of variation and/or error (reducing c_k and k)
4. Reduce the number of parts (a subset of the number of assembly operations)
5. Reduce the part defect probabilities (d_i)

The change that makes the greatest improvement in conformance quality depends on the current levels of performance and the opportunities for improvement in each specific area. To illustrate, we will examine the impact of evolving design changes for a fictitious product where the design team vigorously pursues a single improvement objective at a given time. We will assume that the original product has 32 assembly operations requiring an average of 8 seconds which can be reduced through multiple redesigns to 16 assembly operations taking an average of 4 seconds. We will assume that the level of improvement will follow the law of diminishing returns. The impact of two different strategies for improving yield based on these assumptions are illustrated in Figure 9.3.

Figure 9.3. The process yield as a function of time using two different methods for reducing defects. Strategy A initially targets reduction in assembly operations and switches to reducing assembly difficulty in the middle of the period. In Strategy B, the same objectives are pursued in reverse order. Curves are based on $\bar{k}=1.5$, $c_3=100000$, $t_0=2$ sec/operation using Equation 9.14.

Quality Improvements Must Target the Current Weakness

Figure 9.3 shows that reducing assembly difficulty initially provides a greater improvement in process yield than eliminating assembly operations. However, the opportunity for improvement using a single method is limited, with the benefits of additional effort tapering off. Subsequent improvement, regardless of the initial strategy, requires a change in the focus that address the current weaknesses and opportunities. The pattern of improvement illustrated for design changes, also applies to other quality methodologies such as poka-yoke [24] and Motorola's Six Sigma [5]. This pattern illustrates a potentially dangerous pitfall in quality improvement programs. Implementation of almost any method will produce some improvement. However, if quality planners remain focused on a single methodology based on initial gains, they will often miss the greatest opportunities for reducing defects.

Figure 9.3 also shows that reducing the number of assembly operations to the minimum, the initial objective of Strategy A, did not achieve the maximum process yield. In fact, this was not even the best approach to improving yield. It again reinforces the weakness of focusing on quantity measures of complexity. Neither part nor operation count minimization, or any combination will assure maximum conformance quality.

Comparing Product Concepts

Another significant benefit of the global conformance quality model is that it aids in identifying design changes that will result in the greatest reduction in defect rates. These insights provide a means for comparing the conformance quality potential of different concepts during the earliest stages of product development.

To introduce a method of comparison, we will begin by examining products that share the same defect rate. From Equation 7.8, it was shown that the defects per unit (DPU) could be defined in terms of the DFA predicted assembly time (TM), the number of assembly operations (N_a), and three constants (t_0 , c_3 , and $\bar{k}$) as follows:

$$DPU = \frac{(TM - t_0 \cdot N_a)^{\bar{k}}}{c_3} \quad (9.16)$$

From this equation it can be seen that the number of defects per unit will be constant as long as the following expression is equal to a constant (C):

$$TM - t_0 \cdot N_a = C \quad (9.17)$$

A Plot of iso-Defects per Unit (DPU)

From this it can be seen that the products with the same number of defect per unit (DPU) will fall along a straight line in a plot of DFA assembly time versus the number of assembly operations as illustrated in Figure 9.4. Illustrated in the same figure are five different ways of altering a "baseline design" represented as a point having 100 assembly operations requiring 650 seconds for assembly. This point falls on line of 0.03 defects per unit. Products produced with the same level of quality control below this line will have fewer defects, and products above this line will have more defects. The slope of a lines having constant defects per unit is equal to the threshold assembly time. Thus, a factor that resulted in minor improvement in the correlation between defects and complexity, is a key element in comparing conformance quality potential.

Figure 9.4. Lines of constant defects per unit (iso-DPU) for DFA Assembly time (TM in seconds) versus the number of assembly operations (N_a). The lines of constant defects per unit are based on $t_0 = 1.68$ seconds per operation, $c_3 = 112,370$, and $\bar{k} = 1.316$. Five ways of changing a design are labeled as A through E in the figure. Note the non-uniform line spacing.

Minimizing Operation Count Does Not Assure Fewer Defects

The changes labeled D and E in Figure 9.4 will increase the defects per unit from 0.03 to 0.04. *The change labeled as D, shows that the defects per unit will increase if the number of assembly operations decreases when the DFA assembly time remains constant.* This re-emphasizes the hazards of minimizing quantity measures of complexity. Reducing the number of assembly operation will improve conformance quality only if the assembly operations do not become more difficult as a result of eliminating some operations.

Increasing the Operation Count Can Reduce Defects

By contrast, product changes marked A, B, & C in Figure 9.4 will each reduce the defect rate from 0.03 defects per unit to 0.02 defects per unit. In case A, the number of assembly operations and DFA assembly time is reduced. For case B, the DFA assembly time is reduced, but the number of assembly operations remains constant. In case C, the DFA assembly remains constant, but the number of assembly operations increases, a change that can only be achieved if the difficulty of assembly operations is dramatically reduced.

It may seem somewhat counter-intuitive that the number of defects can be reduced even if the number of assembly operations is increased. However, there is some evidence in support of this prediction from a recent study described by Barkan et al [34] comparing the assembly complexity of instrument panels for light trucks, one domestic and one foreign. The import product had more screws and a total of roughly 20% more parts than the domestic product. The foreign product required 129 assembly operations with a DFA assembly time of 728 seconds. By contrast, the domestic product required only 125 assembly operations but the DFA assembly time was predicted to take 757 seconds. The foreign product, which is recognized for its superior quality, had a higher part count, and operation count but a shorter DFA predicted assembly time. Our model predicts that this combination would contribute to the higher level of conformance quality that was observed.

In Figure 9.4, note that the relative conformance quality potential of products can be determined by comparing their relative distance from any baseline of constant defects per unit. This relative comparison may be made without quantifying the defects per unit represented by the baseline.

Comparing the Concepts Having the Same Yield

We can also examine conditions required to achieve a constant product yield. This can be done by rearranging Equation 9.11 to give:

$$TM = t_0 \cdot N_a + \left\{ (1 - P_Y^{1/N_a}) \cdot c_3 \cdot N_a \right\}^{\frac{1}{k}} \quad (9.18)$$

For a specified yield (P_Y), the number of assembly operations (N_a) can be varied while treating all other elements on the right hand side of the equation as constants to give the DFA assembly time (TM). For high yield processes ($P_Y > .95$), the portion of Equation 9.18 that is to the right of the plus sign has a nearly constant value for any number of assembly operations. In this case, the equation can be reduced to the form given in Equation 9.17 and the resulting evaluation would be virtually identical to the comparisons presented in Figure 9.4.

Comparison of Product Concepts - An Illustrated Example

The techniques for comparing product concepts will be illustrated by examining assembly options for the box described by Olivera [92]. The assembly concepts investigated are illustrated in Figure 9.5.

For each of the proposed assembly concepts, the DFA assembly time and number of assembly operations were determined and plotted in Figure 9.6. Concepts 1, 2, and 4 are all about the same distance below the line of constant defects per unit and will have roughly the same defect rates although they differ in assembly time and number of assembly operations. In this figure, Concept 3 is the furthest below the line representing constant defects per unit, and as a result has the lowest predicted defect rate. In the absence of other constraints, we would select Concept 3. These conclusions have been checked using Equation 9.14 with the results listed in Table 9.1.

Comparing the results of Table 9.1 and Figure 9.6, we can see that the relative conformance quality of the concepts studied was appropriately predicted by the graphical method without the need for any calculations. Table 9.1 shows that the estimated conformance quality of the concepts differ by nearly an order of magnitude, providing valuable input during concept comparison and selection.

Figure 9.5. Alternate assembly concepts for a box. The concept was proposed by Olivera [92].

Figure 9.6. Predicted Design for Assembly (DFA) time versus the number of assembly operations for five products from Figure 9.5. The solid line is for constant defects per unit equal to the original concept labeled "O" (based on $t_0 = 2$ sec/op). Numbers indicate other concepts. Outcomes in the shaded area cannot occur.

Table 9.1. Estimated Defects per Unit (DPU) and yield probability for five product concept alternatives illustrated in Figure 9.5. Calculations are based on an average assembly time model (Equation 9.14 and 9.16) using $\bar{k}=1.3$, $c_3=64,700$, $t_0=2$ sec/op. Note, 1.6 seconds has been added to Concept 4 for assembly operations which are not "top down."

	Original Concept	Concept 1 1 Screw	Concept 2 Centered Screw	Concept 3 Snap Lid	Concept 4 Lock Pin
DFA Ass'y Time (TM-sec)	22.5	14.7	13.8	7	16.1
Number of Operations (Na)	4	3	3	2	4
Estimated DPU	0.0005	0.000257	0.000223	0.000065	0.000234
Estimated Yield (P_Y)	0.9995	0.999743	0.999777	0.999935	0.999766
Conformance Quality Rank	5	4	2	1	3

9.3 A Seven Point Conformance Quality Strategy (CQS)

The ability to identify opportunities for reducing defects and to compare the conformance quality potential of product concepts, as illustrated in the previous section, introduces a new opportunity for defining quality conformance strategies that will maximize improvement for the level of invested effort. This study has revealed five key elements that provide the foundation for improved quality strategies:

1. Assembly complexity (time) can be described by a Pareto distribution
2. Defect rates are clearly linked to assembly complexity
3. The general quality control of each organization can be measured
4. Each organizations strengths and weaknesses in quality control can be estimated
5. The impact of product changes on conformance quality can be estimated

We have shown in several examples that there is no single quality strategy which globally addresses the needs of every organization. *Each organization must formulate its own unique strategy consistent with its strengths, weaknesses, products, opportunities and goals.* Development of sound strategy can be completed in seven basic steps for each organization as follows:

- Step 1. Assess the assembly complexity of existing products and alternate concepts
- Step 2. Assess the organization's current level of quality control.
- Step 3. Estimate the impact of proposed concepts on conformance quality
- Step 4. Establish a conformance quality goal for the next product cycle.
- Step 5. Determine the require improvement ratio for quality control
- Step 6. Assess the current quality control strengths and weaknesses
- Step 7. Target the level of improvement in specific quality control areas

The information flow between these steps is illustrated in Figure 9.7. For example, the ability to estimate the impact of new concepts on product quality depends upon 1) the ability to measure the complexity of product concepts, and 2) an assessment of sensitivity

of quality to complexity for each organization. In the following sections, these steps will be briefly discussed and illustrated, building upon the foundation developed in previous chapters.

Figure 9.7. Information flow in the steps required to define a Conformance Quality Strategy (CQS).

STEP 1: Assess the Complexity of the Product and Alternate Concepts

The assembly complexity of the existing product should be determined by performing a Design for Assembly (DFA) analysis. The assembly complexity of key alternate concepts must also be estimated. This can be done using DFA evaluations, however, for complex alternate concepts substantial analytical effort may be avoided by estimating their assembly complexity using the Pareto distribution as described in Chapter 5.

The DFA evaluations described earlier in this chapter for Olivera's [92] box and four alternate concepts shown in Figure 9.5 illustrate assessment of assembly complexity for simple products. We will use the results obtained for these five product concepts to illustrate the development of a quality strategy in the remaining steps.

STEP 2: Assessing the Current Level of Quality Control.

The second step in establishing a Conformance Quality Strategy (CQS) can be the most difficult. In the ideal case, each organization would perform Design for Assembly (DFA) evaluations of several products currently in production, including the product that is to be replaced. Ideally the products examined should span a range of complexity. For each product, data on the yield or defects per unit must be gathered. Using this data the level of global quality control can be characterized for each organization by determining the values of the constants in Equation 9.16 ($\bar{k}$, c_3 , and t_0) that maximize the correlation with the data.

In some cases obtaining useful data for assessing global quality control may be unreasonably difficult due to extreme product complexity, or the lack of cooperation or

support within the organization. Other organization's may have products of such uniform complexity, that the quality control constants can not be accurately determined. When required, an approximate method of estimating the quality control constants may be used. In these circumstances, it is generally better to underestimate the sensitivity of defects to complexity since this approach will encourage greater improvement in controlling errors and variation. Toward this goal, if defect and complexity data is only available for a single product (or average of similar products), a value of 1.3 should be assumed for $\bar{k}$, and t_0 should can be assumed to equal 2 seconds. The value of c_3 can then be determined by rearranging Equation 9.16 to give:

$$c_3 = \frac{(TM - t_0 \cdot N_a)^{1.3}}{DPU} \quad (9.19)$$

For example, if the number of defects per unit (DPU) for assemblies of Olivera's box shown in Figure 9.5 is 0.0005, the value of c_3 would be approximately 64,700 based on a DFA assembly time of 22.5 seconds and 4 assembly operations.

STEP 3: Assess the Impact of Complexity on Quality

The concept complexities determined in Step 1 and the global assessment of quality control from Step 2 are used to predict the quality potential of each alternate concept using either Equation 9.7, 9.8, or 9.14 in the third step. This step has been previously illustrated for the box assemblies as tabulated in Table 9.1.

In our example, all of the alternate concepts reduce assembly time and defect rates. However, in many situations the addition of new features may result in an increase in product complexity with a potential decline in yield. The addition of air bags, anti-lock braking systems, and turbocharging in automobiles reflect product changes that increase complexity. These examples show that the product concept with the lowest potential defect rate may not be the most acceptable. The snap fit lid represented by Concept 3 in Figure 9.5 has the lowest predicted defect rate but could be rejected because the lid is not secured.

The strongest design concept, indicates the general way that conformance quality is likely to change given that quality control remains unchanged. Assuming that the second concept in Figure 9.5 with the single centered screw is the most favored design concept in our example, the expected number of defects per unit would drop to 223 ppm from 500 ppm for the original Olivera design.

STEP 4: Establish a Conformance Quality Goal

A quality goal is one of the most important elements of a Conformance Quality Strategy and determines how much effort must be dedicated to improvement. Conformance quality goals may be aggressive, but should also be realistic. A reasonable conformance quality

target depends upon 1) changes in design complexity, 2) the current level of quality control, and 3) the performance and anticipated response of competitors.

If the design becomes more complex, maintaining the same conformance quality level in terms of defects per unit may be an optimistic production goal. On the other hand, if the design and assembly is less complex, large reductions in defect rates may be achieved without improved control of variation and error. As a consequence, the proposed design alternatives have an important impact on setting appropriate conformance quality goals.

The ability to achieve conformance quality improvements also depends upon the current level of performance of each organization. For example, a goal of five or fewer defects per million parts in the next product cycle may be unrealistic for an organization that currently has a defect rate of 2000 ppm. By contrast, the same goal could be a reasonable objective for a company that has already achieved a defect rate in the range of 35 ppm.

The level of desired or required improvement should also be influenced by competitor performance and anticipated response. For some products, a very aggressive posture may be required just to remain competitive.

Given an assumed product defect rate from Step 2 of 500 ppm for the original concept defined by Olivera's box, a conformance quality goal for the next product cycle will be set at 75 ppm in our example. We consider this goal to be reasonable since a significant reduction in defects is anticipated for the easier assembly.

STEP 5: Defining the Quality Control Improvement Ratio

The required change in quality control is reflected in the difference between the projected defect rate for the new product given the existing level of quality control and the conformance quality goal. For example, given an unchanged level of control for variation or error, the product defect rate is predicted to drop from 500 ppm to 223 ppm by changing from Olivera's [92] original design to Concept 2, which has a single centered screw holding the lid to the box. Given that Concept 2 is selected, we can now ask how much additional improvement in the control of variation and error is required to meet the goal of a defect rate of less than 75 ppm.

To achieve a defect rate of 75 ppm, defects arising from variation and error must drop from 223 to 75 ppm. The quality control level for the goal is roughly one third the current level of performance. We define the improvement ratio as:

$$I_R = \frac{\text{Current QC Control Level}}{\text{Target QC Control Level}} \quad (9.20)$$

In this equation, the current quality control level is based on the expected defect rate after intended design changes are implemented. In our example, the improvement ratio would be approximately equal three (223 ppm/75 ppm). In other words, defects caused by variation and error must be reduced by a factor of three to meet the intended goal.

STEP 6: Assess the Current Quality Control Strengths and Weaknesses

To identify the strengths and weaknesses of the current quality control methods, the probabilities for the event tree given in Figure 8.2 must be estimated. These probabilities address process control, frequency and quality of inspection, and the frequency and control of errors. Specific evaluations must be performed for each organization, since there can be substantial differences between organizations. Assessment of these probabilities helps organizations recognize those things that they are doing well. It also can aid in exposing opportunities for improvement.

To illustrate the steps in setting a quality strategy, we will assume a level of quality control equivalent to the values listed for traditional Statistical Quality Control from Table 8.2. Based on the values from this table, roughly half of the defects are caused by errors and the other half result from excessive variation. The sensitivity analysis performed in Chapter 8 showed that the greatest improvement could be achieved by reducing and controlling error followed by a reduction in process variation.

STEP 7. Target Improvement in Specific Areas

In the last step of establishing a quality strategy, improvement goals for specific areas of quality control are established to achieve the general product quality goal. Since reducing error offers the greatest opportunity for improvement, our objective will be to achieve the greatest reduction in the defects originating from this source.

Table 9.2 shows the original quality performance factors and one set of improvements that are likely to achieve the new quality goal. There are four specific changes to reduce defects caused by errors: 1) design poka-yoke inspection (α_k) methods that have a 95 percent probability of detecting specified errors, 2) reduce the probability of an error (e_i & e_j) using poka-yoke by a factor of two, 3) incorporate poka-yoke inspection (i_e & i_k) for twenty percent of the error sources that are causing defects. These changes are projected to reduce error defects from 799 to 342 ppm.

Also illustrated in Table 9.2 are changes intended to reduce defects caused by excessive variation. Inspection of the output (i_o) is increased and the defects caused by process variation (b_o) are to be reduced by roughly a factor of two and a half, these are relatively modest improvements compared to Motorola's 6 sigma objective. Collectively these changes should reduce the variation defects from 1176 to 322 ppm.

Note that the defect rates in Table 9.2 have not been adjusted for product complexity and are therefore representative of "typical" values. As a consequence, the defect rates in this table do not match either the predicted product defect rate of 223 ppm for the baseline case or the goal defect rate of 75 ppm. It is more important that the estimated reduction in defects is proportional to the improvement ratio (I_R) which is approximately equal to three.

Table 9.2. Baseline Quality Control Tree factors and targeted improvements to achieve a three fold reduction in defects.

Parameter	Baseline SQC	Target QC Plan	Change
$a_i = a_o$	0.9999	0.9999	Undefined -0.001
$\alpha_i = \alpha_o$	0.15	0.15	
α_e		0.05	
b_o	0.002	0.0008	
$e_i = e_o$	0.0004	0.0002	-0.0002
$i_e = i_k$	0.00	0.20	0.20
i_i	0.01	0.01	0.29
i_o	0.01	0.30	
Variation Defects	0.001176	0.000322	-0.000854
Error Defects	0.000799	0.000324	-0.000475
Total Defects (ppm)	1975	646	$I_R = 3.057$
Ratio Error/Variation	0.68	1.01	

Rather than promoting a nebulous concept of improvement, this strategic plan raises the awareness of the organization regarding improvement opportunities, providing specific courses of action with clearly defined goals. In every area of focus, the goals are relatively modest, and can be reasonably achieved. The strategy does not require tremendous exertion in any single focus.

The proposed strategy targets the areas and extent of improvement, however, it does not provide specifics on how this is to be accomplished. The strategy must be used in conjunction with existing quality control methodologies. In this example, the selected strategy points to the need for implementing poka-yoke techniques for error control, source inspection for controlling input variation, and Taguchi methods, or Six Sigma methods for limiting process variation. Shingo's 100% inspection concepts should be applied to output inspection.

9.4 Evaluating the Impact of Automation and Variety

The Impact of Automation on Yield (P_Y)

Automated assembly may be required in harsh or unusual environments, or for tasks requiring unusual precision or high levels of productivity. In such situations the task objectives exceed the performance capability of human beings. However, in many circumstances the decision to automate assembly is partially justified on the basis of potential improvement in product quality rather than being driven by performance

limitations of human operators. The ability to estimate the global impact on the product yield resulting from the automating a fraction of the production line provides information essential for sound decisions regarding the appropriate level of automation.

In a classic paper, LaRue [119] demonstrated that defects from automated assembly could be treated in a combinatorial manner and that the probability of a defect free product decreased as assembly complexity increased. His observations suggest that the defects caused by automation can be treated in a manner similar to defects arising from human performance. In fact, the correlations between defect rates and complexity observed in our studies involve assembly processes with differing proportions of automated assembly. From these observations, our general model of defects should be equally valid for either automated or manual assembly.

In our model, we can conceptually convert the defect rate of any manual process to an automated process by modifying the quality control constants ($\bar{k}$, c_3 , and t_0) for each operation. An automated assembly having one hundredth of the defects of an equivalent manual assembly would simply have a value of c_3 that is 100 time greater than c_3 for the manual process. We can use a scale factor (s) to represent this difference.

A Model of the Impact of Automation on Product Yield

In those situations where human limitations are not the driving factor in automation, the easiest actions are to most likely to be automated. Thus we can view increasing automation as a sequential replacement of manual assembly operations from the least difficult to the most difficult. Given that "n" operations have been automated, the probability of a defect free product can be found by modifying Equation 9.8 as follows:

$$P_Y = \prod_{i=1}^{N_a} \left\{ 1 - \frac{N_a^{k-1}}{s_i \cdot c_3} (t_{\min} \cdot \left(\frac{N_a}{i} \right)^{\frac{1}{\alpha_c}} - t_0)^k \right\} (1 - d_i) \quad (9.21)$$

Where, s_i = defect reduction factor $\begin{cases} s_i = s & \text{for } i \leq N_a - n \\ s_i = 1 & \text{for } i > N_a - n \end{cases}$

Using Equation 9.19, the yield has been predicted for several specific cases as a function of the level of automation. A typical case illustrating the benefit of automation is shown in Figure 9.8. The illustrated data is based on the distribution of assembly time determined for the instrument panel of a foreign light truck ($\alpha_c = 2.07$, $t_{\min} = 3.45$ sec, $N_a = 129$ operations), and a quality control similar to Motorola's ($c_3 = 110,000$, $t_0 = 2.0$ sec/operation, $k = 1.3$, $d_i = 0$). Plotted in the Figure 9.8 are curves for three ratios of defect reduction achieved by automation compared to manual assembly.

Figure 9.8. Yield in percent versus the fraction of automated operations in percent for three ratios of defect reduction (s) achieved by automation relative to manual processes. The curves are based on $\alpha_c = 2.07$, $t_{\min} = 3.45$ sec, $N_a = 129$ operations, $c_3 = 110,000$, $t_0 = 2.0$ sec/operation, $k = 1.3$, $d_i = 0$.

Figure 9.8 shows that significant improvement in the yield is not realized until a large fraction of the operations are automated. This is due to the fact that automation generally replaces assembly operations that are the least likely source of defects. This suggests that, in many applications, the same level of improvement in quality may be achieved without automation by reducing the complexity of assembly operations and improving quality control [24]. Such an approach can significantly reduce capital investment and time to market, while enhancing flexibility.

Predictions Are Consistent with Production Experience

The predicted pattern of conformance quality improvement is reinforced by observations from the production environment. During a visit at the disk drive manufacturing facility, one manager commented that their company had invested heavily in automation only to find that the general improvement in conformance quality was disappointing.

Womack et al [2] published two figures showing the assembly defects per hundred vehicles versus productivity and percent automation versus productivity. These two figures were digitized and paired data was identified enabling a plot of defects per hundred vehicles versus automation shown in Figure 9.9. This figure shows that the reduction in defects achieved through automation is relatively modest when fewer than 50 percent of the operations have been automated, consistent with our predicted trend.

The ability to automate assembly often depends upon design changes that would also improve the productivity and quality for manual assembly. Consequently, the decision to automate assembly should only be made within the global context of other opportunities to improve design and production. When the decision to automate is influenced by quality considerations, care should be exercised to assure the potentially cost effective methods of quality control and reduced design complexity have been adequately considered as alternatives to automation.

Figure 9.9. Assembly defects per 100 vehicles versus percentage of automated assembly steps for volume producers in 1989 derived from Womack et al [2]. Womack stated, "'Automation' equals the percent of assembly tasks that have been automated. Automation includes both fixed automation such as multi-welders and flexible automation using robots. Automation of materials handling is not included." The correlation coefficient (r) for the linear fit (all data) is -0.22. The legend indicates the operating country (and plant location if different) with the following abbreviations: J=Japan, NA=North America, Ind.=Industrialized, US=United States.

Assessing the Impact of Variety

Variety in complex products requires selection of alternative assembly actions. For example, operators may be required to select parts that match a particular color scheme, or decide whether or not to install a part that adds a feature or style enhancement. Such assembly decisions increase the time required to complete an assembly. Equation 9.7 and 9.14 would predict that variety would increase the defect rate and reduce yield as a consequence of the increase in assembly time.

These trends are consistent with Stalk and Hout's [50] observation that production yield decreased as product variety was expanded in one company. It is also consistent with Gatchell's [37] study which showed that operators with ten parts made 46 percent more errors and needed 13 percent more decision time than operators that could choose from only 4 parts. We note in Gatchell's observations that the increase in defects is greater than the proportional increase in assembly time, a trend that is consistent with our model.

Poka-yoke [24] methods can reduce decision time, assembly time, and defect rates by blocking operator access to all parts that are inappropriate for the specific assembly. Information on an assembly tag can be used to open doors to bins containing the right part in the right sequence for assembly. These methods can overcome most (but not all) of the defects and assembly time penalties resulting from increased variety.

In the case of variety, we can predict the general trends but can not provide a specific example because time factors for mental processes have not been incorporated in the

Design for Assembly (DFA) methodologies. Incorporating factors for decision time would improve the ability of DFA methods to model assembly complexity while alerting designers to the impact of variety and mitigating poka-yoke methods.

9.5 Summary and Conclusion

In this chapter we have shown that a theoretical development as well as correlations for production data lead to the same basic global conformance quality model. These observations reinforce the validity of the of the proposed model relating yield to product complexity determined by Design for Assembly (DFA) evaluations. Collectively, we have shown that the elements of this model can be used to describe defects per part, defects per unit, and the product yield in a manner that is consistent with two different sets of production data.

The new model shows that minimizing the quantity measures of complexity will not necessarily achieve the highest levels of conformance quality. It identifies several distinctly different methods for reducing defects and provides a means for assessing the impact of changes in specific areas. This permits comparison of the quality conformance potential of different product concepts and introduces the opportunity for setting quality improvement strategies that maximize the benefit of invested effort. In this chapter we have used a simple example to illustrate a technique for defining a conformance quality strategy.

We have also shown that the global model of conformance quality offers many insights into design decisions that influence quality such as automation and variation. The insights provided by the model are consistent with trends observed in production and research settings.

The model has potentially broad application in concept comparison and selection. It can also have a profound influence in guiding quality improvement programs, and may prove to be an important aid in design decisions such as automation and variety. These aspects of the model can have significant impact during the earliest stages of concept formation when the impact on the design process has the greatest potential benefit.

Chapter 10

A Global Perspective on the Origin of Defects

A sound strategy for reducing defects has been hampered in most cases by the singular focus of existing quality methodologies. Achieving the highest levels of conformance quality requires a broad perspective, enabling identification of the real source of defects and the corrective actions which will be most effective in eliminating the defects. Toward this end, we have developed a new model of conformance quality that integrates each of the three principle defect sources: 1) Variation, 2) Human Error, and 3) Complexity.

As a result of the broad perspective required in the development of this global model, a complete in-depth treatment of every aspect of conformance quality is beyond the scope of this dissertation. In this chapter, however, we will review the underlying principles that are the foundation for a new view of conformance quality, and summarize the key findings of this work. The potential impact of these quality concepts on product value will also be presented with a discussion of the implications.

10.1 The Foundation for Global Conformance Quality

The soundness of any theory or model depends upon the accuracy and correctness of the underlying assumptions which are frequently unstated. The greatest opportunities for improvement often result from challenging the assumptions of accepted theories. In order to provide an opportunity for scrutiny, and correction or refinement as required, it is our intent to provide, to the best of our ability, a summary of the underlying assumptions and principles which form the basis for our model of conformance quality. We have tried to test these assumptions, however, such tests have been limited to the scope of this study.

The fundamental principles which are the basis for a global conformance quality model are summarized as follows:

1. Complexity, Variation, and Error are different defect sources requiring different methods of control.
2. Probability is the only common method of modeling both error and variation.
3. The probability of defects caused by error and variation increases with complexity.
 - A. Assembly complexity can be measured in relative terms using Design for Assembly (DFA).
4. Probability can be described by combinatorial and Decision Analysis [98] methods.
5. The level of quality control differs among manufacturers.
 - A. The quality control level is a combined function of control of variation and error.
 - B. The relative fraction of error and variation defects differs among manufacturers.

Three New Methods Aid in Conformance Quality Improvement

Based on these fundamental principles three new methods essential for improving conformance quality have been developed, namely: 1) a global Conformance Quality Model (CQM), 2) a Quality Control Tree (QCT), and 3) a Conformance Quality Strategy (CQS). The application and relationship of these tools is illustrated in Figure 10.1.

Figure 10.1. Pyramid representation of the new conformance quality methods and their application. (QC = Quality Control, DPU = Defects per Unit)

The Global Conformance Quality Model (CQM)

As illustrated in Figure 10.1, The global Conformance Quality Model (CQM) is the foundation for a new perspective on quality. It provides the means of assessing the general level of quality control for each organization (Equation 9.16 or 9.19) and a method of benchmarking conformance quality even for manufacturers producing dissimilar products (Equation 7.4). One of the greatest benefits of the global Conformance Quality Model is that it can be used for comparing the conformance quality potential of alternative concepts during the earliest phases of concept development. The global Conformance Quality Model can also be used to predict the product yield, defects per part, or defects per unit (Equation 9.7, 9.8 or 9.14). The global model has wide potential application in guiding design decisions regarding the appropriate level of automation.

The Quality Control Tree (QCT)

Because the control of variation and error can differ between organizations, a separate method is required to identify the general strengths and weaknesses of the existing quality control philosophy for each organization. The Quality Control Tree addresses this need. The impact of the type, frequency and reliability of inspection used in production can be estimated with this method. Sensitivity analysis using the event tree can quickly identify changes that have the greatest potential for reducing product defects, providing critical information essential for establishing a quality strategy.

Conformance Quality Strategy (CQS)

The seven step Conformance Quality Strategy (CQS) from Chapter 9 is the third layer in the pyramid shown in Figure 10.1. It is used to determine what can be improved and determine the how much improvement is required to achieve conformance quality goals. One of the great strengths of this method is that it can be used to target improvement in specific areas of weakness.

Existing Conformance Quality Tools

Although the global perspective is useful in defining what to improve and how much improvement is needed, it does not provide direction on how to improve. This direction can be obtained from existing conformance quality tools. When design teams have identified the required areas of improvement with specific goals, it is relatively easy to identify which of the existing conformance quality tools will be of the greatest help in achieving quality improvement objectives.

The Study Goals Have Been Met

The global Conformance Quality Model is the result of pursuing three specific objectives in our effort to understand the relationship between complexity and defect rates:

- 1) Measure and characterize assembly complexity,
- 2) Test the relationship between assembly complexity and production defects, and
- 3) Based on observed relationships, define a global model of conformance quality.

Each of these objectives have been met. We have found that Design for Assembly (DFA) methods are biased but useful relative measures of assembly complexity. The distribution of assembly complexity ($\equiv$ DFA assembly time) within a product has been shown to follow a Pareto or zeta distribution. We have also shown that defects rates are highly correlated with a simple power function of DFA predicted assembly time and the number of assembly operations. The background, findings and implications resulting from this study will be presented in the following sections.

10.2 The Role of Variation, Error, and Complexity

One of the key observations enabling the development of the global Conformance Quality Model (CQM) has been the distinction of Variation, Error, and Complexity as defect sources requiring different methods of control. This is the first known effort to develop a conformance quality model that spans each of these defect sources. In Table 10.1 typical parameters that affect part and assembly defects for each defect source are listed.

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Table 10.1. Defect sources with typical parameters affecting part and assembly defects.

Defect Source	Parameters Affecting Defects	
	Parts	Assembly
Variation: Naturally occurring process dispersion [5][3]	Operator Skill; Material Properties; Temperature; Vibration; Operating speed; Tool wear; Power....	Adjustment variations; Torque variations; Minor misalignment; Gage variations
Human Error: [47][48] Failure to perform a task, performance of a prohibited action, or a process deviation that exceeds the frequency and magnitude described by variation	Tolerances assignment error; Measurement error; Omission of process steps; Mishaps in handling, transport and storage; Gage reading error; Incorrect procedures...	Gross misalignment; Omitted/incorrect parts; Transposed wires/parts; Handling, test, and transport mishaps; Omitted operation...
Complexity: The number of elements difficulty of generating or executing the elements	Number of: Parts; features; process steps; handling steps... Difficulty of: Material formability; variance control; process step; reproducibility...	Number of: Operations; tools; motions; repetition... Difficulty of: Jumbled parts; reach distance; insertion resistance; tangling; subtle features...

Variation

Statistical methods which address *Variation*, have become the backbone of the majority of quality improvement efforts in this country [23]. When variation is viewed as the only cause of defects, there is an implied assumption that *all* defects are caused by variation, and that sampling is an adequate method of quantifying *all* variation. In the application of Statistical Quality Control (SQC), observations are averaged as a group to *approximate* the Normal distribution [3][4]. We say "approximate the Normal distribution" because data generally follows the Pareto Principle [4] which differs. Using grouped samples, the Normal distribution is traditionally assumed to apply to process variation without qualifying this assumption [3]. We have shown that there are important exceptions to each of these fundamental assumptions.

Limitations of the Variation Paradigm

Although variation will always play a significant role in conformance quality, the limitations identified in this study demonstrate that it is not an complete description of defect rates in complex products. When quality improvement efforts focus on variation, the role of errors and complexity may be overlooked. Furthermore, the probability of excessive variation is frequently evaluated using simplifying approximations that often neglect important interactions. A common example of this approach is a one-dimensional treatment of tolerance studies which we have shown can underestimate the probability of

interference by an order of magnitude. All methods based on variation which eliminate variables to simplify analysis or testing, including the Taguchi method, can lead to conditions where the established limits are inadequate to satisfy the design intent.

Although simplifying assumptions are essential for efficient design, these observations reinforce the value of continuous improvement. Reducing variation by continuous improvement will generally improve conformance quality even when analysis indicates that the limits have been properly set.

Limitations of the Central Limit Theorem

One of the most important observations of this study is that the fundamental assumptions of the central limit theorem do not have universal application to manufacturing processes. This is consistent with Mandelbrot's [76] observation that the variance of many naturally occurring phenomena does not converge as the sample size increases. The Pareto distribution provides a theoretical foundation for this phenomena. Relative to quality, the most important consequence is that traditional statistical methods do not accurately predict the frequency and magnitude rare events essential for accurate control of defects in 1-10 ppm range.

Error

Error is a rare event in production tasks [6]. The production practices of sampling inspection, discarding outliers in the data, and using grouped averages for process control [3][4] virtually assures that the impact of errors is not measured or predicted correctly by traditional Statistical Quality Control [3]. The outcome of many types of error cannot be described in terms of variation. For example, a part omission during assembly or transposition of wires can only be described in terms of probability. Thus, probability is the only way of describing all types of error. Since distributions can be converted to probabilities but probabilities can not always be converted to distributions, the only common method of describing both error and variation is in terms of probability.

In spite of the fact that errors are rare events, they are the cause of most defects in complex products [6][7][8][9][10]. Organizations that have achieved the highest levels of product quality have found that the control of errors is essential [12][24]. Owing to the rare occurrence of errors, they can only be controlled by methods that work essentially 100 percent of the time. Although errors are inevitable, defects resulting from errors are not [22].

Complexity

We have shown that complexity increases defects resulting from both errors and variation. Although some complexity is unavoidable, unnecessary complexity leads to defects that would be eliminated with less complex designs or processes. Thus excessive complexity should be viewed as the root cause of many defects rather than variation or error. This topic is treated in more detailed in Appendix D.

Metrics of the Defect Sources

For each quality model and conformance quality tool a metric is needed to measure Variation, Error, or Complexity. Different metrics for the defect sources are required depending upon the purpose of analysis. For example, in the global Conformance Quality Model probability is used to describe defects resulting from error and variation for consistency. However, to control variation on the production floor, the process distribution must be utilized. It is also convenient to group defect sources such as error and variation in some situations. The metrics and grouping of the defect sources for the different methods are illustrated in Figure 10.2.

		Defect Source			
		Variation	Human Error	Complexity	
				Difficulty	Quantity
Global CQM	Parts				
	Ass'y				
Quality Control Tree	Parts				
	Ass'y				
Existing QC Tools	Parts				
	Ass'y				

Metrics Key: Probability Number Frequency DFA Time μ, σ, C_p, C_{pk} EM, Time

Figure 10.2. Metrics and grouping of defect sources and stages for A) the global Conformance Quality Model (CQM), B) the Quality Control Tree (QCT), and C) existing quality control methods. Note: EM = Assembly Efficiency; QC = Quality Control; DFA=Design for Assembly.

10.3 Key Findings in the Study of Conformance Quality

The global Conformance Quality Model (CQM) and the Quality Control Tree (QCT) reflect several distinctly different opportunities for reducing defects. Following is a list of some of the important factors incorporated in these models which are related to product defect rates:

1. The number of assembly operations
2. The difficulty of assembly operations
3. The part defect rate
4. The number of parts
5. The level of quality control described by:
 - a) The probability of errors
 - b) The level of Process Control (one measure is the Process Capability Index (C_p))
 - c) The types of inspection used (error, source, output...)

- d) The fraction of inspected inputs and processes
- e) The reliability of inspection

As this list illustrates, there is a wide diversity of opportunities for reducing defects. Most conformance quality methods focus on a few of the possible improvement opportunities. We have shown that a single focus will initially reduce defects. However, since the ability to improve any specific parameter is limited, a sustained singular focus eventually leads to a plateau in conformance quality. The new models of conformance quality have shown that the effectiveness of any specific improvement depends upon the current strengths and weaknesses of each organization. The ability to quantify the influence of each specific quality control factor afforded by the global perspective establishes a means of defining a strategic plan.

The Global View of Conformance Quality Enables Strategic Planning

Without the insights provided by a global view of conformance quality, we have found that organizations can expend significant effort which will result in minimal defect rate reductions. This is a particular concern when an organization adopts a new method having the same basic focus as previously endorsed quality efforts. In contrast, the best strategies maximize the reduction in defects for the least expended effort. In general, such a strategy will always target reduction of the most dominant source of defects.

Using sensitivity analysis and the Quality Control Tree, we have been able to identify changes in quality control that have the greatest impact on reducing defects for any given set of initial conditions. We can quickly determine where improvement efforts would be wasted based on those factors that have the least influence on conformance quality. In approximate terms, the relative significance of errors and variation in causing defects can also be estimated for any organization. Building upon these principles, a specific focus for improving quality control can be defined.

Concept Comparison

The global Conformance Quality Model provides a method for comparing the potential defect rates of product concepts. This can be done using either an analytical or simple graphical method. Using these tools, we have found that designers cannot depend upon intuition or simple quantity measures of complexity such as part or operation counts to identify concepts with the lowest potential defect rates.

Although one goal of design is to reduce complexity, the selected replacement concept may be more complex than the original product if features are added or the performance improved. The global Conformance Quality Model can be used to estimate the impact of either of these changes.

Conformance Quality Goal

Conformance quality goals should be challenging, but realistic, and can be influenced by external factors such as aggressive moves by competitors. We have observed that the difference between the goal and the predicted defect rate for the selected concept determines how much improvement must be made in quality control. We have shown that

the required improvement can be allocated among the targeted quality control factors to complete a strategic plan.

Is Automation the Best Method of Reducing Defects?

The most difficult assembly operations are the least likely to be automated. The strong correlations between assembly complexity and defect rates suggest that the most complex assembly operations are also the most likely source of defects. Using these concepts in the global Conformance Quality Model (CQM) we have found that automation may not significantly reduce defects until a majority of operations are automated. These observations are reinforced by data derived from the automotive industry [2] showing that extensive automation resulted in a modest reductions in defect rates.

Compared to automation, we predict that the same levels of quality improvement could be achieved by implementing poka-yoke [24] and reducing assembly complexity in many situations. Simplifying the design and implementing poka-yoke can be made without large capital investments in assembly systems that may prove to be inflexible [34]. Automation may not be the best method of improving quality in many applications. In making decisions regarding the appropriate level of automation, the Conformance Quality Model (CQM) has proven to be a potentially powerful tool.

The Link between Complexity and Defects - The Foundation

A key insight that has enabled the development of the global Conformance Quality Model is the demonstrated link between complexity and defect rates. We believe that prior efforts to establish such a relationship have failed because previous efforts 1) focused on oversimplified measures of complexity, and 2) large differences in quality control between manufacturers obscured the role of complexity in industry wide studies. While sound measures of *part* complexity do not exist, the recent development of Design for Assembly (DFA) methodologies introduced a new opportunity to measure *assembly* complexity, addressing one of the weaknesses in prior efforts. To overcome the quality control differences between manufacturers, comparisons were made between defect rates for products produced by individual companies where the quality control methods are most likely to be consistently applied. A more detailed overview of the findings in this key area are given in Appendix D.

Measuring Assembly Complexity

In the first known effort to characterize assembly complexity, we have demonstrated that the Design for Assembly (DFA) methods are biased and imperfect, but useful metrics. We have demonstrated that DFA predicted assembly times in a product can be described by the Pareto distribution while rejecting the Normal distribution. Since the Pareto distribution does not adhere to the conditions of the Central Limit Theorem, this has broad implications, and clearly demonstrates that statistical methods are inadequate for predicting the frequency and magnitude of rare events. We have also shown, in a clear exception to the Central Limit Theorem, that actual assembly time can be described by convolutions of the Pareto distribution, while rejecting the Normal distribution. Using the

Pareto distribution, the assembly times can be bounded as a function of the number of assembly operations.

The insights obtained in the examination of assembly complexity provide a means for estimating the assembly time of a product without dependence on a Design for Assembly (DFA) database. The Pareto distribution has been shown to be as a powerful predictive tool for estimating the impact on assembly resulting from product redesign. The insights have also led to a new design rule: "**simplify and minimize assembly operations**" which is superior to the widely accepted rule: "minimize the number of parts." The new rule encourages part count reduction, but assures improved assembly and reduces defect rates.

Relating Assembly Complexity to Defect Rates

In a study of more than 30 products from 3 manufacturers reflecting hundreds of millions of assembly operations, we have shown that the predicted Design for Assembly (DFA) times are strongly linked to product defect rates. Although more than more than fifty alternative methods of relating complexity to conformance quality were examined, a simple power model involving predicted DFA assembly time, and the number of assembly operations consistently had the strongest correlation (correlation coefficients (r) >0.95) with defect rates. This power model determined empirically was shown to be consistent with a theoretical model which had been derived independently.

In the process, it has been shown that quality control differs significantly between manufacturers. Such differences explain the reason that industry wide studies have resulted in poor correlation between complexity and defects. We have also shown that simple quantity measures, such as part count, are inconsistently related to defect rates.

Defect rates were found to have a negative correlation with the number of assembly times. This counter intuitive result has been observed in the data provided by each manufacturer. We speculate that this relationship results from the fact that there is a threshold time required to execute the simplest assembly operations. Assembly operations below such a threshold do not exist, and cannot contribute toward assembly errors. Hence, defect rates are related to the predicted Design for Assembly time exceeding the threshold value. Since the threshold is a constant for all assembly operations, it leads to a negative correlation between defect rates and the number of assembly operations.

10.4 Support for the Global Conformance Quality Concepts

This study represents the first known case where a theoretical model relating defects to complexity has been correlated with production experience over a broad range of product complexity. Following is a summary of the observations and literature which support the global conformance quality concepts in this study.

Support for the Global Conformance Quality Model (CQM)

The global Conformance Quality Model (CQM) predicts that increasing assembly complexity will increase defect rates. This trend is consistent with several studies showing increases in defects and errors when the complexity of the task is increased [37][50][51][56][81][82][83][84]. It is also consistent with published Boothroyd Dewhurst [103] data which showed that the quality and reliability improved an average of 68 percent when the Design for Assembly (DFA) time was reduced an average of 62 percent.

One of the strongest evidences supporting the validity of the global Conformance Quality Model is that the theoretically derived form is virtually identical to the form derived entirely independently from empirical correlations (Equation 9.5 and 9.14). Another remarkable observation is that both defects and Design for Assembly (DFA) times follow Pareto distributions, substantiating a basis for correlation between these factors.

One of the peculiar characteristics derived from the Conformance Quality Model, is that the defect rate can be reduced by increasing the number of assembly operations as long as the total DFA assembly time is not increased. A comparison of a domestic and foreign truck instrument panel [34] supports this predicted pattern. The foreign product, known for high quality, had more parts and more assembly operations, but required less time to assemble.

Support for the Quality Control Tree (QCT)

Parameters influencing defect rates in the Quality Control Tree are listed on the left in Table 10.2 in juxtaposition with quality improvement factors identified in the literature on the right side of the table. While we have not identified any new or unique factors in quality control, all of the factors identified separately in the literature have been brought together in a single event tree model.

The Quality Control Tree is completely consistent with the influence of each corresponding factor identified in the literature. For example, the Quality Control Tree model predicts that defects will be reduced by improving the control of variation, a trend that is consistent with a reduction in defects achieved by increasing the Process Capability Index (C_p). Similarly, Source Inspection, 100% Inspection, and poka-yoke [24] techniques which have been observed to reduce defects in production are predicted to reduce defects using the event tree. Thus the observed improvement achieved by each method as identified in the literature supports the Quality Control Tree concept.

Using the Quality Control Tree, we predicted that Motorola's Six Sigma would reduce defect rates by roughly a factor of two compared to Statistical Quality Control. This level of improvement falls far short of Motorola's 3.4 ppm goal, which we attribute to the fact that the Six Sigma method does not address errors. This was later substantiated with Motorola's data showing that they were achieving defect rates in the range of 800 ppm [11]. In a very recent publication, Motorola [12] claims to have achieved defect rates in the range of tens of parts per million by combining mistake-proofing (poka-yoke) concepts

for reducing errors with the Six Sigma methods. The Quality Control Tree also estimates that the combination of Six Sigma and poka-yoke methods will result in defect rates in the tens of parts per million. These observations lend substantial credibility to the Quality Control Tree representation, demonstrating that it is a better method of predicting defects than variation based concepts alone.

Table 10.2. Conformance Quality improvement opportunities for the Quality Control Tree compared to quality control factors identified in existing Quality Control Concepts and Methods. THERP=Technique for Human Error Rate Prediction, HEP=Human Error Probability [78].

Quality Control Tree Factor	Variable	Related Factors in the Literature	Variable
Sampling Inspection Reliability	α_i, α_o	Inspection Error [7][51], Throughput Ratio Method [120]	P_1
Reliability of Inspection for Errors	α_e	Poka-Yoke [24][22]	
Input Variation (relative to limits)	b_i	Supplier Qualification [4]	
Output Variation (relative to limits)	b_o	Process Control [3][4], Taguchi [17], Six Sigma [5]	
Setup & Process Error Frequency	e_i, e_o	Poka-yoke [24][22], THERP [78],	HEP
Frequency of Inspection for Error	i_e, i_k	Poka-yoke, 100% Inspection [24][22]	
Frequency of Input Inspection	i_i	Sampling Inspection [3][4], Source&100% Inspection [24][22]	
Frequency of Output Inspection	i_o	Process control [3][4], 100% Inspection [24]	

Using the model we also observed that adding poka-yoke methods to Statistical Quality Control [3] resulted in more improvement than achieved by any other single change. This is consistent with Shingo's [24] perception that controlling errors through poka-yoke was the fastest way reduce defects. However, the Quality Control Tree shows that source inspection and 100 percent inspection concepts must be added to achieve defect rates in the 1-10 ppm range, observations that are again consistent with Shingo's view of Zero Quality Control [24].

The Quality Control Tree provides useful insights into the relative effectiveness of proposed improvements that surpass any of the methodologies considered independently. It has proven to be consistent with industry observed trends that have not been adequately explained using any other method.

10.5 Implications of a Global Conformance Quality Concept

The Impact of Global Conformance Quality on Product Value

Conformance quality is only one of many elements of product quality per Garvin [16]. Our efforts in this study have focused on conformance quality because defects during the production process are easier to measure and quantify than other aspects of the quality such as reliability. However, from this work it is clear that conformance quality also has a profound impact on reliability and many other elements of product value.

We have clearly demonstrated that reducing the assembly complexity reduces the defect rate. Reducing complexity will also reduce product assembly cost, the frequency of repair, maintenance errors, complexity and cost of assembly equipment, and the size of the factory. As the product complexity is reduced, the product may be easier to develop, allowing a reduction in the development time and cost [111]. Thus, when conformance quality is achieved by reducing complexity, there are broad improvements in many aspects of product value and the return is much greater than the investment. For such changes "*Quality Pays*," a outcome superior to "quality is free."

There are, however, important pitfalls that can occur in applying these global concepts. For example, some organizations will identify an increased frequency of inspection as an important opportunity for conformance quality improvement. If they attempt to achieve this improvement by implementing 100 percent inspection using Coordinate Measuring Machines (CMM), production costs may increase unacceptably. *To be cost effective, 100 percent inspection techniques must be simple and inexpensive.* Shingo [24] states that constructing a poka-yoke device for inspection generally cost less than \$150 and never more than \$500 (Toyota costs in 1985). The goal of increasing inspection frequency should not be confused with doing inspection the same way but more often. As this case illustrates, improvement of both conformance quality and value may require significant changes in the way that we seek to achieve the results.

The Global Perspective Builds Consensus

In a study of over 300 companies Schaffer [121] noted that most activity-centered quality programs do not produce a significant reduction in defects. Among other reasons, he cited a) the inability to link the cause and effect of defects, b) diffused efforts, c) "delusional measures" (equating activity with improvement), and d) the lack of result driven objectives. Change under these conditions is likely to be met with resistance, because individuals feel a sense of uncertainty regarding the purpose and benefit of changing. The global conformance quality perspective, addresses each of the concerns raised by Schaffer, laying a foundation for improved cooperation and participation. Four key factors encouraging social motivation are provided by the global perspective:

1. The benchmarking methods show *why improvement* is required.
2. The Conformance Quality Model and Quality Control Tree reveal *what can and must be improved*.
3. In combination with a goal, the methods show *how much improvement* is needed.
4. Specific improvement objectives point to the tools that show *how to improve*.

When individuals understand why they must act, what they must act on, how much action is required, and the most effective way to act, they will generally be more responsive. The information provided by the global perspective encourages active investigation of opportunities for improvement. It allows team members to test their ideas for reducing defects and perform relative comparisons to other proposals. These activities foster a consensus that focuses on the specific needs of the project. Consequently, the global conformance quality concepts have the potential of being a powerful motivational tool.

Early Application Leverages Product Improvement

The global conformance quality approach influences design concepts at the earliest stage of development when improvements have the greatest leverage. By contrast, most conformance quality methods have little or no influence on during the concept development phase. For example, Statistical Quality Control [3] is basically a production tool. Motorola's Six Sigma [5] method can aid in defining tolerances and selecting processes, but these activities generally occur after the concept has been formulated and detailed design has been initiated. Poka-yoke [24] is one of the few quality tools useful during the concept phase where it may be used to guide part designs that prevent incorrect assembly. Shown in Figure 10.3 is our assessment of the development phase where common methodologies have the greatest application.

Figure 10.3. Approximate representation of the potential conformance quality (CQ) influence as a function of the phase of production. Bars indicate the phase of production where some well known methodologies are applied. Note that the global conformance quality concepts influence the concept phase when the leverage is greatest.

As illustrated in Figure 10.3, the global conformance quality concepts are the only ones that are specifically intended for the concept phase when the influence on the product quality has the greatest potential leverage. At the earliest stage of development, it

continually reminds designers that the complexity of the product has an impact on the conformance quality. It allows designers to consider conformance quality potential as part of the concept selection process. By identifying quality improvement opportunities before production plans have been formulated, the improvements can be implemented during the production process with a minimum amount of effort and late changes.

10.6 Limitations of the Global Quality Concepts

Not an In-Depth View

The global view of complexity presented in this work does not identify the specific cause of defects for any individual part, process, or assembly operation. Thus, it does not eliminate the need to investigate the cause of specific defects, nor does it suggest a particular remedy for specific cases. From a global perspective it can point to improvements or actions that may not have been considered, and it can encourage a broader search for the true source of the defect. For example, it may help identify errors as the cause of a defect rather than variation.

The Methods Predict General Trends

In applying these concepts it should be kept in mind that the distribution of assembly complexity and defects rates are on the border between order and chaos as evidenced by the acceptance of the Pareto distribution. On this basis, the tools introduced in this research must be viewed as approximate methods providing clear descriptions of general trends rather than precise predictions. While the trends provide sound and useful guidelines, special attention or effort may result in more improvement than anticipated while carelessness and neglect can lead to significantly higher defect rates than predicted.

10.7 Summary and Conclusions

In this research we have shown that there are three principle sources of defects, 1) Variation, 2) Error, and 3) Complexity. Although errors occur rarely in production, they are the most significant source of defects in complex products[6][7][8][9][10]. We have shown that traditional statistical methods are not capable of measuring, predicting or controlling errors, which require detection and correction methods that are effective essentially 100 percent of the time. Since complexity increases the probability of defects resulting from either variation and error, it is a root source of defects to the extent that it can be reduced.

We have defined a global combinatorial model of defects that spans variation, errors, and complexity. We have shown that this model is highly correlated with production data spanning tens of millions of assembly operations, two different manufacturers, and fifteen products. Although other models relating defects or errors to complexity have been

proposed, this is the first known case where a theoretical model has proven to be correlated with production experience over a broad range of product complexity.

A Quality Control event Tree (QCT) model was defined to distinguish between the relative importance of error and variation for each organization. Using this model we predicted that Motorola's Six Sigma methods would reduce defects by roughly a factor of two compared to traditional quality control methods, and that additional improvement would require methods to minimize error. Motorola's data showed defect rates in the range of 800 ppm until they used mistake proofing which dropped the defect rate to tens of parts per million, reinforcing the superiority of our model in describing defects.

We have used the global Conformance Quality Model (CQM) to show that the potential defect rates of product concepts can be compared early in development. Together the global Conformance Quality Model and Quality Control Tree have been used to define a clear quality improvement strategy. This strategy reveals: 1) **what changes will be most effective in reducing defects**, 2) **how much improvement is needed**, and 3) aids in identifying existing quality improvement tools that show **how to improve**.

We have also shown that the global Conformance Quality Model can be used to predict the quality impact of automation. These studies have shown that automation is not likely to significantly improve quality until the majority of assembly operations in a product are automated. This result is consistent with trends observed in the automotive industry.

Perhaps the greatest contribution of this work is that it reinforces the importance of a global perspective in design. When the broader perspective is missing, we have shown repeatedly that decisions can be based on a false sense of precision, and that focusing on the quantity measures of complexity can lead to poor design choices when the difficulty measures of complexity are neglected. Design axioms have led to many inappropriate decisions demonstrating that they should never be viewed as rigid rules, but should be applied with judgement and flexibility.

10.8 Suggestions for Further Research

Seeking the "One Best Way"

Since assembly processes have been shown to be on the boundary between order and chaos, relatively small improvements in the structure of the process have significant impacts on the effectiveness of assembly. The approach used by Gilbreth [46] to standardize assembly through the pursuit of the "one best way" contains the same basic elements which have proven effective in assembly work at Toyota and NUMMI [58].

Both approaches share these common characteristics:

- 1) The outstanding performers are identified.
- 2) Their methods are studied and improved with their participation.
- 3) The improved methods are taught to all workers performing the task.

- 4) The choreographed method becomes the standard of performance.
- 5) The *team* continually seeks opportunities for improving the "one best way."

It is possible that design, development, and other elements of the production process may also be on the border between order and chaos, suggesting that Gilbreth's pursuit of the "one best way" could have potentially important application in improving design. For example, compared to Japanese design teams, on the average our development cycles are longer and our products have not been as competitive. Thus, basing design improvement on studies of the average U.S. designers may simply improve and/or standardize practice that is less than optimum. Improvement may be accelerated by intensive study and standardization of the processes used by outstanding performers.

Statistics and the Pareto Distribution

This work has not invalidated the fundamental assumptions of statistics, however, it has demonstrated that there are important exceptions that have not been adequately addressed. To assess how wide spread these exceptions are, we must first determine the minimum sample size necessary to distinguish between distributions that are consistent with the central limit theorem and distributions that are not. Once this has been determined, the distributions of adequate samples should be evaluated without discarding outliers for a broad class of problems where the normal distribution has been traditionally accepted. This is especially critical in fields where research is attempting to predict the frequency and magnitude of rare events, such as defects.

Although we have shown that convolutions of the zeta distribution have potentially broad application, it is unlikely that this model will be given adequate consideration until methods for estimating function parameters are simplified and improved. A technique for rapidly estimating the most appropriate number of convolutions and zeta function parameters would address the most difficult factors in fitting data.

We have also noted that the existing methods of estimating Pareto parameters do not adequately address non-linearities at the extremities of the Pareto curve. The Kolmogorov-Smirnov "goodness of fit" criteria provides a potential basis for developing improved estimates of Pareto parameters.

Research on Design for Assembly (DFA) Methods

Several opportunities have been identified for improving the Design for Assembly (DFA) methods as standards of assembly complexity. In particular, important gaps in the factors addressed by the various methodologies could be eliminated by addressing the following factors as needed by each method:

- 1) Add factors for the distance from the part pick-up point to the insertion point.
- 2) Add factors for part presentation (orientation and order).
- 3) Add factors for decision processes required in selection among alternatives.
- 4) Add factors for Class II assembly operations that cannot be completed in a fixed number of actions such as braze grinding.

- 5) Modify computations to reflect the improvement in assembly time resulting from sequentially repeated identical assembly operations such as insertion of 5 identical screws in a row.

Having selected the Boothroyd Dewhurst method as the standard for this study, the additional exposure led to identification of two additional opportunities for improving this specific methodology as follows:

- 1) Refine the insertion codes in range of 1.5 to 6 seconds to a) reflect the frequency of usage and b) reduce the incremental step size between options.
- 2) Re-evaluate fastener insertion times which appear to excessive based on 4 studies.

The Need for a Broader Understanding of Complexity

This study has shown that assembly complexity can be bounded, and that these bounds can be used to guide decisions during the earliest stages of concept development when detailed information is not available. It is during this phase that design decisions have the greatest leverage in reducing cost and accelerating the development process. The success of this study suggests that there may be many aspects of product complexity that can be bounded in a similar fashion.

In particular, there is an opportunity and a *need* to develop a better understanding of part complexity. The decisions to simplify assembly by combining parts are generally made during the concept phase when the design is immature. Designers must frequently choose between part complexity and assembly complexity at a point in the design when there is insufficient detail to accurately guide decisions. We have shown [34] that even very successful design teams are making significant errors in these choices, creating unnecessary cost, delay and difficulty during development. Bounding part complexity using the techniques developed in this research may be a key element to developing better guidelines in this critical area.

Among other factors, part manufacturing processes, part feature complexity, tolerances, and material costs are just a few of the many elements of design which could be studied from a broader perspective.

As we have demonstrated, global studies of design characteristics have the potential benefit of revealing errors in commonly accepted design axioms and can lead to improved design objectives that can have a profound influence on product concepts. We have shown that assembly complexity and assembly pace are distinctly different characteristics even though they are described in the same units such as assembly time per product. The optimum pace of assembly for quality, may differ from the optimum pace for productivity. The differences in optimum pace for these two objectives may be relative small, but could have an important influence on quality. This suggests that pace is a potentially important element of a quality strategy that is poorly understood at the present.

The Relationship between Defects and Complexity

Although we have laid a foundation for relating defects to complexity, there are many opportunities for testing and refining these concepts. The response to our requests for data on product complexity and defects has been limited. The opportunity to obtain such data will improve as more companies put into production products which have been evaluated using Design for Assembly (DFA) methods. Expanding the database and testing the correlation between complexity and defects over a broad range of products may identify necessary changes or improvements to our approach and substantiate generalization.

APPENDIX A

List of Data and Programs

List of Data and Programs

A 3.5 inch floppy disk is available on request. This disk has been formatted on an IBM compatible personal computer. The disk contains A) Data evaluated in this study, and B) MATLAB [115] programs used in the analysis. The data is contained in a directory labeled Data, and the programs are contained in a directory labeled Matlab. The programs require MATLAB™ software for execution.

Directory: Data

File Name	Contents
DFA_ASSY.TXT	Boothroyd Dewhurst Design for Assembly (DFA) summary data for 241 assemblies and subassemblies. Format: ASCII
DFA_DTAL.TXT	A detailed list of Boothroyd Dewhurst Design for Assembly (DFA) analysis for 32 projects. The number of assembly operations falling within defined time increments is provided for each product. The cumulative number of operations in each time increment for all 32 projects is also provided. Format: ASCII
DFA_KS.TXT	A detailed list of Boothroyd Dewhurst Design for Assembly (DFA) times for 18 projects. These projects were studied in detail in the report (see Table 5.1 page 86) to assess the suitability of using the Pareto distribution to describe assembly complexity. Format: ASCII
REALTIME.TXT	Detailed list of assembly time distributions observed in actual assembly for 23 separate cases. The observed assembly times have been obtained from research and production environments. Format: ASCII
VCR.TXT	Summary of Boothroyd Dewhurst results obtained by 26 separate teams evaluating a common VCR tape. Format: ASCII

Directory: Matlab

File Name	Contents
CONVOLVE.M	An executable PC-MATLAB file which calculates the distribution resulting from convolutions of the zeta function (see text section 6.1 page 109). The program can calculate up to 350 convolutions (IBM 486 w/ 8M RAM). For an accurate assessment of the distribution, the matrix size (N) should always be larger than the number of convolutions being studied. This program is required for the FIT.M Program.

File Name	Contents
FIT.M	<p>An executable PC-MATLAB file which searches for the optimum fit of zeta convolutions to the cumulative distribution function of data given the zeta coefficient alpha and level of truncation (See section 6.3 pages 117 to 119).</p> <p>Note: Because the zeta function is a discrete distribution, the optimum fit converges erratically as a function of the number of convolutions in some cases. As a result, most convergence routines fail. For this reason the program plots the Kolmogorov Smirnov test statistic, a measure of the goodness of fit, and the operator must input the range of convolutions to be investigated.</p>
SMOOTH.M	An executable PC-MATLAB file which converts discrete Boothroyd Dewhurst predicted assembly times into "smoothed" distributions which more accurately reflects the assembly time distribution likely to be encountered in a production environment.
PARETO.MAT	A Matlab data file containing values of the zeta constant α_d and the corresponding solutions for $1/(\zeta(\alpha_d + 1))$ where ζ is the Riemann zeta function. These constants are required to determine the probability distribution of the zeta function. This file is used in the CONVOLVE.M program.
BARN4.TXT	A two column matrix representing the cumulative distribution of Turnball's block tossing experiment used by the "FIT.M" program to illustrate fitting zeta convolutions to data. Format: ASCII.
DFA_DAT.TXT	A two column matrix representing the distribution of assembly operations for the eighteen cases examined in detailed to identify the most appropriate model of DFA assembly time. Each set of data is separated by a row of zeros and the data is presented in the same order as given in the DFA_KS.TXT
WNORM.TXT	A cumulative distribution file for the Normal distribution used by the FIT.M program.

Note: For program execution refer to the MATLAB manuals. Programs are initiated by typing the program name in lower case letters without the extension at the MATLAB prompt. For example typing "fit" will execute the FIT.M program. The programs prompts the user for input. A list and description of input and output variables is included in the comment section of each program.

APPENDIX B
Sample Request for Data

Sample Request for Data

Following is a typical example of requests submitted to companies invited to participate in this study:

Date
1111 Douglas Fir Drive
Manteca, CA 95336

Address

Dear Sir:

I appreciated the opportunity of visiting with you and the other XXX representatives last week. As described in our meeting, we have shown that assembly complexity is related to the quality conformance of products. Attached is a brief outline of the work that we have done, and the type of additional information being sought to determine if these principles may be generalized.

We recognize that the type of data being sought is sensitive and will not disclose any information that you may choose to supply without your review and consent. In return for participation, we will provide an analysis of the data which has proven to be helpful to organizations participating in the study.

I can be reached most easily at home. My address is listed above, and my home phone number is (209) 239-2464. I would be happy to answer any question you may have and hope that you will consider participating in our study. If you choose to participate, we would need to receive the data by July.

Sincerely,

C. Martin Hinckley

In late 1991 Motorola published the data shown in Figure 1. Their data showed that the number of defects per part decreased as the manual assembly efficiency determined by the Boothroyd Dewhurst™ method improved. The assembly efficiency is a measure of the ease of assembling a product.

Figure 1. Observed Defects per Million Parts versus the Manual Assembly Efficiency published by Motorola. The bounds illustrated in the figure are theoretical predictions and show general agreement with the observed trends.

Our interest in this data was piqued by the possibility that such a relationship could provide a basis for a general, quantitative predictive tool. Based on this data, we speculated that some product defects must be related to the difficulty of the assembly operation gaged by the estimate of the time required to complete each assembly operation. Recognizing the potential for a quantitative tool that could estimate product defect probabilities, Dave Gebala at Motorola provided data for the defects caused by assembly errors on several recent projects. Fifty distinct relationship between assembly defect rates and product characteristics were examined. The correlation between the average defect per operation and the predicted average assembly time per operation had a stronger correlation than any other combination of factors examined. This relationship is shown in Fig. 2.

In the process of evolving a theory which would explain the data shown in Figure 1, the following additional milestones have been achieved:

- 1) Demonstrated that the predicted assembly times per operation follow a Riemann zeta (Pareto) distribution.
- 2) Using this relationship, we have demonstrated that the part count, assembly time, and assembly efficiency can be bounded within narrow limits for any design when two easily determined product parameters are known (Number of assembly operations and Boothroyd Dewhurst Theoretical Minimum number of parts). This has been substantiated by a large database of electro-mechanical assemblies.
- 3) Demonstrated that minimizing part count, one of the most commonly accepted rules for Design for Manufacturability (DFM), can lead to inefficient product assembly and lower quality. A superior design objective is minimizing and simplifying assembly operations. This will tend to reduce part counts while assuring that the assembly process is improved.

Figure 2. Average Number of Assembly Defects per Operation versus the Predicted Average Assembly time per Operation for Motorola data. The correlation coefficient for a linear fit represented by the line is 0.942.

The theory that has evolved which shows general agreement with the Motorola data reveals five fundamental factors that can contribute to assembly defects:

- 1) The number of assembly operations
- 2) Quality Control: The capability of completing an operation without introducing a defect, [A measure of the organizations skill and effectiveness]
- 3) The complexity of assembly operations gaged by the *predicted* time required to perform the operation
- 4) The number of parts (a subset of the number of assembly operations)
- 5) Part defect probabilities

Each of these factors suggests specific independent strategies which must be pursued in reducing assembly defects in quality products. The best strategy to improve product quality depends upon the current level of performance in each of these respective areas. For example, if part defect rates are very low but assembly errors are frequent, further reduction in part defect rates will not substantially improve quality conformance. In this case, the maximum improvement in quality can be achieved by reducing the frequency of assembly errors. In other instances, reducing the number or complexity of assembly operations may be sufficient to achieve quality conformance goals without reducing part defects.

We believe that it may be possible for organizations to estimate current levels of performance in each of these areas with a minimal amount of data. This leads to an efficient and effective method of establishing quality strategies early in the concept development phase. However, to achieve this goal a database of performance must first be established. On the following page is a table which is illustrative of the type of data that we are seeking. Any information that you have to share may be received by FAX, but must be prearranged by calling (209) 239-2464. I hope that you will give serious consideration to participating in this study. Thanks for your consideration.

Data for Defining a Quality Strategy

Company: _____ Contact: _____

Address: _____ Phone: _____ Fax: _____

Data Record Number	Product ID ²	Total Number of Defects per Unit (DPU)	Number of Assembly Defects per Unit ³	Number of Assembly Operations per Unit ⁴	Number of Parts per Unit	Predicted Total Assembly Time(TM) ⁵	Theoretical Minimum No. of Parts (NM) ⁶
1							
2							
3							
4							
5							
6							
7							
8							
9							
10							
11							
12							

Notes:

- 1) Data is sought for assemblies or **subassemblies** and not for individual operations. Where possible, data for several products/subassemblies of varying assembly complexity per organization or factory setting are desired.
- 2) The Product ID may be a code which conceals the true product identity.
- 3) If available, assembly defects are those defects that can be traced to assembly deficiencies.
Examples: Omitted parts, incorrect parts, parts damaged by assembly operations or handling, or parts placed in an incorrect orientation. Defects that results from insertion into test or inspection equipment would also be considered as assembly defects. Examples of defects which are not assembly defects are: material defects, warped parts, parts with feature defects. Defect data for the "steady state" condition after the start-up transition is desired.
- 4) Assembly operations include part insertions and operations that secure inserted parts such as spot welds, brazing, and adhesive bonding. Each part requires at least one insertion operation. Repeated identical operations are counted separately. For example, 5 identical spot welds, would be counted as 5 operations. The need to reorient a part for a subsequent part insertion is also counted as an operation.
- 5) Predicted operation times using any Design For Assembly (DFA) methods such as Boothroyd Dewhurst or Predetermined Motion Time System based methods is desired.
- 6) If available, the Boothroyd Dewhurst™ Theoretical Minimum Number of Parts are those parts in the design which must be separate for one of the following reasons:
 - a) During operation, must the part move relative to other parts already assembled.
 - b) Must the part be a different material, or be isolated from already assembled parts.
 - c) Must the part be separate to make assembly or disassembly possible.

APPENDIX C

Coefficients of Determination for Complexity to Defect Correlations

Coefficients of Determination for Complexity to Defect Correlations

Following are two table listing the coefficients of determination for comparison of complexity measures to defect rates for two manufacturers. The strong correlations ($|r| > .9$ or $r^2 > .81$) are highlighted with a double outline box.

Table C.1. The coefficients of determination (r^2) for linear regression between pairs of complexity and defect measures for data supplied by Motorola [102]. The best correlations (not constrained to pass through the origin) are indicated by double outlines. The columns and rows are ordered from the best average level of correlation to the weakest.

Complexity Measures	Defect Measures				
	Defects per Operation	Defects per Part	Defects per Unit	Defects per NM	Defects per Time
Average Ass'y Time per Operation (TM/N_a)	0.89	0.84	0.34	0.16	0.43
Total Manual Assembly Time (TM)	0.38	0.36	0.81	0.69	0.59
Parts per Theo. Min. No. of Parts (N_p/NM)	0.04	0.02	0.59	0.71	0.39
Average Ass'y Time per Part (TM/N_p)	0.52	0.68	0.11	0.04	0.17
Assembly Efficiency (EM)	0.27	0.32	0.63	0.56	0.48
Number of Parts (N_p)	0.08	0.05	0.63	0.62	0.41
No. of Operations (N_a)	0.01	0.01	0.39	0.41	0.18
Operations/Theo. Min. No. Parts (N_a/NM)	0.01	0.00	0.26	0.39	0.12
Theo. Min. No. of Parts (NM)	0.35	0.28	0.20	0.06	0.14
Assembly Operation per Part (N_a/N_p)	0.19	0.06	0.18	0.13	0.17

Table C.2. The coefficients of determination (r^2) for linear regression between pairs of complexity and defect measures for data supplied by a **Disk Drive Manufacturer**. The best correlations are indicated by double outlines.

Complexity Measures	Defect Measures			
	Defects per Operation	Defects per Part	Defects per Unit	Defects per Time
Average Ass'y Time per Operation (TM/Na)	0.531	0.680	0.688	0.913
Total Manual Assembly Time (TM)	0.587	0.221	0.913	0.628
Average Ass'y Time per Part (TM/Np)	0.210	0.574	0.029	0.186
Assembly Efficiency (EM)	0.940	0.909	0.405	0.674
Number of Parts (Np)	0.330	0.054	0.906	0.637
Number of Operations (Na)	0.543	0.195	0.983	0.809

APPENDIX D

The Link Between Assembly Complexity and Defects

The Link Between Assembly Complexity and Defects

We have found that assembly time based on Design for Assembly (DFA) predictions is highly correlated with defect rates observed in production. While many studies in the literature have suggested a link between complexity and errors or defects, this may be the first study to successfully quantify such a relationship on a broad scale.

The link between defects and assembly complexity reinforces the importance of continuous process improvement and promotes a broader view of improving design concepts. It demonstrates that quality has its roots in the basic complexity of the product concepts.

D.1 Review of the Literature Relating Defects to Complexity

Among the sources of defects, complexity has been the least understood. Researchers in the field of human error have proposed a link between task complexity and error rates [27][28][29][79], but have not quantified this relationship [28]. Many studies have demonstrated an association between errors or defects and some elements of complexity such as variety, task duration, motor skills, etc.. [37][50][51][56][81][82][83][84]. However, these studies have not led to global relationships useful in the production environment.

To describe the intuitively sound relationship between errors (or defects) and complexity several theoretical models have been developed [14][51][78][119][122]. However, correlations between these models and production experience over a wide range of complexity has not been attempted. Moreover, industry wide studies have not revealed useful correlations between complexity and defects [2][68][69].

Factors Confounding Correlations between Defects and Complexity

We speculated that the weak correlations between complexity and defect rates observed in broad scaled studies stem from two principle causes: 1) there are wide variations in the level of quality control between organizations, and 2) attempts to demonstrate correlations have been based on an oversimplified view of complexity.

Minimizing the Confounding Influence of Quality Control

Toyota [13] found that the conformance quality of suppliers could differ by orders of magnitude, supporting our concern that differences in quality control are a major confounding factor in characterizing the relationship between complexity and defects. To minimize the influence of quality control differences, we focused on comparing the defect

rates for products within individual organizations. Under these conditions, we postulated that the rules regarding quality control would be most consistently interpreted and applied.

Complexity Requires a Broader Definition Than Quantity Measures

An oversimplified view of product complexity has also contributed to the difficulty in relating defects to complexity. Typical descriptions of complexity have focused on quantity measures such as the number of parts, the number of processes, or the number of operations [14]. From our perspective, a sound description of complexity must address:

- a) **a quantity measure** - identifying the number of elements which contribute to complexity
- b) **a difficulty measure** - a relative measure of the difficulty in generating or executing each of the elements.

Adding to the confusion, some researchers have attempted to use the average production assembly time as a measure of complexity [68][69]. However, this measure can reflect differences in assembly pace, levels of automation, and processing delays which are poorly related to the actual complexity of the assembly task.

DFA - A New Opportunity to Gauge Assembly Complexity

A study published by Motorola [35] showed a strong trend between part defect rates and a Design for Assembly (DFA) complexity measure that piqued our interest because it suggested that a new, global model of defects could be developed which would be a useful tool in defining quality strategies and comparing product concepts in the earliest stages of design.

Design for Assembly (DFA) [36][57][58] methodologies provide a new opportunity for measuring assembly complexity. Using these methods, the number and *difficulty* of the assembly operations can be determined. These methodologies use time as the standard for gaging assembly difficulty, an approach that is consistent with Predetermined Motion Time Systems [46] and Fitt's law [54].

There Are No Measures for Part Complexity

Although the Design for Assembly (DFA) methods provide a standard for measuring assembly complexity, we are not aware of any standards that can be used as a relative measure of part complexity, an important limitation in this study.

D.2 Evaluating DFA as a Standard of Assembly Complexity

A sound model relating defects to complexity depends upon a useful standard for gaging complexity. Since no absolute measure of assembly complexity exists, a standard needed to be identified and its limitations characterized. The Boothroyd Dewhurst [36] Design for Assembly (DFA) method was selected as the standard in this study. It provides a structured method for assessing the time or difficulty of assembly operations and is the most widely known DFA methodology in this country. Since useful standards need to be readily available, the popularity of the Boothroyd Dewhurst method was an important element in this decision.

DFA Methods - A Measure of Part Complexity and Defect Probabilities

Because there are no absolute standards for measuring assembly complexity, we could not be certain that the Design for Assembly (DFA) methods were providing meaningful measures of complexity. Rather than assuming that these methods are adequate standards, we initially examined several assemblies to determine if a theoretically sound link between assembly time, complexity, and defect rates could be established. For the assemblies, we found that the number of degrees of freedom of the interface features increased as the Design for Assembly (DFA) time increased. Thus, the Design for Assembly (DFA) methods do provide a measure of the part and interface complexity, as well as the difficulty of part and assembly manipulation.

The probability of interference during assembly was also estimated using Monte Carlo simulations of part feature variations. We concluded that the frequency of interference, and defects, will generally increase with the Design for Assembly (DFA) time.

Our analysis addressed feature variations in multiple dimensions and included computer routines that searched for positions of fit if an interference was initially predicted. We found that commonly used one-dimensional analysis [93] can significantly underestimate interference probabilities.

DFA Methods are Biased but Useful Measures

Having established a theoretical basis for relating assembly time to complexity, the relative bias of two DFA methods and a Predetermined Motion Time System (PMTS) method were tested. This was achieved by comparing predictions of assembly time for specific operations using the different methods. This approach differs from that of Darlow et al [123] who developed a technique for subjectively comparing DFA methodologies.

Our comparisons revealed that the all Design for Assembly (DFA) and Predetermined Motion Time Systems (PMTS) were significantly biased relative to each other. This led to the conclusion that none of these methods are ideal standards of assembly complexity. In

support of this conclusion each method had gaps in the factors which they address that contributed to the bias.

In spite of these limitations, all methods reflect the same general trend of increasing assembly time for increasing task difficulty. This trend indicates that the methods are useful relative measures of assembly complexity.

At a highly significant level, we demonstrated that DFA predictions are not a random process. This observation reinforces the conclusion that there is a causal relationship between assembly complexity and DFA assembly times.

Individual Operation Times are not Predicted Consistently

Assembly time predictions for individual operations using different Design for Assembly (DFA) and Predetermined Motion Time System (PMTS) methods were very inconsistent. These inconsistencies lead to the conclusion that assembly processes have extremely large variances. Many of the subtle differences between test conditions used to develop the databases have not been captured in the database descriptors or they would predict the same assembly time for commonly defined operations.

These observations are consistent with those of Hancock [97], who found that predictions of the cycle times for the shortest operations had the greatest differences using several related Methods-Time Measurement techniques (MTM), a class of Predetermined Motion Time System (PMTS) methods.

The Distribution of Assembly Time-The Best Measure of Complexity

Although the individual assembly times were not predicted consistently, the *distributions* of assembly time determined by different methods are virtually identical when multiplied by a scale factor. This indicates that there are no strong reasons for preferring one DFA method over another as a measure of complexity. The *distribution* is a better measure of assembly complexity than the predictions for individual operations. This is again consistent with the work of Hancock [97] who found that the percentage difference in the predicted cycle time using different PMTS methods decreased as the duration of the task increased.

Total Assembly Time and Operation Count are Consistently Predicted

A useful standard should be consistently interpreted. The consistency of interpreting the Boothroyd Dewhurst database was tested by having 26 design teams consisting of two to four graduate students in a Design for Manufacturability course (ME 217) at Stanford [102] perform separate DFA evaluations on the same product, a Video Cassette Recorder (VCR) tape.

These teams were most consistent in predicting the total number of assembly operations and the total assembly time. Although a complete description of the distribution of

assembly time is the best measure of complexity, in its absence, the number of assembly operations and total assembly time are the best measures of assembly complexity

Assembly Efficiency - A Poor Measure of Complexity

There were large differences among the groups in determining the theoretical minimum number of parts and the Assembly Efficiency. As a consequence, Assembly Efficiency is not a useful measure of complexity, even though it is helpful in estimating the opportunity for improving a design.

D.3 MEASURING ASSEMBLY COMPLEXITY

Having characterized the Boothroyd Dewhurst method as a measure of complexity, our first major objective was to use this method to measure and assess the complexity of real products. Data was collected from graduate student evaluations [102] of more than 50 projects representing roughly 150 different products with more than 240 assemblies and subassemblies spanning a wide variety of electro-mechanical devices.

DFA Assembly Time Follows Pareto's Law

The Pareto distribution was accepted as a description of the predicted Design for Assembly (DFA) times in every one of the eighteen detailed cases examined while other common distributions, including the normal distribution, were rejected at highly significant levels.

Similarity in Pareto Curves Before and After Redesign

Although Pareto parameters differed significantly between products, the slope, and minimum assembly time of Pareto curves for products before and after redesign were remarkably constant in several cases that were examined. Thus, a Design for Assembly (DFA) assessment of a product that is being replaced can provide the basis for rapidly estimating the impact of design changes. This can be achieved without dependence upon databases or detailed analysis.

Assembly Time and Assembly Efficiency can be Bounded

The Pareto distribution led to the ability to bound assembly time in probabilistic terms as a function of the number of assembly operations. Based on these bounds, we have found that Assembly Efficiency falls within very narrow limits over a broad range of values. *This allows reasonably accurate estimates of Assembly Efficiency to be made without dependence upon a database or detailed Design for Assembly evaluations.*

In many situations the ability to rapidly estimate the total assembly time or assembly efficiency without a detailed DFA analysis is very helpful. For example, this may allow approximate comparison of product concepts before extensive effort is invested in concept refinement. It may point to the urgent need for improvement in the assembly, without requiring a time consuming and detailed analysis. These techniques can be particularly helpful for complex products where DFA evaluations could be very time consuming.

Minimizing Part Count Does Not Assure Minimum Assembly Difficulty

A surprisingly large fraction of the products which had part counts approaching the theoretical minimum value had very low Assembly Efficiencies. Thus, "minimizing the number of parts" [30][31], one of the most commonly accepted rules in Design for Manufacturability (DFM), does not assure that assembly is improved. In fact, it is possible to minimize the part count and make assembly more complex!

"Simplify and Minimize Assembly Operations" - A Superior Design Rule

By contrast, when the number of assembly operations approached the theoretical minimum number of parts, extremely low Assembly Efficiencies were rarely observed. Since minimizing the number of assembly operations improves assembly and tends to reduce the part count, it is a better approach. The best rule, "Simplify and minimize assembly operations," further promotes improvement in the ease of assembly. However, even this superior design rule should not be viewed as absolute. It should be used in the context of minimizing the global complexity of parts and assembly processes.

Actual Assembly Time - A Check on the Pareto Model of Complexity

If the Pareto distribution is a sound model of assembly complexity, we would expect this model to describe both the predicted Design for Assembly (DFA) times and the actual distribution of performance in the production environment. Thus, fitting the same model to predicted and actual assembly time provides an important litmus test for validity of the model. In all, 23 distributions of actual assembly performance have been studied for this purpose, including data obtained from both research and production environments. Zeta convolutions, reflecting the cumulative outcome of multiple trials from a Pareto distribution, were accepted as a model of actual assembly time in every case examined.

We found that zeta convolutions were significantly better models of assembly time than two commonly assumed functions, the normal distribution and the lognormal distribution, which were both rejected at highly significant levels. Zeta convolutions modeled the change in mean, variance, and kurtosis resulting from different assembly paces observed by Applewhite [112] by changing a single constant. Zeta convolutions also explain the decreasing skewness as task complexity increases, a trend noted in data supplied by General Motors [101].

Acceptance of Pareto's law as a description for both DFA and observed assembly times reinforces its appropriateness in this application.

D.4 Testing the Link between Complexity and Defects

The second major objective in this study was to characterize the relationship between assembly complexity and production defects. To minimize company differences in process control as a confounding factor in this study, the complexity and defects for multiple products within individual companies were compared. DFA and defect data was solicited from 18 companies. Of these, three companies agreed to participate in the study, providing data for 28 different products, reflecting *hundreds of millions* of assembly operations. The level of detail provided for each product differed significantly by company. The data of each manufacturer were studied to identify the strongest correlations between the measures of complexity and product defect rates.

Quantity Measures of Complexity Are Poorly Related to Defects

The part and operation counts were not consistently correlated with defect rates. These correlations were extremely weak for the automotive manufacturer, but relative strong for the disk drive manufacturer. The strength of these correlations were greater when the part or operation count was approximately proportional to the Design for Assembly (DFA) time.

Based on these observations, the part count and operation count cannot be used independently to predict defect rates. The poor correlations and lack of consistency between the part or operation count and defects reinforces the weakness of using oversimplified complexity measures based only on quantities. This again demonstrates that a singular focus on the quantity measures of complexity can obscure greater opportunities for design improvement.

Defects Are Strongly Correlated with DFA Assembly Time

Design for Assembly and defect data for 15 products having a range of complexity was obtained from two different manufacturers. Collectively, the defect rates reflect tens of millions of assembly operations. The defects per unit were highly correlated to a function of Design for Assembly (DFA) time and the operation count (correlation coefficient (r) = 0.969 and 0.989) and verified using Analysis of Variance [104]. The power fits and data are shown in Figure D.1. These correlations were superior to every other model examined. One of the strongest evidences reinforcing the link between assembly complexity and defects is that both assembly complexity and defects can be described by Pareto distributions.

Figure D.1. Defects per unit versus the Design for Assembly (DFA) total assembly time for data from two manufacturers. The lines are predictions using the correlated model.

The strong correlations identified in this study clearly demonstrates a cause and effect link between complexity and defects. This evidence points to complexity as principle source of defects, a fundamental principle that has played a critical role in the development of a global perspective of conformance quality.

Although the observed link between complexity and defects suggests that there is a tendency for longer assembly operations to result in a higher probability of a defect, there is no evidence supporting a one to one correspondence between Design for Assembly (DFA) time per operation and defects per operation. In other words, we can not say that the operation with the shortest predicted assembly time has the lowest defect rate or that the operation with the highest predicted assembly time has the highest defect rate.

Literature Support for the Link Between Complexity and Defects

The global Conformance Quality Model (CQM) predicts that increasing assembly complexity will increase defect rates. This trend is consistent with several studies showing increases in defects and errors when the complexity of the task is increased [37][50][51][56][81][82][83][84]. It is also consistent with published Boothroyd Dewhurst [103] data which showed that the quality and reliability improved an average of 68 percent when the Design for Assembly (DFA) time was reduced an average of 62 percent.

Large Differences in Quality Control Among Companies Affirmed

For the same level of complexity the defect rates differed by roughly a factor of four between Motorola and the disk drive manufacturer. Useful models relating defect rates to complexity must address quality control differences, an important contribution of our global Conformance Quality Model (CQM).

The global Conformance Quality Model (CQM) also addresses differences in the level of quality control among manufacturers, which can be several orders of magnitude as we

have shown in this study. The need to address differences in quality control is substantiated by Toyota's [13] data which showed large differences in defect rates among suppliers. However, previous models for predicting error and defect rates have not explicitly identified differences in quality control levels as an essential element [14][51][78][118].

The relationship between defects and assembly time demonstrates that the level of quality will improve for a given manufacturer as the assembly complexity is reduced. However, it does not mean that the manufacturer with the simplest assembly will have the lowest defect rates, since manufacturers can have different levels of quality control.

Quality Control Differences Degrade the Defect to Complexity Correlation

Although strong correlations between defect rates and assembly complexity were demonstrated for products from the same company, collectively differences between the manufacturers were so great that correlations were weak. Factory correlations were stronger than company correlations involving several factories which were stronger than published industry-wide correlations (Womack [2]). A consistent trend shown in this data is that the correlation between complexity and defects is degraded as the breadth of the study increases. Industry-wide studies of complexity and defect rates are not likely to provide useful correlations until the quality control levels of the manufacturer's can be accurately characterized.

D.5 Implications

The Risk of Focusing on the Quantity Measures of Complexity

In the course of this study we have repeatedly found that a focus on the quantity measures of complexity can result in significant design errors. For example, we found that minimizing part count can lead to poor assembly. Ulrich [111] observed that reducing the part count by combining parts can lead to complicated parts that increase development time and cost. In one case we examined, reducing the number of assembly operations did not reduce defects as effectively as reducing the assembly time.

These observations point to the need for caution in establishing arbitrary quantity goals. It is tempting for managers to set quantity goals such as: 1) reduce the part count, 2) use no screws, or 3) use no more than three processes per part. These goals are attractive because they are easy to define and measure.

Designers are accustomed to dealing with precise measures of high accuracy. Global objectives generally have the characteristic of being more difficult to define, and measure. In dealing with them, there is always some sense of uncertainty. However, as we have

shown, global measures provide important insights and direction, even when bounds may be very broad.

The Continuous Search to Reduce Complexity

Complexity cannot be eliminated in product design or production, but it can always be reduced. Thus, the never ending search for Gilbreth's "one best way" [100], must be a central theme of every effort to improve both quality, and productivity. Gilbreth's search for the "one best way" is conceptually the equivalent of Ohno's [2] objective for eliminating *muda*, the Japanese term for waste.

When eliminating waste is a management mandate, great strides may be made in a few selected areas. However, when it is an attitude engrained in every employee, continuous and effective progress can be sustained across a spectrum of improvement opportunities.

A barrier in the effectiveness of many efforts to eliminate waste is the difficulty of choosing an appropriate focus. To illustrate, Shingo [24] pointed out that:

"I have come across many plants where, as described above, operational efficiency is stressed to the neglect of process efficiency. In other words, I have seen a number of cases in which homogeneous machine layouts mean extra transportation or stock accumulates all over plants because batch systems or process systems have been adopted in the hope of pushing machine capacities to the limit." [24]

This example illustrates the problems that arise when local optimization dominates the global issues. It points to the essential need of broad perspectives in guiding improvement decisions

Complexity - A Broader View

In this work we have focused on aspects of product complexity that can be measured. However, the principles presented here have broad implications for many elements of human activity. For example, based on the pattern observed in this study more errors can be expected filling out long complicated forms than on simple forms when prepared by the same organization. If a document requires more routing, the likelihood of loss or delay increases.

Based on the correlation between defects and complexity identified in this study, we predict that the organizational complexity [8], and the complexity of every supporting production activity has an impact on conformance quality. From this it follows that "lean" organizations will tend to have lower defect rates, a trend which has been observed in the automobile industry by Womack et al [2]. The influence of the organizations complexity is reflected in the quality control constants of the global Conformance Quality Model (CQM).

Our observations would suggest that efforts to reduce the complexity of the organization, processes, operations, information flow, handling, parts, or any activity of the organization

will also reduce defect rates. However, improvements in some areas may result in inefficiencies in other areas. The global defect rate will decline, only if the global efficiency improves. Thus for every proposed improvement, the system impacts need to be considered.

D.6 Problems and Limitations

We have shown that DFA predictions are biased and imperfect gages of assembly complexity. The processes that they model have large variances. From these observations, the results obtained from DFA evaluations should be viewed as approximate indicators of complexity, and are most useful for relative comparisons. These concerns limit the confidence that can be placed in the results obtained in this study. The correlations between defects and assembly complexity that have been identified should not be viewed as exact or precise relationships, but rather descriptive of general trends.

In this study we have been able to identify and eliminate differences in the effectiveness of quality control among organizations as an important confounding factor in the comparison of defects and complexity. We have also used a common standard for assessing complexity, minimizing differences in interpretation. There are still potential confounding factors that could not be investigated including: a) differences in product maturity, b) production pace, and perhaps most importantly, c) variations in part complexity. Consequently, there are significant opportunities for continued refinement of the defined model. In particular the role of part complexity is poorly understood and merits increased attention.

We have been somewhat disappointed in the amount of defect data that we have been able to obtain. While the data that we have received strongly supports our thesis we had hoped to obtain data across a broader spectrum of products. Clearly there is an opportunity to broaden the basis of these conclusions.

D.7 Conclusions About Complexity and Defects

Design for Assembly (DFA) methods show that considerable effort has been expended in trying to learn how to make assembly less complex. However, this is the first known study that has had the objective of determining how complex assembly is. From this work we have learned that our ability to measure complexity is immature.

We have shown that Design for Assembly (DFA) is linked to part and interface complexity in addition to the difficulty of assembly manipulations. However, Design for Assembly (DFA) methods are biased, and there is some variation in interpretation. There is a consistent trend of increasing predicted assembly time for increasing task complexity

among the various methods. We have also learned that the distribution of predicted assembly time is virtually identical regardless of the method used, suggesting that the distribution is in fact the best measure of complexity.

We have shown that the distribution of Design for Assembly (DFA) times can be described by a Pareto distribution. This allows us to bound assembly time in probabilistic terms as a function of the number of assembly operations, providing the ability to accurately predict assembly efficiency over a wide range of values without dependence upon detailed analysis or a database. We can also use the Pareto distribution to predict the impact of product redesign. We have also shown that zeta convolutions describe the actual assembly time of real products, substantiating the selection of Pareto based functions in this application.

Two factors have hampered efforts to correlate defect rates with complexity in the past: 1) there are large difference in quality control among manufacturers, and 2) the measures of complexity have been oversimplified, focusing on quantity measures such as part and operation counts. These limitations were overcome by comparing defects and complexity of products within individual companies where control of quality is most consistent, and by using Design for Assembly (DFA) methods to measure assembly complexity.

We have found that assembly complexity is highly correlated with product defects. This relationship has been used to formulate a global Conformance Quality Model (CQM).

The results of this investigation point to the value of continuous efforts in reducing complexity across a broad spectrum of production activity. It also reinforces the importance of global perspectives in design and development decisions at all levels.

REFERENCES

References

1. Buzzell, Robert D., and Bradley T. Gale, The PIMS (Profit Impact of Market Strategy) Principles-Linking Strategy to Performance, Chapter 6, 1987, pp. 103-131.
2. Womack, James P., Daniel T. Jones & Daniel Roos, The Machine that Changed the World, Rawson Associates, New York, 1990, p. 93, 96.
3. Ishikawa, Kaoru, Guide to Quality Control, Asian Productivity Organization, Quality Resources, White Plains, Seventh Printing 1990.
4. Juran's Quality Control Handbook, J. M. Juran, editor in chief, Frank M. Gryna associate editor, Fourth Edition, McGraw-Hill, New York, 1988., pp. 24.6.
5. Harry, Mikel J. and Reigle Stewart, "Six Sigma Mechanical Design Tolerancing," Motorola Publication No. 6s-2-10/88, Scottsdale, AZ, 1988.
6. Rook, L. W., Jr., Reduction of Human Error in Production, SCTM 93-62(14), Sandia National Laboratories, Division 1443, June 1962.
7. Harris, Douglas H., and Frederick B. Chaney, Human Factors in Quality Assurance, Wiley, New York, 1969, p. 9.
8. Voegtlen, H. Dean, Complex Industries, Section 31., Juran's Quality Control Handbook, J. M. Juran, editor in chief, Frank M. Gryna associate editor, Fourth Edition, McGraw-Hill, New York, 1988., pp. 31.1-31.24.
9. Student report submitted for ME217A at Stanford University, December 1992.
10. The Associated Press, "Space shuttle workers afraid to report errors, study finds," The Modesto Bee, Modesto, July 27, 1993.
11. Gebala, D., Correspondence, Motorola, Inc., Advanced Manufacturing Technologies, Fort Lauderdale, FL, August 6, 1992.
12. Smith, Bill, "Making a War on Defects-Six Sigma Design," *IEEE Spectrum*, September, 1993, pp. 43-47.
13. Sanger, David E., "U.S. Suppliers Get a Toyota Lecture," *The New York Times*, November 1, 1990.
14. Improving Engineering Design-Designing for Competitive Advantage, Committee on Engineering Design Theory and Methodology Manufacturing Studies Board, Commission on Engineering and Technical Systems, National Research Council, National Academy Press, Washington, 1991, p. 7.
15. Moss, Marvin, Designing for Minimal Maintenance Expense-The Practical Application of Reliability and Maintainability, Macel Decker, New York, 1985, p 9.
16. Garvin, David A., "Competing on the Eight Dimensions of Quality," *Harvard Business Review*, Nov.-Dec. 1987, pp. 101-109.
17. Ross, Phillip J., Taguchi Techniques for Quality Engineering, McGraw-Hill, New York, 1988.
18. Gryna, Frank M., Manufacturing Planning, Chapter 16, Juran's Quality Control Handbook, J. M. Juran, editor in chief, Frank M. Gryna associate editor, Fourth Edition, McGraw-Hill, New York, 1988., pp. 16.19-16.21.
19. Trucks, H. E., Designing for Economical Production, Society of Manufacturing Engineers, Dearborn, 1976.
20. Heggem, Rick, Proactive Tolerance Analysis, Applied Applied Computer Solutions, Santa Clara, April 30, 1992.
21. Held, David O., "Quality Advisor," *Manufacturing Engineering*, Vol. 110, No. 6, June 1993, pp.12-14.

22. Poka-yoke-Improving Product Quality by Preventing Defects, Edited by Nikkan Kogyo Shimibun, Ltd./Factory Magazine, Productivity Press, Cambridge, 1988 (English).
23. Lafferty, John P., "Quality Advisor," *Manufacturing Engineering*, October 1992, p. 10.
24. Shingo, Shigeo, Zero Quality Control: Source Inspection and the Poka-yoke System, Translated by Andrew P. Dillon, Productivity Press, Cambridge, Conn., 1986.
25. Rasmussen, Jens, "Trends in Human Reliability Analysis," *Ergonomics*, 28(8), 1985, pp. 1185-1195.
26. Rook, L. W., Motivation and Human Error, SC-TM-135, Sandia National Laboratories, Albuquerque, September 1965, p. 5.
27. Tsuda, Yoshikazu, "Implications of Fool Proofing in the Manufacturing Process," Quality Through Engineering Design, Edited by W. Kuo, Elsevier, 1993, pp. 79-95.
28. Rasmussen, J., Human Errors, A taxonomy for describing human malfunctions in industrial installations, Report No. RISØ-M-2304, Roskilde, Denmark: RISØ National Laboratories, August, 1981.
29. Seidenstein, Sidney, Presentation for Lockheed Missiles & Space Company, Inc, Sunnyvale, CA
30. Bralla, James G., Handbook of Product Design for Manufacturing, McGraw-Hill, New York, 1986, p 1-18.
31. Dactz, Douglas, "The Effect of Product Design on Product Quality and Product Cost", *Quality Progress*, June, 1987, pp 63-67.
32. Nam Suh, The Principles of Design, Oxford University Press, 1990, p. 9.
33. Bruhin, Alfred C., Presentation at Industrial Forum on Supply Chain Management, May 6, 1993.
34. Barkan, Philip, and C. Martin Hinckley, "Benefits and Limitations of Structured Methodologies in Product Design," *Manufacturing Review*, Vol. 6, No. 3, September, 1993, pp. 211-219.
35. Brannan, Bill, "Six Sigma Quality and DFA-DFMA Case Study/Motorola Inc.", *Boothroyd & Dewhurst DFM Insight*, Vol. 2 Winter 1991, pg 1-3.
36. Boothroyd, G., Dewhurst, P., Product Design for Assembly, Boothroyd Dewhurst, Inc., Section 2, Kingston, 1985.
37. Gatchell, Susanne M., "The Effect of Part Proliferation on Assembly Line Operators' Decision Making Capabilities," *Proceedings of the Human Factors Society*, 23rd Annual Meeting, 1979 (Santa Monica : The Human Factors Society, 1979).
38. Gilbreth, L. M., "The Quest for the One Best Way," a sketch of the life of F. B. Gilbreth published by Mrs. Gilbreth, 1925. p. 16.
39. Juran, J. M., "Then and Now in Quality Control- The Non-Pareto Principle; Mea Culpa," *Quality Progress* 8, May 1975, pp. 8-9.
40. Busino, Giovanni, Vilfredo Pareto ŒUVRES COMPLÈTES Tome III - Ecrits Sur La Courbe De La Répartition De La Richesse, published under the direction of Giovanni Busino, Librairie Droz, Genève Switzerland, 1965, pp. xviii, 2.
41. La courbe de la répartition de la richesse, Université de Lausanne, Recueil Publié par la Faculté de Droit a L'occasion de l'Exposition nationale suisse, Genève 1896, Lausanne, Ch. Viret-Genton Impr., 1896, pp. 373-387, et puis en appendice au livre de J. Seailles. La répartition des fortunes d'après les statistiques successorales en France, Paris, Alcan 1909, pp. 127-137.
42. Johnson, Norman L., and Samuel Kotz, Continuous Univariate Distributions-1: Distributions in Statistics, Wiley & Sons, New York, 1970., pp. 233-249.
43. Ross, Sheldon, A First Course in Probability, Macmillan, New York 1988. pp. 142, 346.

44. Ergonomic Design for People at Work, Vol 2., prepared by the Ergonomics Group, Health and Environment Laboratories, Eastman Kodak Co., Van Nostrand Reinhold, New York, 1986., p. 232.
45. Telephone Conversation with Steve Dalaet, Warren Michigan, February, 1993.
46. Barnes, Ralph M., Motion and Time Study-Design and Measurement of Work, Wiley & Sons, Seventh Edition, New York, 1980, pp. 12-21, 63, 292-295, 363-365.
47. Hagen, E. W., Editor, "Human Reliability Analysis," *Nuclear Safety*, 17, 315-326 (1976).
48. Dhillon, B. S., and C. Singh, Engineering Reliability: New Techniques and Applications, Wiley, Inc., New York, 1981, p. 161
49. Meister, David, Analysis of Human Initiated Equipment Failures During Category I Testing, OSTF-1, Report REL R-54. General Dynamics/Astronautics, San Diego, 1961.
50. Stalk, George, Jr., and Thomas M. Hout, Competing Against Time-How Time-Based Competition is Reshaping Global Markets, The Free Press, 1990.
51. Park, Kyung S., Human Reliability - Analysis, Prediction, and Prevention of Human Errors, Elsevier, Amsterdam, 1987. p 197.
52. Bloomfield, J. R., "Studies in Visual Search," Paper I:2, Human Reliability in Quality Control, Edited by C. G. Drury and J. G. Fox., Halsted Press, New York, 1975. pp. 19-43.
53. Segur, A. B., "Motion-Time-Analysis", in Industrial Engineering Handbook, H. B. Maynard, editor, McGraw-Hill Book Co., New York, 1956, pp. 4-101 to 4-118.
54. Fitts, P. M., "The Information Capacity of Human Motor System in Controlling the Amplitude of Movement," *Journal of Experimental Psychology*, Vol. 47, No. 6, June 1954.
55. MacKenzie, I. S., "A Note on the information-theoretic basis for Fitt's law," *Journal of Motor Behavior*, Vol 21, 1989, pp 323-330.
56. MacKenzie, I. Scott, Abigail Sellen, and William Buxton, "A Comparison of Input Devices in Elemental Pointing and Dragging Tasks," *Human Factors in Computing Systems-Reaching Through Technology, CHI 1991 Conference Proceedings*, Edited by Scott P. Robertson, Gary M. Olson, and Judith S. Olson, Addison Wesley Publishing Co., Reading, April 27-May 2, 1991, pp. 161-166.
57. Design for Assembly Workshop, GM Education & Training, M-1354, EIS 0316, 1984.
58. Assembly View™-Design for Assembly Analysis for the Macintosh, User Manual, Sapphire Design Systems, 1989.
59. Lewis, G. M., Editor, "Design for Assembly and Automation," Xerox Automation Institute, Webster, N. Y., 1985.
60. Watson, Ronald G., Ellen M. Theis, and Robert S. Janek, "Mechanical Equipment Design for Simplicity," *AT&T Technical Journal*, Design for X, Vol 69, No. 3, May/June 1990, pp 14-27.
61. Bothun, M., et al., "Design Guide for Assembly and Automation," Xerox Automation Institute, Webster, N.Y., 1985.
62. General Electric, Design for Assembly, McGraw-Hill, New York, 1982.
63. Latombe, Jean-Claude, Robot Motion Planning, Kluwer Academic Publishers, Boston, 1991.
64. Wilson, Randall H. and Jean-Claude Latombe, Reasoning About Mechanical Assembly, Department of Computer Science, Stanford University, Report No. STAN-CS-92-1442, September 1992.
65. Weschler, David, The Range of Human Capacities, 2nd ed, Williams and Wilkins, Baltimore, 1952, p. 94.
66. Gilbreth, F. B., Motion Study, D. Van Nostrand Co., Princeton, N. J., 1911.
67. Hancock, Walton M., and Franklin H. Bayha, "The Learning Curve," Chapter 4.3, Handbook of Industrial Engineering, Edited by Gavriel Salvendy,

68. Krafcik, John F. and John Paul MacDuffie, Explaining High Performance Manufacturing: The International Automotive Assembly Plant Study, International Motor Vehicle Program, MIT, May 1989.
69. Krafcik, John F., The effect of Design Manufacturability on Productivity and Quality: An Update on the IMVP Assembly Plant Study, International Motor Vehicle Program, MIT, January 1990.
70. Olkin, Ingram, Leon J. Gleser, and Cyrus Derman, Probability Models and Applications, Macmillan, p. 210.
71. Lorenz, M. O., "Methods of Measuring the Concentration of Wealth," *American Statistical Association Publication*, Vol. 9, (1904-1905), pp. 200-219.
72. Kenett, Ron S., "Two Methods for Comparing Pareto Charts," *Journal of Quality Technology*, Vol. 23, No. 1, January 1991, pp. 27-31.
73. Relyea, Douglas B., "The Simple Power of Pareto," *Quality Progress*, May 1989, pp. 38-39.
74. Zipf, George Kingsley, Human Behavior and the Principle of Least Effort-An Introduction to Human Ecology, Addison-Wesley Press, Inc., Cambridge, MA, 1949.
75. Zipf, George Kingsley, National Unity and Disunity-The Nation as a Bio-Social Organism, The Principia Press, Inc., Bloomington, Indiana, 1941.
76. Berger, J. M., and B. Mandelbrot, "A New Model for Error Clustering in Telephone Circuits," *IBM Journal of Research and Development*, July 1963, pp. 224-236.
77. Patterson, S. J., An Introduction to the Theory of the Riemann zeta-function, Cambridge University Press, New York, 1988, p. 2.
78. Swain, A. D. and H. E. Guttman, Handbook of Human Reliability Analysis with Emphasis on Nuclear Power Plant Applications, NUREG/CR-1278, SAND80-0200, RX, AN, Sandia National Laboratories, Albuquerque, August, 1983.
79. Meister, David, "The Problem of Human Initiated failures," *Proceedings of the Eighth National Symposium on Reliability and Quality Control*, IEEE, New York, 1962, pp. 234-239.
80. Clark, Kim B., and Takahiro Fujimoto, Product Development Performance, Harvard Business School Press, Boston, 1991, pp 198-201.
81. Ekins, J. Douglas, "Assembly Industries," Juran's Quality Control Handbook, Section 30, J. M. Juran, editor in chief, Frank M. Gryna associate editor, Fourth Edition, McGraw-Hill, New York, 1988., pp. 24.6.
82. Card, S., W. English, and B. Burr, "Evaluation of mouse, rate-controlled isometric joystick, step keys and text keys for test selection on a CRT," *Ergonomics*, 21(8), 1978, pp 601-613.
83. Jerison, Harry J., "On the Decrement Function in Human Vigilance." In D. N. Buckner and J. J. McGrath (Eds.), *Vigilance: A symposium*, New York, McGraw-Hill, 1963, pp. 199-216.
84. Harris, Douglas H., "The Effect of Equipment Complexity on Inspection Performance." *Journal Applied Psychology*, 1966, 50, 236-237.
85. Chapman, D. Elizabeth, and M. A. Sinclair, "Ergonomics in Inspection Tasks in the Food Industry," Human Reliability in Quality Control, Edited by C. G. Drury and J. G. Fox, Halsted Press, 1975, pp. 231-251.
86. Buck, J. R. "Dynamic Visual Inspection: task factors, theory and economics," Human Reliability in Quality Control, Edited by C. G. Drury and J. G. Fox, Halsted Press, 1975, pp. 165-187. 231-251.
87. Fucini, Joseph J. and Suzy, Working for the Japanese, The Free Press, New York, 1990.
88. Billings, Tim, a NUMMI employee, Conversations w/ Martin Hinckley and Phil Barkan, February, 1993.
89. Adler, Paul S., "Time-and Motion Regained," *Harvard Business Review*, January-February, 1993, pp. 97-108.

90. Adler, Paul S., Robert E. Cole, "Designed for Learning: A Tale of Two Auto Plants," *Sloan Management Review*, Spring 1993, pp. 85-94.
91. Halliday, David and Robert Resnick, Fundamentals of Physics, Wiley, New York, 1970., p 2.
92. Olivera, R., "6 Sigma/Fit Tolerance Analysis.", Communications Sector, Motorola Inc., Schaumburg. Ill., 1988.
93. Research Needs and Technological Opportunities in Mechanical Tolerancing, Results of an International Workshop, Select Panel on Research Opportunities in Mechanical Tolerancing held in Orlando Florida, Sep 28-Oct 2, 1988, for the US National Science Foundation Design and Manufacturing Systems Division, ASME CRTD-15, New York.
94. Brownlee, K. A., Statistical Theory and Methodology in Science and Engineering, (2nd Edition, New York: John Wiley and Sons, Inc.
95. Roth, Edward, *Tolerances Should Be Functional Not Impossible, Tooling and Production*, February, 1981.
96. Held, David O., "Quality Advisor-How Chrysler Manages Assembly Variation," *Manufacturing Engineering*, June 1993, p. 12.
97. Brisley, Chester, L., and Karl Eady, "Chapter 4.5, Predetermined Motion Time Systems," Handbook of Industrial Engineers, 2nd Ed., Edited by Gavriel Salvendy, Wiley, 1991, pp 4.5.1-4.5.7
98. Readings on The Principles and Applications of Decision Analysis, Edited by Ronald A. Howard, and James E. Matheson, Strategic Decision Group, California, 1989.
99. Student Report (Confidential Source) for Design for Manufacturability course in Mechanical Engineering (ME217) at Stanford University taught by Professor Philip Barkan. Submitted March 4, 1992.
100. Gilbreth, F. B., Motion Study, D. Van Nostrand Co., Princeton, N. J., 1911.
101. Peterson, Kent, General Motors North American Operations, Correspondence to C. Martin Hinckley dated February 16, 1993.
102. Student Reports submitted for a Design for Manufacturability course in Mechanical Engineering (ME217) at Stanford University taught by Professor Philip Barkan. Data has been compiled from reports submitted between December of 1991 and June of 1993.
103. Boothroyd Dewhurst, Inc., Advertisement for the "1993 International Forum on DFMA," Wakefield, RI, 1993.
104. Walpole, Ronald E., Raymond H. Myers, Probability and Statistics for Engineers and Scientists, MacMillan, New York, 1972, pp. 293-295.
105. Bethea, Robert M., and R. Russel Rhinchart, Applied Engineering Statistics, Marcel Dekker, Inc., New York, 1991, pp 259-261.
106. Palgrave's Dictionary of Political Economy, MacMillan, London, 1926, pp. 712-713.
107. Lehmann, E. L., Theory of Point Estimation, Wiley & Sons, pp 453.
108. The Rauch Guide to the U.S. Plastic Industry- Data for 1988-1990, Estimates for 1991 and forecasts for 1995, Rauch Associates, Bridgewater, N.J., 1991, pp 103-104.
109. Predicast's Forecasts, 1992 Annual Cumulative Edition, August 5, 1992.
110. Metal Statistics- 1981-1991, 79th Edition, Metallgesellschaft AG, Frankfurt, 1992, pp. 4-5.
111. Ulrich, Karl, David Sartorius, Scott Pearson, and Mark Jakiela, "Including the Value of Time in Design-for Manufacturing Decision Making," *Management Science*, Vol 39, No. 4, April 1993. pp. 429-447.
112. Applewhite, Philip B., Drive State Prediction from Work Performance Parameters, Dissertation, Stanford, 1965.
113. Hillier, Frederick S. and Gerald J. Lieberman, Introduction to Operations Research, McGraw Hill, New York, Chapter 15, 1990, p. 561-586.

114. Gill, Philip E., Walter Murray, and Margaret H. Wright, Practical Optimization, Academic Press, San Diego, 1981, pp. 83-92.
115. PC-MATLAB™ User's Guide, 386-MATLAB for 80386 Personal Computers, The MathWorks Inc., South Natick, May 6, 1989,
116. Karger, D. W. and Bayha, F. H., Engineered Work Measurement. New York: The Industrial Press, 1957.
117. Albin, Susan L., "The Lognormal Distribution for Modeling Quality Data When the Mean is Near Zero," *Journal of Quality Technology*, Vol. 22, No. 2, April 1990, pp. 105-110.
118. McCormack, R., Inspector Accuracy: A Study of the Literature, Report SCTM-53-61(24), Sandia Corporation, Albuquerque, 1961
119. LaRue, Arthur J., "Some Quality Considerations in the Design of Automatic Assembly Machines," ASTME Technical Paper number 263, Collected Papers, 28th Annual Meeting, ASTME, Detroit, April 21-26, 1960.
120. Dhillon, Balbir S., Human Reliability with Human Factors, Pergamon Press, New York, 1986, p. 69.
121. Schaffer, Robert H., and Harvey A. Thomson, "Successful Change Programs Begin with Results," *Harvard Business Review*, Reprint 92108, January-February, 1992, pp. 80-89.
122. Dhillon, B. S. and S. N. Rayapati, "Human Reliability Analysis Methods," Proceedings 3rd Int. Conf. Human Factors in Manufacturing, IFS (Conferences) Ltd., November 1986, pp. 237-248.
123. Darlow, M. S., D. M. Avidar, M. W. Steiner, "A Procedure for Comparative Evaluation of Design for Assembly Methodologies," Advances in Design Automation-1987, Vol. On: Design Methods, Computer Graphics, and Expert Systems, edited by S. S. Rao, The 1987 ASME Design Technology Conferences, The Design Automation Conference, Boston, September 27-30, ASME DE-Vol.10-1, New York, 1987, pp. 301-306.

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