

Autonomous and Intelligent Neurofuzzy Decision Maker for Smart Drilling Systems, DOE SBIR Contract No. DE-FG03-98ER82634

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In Phase I, we designed an IDMA for intelligent drilling control, and demonstrated its feasibility. We successfully reached the Phase I goals by demonstrating the feasibility of an intelligent and autonomous drilling system integrating data fusion, neurofuzzy classification, and hybrid training. POC also designed in Phase I the overall Phase II IDMA architecture so that Phase II can begin with building the Phase II prototype.

The proposed IDMA will be useful in many areas of national interest such as exploration for mineral and energy resources, environmental monitoring, infrastructure development, and scientific studies of the Earth's subsurfaces. The IDMA module will increase the speed, success rate, and overall cost-effectiveness of petroleum drilling. It can also be adapted for use in various control systems such as traffic control, manufacturing control, and automation.

If Phase II is funded we plan to complete development IDMA, work with a drilling company and Sandia National Laboratory to demonstrate the Phase II prototype, and introduce an IDMA as a product to the market with Phase III private funding.

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Autonomous and Intelligent Neurofuzzy Decision Maker for Smart Drilling Systems

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1.0 IDENTIFICATION AND SIGNIFICANCE OF THE PROBLEM OR OPPORTUNITY, AND TECHNICAL APPROACH

1.1 Identification and Significance of the Problem or Opportunity

Drilling technology is a key to exploration for and extraction of oil, gas, geothermal energy, and other mineral resources, and also for infrastructure development, environmental monitoring and remediation, and for the scientific study of the earth's subsurface [1]. Improvements in drilling technology that lower overall drilling cost, reduce drilling time, and increase the rate of success in finding and extracting petroleum and geothermal energy will have great and direct benefits to the United States in terms of greater energy resources, stable and low energy costs, and improved economic competitiveness in the drilling and petroleum service industries.

Drilling involves a complex set of mutually interacting components -- mechanical, hydraulic, and electrical -- that must function in unison. Therefore, it is necessary to develop an integrated system approach to ensure that these components do function at near-peak performance, and to prevent or minimize discontinuities as the result of kicks, washouts, loss of circulation, mud motor failure, stuck pipe, and junk in the hole. The way has been prepared for such an intelligent drilling system by recent dramatic advances in directional drilling and measurement-while-drilling, and by related diagnosis and detection technologies [1-9].

Through the twentieth century, U.S. drilling technology has dominated the worldwide drilling industry, much of the excavation industry, and the markets for drilling machinery and equipment. To maintain the technical superiority of U.S. drilling technologies, and to find better and less costly ways of penetrating rock in order to harness geothermal energy resources more efficiently, the Geothermal Division of the U.S. Department of Energy asked [1] the National Research Council to establish a committee to examine opportunities for advancing drilling technologies that would have broad industrial and national interest and benefits. DOE also solicited intelligent drilling system and software technology through its SBIR Program in 1998.

In response to this need, Physical Optics Corporation (POC) in Phase I began developing unique Intelligent Decision Making Aid (IDMA) technology for intelligent drilling control in energy exploration and production (oil, coal and geothermal), mining, and drilling for nuclear and chemical waste storage. IDMA, which builds on POC's soft computing and sensor fusion technologies, is a unique integration of neural network, fuzzy logic, and sensor fusion. POC demonstrated in Phase I that the IDMA concept not only is feasible but has strong advantages over existing techniques. We demonstrated that all of the basic components of the system can be fabricated and assembled cost effectively. In particular we demonstrated the IDMA concept by integrating a neurofuzzy system with a conventional decision making neural network. In addition, IDMA was successfully implemented for intelligent drilling and simulation of rock type classification. POC also demonstrated that the IDMA prototype can monitor drill penetration rate, drill speed, torque, and thrust.

Based on our successful Phase I demonstration, POC believes that further development of this IDMA technology and its integration into a full preproduction prototype as a intelligent drilling system in Phase II will produce a key breakthrough in oil and gas exploration.

1.2 Current State-of-the-Art

Most existing drilling systems have little or no downhole sensing of rock or bit conditions, and automated guidance systems, if present, are either primitive or laboratory prototypes [1]. Since the

Committee on Advanced Drilling Technologies formed in 1993, a few attempts have been made to develop technology for transmitting data from downhole to the surface. These include acoustic borehole viewers as a part of measurement-while-drilling and logging-while-drilling technologies to overcome the drawbacks of current sensing methodologies, which require interrupting the drilling process to insert special tools to gather data from the borehole. These efforts have been performed under the direction of the Geothermal Division of DOE and Sandia National Laboratories.

The definition of an intelligent drilling system by the National Research Council is that, "An intelligent drilling system is a system capable of sensing and adapting to conditions around and ahead of the drill bit to reach the desired target. This system may be guided from the surface, or it may be self guided, utilizing a remote guidance system that modifies the trajectory of the drill when the parameters measured by the sensing system deviate from expectations." [1] Such a system can only be built by integrating many of the technological advances made available by the rapid innovations in microelectronics, computer science, advanced sensor technology, and many other disciplines.

1.3 Phase I Investigation

In Phase I POC investigated an Intelligent Decision Making Aid (IDMA) integrating our innovative and advanced soft computing technologies and multisensor data fusion. Specifically, IDMA combines data fusion, artificial neural networks, and fuzzy logic as illustrated in Figure 1-1.

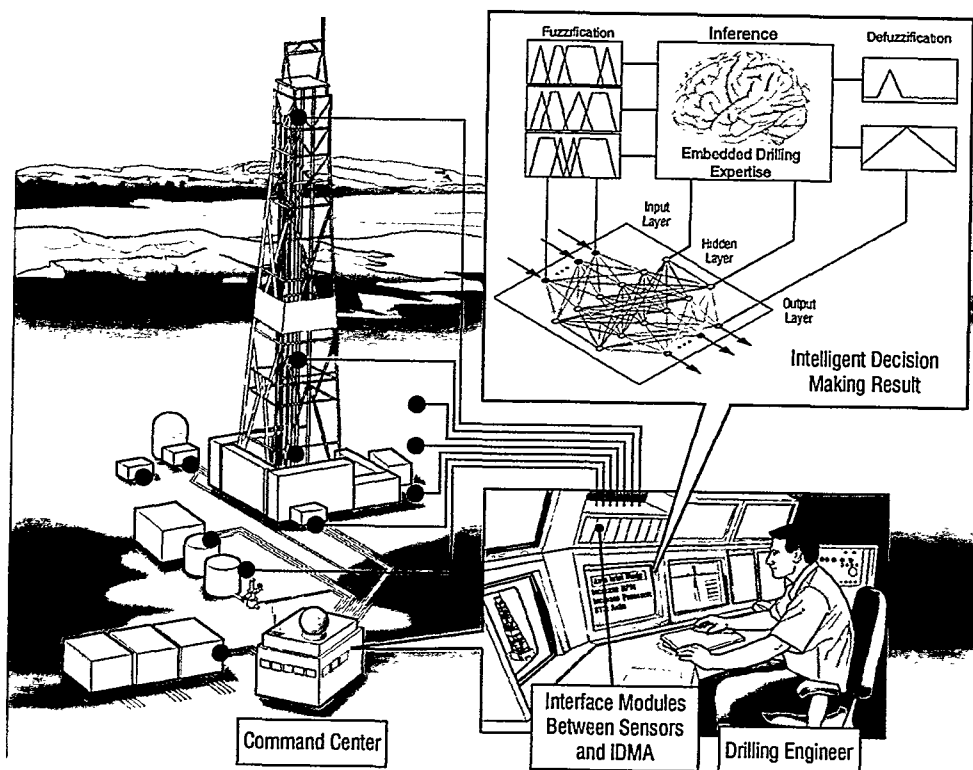


Figure 1-1
Intelligent drilling using POC's IDMA.

The neurofuzzy system consists of three submodules -- input, hidden, and output layers -- for fuzzification, inference processing, and defuzzification, respectively:

- **Fuzzification** is a mapping from the observed input to the fuzzy sets defined in the corresponding universe of discourse.
- **Inference processing** is a decision making logic that determines fuzzy outputs corresponding to fuzzified inputs with respect to the fuzzy rules.
- **Defuzzification** produces a crisp output by one of three methods: center of gravity, MAX criterion, or Mean of Maxima.

The main tasks of the neurofuzzy system are preclustering and defuzzification on the basis of current sensor data from the fuzzy data associator. It interprets current drilling status into a defuzzified form such as 5% of N_0 , 10% of N_1 , 2% of N_{M-1} . This defuzzified interpretation of the current situation is fed into the decision making neural network.

A conventional neural network would have to be retrained whenever the drilling system configuration changed -- sensors, equipment, or any other components of the drilling system involved in the decision making process. Changing the sensor configuration would then require retraining the entire neural network, which is time-consuming and not guaranteed to converge to the global optimum. In contrast, IDMA would only require training the module associated with the new component.

In summary, POC's IDMA is an intelligent and autonomous artificial drilling aid that reduces many current problems such as stuck pipe and loss of circulation. Loss of circulation costs represent an average of more than 10% of total drilling costs in mature geothermal areas [2]. Applying IDMA to geothermal drilling, and thus reducing the costs of loss of circulation, will significantly reduce overall geothermal costs and help expand the role of geothermal energy. IDMA is characterized by robust operational performance, extended spatial and temporal coverage, increased confidence, reduced false alarm rate, reduced ambiguity, improved detection, enhanced spatial resolution, and increased dimensionality thanks to sensor fusion and embedded drilling expertise in the artificial neural network, and fuzzy logic control of the neurofuzzy structure. Key advantages of the IDMA include:

- Reduced overall drilling costs and time by minimizing drilling failures such as loss of circulation, washouts, kicks, stuck pipe, mud motor failure, and junk in hole
- Maximized usage of sensing and monitoring systems thanks to computerization of the IDMA system, and consequent reduced human errors
- Increased decision confidence thanks to the expertise embedded in the neural networks with continuous and consistent monitoring
- High system adaptability thanks to neural network modularity. Current sensing at the drill bit area is immature. As it advances, sensing technology will improve and the proposed system will require retraining only of the channel related to the new sensor.

The above advantages are due to the following unique technology element implementations:

- Unique neurofuzzy system architecture
- Highly precise fuzzification and defuzzification methodologies
- Advanced sensor fusion technology

- Innovative combination of unsupervised and supervised training
- Efficient modular retraining.

Based on a successful Phase I feasibility demonstration, POC has great confidence that IDMA methodology, supported by POC's R&D capabilities in all required areas, will produce a near-term product that will have remarkable commercial potential.

Although Phase I demonstrated the feasibility of our approach, significant efforts are still necessary to prepare IDMA for drilling, and to develop the final software package.

2.0 PHASE I EXPERIMENTAL RESULTS

2.1 Highlights of Phase I Findings and Achievements

The following is a summary of the IDMA Phase I findings and achievements.

1. Overall current sensing and monitoring technologies were studied and analyzed as a basis for designing the IDMA neurofuzzy system. In order to use artificial intelligence for control, it is essential to understand current sensing technology.
2. POC contracted with two drilling experts to serve as consultants to the IDMA project; since the neural network approach is to embed expertise in matrix form, it is essential to have drilling experts formalize the training sets for the neural network. POC reached an agreement with Mr. A.J. Mansure of Sandia National Laboratories under which Sandia shared its field drilling experience and expertise in sensor data interpretation. In addition, Mr. Bill Anderson of Epoch Well Logging, Inc. served as a subcontractor for the data acquisition and data analysis that is the basis of the training sets.
3. A fuzzy data associator for data association was developed. Defuzzification normalizes the data streams of the sensor data formats into a single data format encoding spatial, temporal, and dimensional parameters.
4. POC designed the overall IDMA structure, including neurofuzzy system and conventional decision making neural network. The neurofuzzy system classifies the current drilling status based on the current sensor reading, while the conventional neural network makes decisions based on the current drilling situation from the neurofuzzy system. A cascading system architecture was selected after careful analysis of current drilling technology, including data acquisition systems and sensors, and discussions with our consultant drilling experts.
5. We designed innovative training for both the neurofuzzy system and the decision making neural network. Defuzzified unsupervised training (vector quantization) was selected for neurofuzzy training, while supervised training (perceptron learning) was selected for the decision making neural network.
6. We selected the specific initial IDMA application for intelligent drilling. POC initiated a specific IDMA design for loss of circulation, with immediate application and real benefits for the near future.
7. We demonstrated Phase I IDMA simulation for rock type classification. POC has designed and built a Phase I IDMA prototype for rock classification and monitoring of penetration rate, drill speed, torque, and thrust.
8. We prepared recommendations for Phase II IDMA. POC recommended a Phase II IDMA system architecture, functional structure, and other parameters based on the results of the Phase I work.

2.2 Phase I Results

The Phase I IDMA project was a success. **The successful feasibility demonstrations and system architecture design not only met all objectives proposed for Phase I, but also exceeded them in a number of areas.** Most importantly, the modular approach ensures system adaptability to drilling system advances. The goal of Phase I was to demonstrate the feasibility of an intelligent and autonomous drilling system by integrating multisensor data fusion, neurofuzzy decision making, and hybrid training. To meet this goal, POC established seven tasks, including four technical tasks. The next few subsections present the results of these technical tasks.

2.2.1 Results of Task 1 (Study Existing Sensing and Monitoring Technology)

In preparation for designing the IDMA, POC studied existing technologies for sensing and monitoring the drilling process. POC met with Mr. Anderson of Epoch Well Logging, Inc. and Mr. Mansure of Sandia. In past years, drilling technology has advanced most in the development of sensors, especially for downhole sensing. This is called measuring while drilling (MWD). As a result, state-of-the-art drilling systems are completely networked, and equipped with various kinds of sensors for continuous real-time monitoring. A good example is Epoch Well Logging's RIGWATCH. In RIGWATCH, real-time sensory data are collected and transmitted via multi-conductor cables to a central data acquisition control unit. These data are processed and transmitted on PCs at various locations, such as the driller's workstation, rig floor/dog house, or tool pusher's office. The networking can include remote offices communicating via modem. At any station, log data are displayed in real time and plotted on hard copy.

In fact, these types of advanced monitoring technologies are beneficial and supportive for the development of IDMA because the advanced monitoring systems record data and at most produce summary reports or comparisons. Real-time rig parameter data keep key personnel (e.g., driller, company man, tool pusher, drilling engineer, and geologist) informed of all critical drilling, tripping, and circulating operations.

The growing flood of sensor data could soon overwhelm the operator with masses of information, causing fatigue after long hours of continuous monitoring. The need for an intelligent expert system is becoming critical. Therefore, the goal of IDMA is an intelligent system that not only alerts the operator to potential critical situations that are about to occur, but also suggests actions and explains the situations and the suggestions in real time, in parallel with the logged data. In addition, POC surveyed and studied current intelligent drilling methodologies, and determined the IDMA structure.

2.2.2 Results of Task 2 (Develop Data Association and Formation Methodology)

In this task, we evaluated current sensor fusion technology relevant to IDMA, and designed the data association mechanism. The definition of sensor fusion is: "A multilevel, multifaceted process dealing with the detection, association, correlation, estimation, and combination of data and information from multiple sources to achieve refined state and identify estimation, and complete and timely assessments of situation." [10]

Data fusion is performed on multisource data at several levels, each of which represents a level of data abstraction. For example, in the context of drilling control:

- Level 1: Fuse drill head position data and estimate credibility of data
- Level 2: Assess normalcy of situation
- Level 3: Recommend response.

The process of data fusion includes detection (level 1), association (level 1), correlation (level 1), estimation (level 2), combination of data (level 2), and finally decision making (level 3).

Figure 2-1 sketches the top level structure of the Phase I fuzzy data associator. Tentatively, POC has set the number of output levels at five. A detailed study to set the adequate and necessary number of levels is planned for Phase II.

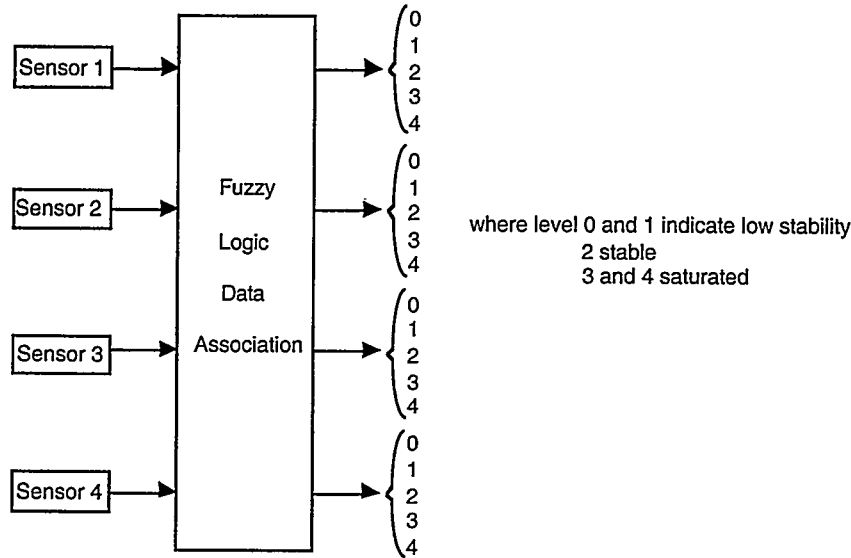


Figure 2-1
Phase I fuzzy data associator.

Since inflow and outflow volumes are critical to determining current drilling status (loss of circulation), POC selected control of these parameters for the first model fuzzy data associator. The fuzzy data associator was set up as:

1. If $0 \leq FP \leq 0.1$, loss of circulation (0)
2. If $0.1 < FP \leq 0.5$, possible loss of circulation (1)
3. If $0.5 < FP \leq 0.9$, slow circulation (2)
4. If $0.9 < FP \leq 1$, good drilling status (3)
5. If $FP > 1$, hit water or other liquid (4)

$$\text{where } FP \text{ (flow parameter)} = \frac{\text{Outflow}}{\text{Inflow}}.$$

In this case, the outputs of the fuzzy data associator, 0, 1, 2, 3, and 4, are passed to the neurofuzzy classifier.

2.2.3 Results of Task 3 (Design a Neurofuzzy System)

In Phase I, POC designed the neurofuzzy system, which is the key module of IDMA. Initially, POC selected the IDMA structure shown in Figure 2-2.

Neurofuzzy system architectures include:

- (1) Neural network-embedded fuzzy system
- (2) Fuzzy system-embedded neural network
- (3) Cascading fuzzy logic and neural network
- (4) Combination of (2) and (3)

After careful evaluation of drilling technologies and procedures, POC optimized and redesigned IDMA as a modular neural network. We divided the hybrid training algorithm-based neurofuzzy system into two separate neurofuzzy classifiers and the conventional decision making neural network as shown in Figure 2-3.

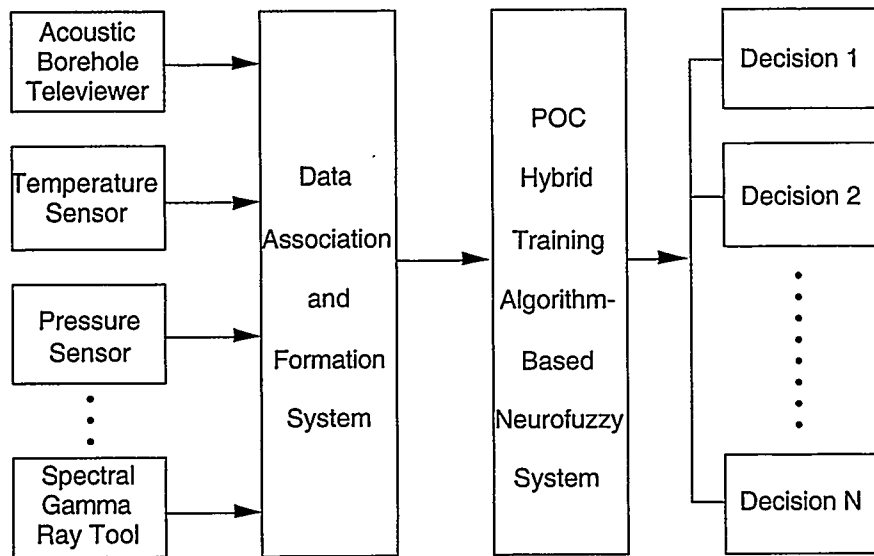


Figure 2-2
Initial Phase I IDMA system.

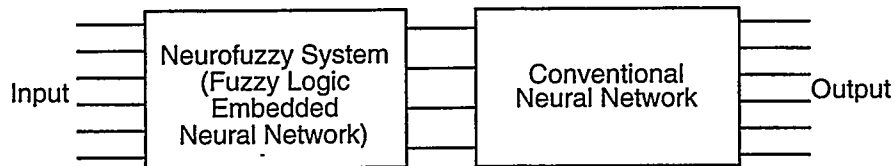


Figure 2-3
The cascading Phase I neurofuzzy structure.

The selected modular approach is (4), the combination of (2) and (3). The first neurofuzzy classifier is the fuzzy system-embedded neural network, primarily performing preclustering and defuzzification of the current drilling status based on the current data reading. In order to perform such drilling status classification, it will receive unsupervised training. The output of the neurofuzzy classifier system will be fed into the decision making neural networks.

The conventional neural network will be trained by supervised training to make a decision based on the current drilling status, which will come from the neurofuzzy classifier system.

One of the important characteristics of this hybrid neurofuzzy modular architecture is the adaptability of the IDMA. Since current sensing and telemetry techniques are primitive, new sensing and telemetry methods are being developed; it will be necessary to adapt IDMA to the new sensors. In general, any neural network has to be retrained entirely. In our hybrid system architecture, one needs to retrain only the module that has changed.

2.2.4 Results of Task 4 (Train Neurofuzzy System, and Conduct Computer Simulation and Demonstration with Neurofuzzy System)

2.2.4.1 Simulation Results

In Phase I, we implemented a program to demonstrate the feasibility of applying a neurofuzzy network to drilling control. The program had two purposes: (1) Demonstrate the application of a neural network and fuzzy logic to drilling as an intelligent decision making assistant. This is needed to show the feasibility of the proposed IDMA system. (2) Demonstrate the general concept of the neural network and fuzzy logic. This serves as a brief introduction to give future IDMA users an understanding of applying neurofuzzy processing. Drilling involves many processes in a broad range of environments. For IDMA to perform its functions in all drilling situations, it must adapt dynamically to each specific situation, and the user will need to tune the neurofuzzy network for optimal performance.

Figure 2-4 shows the initial screen of the IDMA demonstration program implemented under Matlab. As shown in the figure, the screen is partitioned into windows for topics, briefs, and subtopics. When the user selects a topic in the left window, a brief description of the topic is shown at top right. At the same time, the associated subtopics appear at bottom right as shown in Figure 2-5. The user is prompted to run any subtopic.

Drilling is dangerous, and often takes place in hostile environments. It would be at best difficult to arrange field tests of any hardware or software without special arrangements with a drilling company. Thus, only computer simulations were performed in Phase I. Two simulation programs are shown here, one for the neural network application and the other for fuzzy logic control.

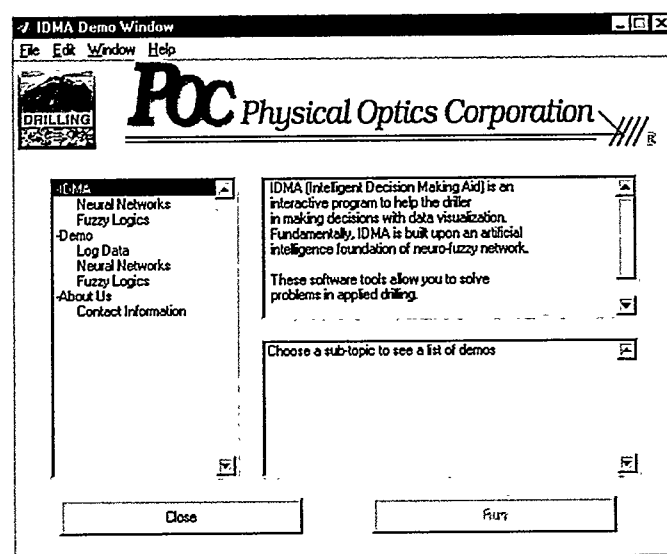


Figure 2-4
Initial screen of the demonstration program.

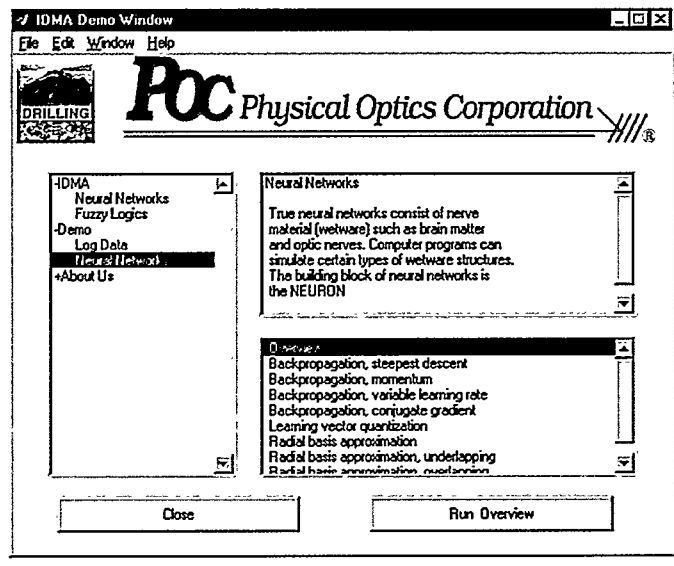


Figure 2-5

The demonstration program allows the user to navigate each subtopic in detail. In the figure, Demo->Neural Networks-> Overview is selected. The button at bottom right prompts for execution of the selected subtopic.

2.2.4.2 Rock Classification while Drilling

This simulation identifies the types of rocks encountered while drilling. A multi-layered feedward network with learning vector quantization (LVQ) is used for the simulation. LVQ was selected over a number of other potentially appropriate networks for this simulation, such as unsupervised competitive learning and radial basis function networks.

It is known that there is a correspondence between the specific energy of drilling as a function of torque, thrust, penetration rate, rotation rate, the area of the hole, and the unconfined compressive strength of the drilling medium [11].

$$e = F/A + 2 p NT/Au, \quad (2-1)$$

where e =specific energy of drilling, F =thrust, A =area of hole (m^2), N =rotation rate (rpm), T =torque (J), and u =penetration rate (m/min.)

Based on Eq. (2-1), training and testing data are derived, mixed with randomly generated noise. Table 2-1 shows sample data at five successive times. Figure 2-6 illustrates the architecture of the LVQ network, with four input neurons and three output neurons. The network is first trained, associating each data stream with the correct rock classification. Figure 2-7 captures some of training data samples. Figure 2-8 captures two simulation runs using the trained network. The figure shows, as time progresses during drilling, the rock classification as the input neurons receive the corresponding sensory data.

Table 2-1. Sample Data for Rock Classification Simulation

Time	u	F	N	T
0	0.161	1250.40	24.28	3.78
1	0.187	1320.00	23.30	2.86
2	0.158	1123.44	23.39	3.42
3	0.132	1223.23	24.18	2.98
4	0.111	1234.00	24.25	3.27

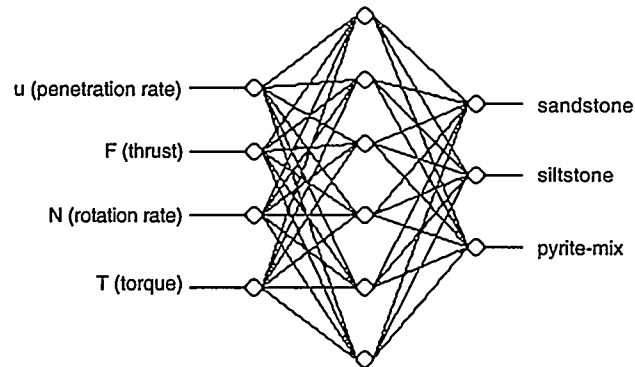


Figure 2-6

The LVQ network is trained with four input neurons, u, F, N, and T, and output neurons representing sandstone, siltstone, and pyrite-mix.

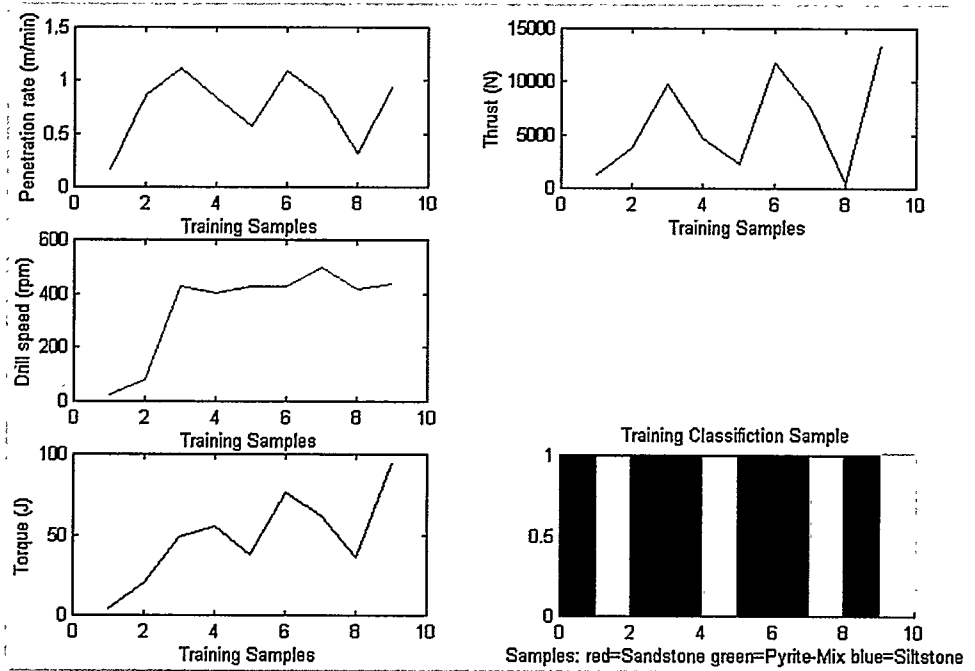


Figure 2-7

The LVQ network is trained on sample training data as shown here. Note that nine sample training data sets are shown. Since LVQ is a supervised network, each training data set contains not only input neuron values, but also the correct rock classification.

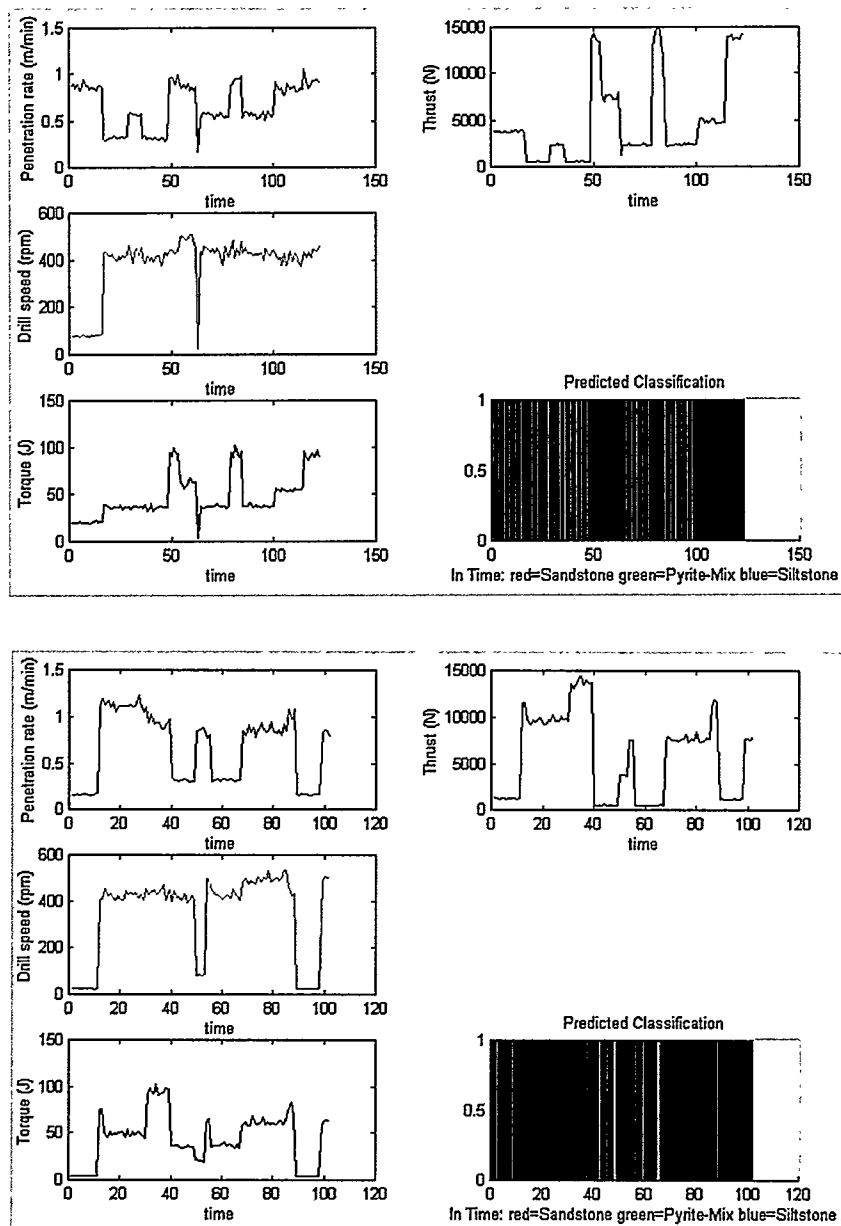


Figure 2-8
LVQ network demonstration.

2.2.4.3 Fuzzy Control of Drilling

Among the many parameters relevant to drilling control, inflow and outflow rates are critical to determining current process status. As above, let us denote the flow rate as FP. Assume a drill pipe is continuously being filled with fluid and continuously drained. The flow rate is measured and compared to a flow rate setpoint to determine flow rate error. The error is used by a controller to set the motor voltage to keep the measured flow rate close to the desired flow rate.

This is clearly a nonlinear control problem, because of the nonlinearities of the flow characteristics. Therefore, a fuzzy controller is an appropriate control mechanism. The fuzzy controller we simulated has two input variables to control the motor voltage.

$$[FP, d(FP)/dt], \quad (2-2)$$

The membership functions were chosen to be:

FP: nb, ns, z, ps, pb
d(FP)/dt: p, ze, n
Control voltage: vh, high, med, low, vl

where:

nb, ns, z, ps, pb = negative big, negative small, zero, positive small, positive big
p, ze, n = positive, zero, negative
vh, high, med, low, vl = very high, high, medium, low, very low

Fifteen fuzzy rules are used to account for each combination of input variables:

1. if (FP is nb) AND (del_FP is n) then (control is high) ELSE
2. if (FP is nb) AND (del_FP is ze) then (control is vh) ELSE
3. if (FP is nb) AND (del_FP is p) then (control is vh) ELSE
4. if (FP is ns) AND (del_FP is n) then (control is high) ELSE
5. if (FP is ns) AND (del_FP is ze) then (control is high) ELSE
6. if (FP is ns) AND (del_FP is p) then (control is med) ELSE
7. if (FP is z) AND (del_FP is n) then (control is med) ELSE
8. if (FP is z) AND (del_FP is ze) then (control is med) ELSE
9. if (FP is z) AND (del_FP is p) then (control is med) ELSE
10. if (FP is ps) AND (del_FP is n) then (control is med) ELSE
11. if (FP is ps) AND (del_FP is ze) then (control is low) ELSE
12. if (FP is ps) AND (del_FP is p) then (control is low) ELSE
13. if (FP is pb) AND (del_FP is n) then (control is low) ELSE
14. if (FP is pb) AND (del_FP is ze) then (control is vl) ELSE
15. if (FP is pb) AND (del_FP is p) then (control is vl)

The membership functions were manually tuned by trial and error to give good controller performance. Membership functions could also be tuned automatically by means of neuro-fuzzy control. The resulting membership functions are as shown in Figure 2-9.

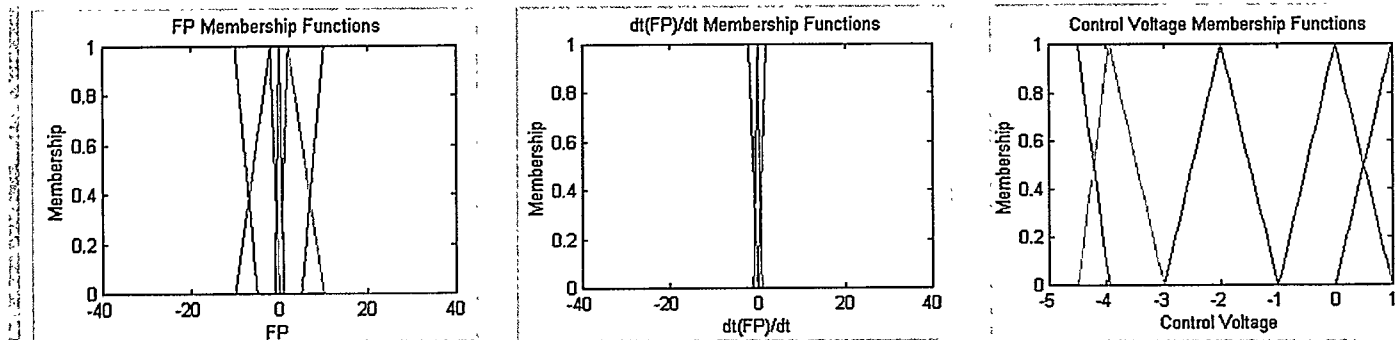


Figure 2-9
Membership functions for the input and output variables.

Figure 2-10 shows the outcome of the simulation program based on an input of $(FP)=-8.1$ and $d(FP)/dt=0.3$: the voltage control should be -3.4 . The five detailed steps of fuzzy control are as follows:

- **Fuzzification:** Create membership functions for each variable, and elicit the fuzzy rules from the experts, as exemplified in Figure 2-9 and the 15 fuzzy rules above.
- **Application of Fuzzy Operator:** Gather the input values from sensors. The degrees of fulfillment of the antecedent membership functions are then calculated based on the input values. For example: $FP=-8.1$ is both negative small (ns) and zero (z), since it has membership in ns by intersecting triangle $[-10 \ 2 \ 0]$ and also has membership in z by intersecting triangle $[-1 \ 0 \ 1]$; similarly, $d(FP)/dt=0.3$ has membership in ze (triangle $[-1 \ 0 \ 1]$) and n (trapezoid $[0 \ 2 \ 40 \ 40]$).
- **Application of Implication Operator:** The fuzzy relation operations defined in the rules (e.g., the 15 rules) are applied. Continuing the example, rules 4, 5, 7, and 8 are satisfied, since (FP) is negative small (ns), and zero (z), and $d(FT)/dt$ is zero (ze) and negative (n).
- **Aggregation:** The fuzzy output sets are aggregated to form a single fuzzy output set. Various methods can be applied. A popular approach is to take the maximum of the curve.
- **Defuzzification:** The output fuzzy set is defuzzified to find the crisp output voltage. The most popular method of defuzzification is based on centroiding.

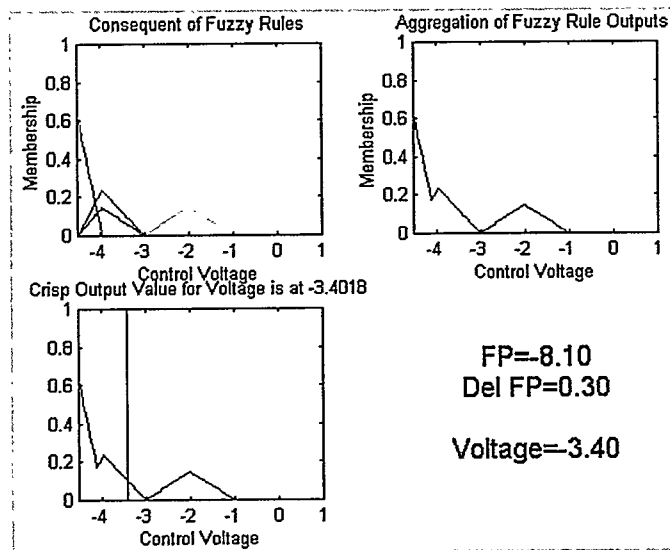


Figure 2-10
Simulation example of applying the fuzzy control program

2.2.4.4 Commercialization

In Phase I, we completed not only the technical tasks as described and discussed above but also initial commercialization of IDMA technology, demonstrating that IDMA can make oil drilling more efficient at lower cost. Using sensor data from Sandia, we concluded that the IDMA can be directly applied to drilling field operations. As a result of the initial IDMA prototype development and demonstration, we have attracted serious interest from oil companies and oil well drillers. One of the oil drillers we came in contact with during Phase I is Epoch Well Logging, Inc. which is

quite interested in working with us in Phase II. Mobil Exploration & Producing Technical Center has expressed interest in applying IDMA technology to their drilling operations and in commercialization of it after Phase II. Realizing the market potential, Panatec Associates, Inc. has agreed to invest in Phase III commercialization of IDMA technology. We believe that during Phase II we will see more such commercial interest leading to joint ventures, licensing, or a strategic partnership. We plan to explore these opportunities in Phase II.

3.0 TECHNICAL DISCUSSION

Since the goal of this project is intelligent drilling control, it is necessary to predict what happens next based on the current sensor readings. We now describe a method for predicting failure events such as loss of circulation and stuck pipe once sufficient instrumentation is in place on a rig. It is easy to tell from current sensor values whether a failure has already taken place; the difficulty is in predicting an incipient failure and taking appropriate steps.

Once the sensors are operational, a record should be written every increment of time Δt while the rig is active. The record should contain the current set of sensor readings $s(t)$; the current set of control settings $c(t)$; and the diagnosis of the current situation $d(t)$, i.e., whether the operation is successful at present or whether the system is in a particular failure mode. (Note that the diagnosis can be added in postprocessing and need not be computed and recorded in real time.)

After the rig has collected these data for many operational cycles, presumably including examples of all failure modes, the information should be sufficient to train a network for prediction. The i th training fact consists of: the sensor readings at time t_i ; the control settings at time t_i ; and the diagnosis at time t_{i+1} as output (see Table 3-1).

Table 3-1. Preparation for Training Recorded Values at Each Time Increment.

Time	Sensor values	Control settings	Diagnosis
t	$s(t)$	$c(t)$	$d(t)$
$t + \Delta t$	$s(t + \Delta t)$	$c(t + \Delta t)$	$d(t + \Delta t)$
$t + 2\Delta t$	$s(t + 2\Delta t)$	$c(t + 2\Delta t)$	$d(t + 2\Delta t)$
...

(a)

Construction of Training Facts for Failure Prediction Network.

Fact	Inputs		Outputs
1	$s(t_1)$	$c(t_1)$	$d(t_2)$
2	$s(t_2)$	$c(t_2)$	$d(t_3)$
3	$s(t_3)$	$c(t_3)$	$d(t_4)$
...

(b)

A back-propagation network trained on this set of facts will make a prediction, based on current sensor values and control settings, of the diagnosis at a time Δt in the future. This network will thus be able to warn the drill operator of incipient failure.

3.1 Multisensor Data Association

Any drilling system potentially generates many types of sensor data. As an example, Epoch's RIGWATCH Drilling Monitoring System data acquisition system acquires depth, hit depth, block speed, mud motor rpm, flow in (gal/min.), return flow (%), strokes per fill, weight on bit, and others. These data streams all differ in their spectral and temporal parameters and even their dimensionality. Therefore, it is necessary to have a way to associate all of these in a single data format. This section describes two methods, one in which all data have the same dimensionality, and one in which they differ in dimensionality.

3.1.1 Data Association with Common-Dimensionality Sensors

The most straightforward static association requirement is between measurements from similar or dissimilar sensors that have a common dimensionality. The principal approaches include using one-dimensional measures to quantify the sensor measurements for association. These measures have the following uses:

1. Ranking the sensor measurements to select the sets that are most likely associated, using a decision rule, in this program fuzzy logic.
2. Establishing a hypothesis testing (or gate) criterion to determine whether the measurements are associated or not.

Association tests are performed by using spatial measures, statistical measures, and temporal measures [17,18].

Spatial Measure -- The simplest sensor measure is the magnitude of the one-dimensional observations.

Statistical Measure -- The measurement error statistics of an individual measurement can be accounted for given a means of normalizing the spatial observations to the relative variance of the measurements.

Hypothesis Test -- Instead of computing a difference between measurement, a hypothesis test can be developed to determine if the observations are associated within a specified decision confidence level.

Each of these approaches can be applied to the iterative association tests performed in dynamic data association, described below. In fact, dynamic association processes simply apply these kinds of association tests for Bating decisions to select "neighboring" observations to predicted target locations and to quantify the "goodness" of each candidate neighboring observation to (predicted) observation pairing. Scores can then be derived for competing hypotheses that partition the sets of pairings into mutually exclusive assignments of all observations from one sensor to the observations from another sensor.

3.1.2 Data Association with Sensors that Differ in Dimensionality

The association process is significantly complicated by attempting to associate measurements from sensors whose measurements differ in their numbers of spatial measurement dimensions. A common example is associating a two dimensional image with a one dimensional electronic support measure (ESM) such as rpm or temperature. The image measures a plane, whereas the ESM sensor measures a speed, temperature, or volume.

In these cases, the spatial association must be made in the common dimensions of measurement, and extension to a dynamic association problem may be required for satisfactory performance. In the image-ESM example, a static association is generally considered unreliable because the ESM volume is so large that misassociation probabilities are unacceptable even at low data rates. Temporal measurement has been explored [12] to achieve acceptable association using a time sequence of measurements.

3.2 Fuzzy Control Using If-Then Rules

For information processing systems such as classifiers and controllers, two kinds of information are available. One is numerical information from measuring instruments, and the other is linguistic information from human experts. Most of the supervised learning methods for neural networks use only numerical data. On the other hand, fuzzy control is one of the most useful ways to make use of expert knowledge. Since fuzzy control research began in Mamdani's work [13], many fuzzy control systems based on fuzzy if-then rules have been developed [14,15]. In most fuzzy control systems, fuzzy if-then rules are elicited from human experts. Recently, several methods have been proposed for deriving fuzzy if-then rules from numerical data [16-18]. Many hybrid [19-22] fuzzy control systems and neural networks have been proposed for use with numerical data. These hybrid approaches incorporated the learning ability of neural networks into fuzzy control systems. That is, fuzzy if-then rules were generated and adjusted by learning using numerical data.

IDMA fuzzy if-then rules for constructing classification systems are, for example, as follows:

$$\begin{aligned} &\text{If } x_{p1} \text{ is small and } x_{p2} \text{ is large} \\ &\quad \text{then } x_p = (x_{p1}, x_{p2}) \text{ belongs to class 1.} \end{aligned} \tag{3-1}$$

$$\begin{aligned} &\text{If } x_{p1} \text{ is large and } x_{p2} \text{ is large} \\ &\quad \text{then } x_p = (x_{p1}, x_{p2}) \text{ belongs to class 2.} \end{aligned} \tag{3-2}$$

Here “small” and “large” are linguistic values defined by membership functions on a real line. Here we restrict linguistic values to convex and normal fuzzy sets on a real line in order to simplify the computation in neural networks. A convex and normal fuzzy set on a real line is referred to as a fuzzy number.

Let us consider two-class classification problems in an n-dimensional pattern space. We assume that s patterns $x_p = (x_{p1}, \dots, x_{pm})$, $p = 1, 2, \dots, s$, are given from two classes (class 1 and class 2), where: x_p is an m-dimensional real vector. That is, we assume that the following numerical data are given:

$$x_p = (x_{p1}, \dots, x_{pm}) \text{ belongs to } G_p, p = 1, 2, \dots, s, \tag{3-3}$$

where G_p is either class 1 or class 2. These numerical data are usually used in conventional supervised learning methods for classification problems.

We also assume that the following (m—s) fuzzy if-then rules have been elicited from drilling experts:

$$\begin{aligned} &\text{If } x_{p1} \text{ is } A_{p1} \text{ and ... and } x_{pn} \text{ is } A_{pn} \\ &\text{then } x_p = (x_{p1}, \dots, x_{pn}) \text{ belongs to } G_p; \\ &p = s + 1, s + 2, \dots, m, \end{aligned} \quad (3-4)$$

where A_{pi} is a linguistic value such as "large," "small," or "medium." We assume that A_{pi} is a fuzzy number in order to simplify the computation in neural networks. Fuzzy numbers of exponential type or triangular type are usually employed in fuzzy control systems.

Since each fuzzy if-then rule in (3-4) requires that the patterns in the fuzzy subspace defined by the if part belong to G_p , (3-4) can be rewritten as the fuzzy data:

$$\begin{aligned} &A_p = (A_{p1}, \dots, A_{pn}) \text{ belongs to } G_p, \\ &p = s + 1, s + 2, \dots, m, \end{aligned} \quad (3-5)$$

where A_p is a fuzzy vector. The membership function of a fuzzy vector $A = (A_1, \dots, A_n)$ is defined as

$$\mu_A(x) = \min\{\mu_{A1}(x_1), \dots, \mu_{An}(x_n)\}, \quad (3-6)$$

where $x = (x_1, \dots, x_n)$, and $\mu(\bullet)$ denotes a membership function. Operations on fuzzy numbers are defined by the extension principle. The interval activation function for the fuzzy data associator is shown in Figure 3-1. The following addition and multiplication of fuzzy numbers will be used in Phase II to implement the fuzzy data associator.

$$\mu_{A+B}(z) = \max\{\mu_A(x) \wedge \mu_B(y) : z = x + y\} \quad (3-7)$$

$$\mu_{kA}(z) = \max\{\mu_A(x) : z = kx\}, \quad (3-8)$$

where A and B are fuzzy numbers defined by $\mu_A(x)$ and $\mu_B(y)$, respectively. The activation function is extended to a fuzzy input-output relation as

$$\mu_{f(\text{Net})}(z) = \max\{\mu_{\text{Net}}(x) : z = f(x)\}, \quad (3-9)$$

where Net and $\mu(\text{Net})$ are a fuzzy input and a fuzzy output, respectively. We show the fuzzy activation function defined by (3-9) in Figure 3-2.

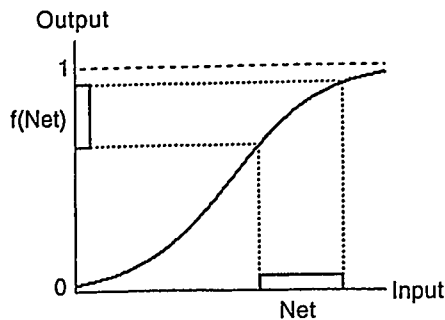


Figure 3-1

Interval activation function of each unit of a neural network. Net and $f(\text{Net})$ are an interval input and an interval output, respectively [27].

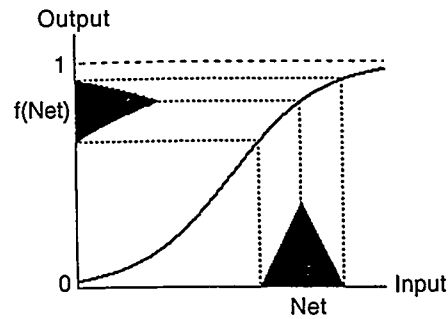


Figure 3-2

Fuzzy activation function of each unit of a neural network. Net and $f(\text{Net})$ are a fuzzy input and a fuzzy output, respectively [27].

3.3 Fuzzification and Defuzzification

Construct and Apply Fuzzy Expert System -- The steps in a fuzzy expert system process are fuzzification, inference, composition, and defuzzification. Fuzzification is the assessment step. Information about the circumstances is assessed into fuzzy sets, establishing the knowledge base. Inference is the reasoning step. Composition and defuzzification are the action steps. Composition produces a single fuzzy conclusion, while defuzzification translates it back to a raw action. Figure 3-3 illustrates the basic architecture of fuzzy expert system control.

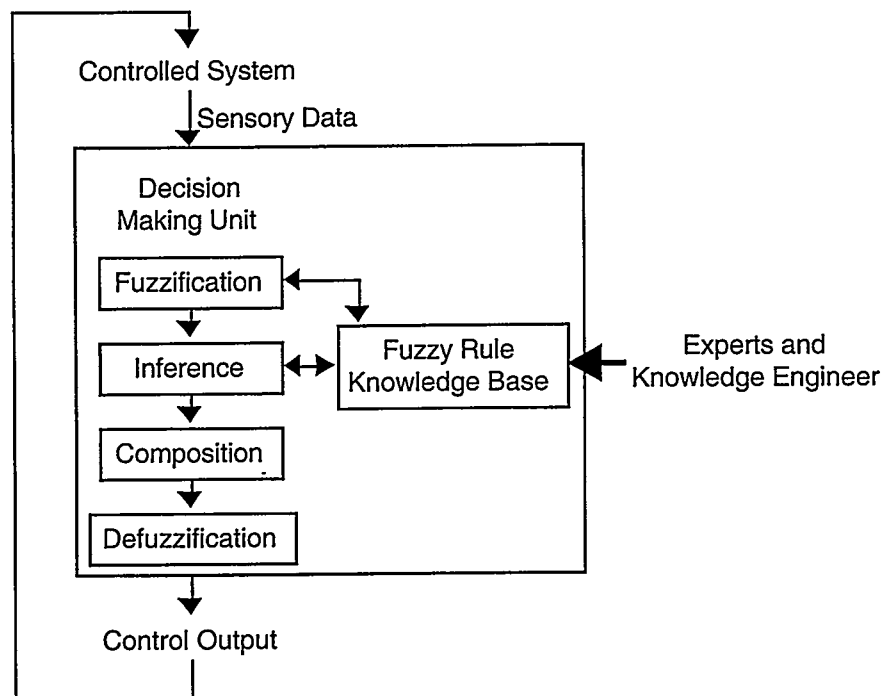


Figure 3-3

Basic architecture of fuzzy control system

Fuzzification -- Fuzzification is the process by which fuzzy values are derived from raw data. **Fuzzy logic is not logic that is fuzzy – it is the logic of fuzziness.** It extends conventional Boolean logic to recognize partial truths and uncertainties. In fuzzy logic, everything is true to a certain extent -- the extent can be zero or one, but it need not be. That is, an attribute,

such as tallness, is represented as a set of values of truth, rather than a single truth value. Membership functions or fuzzy sets are used in such representations. Membership functions are often symmetric, but not always, as seen in Figure 3-4(b). The description of a temperature of 60°F has the following set of values: $60d=\{0.1c, 0.9n, 0.3w, 0h\}$, where d is temperature in °F, c is cold, n is nice, w is warm, and h is hot. Similarly, $68d=\{0c, 1n, 0.8w, 0.5h\}$ and $70d=\{0c, 0.85n, 0.3w, 0.55h\}$. Triangular and trapezoidal membership functions are widely used.

As an example, a temperature of 70°F and a humidity of 40% could translate into fuzzy sets that tend to indicate that the air is nice and a bit dry. Also, a third fuzzy set could be used to reflect the need to circulate the air — {minimal, slight, much}. Thus, applying fuzzification to drilling control could involve defining the fuzzy sets for inflow rate, outflow rate, voltage, thrust, penetration rate, etc.

In addition, the knowledge of the experts is transformed into if-then fuzzy rules based on the defined fuzzy sets combined using the logical operators AND, OR, XOR, and NOT.

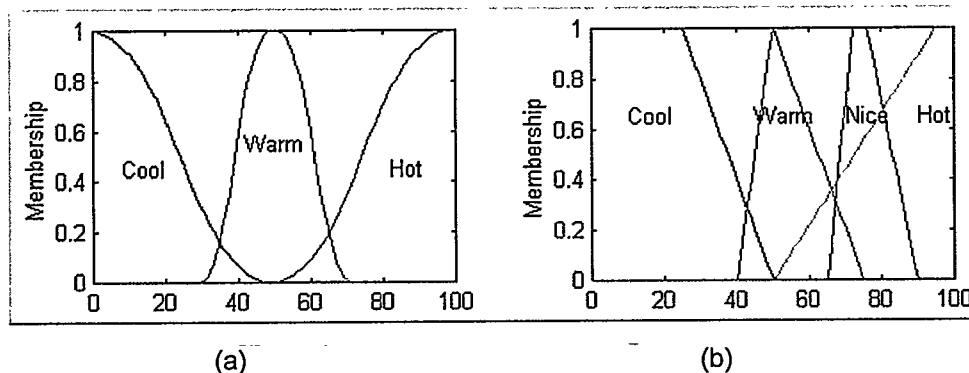


Figure 3-4
Examples of symmetric and asymmetric fuzzy sets, i.e., membership functions.

Inference -- Inference is the reasoning step, chaining through the fuzzy rules. Using the example of the fuzzy rule, "If the temperature is hot and moist, then the air requires strong circulation," the condition has a combined degree of truth based on the logical expression, "The temperature is hot AND the room is moist." From the fuzzy definition of AND, we realize that this expression has a fuzzy value of 0.2, which is the truth of, "the room is moist." Because the truth value of the condition is greater than zero, this rule fires, and we assert that the atmosphere requires strong circulation.

There are several ways to determine the fuzzy value of the conclusion. One method is to simply define the truth of the conclusion to be the same as the truth of the condition, so "the atmosphere requires strong circulation" is assigned a fuzzy value of 0.2 in our example. This method, while easy to explain, is rarely used. However, the description of the common methods involves more mathematics than we wish to delve into here.

Composition -- The composition step takes the results of the rules and combines them into a single fuzzy result. As you can imagine, the results of these rules can conflict -- some say strong circulation is needed, others say minimal.

Let us consider that we have nine rules. One might be, "If the room is cool and dry, then the room needs minimal circulation." The other eight rules correspond to the other possible pairings of

fuzzy values: cool and moist, cool and wet, warm and dry, etc. As each of the rules fires, the conclusions {minimal, slight, strong} are all assigned fuzzy values. The following describes how we could reconcile these results to produce a single fuzzy value.

A number of composition methods are available. Generally speaking, the composition method used is based on the inference method. The MAX method is very common and involves the least mathematics, so we describe it here.

The goal is to create a single final set composed of fuzzy values for each of "minimal," "slight," and "strong." The MAX method looks at "minimal" first, and assigns it the largest fuzzy value given by the rules that deduced "minimal." In the above case, this method would assign a fuzzy value of 0.35 to "minimal."

Defuzzification -- Defuzzification plays a large role in a fuzzy control system. Defuzzification is the process that maps from a space defined over an output universe of discourse into a space of nonfuzzy (crisp) numbers. In other words, defuzzification is essentially the opposite of fuzzification. Once the final fuzzy set is measured, it can be converted to an action, such a "set the fan speed to a particular rpm." When the final fan setting is determined, the process starts over and goes on continuously. Many cycles can be done within a second, so the fan adjustments will generally be slight in any one cycle.

Defuzzification, however, is often much more complex than simply reverse fuzzification because the resulting fuzzy set does not always translate directly into a crisp value. For example, 450 rpm might not correspond to 0.35 minimal, 0.7 slight, and 0.6 strong; it might correspond to a similar ratio of those fuzzy values. In addition, it is impossible to convert a fuzzy set into a numeric value without losing some information during defuzzification, and it is hard to find the number that best represents a fuzzy set.

A large number of "defuzzification" methods are in use, notably COG (center-of-gravity) and, MOM (mean-of-maxima). The particular method is often selected according to the inference and composition methods used. No standard rules are accepted as guiding how to select a method that is suitable to a given problem.

When the output fuzzy set is normalized and convex, most of the popular methods are good enough, but for a non-convex or unnormalized fuzzy set the situation is quite different and comparing all the defuzzification methods is not easy. In defuzzification, the most important thing to be considered is the "sequence of control action." Many researchers have attempted unsuccessfully to solve problems of non-convex fuzzy sets or worst cases. Some have suggested methods that can be tailored to specific system parameters. Adaptive fuzzy control is a field that is being extensively studied. Defuzzification methods such as COG and MOM have been used without comparison in adaptive fuzzy control. One method of adaptive fuzzy control, model-based adaptive fuzzy control, has a stage that updates fuzzy control rules. We expect that in adaptive fuzzy control each method influences system performance. In Phase II, we will evaluate various defuzzification methods.

Center of Gravity Method -- The center of gravity method is one of the most widely used. The defuzzified value z_o tends to move smoothly around the output fuzzy region, and is relatively easy to calculate. COG is rather complex computationally, and results are unsatisfactory if the output fuzzy set is not unimodal, but this method is the most popular.

Center of Sums Method -- This method enables a user to consider the distribution of the area of inference results from each fuzzy rule individually. Inference results overlap, and each area is counted more than once. This method is similar to COG.

Mean of Maxima Method -- The defuzzified value z_o is an average of the elements that reach the maximal grade in output fuzzy set C. This method and the center of maxima method are limited to certain classes of problems because the expected value is very sensitive to a single rule that dominates the rule set. If the fuzzy region changes, the expected value tends to jump from one membership function to another.

z_j is an element giving the maximal grade and $z_o = \frac{\sum_{j=1}^n z_j}{m}$ is the number of such maximal elements.

Center of Maxima Method -- This method is a simplified version of the mean of maxima method. Instead of taking all elements that give the maximal grade, the smallest element z' and the largest element z'' among them are found and the midpoint of z' and z'' is given as the representative point z_o .

Evaluation Indices for Defuzzification -- Driankov's [23] five criteria mentioned above indicate that the "ideal" defuzzification method should meet these conditions:

- Continuity
- Unambiguity
- Plausibility
- Computational complexity
- Weight counting.

They only consider the output fuzzy set, not control action. However, the fact that an output fuzzy set is not only a fuzzy set but also a sequence of control actions [15] suggests four new criteria that describe a sequence of control actions from experiments. These indices help to classify the characteristics of defuzzification methods:

- Confidence level loss
- Trajectory following
- Discrete version availability
- Parameter variation.

3.3.1 Neurofuzzy Classifier Systems

The key benefit of fuzzy logic is that it lets you describe system behavior with simple "if-then" relations. In many applications, this gets you a simpler solution in less time. You can also use all available engineering know-how to directly optimize the performance. While this is certainly the beauty of fuzzy logic, it is also a major limitation. In many applications, the knowledge that describes a system's behavior is contained in data sets. Neural networks are used in applications with limited capacity for several reasons. First, a neural net solution remains a "black box." You cannot interpret what causes a certain behavior, or manually modify a neural net to change a certain behavior. Second, neural nets require prohibitive computational effort for most mass-market prod-

ucts. Third, selecting an appropriate net model and setting the parameters of the learning algorithm is still a "black art" that requires extensive experience. But of all these, the lack of an easy way to verify and optimize a neural net solution is probably the greatest limitation. Both neural nets and fuzzy logic are powerful design techniques with their own strengths and weaknesses. Neural nets can learn from data sets, while fuzzy logic solutions are easy to verify and optimize. If you compare these properties, it is apparent that a clever combination of the two technologies can deliver the best of both worlds, combining the explicit knowledge representation of fuzzy logic with the learning power of neural nets.

When you start with a neurofuzzy design, the first step is to obtain the datasets that represent the desired behavior (intelligent and autonomous drilling control). Each dataset gives sample output values for a given combination of input variables. The neurofuzzy training process starts with a fuzzy logic system. If you have not already set up your fuzzy logic system, the neurofuzzy module can automatically set up an initial system for you. It analyzes the datasets and proposes a system structure. You can either accept this structure or modify it, before neurofuzzy generates this system with default membership function definitions and default rules. The following sections presents a detailed technical description of the neurofuzzy classifier system.

3.3.2 What are Neurofuzzy Classifiers?

In the current neurofuzzy research, original views are clearly becoming vague, as some of the most fundamental neural networks such as the one-hidden-layer MLP or RBF networks have been shown to have very close connections to statistical techniques with fuzzy logic embedded. Figure 3-5 charts the neural characteristics of some of the classification methods. The horizontal axis measures the flexibility of a classifier architecture in the sense of the richness of the discriminant function family encompassed by a particular method. High flexibility of architecture is a property often associated with neural networks. In some cases (MLP, RBF, CART, MARS) the flexibility can also include algorithmic model selection during training [22]. In the vertical dimension, the various classifiers are categorized on the basis of how they are designed from a training sample. Training is considered non-neural if the training vectors are used as such in classification (e.g., K-NN, KDA), or if some statistics are first estimated in batch mode and the discriminant functions are computed from them. Neural learning is characterized by simple local computations in a number of real or virtual processing elements. Neural learning algorithms are typically of the error correction type; for some such algorithms, not even an explicit cost function exists. Typically, the training set is used several times (epochs) in an on-line mode. Note, however, that for some neural networks (MLP, RBF) the current implementations in fact often employ sophisticated optimization techniques which would justify moving them downwards in our map to the lower half plane.

3.4 IDMA Neurofuzzy Classifier System

Candidates for the neurofuzzy classifier system to classify current drilling status based on the current sensor reading include: the multiple MLP classifier, the hidden Markov model (HMM)/MLP classifier, and the structure-adaptive self-organizing map (SOM) classifier.

3.4.1 Multiple MLP Classifier

The basic idea of the multiple network classifier is to develop n independently trained neural networks with particular features, and to classify a given input pattern by obtaining a classification from each copy of the network and then using a consensus scheme to decide the collective classification by means of combination methods [22] (see Figure 3-6). Two general approaches, one based on fusion and the other on voting, form the basis of the methods presented.

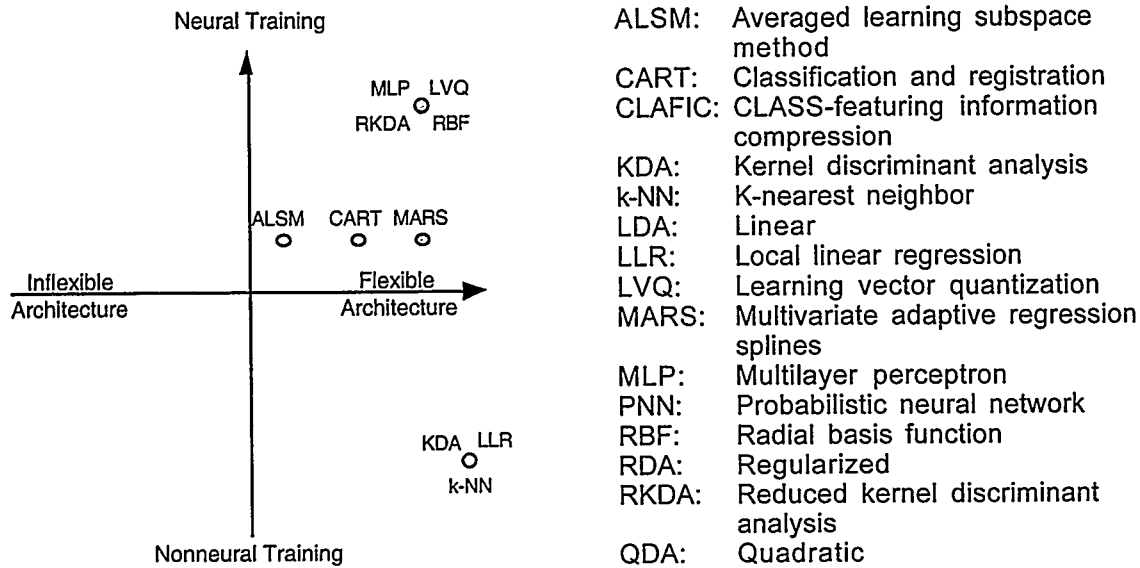


Figure 3-5
A schematic depiction of the neural characteristics of some classification methods.

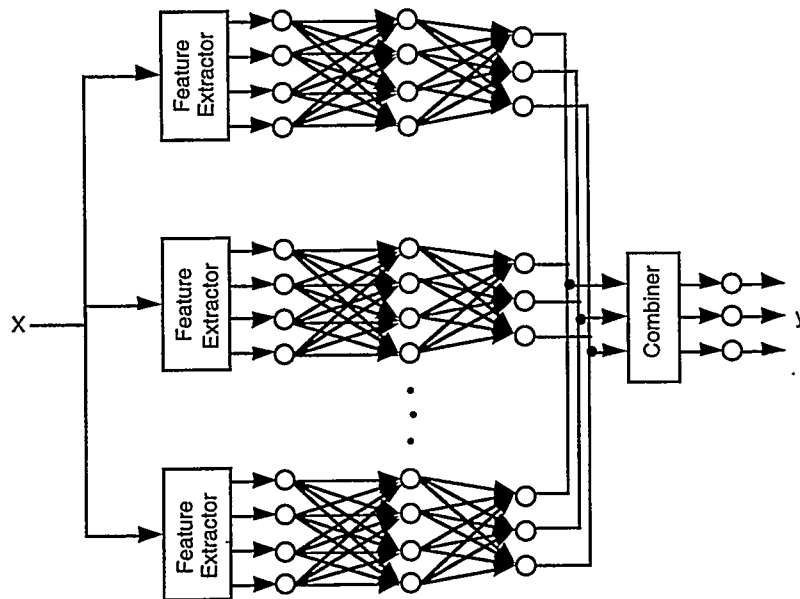


Figure 3-6
In multiple MLP classifier with consensus scheme, n independently trained neural networks classify a given input pattern by using a consensus to decide the collective classification [28].

Table 3-2 shows the recognition rates with respect to the three networks and their combinations, using consensus methods -- majority voting, average, and fuzzy integral. The reliability in the table is computed with the following equation:

$$\text{reliability} = \frac{\text{recognition rate}}{\text{recognition rate} + \text{error rate}} \times 100, \quad (3-10)$$

where the error rate is the percentage of patterns classified incorrectly by the method. As can be seen, every method of combining multiple MLP produces better results than individual networks, and the overall classification rate for the fuzzy integral is higher than those for other consensus methods.

Table 3-2. Results of Recognition Rates (%)

Methods	Recognized	Substituted	Rejected	Reliability
MLP ₁	89.05	7.00	3.95	92.71
MLP ₂	95.40	3.75	0.85	96.22
MLP ₃	93.95	4.10	1.95	95.82
Voting	96.70	3.05	0.25	96.94
Average	97.15	2.35	0.50	97.64
Fuzzy	97.35	2.30	0.35	97.69

3.4.2 The HMM/MLP Hybrid Classifier

The HMM/MLP classifier 1) first converts a dynamic input sample to a static pattern sequence by using an HMM-based recognizer and 2) then recognizes the sequence by using an MLP-trained classifier (see Figure 3-7).

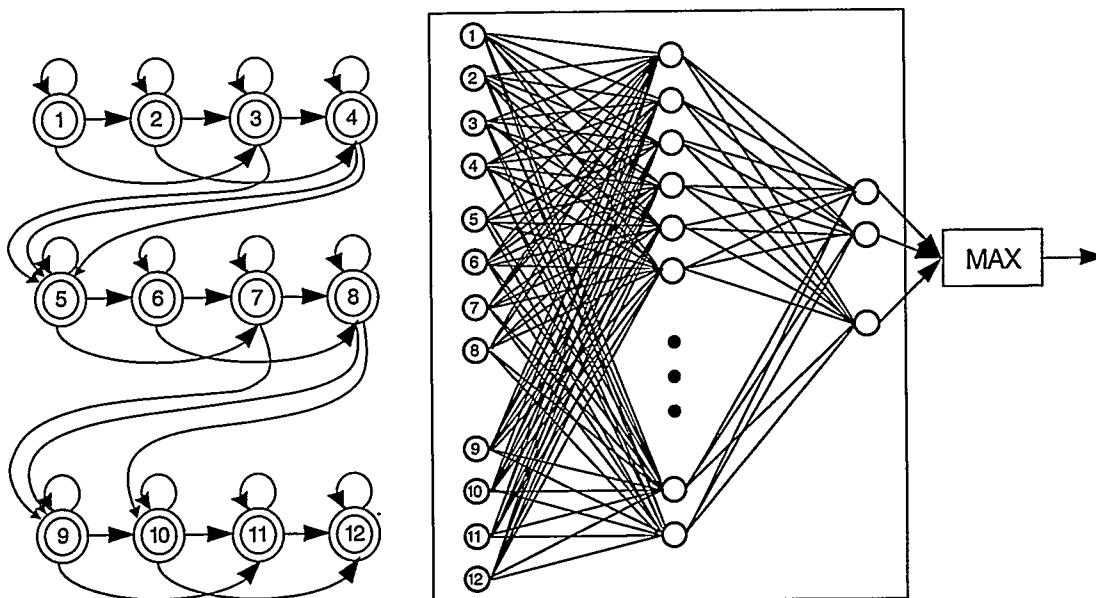


Figure 3-7
The HMM/MLP recursive hybrid classifier [28].

A standard HMM-based recognizer assigns one Markov model for each class. Recognition by HMMs involves accumulating scores for an unknown input across the nodes in each class model, and selecting the class model with the maximum accumulated score. In contrast, the proposed classifier replaces the maximum-selection step with an MLP classifier.

The hybrid classifier automatically focuses on those parts of the model that are important for discriminating among sequentially similar patterns. In the conventional HMM-based approach,

only the patterns in the specified class are involved in the estimation of parameters; there is no role for any patterns in the other classes. The hybrid classifier uses more information than the conventional approach; it uses knowledge of the potential confusions in the particular training data to be recognized. Since it uses more information, there are certainly reasons to suppose that the hybrid classifier will prove superior to the conventional approach. In this classifier, the MLP will learn prior probabilities as well as to correct the assumptions made about the probability density functions used in the HMMs.

3.4.3 Structure-Adaptive SOM Classifier

Kohonen's self-organizing map (SOM) is an iterative version of the *k-means algorithm*, although SOM also has many of the intrinsic merits of a neural network model [22]. Therefore, it is not appropriate to use the SOM for classification problems because decision accuracy cannot be fine tuned with a conventional SOM. Also, it is quite difficult to determine the size and structure of the network. A SOM can simultaneously determine a suitable number of nodes and the connection weights between the input and output nodes. The basic idea is simple:

1. Start with a basic neural network (in our case, a 4×4 map in which each node is fully connected to all nodes in the next layer).
2. Train the current network with Kohonen's algorithm
3. Calibrate the network using known input-output patterns to determine
 - a) which node should be replaced with a submap of several nodes (in our case, a 2×2 map) and
 - b) which node should be deleted.

The structure of the network is similar to Kohonen's SOM shown in Figure 3-8, except for the irregular connectivity in the map.

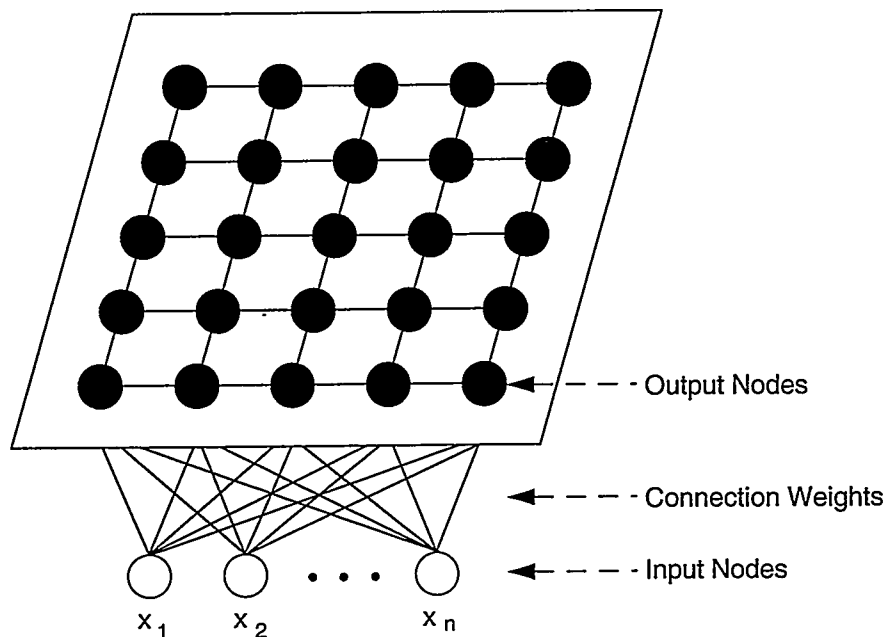


Figure 3-8
Kohonen's self-organizing map [28].

3.5 Training Methodology

We compare two possible architectures for mapping the n processed sensory inputs (typical value: $n=200$) to m control outputs (typical value: $m=10$). The first (denoted A) is a supervised learning network such as a back propagation neural network. The second is POC's proposed hybrid unsupervised-supervised architecture (denoted B), in which the sensory inputs are *diagnosed* by an unsupervised network such as a Kohonen network, yielding p intermediate values (typical values of p are not yet known but will probably be 10-20). The intermediate values are inputs to a supervised network, which computes the control outputs.

Supervised networks require training using a set of known training facts. For scheme A, each training fact would be a set of processed sensor input values together with the corresponding set of control output values. This has the following problems:

- Training facts are not available in this form, and
- The number of training facts needed is unacceptably high.

The first problem concerns the nature of available information. The knowledge base for control of drill operations resides in the brains of experienced drilling engineers and operators. These personnel have not been accustomed to working with the quantity of sensor input now becoming available. The needed association of sensor inputs with control outputs does not, therefore, yet exist.

The second problem concerns the information capacity of a neural network and the quantity of training data needed to achieve full training. Assume the input values are effectively discretized so that each can take on N_I values. Logical or binary inputs (on or off; true or false) have $N_I = 2$, while continuous inputs with a fractional resolution of 0.1 have $N_I \approx 10$. The number of distinguishable input vectors is then

$$N_{in,max} = \prod_k N_{I,k}, \quad (3-11)$$

where $N_{I,k}$ is the effective number of values of input k . This is a very large number: for example, if $n=200$ and binary inputs are used, the number of possible input vectors is 2^{200} , or greater than 10^{70} .

Fortunately, a much smaller set of training facts can be used, provided the set adequately represents the complete transfer function the network is to model. Two effects are important here:

- The transfer function of a trained neural network interpolates the training data to produce an approximation of the real transfer function. Therefore, the number and choice of training facts must be appropriate to the character of the function. In a region where the function is smooth, few facts are needed, while in a region where nonlinearities or discontinuities occur, many facts are needed.
- Physical problems often exhibit correlation among the inputs, so that the effective size of the input space (number of distinguishable input vectors) can be far smaller than the large value given above. When this is the case, a change of variables is generally required as discussed below.

For the intelligent drilling control network, these considerations are paramount. Sharp nonlinearities are known to exist, for example, near the transition to loss of circulation and near conditions causing catastrophic bit failure. Moreover, the sensor inputs will certainly exhibit a high degree of correlation (redundancy), so that only a small subset of the possible set of sensor vectors make sense as representing actual physical conditions.

The information content of a neural network is proportional to the size of the weight matrix. Assuming one hidden layer of h hidden neurons, where h is given by the heuristic criterion

$$h = \text{ceiling} \sqrt{nm}, \quad (3-12)$$

with n inputs and m outputs, the size of the weight matrix is

$$N_W = (n+1)h + (h+1)m \cong \sqrt{nm}(n+m), \quad (3-13)$$

where one threshold neuron in each layer is assumed. For the typical numbers assumed above ($n=200$ and $m=10$), the weight matrix consists of 9500 neurons.

Experience with back-propagation networks has shown that the number of training facts should in general be of the same order as the information content. Thus, the typical numbers for scheme A call for of order 10,000 training facts.

It is crucial to realize that the information content of the network does not take into account correlation of the inputs. The practical result of this is that when the network has a large number of highly correlated inputs it may train to completion on a representative set of training data but will fail to *generalize*; in other words, it will act as a poor interpolant or extrapolant.

A related example illustrates this effect. Our consultant has years of experience assisting industrial customers with neural network design. In this experience, the question of networks for image processing and classification often arises. This type of problem is the same as the present one: whereas the number of possible input vectors is enormous, only a small fraction of these inputs represent likely drilling conditions. **It is invariably found that the problem can be solved by a neural network only if the inputs can be transformed using feature extraction.** For instance, a medical application required classification of human skeletal images by age of the skeleton. Only a small fraction of possible images look like skeletons. The problem became tractable when a program was written to convert an image into a list of bone sizes and separations. The successful network was then trained using known facts, with the extracted bone data as inputs and the skeletal age as output.

For the intelligent drilling problem, the set of features to be extracted and the method of extraction are not known. On the other hand, it is expected that the sets of sensor inputs will cluster into identifiable groups depending on conditions. This situation is exactly the appropriate one for classification using unsupervised learning.

In unsupervised learning, only known input vectors are presented to the network during training. No known outputs are used in training. The point of the training is to discover the clustering of inputs, to learn the correlations present among physically likely sensor inputs. Supervised and unsupervised networks thus are appropriate for problems at opposite ends of a spectrum.

As described above, the high degree of correlation present among sensor inputs in the intelligent drilling problem renders impractical the direct supervised solution via scheme A. **However, it is exactly this situation in which classification by an unsupervised network is so attractive.**

In the POC hybrid architecture, the first part of the operation is classification (diagnosis) of sensor inputs into categories. Successful training of the unsupervised diagnosis network will lead to identification of the categories, one of which will be represented by each of the p outputs of the diagnosis network.

The training data will be assembled in a very straightforward way. As sensors come on line on existing rigs, drill logs will be compiled that contain the sensor data. Over time the complete range of events will occur: bit breakage, drill sticking, loss of circulation, unplanned change of direction, etc., as well as a great deal of successful drilling. The drill logs will then contain sensor data that span the likely set of inputs.

The diagnosis network will train by clustering the logged sensor inputs into categories. After training is complete, the meaning of each output neuron will be identified in consultation with drilling experts. For example, certain sets of sensor inputs will be easily identifiable as representing lost circulation, for instance.

Once the correspondence has been made between each output of the diagnosis network and a corresponding physical situation, the training facts for the control network are set up. Since it is not known a priori what the appropriate control actions should be in any given situation, consultation with experts is again needed.

The three leading learning paradigms are: *supervised*, *unsupervised*, and *hybrid*. Table 3-3 compares learning algorithms. In supervised learning, or learning with a "teacher," the network is given a correct answer (output) for every input pattern. Weights are found that allow the network to produce answers as close as possible to the known correct answers. Reinforcement learning is a variant of supervised learning in which the network is given only a critique on the correctness of network outputs, not the correct answers themselves. In contrast, unsupervised learning, or learning without a teacher, does not supply a correct answer associated with each input pattern in the training data set. It explores the underlying structure in the data, or correlations between patterns in the data, and organizes patterns into categories based on these correlations. Hybrid learning combines supervised and unsupervised learning.

POC's innovative hybrid learning, which is totally different from the conventional hybrid paradigm, combines unsupervised and supervised learning for more accurate, efficient, and adaptive control. The two methodologies for implementing hybrid learning are: first, unsupervised learning with fuzzy control logic to form approximate clusters of sample data. Then the supervised learning algorithm together with fuzzy control logic tunes the patterns. Second, supervised learning is tuned by fuzzy control logic, followed by unsupervised learning to perform clustering, again tuned by fuzzy control logic.

Table 3-3 Comparison of Various Learning Algorithms

Paradigm	Learning rule	Architecture	Learning algorithm	Task
Supervised	Error-correction	Single- or multilayer perceptron	Perceptron learning algorithm Back-propagation Adaline and Madaline	Pattern classification Function approximation Prediction, control
	Boltzmann	Recurrent	Boltzmann learning algorithm	Pattern classification
	Hebbian	Multilayer feed-forward	Linear discriminant analysis	Data analysis Pattern classification
	Competitive	Competitive	Learning vector quantization	Within-class categorization Data compression
		ART network	ARTMap	Pattern classification Within-class categorization
Unsupervised	Error-correction	Multilayer feed-forward	Sammon's projection	Data analysis
	Hebbian	Feed-forward or competitive	Principal component analysis	Data analysis Data compression
		Hopfield network	Associative memory learning	Associative memory
	Competitive	Competitive	Vector quantization	Categorization Data compression
		Kohonen's SOM	Kohonen's SOM	Categorization Data analysis
		ART networks	ART1, ART2	Categorization
Hybrid	Error-correction and competitive	RBF network	RBF learning algorithm	Pattern classification Function approximation Prediction, control

4.0 CONCLUSION AND RECOMMENDATION

4.1 Conclusions

In Phase I, POC designed an Intelligent Decision Making Aid (IDMA) for intelligent drilling control, and demonstrated its feasibility. POC has successfully reached its Phase I goal by demonstrating the feasibility of an intelligent and autonomous drilling system integrating data fusion, neurofuzzy decision making, and hybrid training. Additionally, POC has designed the overall Phase II IDMA structure so that Phase II can begin with building the Phase II prototype.

4.2 Recommendations

We believe that the IDMA technology is critical for cost effective energy production. Specifically we recommend addressing the following issues in IDMA Phase II development:

1. Design optimization and development of fuzzy data associator
2. Design optimization of neurofuzzy system
 - Selection of fuzzification methodology
 - Selection of defuzzification methodology

- Determination of neural network architecture such as the number of hidden layers and transfer function
 - Determination of training methodology with various training parameters
3. Acquisition of training data sets from drilling experts
 4. Research into existing sensing and telemetry technology
 5. Development of interface between sensors and IDMA
 6. Development of accelerator board for real-time processing
 7. Development of clear graphic interface
 8. Demonstration of the Phase II IDMA system in field test
 9. Establishment of commercialization plans, partners, and marketing.

In Phase I, POC significantly advanced and combined several critical soft computing technologies to prove the feasibility of producing a key breakthrough in intelligent drilling decision making aid technology. POC was in a unique position to develop and combine these enabling technologies, building on extensive research in sensor imaging, neural networks, sensor fusion, and soft computing. We demonstrated that integrating soft computing, neural networks, fuzzy logic, and sensor fusion can produce a unique IDMA system that has strong advantages over existing techniques.

POC believes that IDMA system technology will improve drilling performance and offer totally new features at low cost. These feature include minimizing drilling failures such as loss of circulation, washouts, and stuck pipe, reduction in human errors, and increased decision confidence. Other commercial IDMA system advantages will be its continuous and consistent monitoring capability and high system adaptability. These advantages give IDMA a strong competitive edge, and will accelerate Phase III commercialization.

5.0 GOVERNMENT AND COMMERCIAL APPLICATIONS

The national importance of drilling, and especially of intelligent drilling technology, is well stated in Ref. [1]. Drilling has a number of applications of national importance. These applications include exploration for and extraction of oil, gas, and geothermal energy, for environmental monitoring and remediation, for infrastructure development of utilities, transportation, and communication facilities, and for scientific studies of the Earth's subsurface.

Improved drilling technology will lower overall drilling costs, shorten the drilling period, increase the rate of drilling success, and have a direct benefit to the U.S. in terms of higher energy resources, low and stable energy costs, better environmental protection through geothermal energy, and improved economic competitive position of the U.S. drilling industry. Horizontal drilling activity alone in 1997 cost 1.1 billion dollars with 1,111 horizontal wells completed and overall drilling expenditures exceeding \$10 billion per year according to Oil & Gas Journal [16]. At that, horizontal drilling is a small part of overall oil drilling, and oil drilling is only one of the many segments of the vital domestic drilling industry. POC's IDMA offers the maximum number of advantages without any disabling disadvantage.

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