"IGENPRO Knowledge-Based Digital System for Process Transient Diagnostics and Management"*

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IGENPRO KNOWLEDGE-BASED DIGITAL SYSTEM FOR PROCESS TRANSIENT DIAGNOSTICS AND MANAGEMENT

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Abstract

Verification and validation issues have been perceived as important factors in the large scale deployment of knowledge-based digital systems for plant transient diagnostics and management. Research and development (R&D) is being performed on the IGENPRO package to resolve knowledge base issues. The IGENPRO approach is to structure the knowledge bases on generic thermal-hydraulic (T-H) first principles and not use the conventional event-basis structure. This allows for generic comprehensive knowledge, relatively small knowledge bases and above all the possibility of T-H system/plant independence. To demonstrate concept feasibility the knowledge structure has been implemented in the diagnostic module PRODIAG. Promising laboratory testing results have been obtained using data from the full scope Braidwood PWR operator training simulator. This knowledge structure is now being implemented in the transient management module PROMANA to treat unanticipated events and the PROTREN module is being developed to process actual plant data. Achievement of the IGENPRO R&D goals should contribute to the acceptance of knowledge-based digital systems for transient diagnostics and management.

1. INTRODUCTION

Argonne National Laboratory (ANL), Commonwealth Research Corporation (CRC)/ComEd and Purdue University are collaborating together on a Joint Cooperative Research and Development Agreement Project [1] sponsored by the United States Department of Energy (US DOE). The focus of the project R&D is on the use of Artificial/Machine Intelligence (AI) techniques with on-line knowledge bases to provide real-time operator assistance during off-normal plant transient conditions. This advanced technology could improve the availability and reliability of water cooled nuclear power plants. The resultant knowledge-based digital system for process transient diagnostics and management is referred to as the IGENPRO package. Verification and Validation (V&V) goals [2,3] have been perceived as an important factor in the large scale deployment of such digital systems for plant transient diagnostics and management. Operator confidence in the V&V of such systems is crucial. The IGENPRO approach to this issue is to construct a generic plant- and thermal-hydraulic system-independent package. This would then, conceptually, limit the V&V requirements to a generic once-through qualification. This approach is analogous to that taken for the quantitative analysis thermal-hydraulic (T-H) codes such as RELAP-5 and TRAC where the generic Navier-Stokes equations are codified as a generic quantitative core knowledge base thus allowing a given T-H system from a given plant to be simulated as a configuration of generalized energy slabs/momentum junctions/mass volumes. The IGENPRO approach is to structure the knowledge database on the generic T-H first principles

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of mass, momentum and energy conservation and not use the conventional event-basis structure [1,4]. Thermal-hydraulic function and T-H component characteristics form the basis. This then allows for comprehensive generic knowledge, relatively small knowledge bases, and above all the possibility of T-H system/plant independence. The qualitative analysis IGENPRO T-H code would also have TRAC-like T-H system/plant independence. Universal V&V can then be performed on the core knowledge bases and application-specific V&V would only be required for the plant configuration database. All these attributes of the IGENPRO approach allow a simpler V&V effort.

The objective of the IGENPRO system is to diagnose on-line the onset of off-normal conditions, identify the component malfunction which caused the off-normal conditions and then recommend a sequence of operator actions which would best manage the off-normal conditions. However, the application of the package is not restricted to on-line usage. Given the novel non-event-based approach to the knowledge base structure, it could also be used off-line for root-cause analyses, the automated generation of procedures, the alignment design of thermal-hydraulic systems, operator training and perhaps predictive maintenance. In essence, off-line it could be utilized as an intelligent CAD tool to aid plant system engineers and design engineers. In the step-by-step phased approach to verification and validation (V&V) of this package it is envisioned that off-line usage would come first as a confidence building measure for ultimate on-line applications. Different parts of the package can be put to different usage thus implementing a phased approach to V&V. The next sections describe the general structure, approach and modules of the IGENPRO package.

2. IGENPRO APPROACH

Figure 1 shows the modular structure of the IGENPRO package. There are three modules in the Supervisory Module. The first module performs signal processing. Sensor/signal validation is performed before the plant instrument signals reach the IGENPRO package. The signal processing module PROTREN basically extracts signal trends from noisy signals. These signal trends are then used by the process diagnostics module PRODIAG to identify the malfunctioning component which initiated the transient off-normal conditions. Finally the last module, the process management module PROMANA, utilizes this diagnosis to recommend a sequence of operator actions which would best manage the off-normal conditions.

The knowledge base structure shown in Fig. 1 is one where the "simpler" T-H knowledge is expressed in terms of IF-THEN rules encoded in an Expert System (ES); the more "complicated" T-H knowledge is encoded into a hierarchy of neural networks (ANNs) and finally the most "complex" T-H knowledge is encapsulated in a simulator code. We focus here on the ES and the ANNs. Interfacing will be developed in the future for the simulator. As mentioned in the introduction, the IGENPRO approach to the knowledge base structure is founded on generic first-principles T-H. Since the development of the PRODIAG diagnostics module is the most advanced of the three modules we discuss the approach in terms of the work on the diagnostics. But the same approach is also used for the PROMANA management module.

T-H phenomena play a major role with a wide range of behavior for many different fields of application. The physics of T-H is therefore a complex area. However there already exists a universal description of T-H regardless of the type of application. This is the mathematical description inscribed in the Navier-Stokes conservation equations with various equations of state and transport properties. This T-H knowledge base has to be translated into the language of AI using a few key general physical concepts if the generic T-H system independence is to be preserved. The mathematical description has to be transformed into the AI system of rules, representations and supervisory flow logic. If not, heuristics would inevitably creep in and render the concept of T-H system independence meaningless. This is a first-principles approach. To perform this transformation the IGENPRO approach is to translate the dynamic behavior first by
decomposing the instrument signal history for each T-H variable into a first order trend and higher order frequencies. The three T-H conservation equations are then used, with qualitative analysis [1,5], in quasistatic form with the first order trends to compose spatial correlations across the T-H system. These spatial correlations are expressed in the form of IF-THEN rules and are therefore part of the ES shown in Fig. 1. They correlate changes in the three T-H functions of mass, momentum and energy to the signal trends and can be used in the localization of the component fault. Details are available in [6] and are summarized below in Section 2.1. Time windows [7] are used to broaden the validity of the use of the quasistatic conservation equations but in general the higher order frequency part of the signals is utilized in the hierarchy of ANNs shown in Fig. 1. This is where changes in component T-H characteristics, such as valve characteristics, are utilized to further sharpen the diagnostic focus. A method, denoted as the method of component characteristics [6], has been developed to help further localize the identification of the malfunctioning component. This is described in Section 2.2. Additional methods are being investigated to utilize other T-H component characteristics in this ANN part of the diagnostics. As one proceeds down the knowledge base shown in Fig. 1, invariably the diagnostic methods become more dependent on specific component data until the interfacing with the simulator is reached when T-H system dependent information such as volume sizes and tube heat transfer areas are crucial. But even so, in keeping with the non-event based approach the effort is focused at developing methods that do not require knowledge of the faulted component T-H characteristics. In summary the IGENPRO approach is a first-principles T-H function and T-H component-characteristics-based approach. The focus is to preserve the T-H system-independence by not requiring preknowledge of event-based signal data. While this discussion has focused on the PRODIAG diagnostics similar remarks can be made for the approach taken for the PROMANA transient management module.

2.1. T-H Function ES

Figure 2 illustrates the three types of knowledge of the proposed diagnostic ES and their corresponding usage, in a three-step mapping, that relates process symptoms into component faults [8]. When a process component fails, it causes the process T-H variables, e.g., pressure p, flow w, temperature T, and level L, to
FIG. 2. Knowledge Base Structure of T-H Function ES.

vary or trend from their expected values. The physical rules database (PRD) is used to map the trend in the T-H variables into imbalance trends in the three conservation types of mass, energy, and momentum, e.g., mass increase, momentum decrease. Then, the component classification dictionary (CCD) is applied to map the identified imbalance type and trend into generic faulty component types, e.g., pump, valve, heat exchanger, whose failure could have been responsible for the identified imbalance, i.e., the inadequate performance of one of the three T-H functions, mass transfer, energy transfer, or momentum transfer. Finally, the piping and instrumentation diagram (PID) containing the process schematics information, the only system-dependent portion of the knowledge base (KB), is applied to identify specific faulty components, e.g., pump A, valve CV-121, regenerative heat exchanger C, as the possible faulty component candidates.

This is a novel function-oriented first-principles-based concept for developing process diagnostic ESs that overcomes previous limitations of T-H system dependence. Except for the self-contained process schematics representation, the KB of the proposed system is process-independent, which allows for usage of the same diagnostic system with different processes and plants. This possibility not only decreases the effort involved in developing a new system, but it also eliminates the time-consuming process of KB verification and validation, which needs to be performed only once in the proposed approach. The process-independent diagnostic capability of the proposed ES is attained through the use of qualitative reasoning where a small number of values are taken to represent the values of continuous real-valued variables.

2.2. T-H Component Characteristics ANNs

We now turn to detailing the ANN implementation developed to this point for PRODIAG. It performs diagnostics at the plant level to supplement the ES diagnostics. The role of this plant-level ANN is to aid in the diagnosis of mass or momentum malfunctions through the use of component characteristics. We use here the momentum characteristics

\[ \Delta p = f(w) = \text{pressure difference across component.} \]  

(1)
We illustrate the use of the method of component characteristics for mass and momentum plant-level diagnostics with an open loop configuration [5]. For an open loop with two end conditions and no junctions, the quasistatic momentum equation is

\[ p_1 - p_2 = f_1(w) + f_2(w). \]  

(2)

The loop has been divided into two segments. Segment 1 has momentum characteristic \( f_1(w) \) while segment 2 has momentum characteristic \( f_2(w) \). Each segment's momentum characteristic is a combination of the component characteristics in the segment. The two end conditions are at pressures \( p_1 \) and \( p_2 \), respectively, and the flow is from \( p_1 \) to \( p_2 \). The flow \( w \) is measured in segment 1. Manipulating Eq. (2) gives us

\[ (p_1 - p_2) - f_1(w) = f_2(w). \]  

(3)

If there is a pressure transducer which measures the pressure \( p \) at the intersection of segments 1 and 2, then by Eq. (1) which is the definition of momentum characteristics, we have for segment 2

\[ \Delta p = f_2(w) = p - p_2. \]  

(4)

We also have from Eqs. (3) and (4)

\[ \Delta p = (p_1 - p_2) - f_1(w). \]  

(5)

If we plot Eq. (5) in \( \Delta p \) w space, we have a curve 1 which will intersect with a plot of Eq. (4) in \( \Delta p \) w space, denoted as curve 2. The intersection point is the operating point, as it gives the value of \( \Delta p \) and \( w \) in steady-state normal operation of the open loop. A momentum function malfunction in segment 1 alters the momentum characteristic \( f_1(w) \). This changes curve 1 in \( \Delta p \) w space. However, the momentum characteristic \( f_2(w) \) does not change, so curve 2 remains the same. The operating point, therefore, moves along curve 2. If an ANN is trained to recognize curve 2, which is the component characteristic \( f_2(w) \), then this ANN can be used to recognize momentum malfunctions in segment 1. However, mass malfunctions in segment 1 would also alter \( f_1(w) \) so there would be an ambiguity in the diagnostic resolution. If the mass malfunction is in between the flow measurement and the pressure measurement, this would effectively also change \( f_2(w) \), so the operating point would move off both curve 1 and curve 2. This type of diagnostic behavior in \( \Delta p \) w space allows the following conclusions to be drawn.

- No malfunctions - operating point does not move;
- Mass or momentum malfunctions in segment 2 - operating point traces out curve 1;
- Mass malfunction (upstream of \( w \) measurement) or momentum malfunction in segment 1 - operating point traces out curve 2; and
- Mass malfunction (downstream of \( w \) measurement) in segment 1 - operating point traces out neither curve 1 or curve 2.

With this representation of malfunctions, an ANN can be constructed to recognize the component characteristic combinations and, therefore, support the diagnosis of mass and momentum malfunctions at the plant level. No preknowledge of faulted component characteristics is required. This illustrates the PRODIAG ANN plant-level diagnostic technique for a model open loop configuration.
3. PROTREN MODULE

The primary function of the PROTREN module is to provide trending information to the diagnostic program PRODIAG. The module uses signal processing and fuzzy logic techniques for the purpose of classifying incoming signals into increasing, decreasing and steady-state categories which may subsequently be utilized by the diagnostic program PRODIAG. Usually, signal trending is performed in relation to the expected operating values of the signals monitored and with the use of various threshold parameters, such as, for example, thresholds for determining the onset of a transient or thresholds for obtaining a trend. In PROTREN, the signals are preprocessed and features signifying broad, but system-specific, fuzzy classes indicating signal direction are extracted. It is desirable, and certainly advantageous from the point of view of trend management, to obtain accurate trending information before the onset of various plant automatic control actions, which may mask the phenomena involved and somewhat complicate the successful realization of diagnostic tasks. Hence, successful trending is expected to be performed within appropriate time constraints and in a computational framework where reliability and accuracy objectives are balanced by speed and efficiency requirements; a situation that has called for the investigation and implementation of fuzzy techniques [9].

3.1. PROTREN’s Overall Approach

Nuclear power plants are complex systems with numerous variations in the design and operation of their components and subsystems. They typically operate about a steady-state, such as full power, with any substantial deviation from such a state constituting a transient. Trending of plant signals helps to identify transients in a timely and reliable manner particularly if both general and specific characteristics of various signals can be captured in the right mixture and in a way that satisfies the overall computational economy of the problem. Flow and pressure signals, for example, tend to indicate plant trends in a much faster manner (since incompressible fluids are present); while temperatures and levels reflect processes with greater inertia and hence may indicate plant trends with considerable delay. On the other hand, flow and pressure signals tend to be noisier and hence may require more preprocessing to be performed for extracting significant features. Thus, trending tasks require taking into account the general nature of the signals under consideration as well as specific issues including, but not limited to, sampling rates, location of sensors, and steady state signal statistics.

For the purpose of correctly identifying transients via trends of relevant plant signals, the PROTREN module receives individual signals and processes them through three subsystems: feature extraction, determination of expected values, fuzzification of trend. In feature extraction, a signal may be filtered or averaged in a moving-average sense to remove high frequency noise. From past data a detailed understanding of signal spectra is obtained and after determining expected values, error terms are formed by comparing expected with measured values. The fuzzification of trends calls for fuzzy rules (whose principal advantage is computing speed) for determining if there is a transient and if a trend is in the upward, downward or about the same direction.

3.2. Feature Extraction

The main purpose of feature extraction is to remove high frequency noise from the data and produce the most important features of the signal. It is assumed that the useful transient information is found in the low-frequency components of the signals [10]. Having built a detailed understanding of the nature of plant
signals under consideration through off-line analysis, a filtering mechanism somewhat similar to that of an RC integrator which averages the data in a moving-average sense is used for removing the high frequency noise in online analyses. This simple approach is intended to facilitate meeting the overall diagnostic time requirements (e.g., less than 5s in the diagnostic system PRODIAG).

From historical data, the probability distribution functions (PDFs) or histograms of signals are obtained. The PDFs contain prototypical information about the nature of a signal which can be used as a reference during the online analysis. When new data arrives from the data acquisition system two features have been found to be significant: a threshold below which a transient may be likely and how the data clusters in certain regions of the PDF. For example, if the data is below the 0.1 level of the PDF or if it clusters around the 0.02 area, we have a situation possibly indicating the presence of an upward trend. At present we seek to automatically set the size of the appropriate time window for on-line filtering and feature extraction depending upon past experience and time constraints imposed by the larger time window within which transient identification decisions need to be made.

3.3. Determining Expected Values

For each signal, an error $e(t)$ can be formed by comparing expected with measured signal values. A quantitative measure of the error uncertainty (an error bar, $\Delta e(t)$) can also be obtained where an increasing error bar provides a strong indication that the observed signal is related to a transient with an upward direction. A stable error and an error bar criterion (e.g., $\Delta e(t)$ crosses the 0-axis at least 4 out of 6 times in the last six measurements) may be used to reliably identify steady state. In addition, a decreasing error may indicate a transient where the signal is going down. Thus trends of expected and measured values for a certain number of past time steps (e.g., the last six) can be compared and a decision can be made as to the direction of a transient, should one be present.

Currently an investigation is underway to reveal if there is any useful reliable relation between error bars and plant transients. An important question in this regard concerns the length of time for which historical data may be used, in other words, how many past values do we really need to use, e.g., 100 points or 5 points and with what type of weighting function to include them in trending calculations.

3.4. Fuzzification of Trends

The purpose of the fuzzification subsystem is to categorize a signal by placing it in one of the following signal classes: increasing, decreasing or steady-state. Several approaches are under investigation regarding this objective, including neural networks, fuzzy IF-THEN rules and sequential probability ratio testing (SPRT). Feedforward neural networks may be used to output the membership functions of the increasing, decreasing or steady-state classes directly through mapping incoming signals to membership function parameters. Determining the appropriate shape of membership functions for a number of important plant (or simulator) signals relies heavily on off-line analysis of historical data and the nature of the PDFs as described in Section 3.2. A self-organizing neural network may also be used for clustering errors and producing membership functions for the trend categories.

PROTREN's identification of trends requires quantified probabilistic uncertainty estimates and significant efforts to verify and validate its workings under all possible conditions. An advantage of fuzzy rules in this regard may be that no single item is used for making a decision, but rather there is built-in methodological redundancy that enhances the reliability of the overall system.
4. PRODIAG MODULE

The knowledge based structuring concepts have been implemented in the current laboratory-scale version of PRODIAG using Quintus Prolog for the following range of applicability: single-phase liquid plus noncondensible gas T-H systems; non-neutronic heat sources; coolants with bulk moduli and thermal expansion coefficients similar to water; single fault initiated transient scenarios; transient severity should be sufficient for instrumentation in single-phase liquid components to respond; use of instrumentation signal data which has been filtered for noise; and diagnostic window closure upon initiation of control action. To demonstrate the scale-up feasibility of the proposed diagnostic system it was developed for use with the Chemical Volume Control System (CVCS) of the Braidwood pressurized water reactor (PWR) plant. A full-scope operator training simulator representing the Braidwood nuclear power plant is being used both as the source of development data and as the means to evaluate the advantages of the proposed diagnostic system. One particular CVCS configuration for one specific operating mode was selected. This configuration is normal charging/letdown mode at 100% power. Simplifications were therefore made in the CVCS layout [6]. Only T-H signals, excluding the external systems measurements, are utilized and it should be adequate to treat a smaller set of local controllers. The full-scope Braidwood simulator malfunctions for CVCS operator training are used as the basis for the selection of the test matrix of transients. Each single-fault transient event was simulated for 40s, including 3s of null transient, starting from a steady-state normal mode of the CVCS operation. Initial results obtained by using the initial 'first-principles ES' portion of the PRODIAG module to diagnose transient events were summarized in [1]. Additional ES validation results are reported here. The validation matrix consists of both semi-blind and blind testing. Some testing of the ANN representations was also performed.

A total of ninety-seven transients corresponding to twenty distinct single-component malfunctions have been simulated and used for testing. Thirty-nine out of the 97 transients were used to blind test the diagnostic system where the identity of the transient was not provided until after the analysis. Table 1 shows that, out of the 39 transients, 95% were correctly identified within the first 40 seconds into the transient with graded degree of accuracy, i.e., uniquely identified, identified as one of two candidates, etc. The remaining transients, with very mild severity levels, were not identified. Forty-nine % of the simulated transients are uniquely identified, 8% are identified as one out of two possibilities, 33% are identified as one out of three, 5% are identified as one out of four possibilities, and 5% are not identified. As discussed in Section 2, instrumentation failure should be detected by the classical techniques of signal validation. The two unidentified simulations refer to pressure transmitter failure which cannot be diagnosed. Overall, PRODIAG correctly diagnosed 95% of the transients with varying precision and did not identify 5% of the transients. No transients were misclassified. These results indicate that the PRODIAG system is a significant step in the direction of addressing the major limitations of existing AI-based advisory systems.

<table>
<thead>
<tr>
<th>Uniquely Identified</th>
<th>2 Possible Candidates</th>
<th>3 Possible Candidates</th>
<th>4 or more Candidates</th>
<th>Incorrect Diagnostics</th>
<th>No Diagnostics</th>
</tr>
</thead>
<tbody>
<tr>
<td>49%</td>
<td>8%</td>
<td>33%</td>
<td>5%</td>
<td>-</td>
<td>5%</td>
</tr>
</tbody>
</table>
Testing of the component characteristics approach using ANNs developed for PRODIAG is shown in Fig 3. These results were obtained for the CVCS configuration discussed previously. The ANN representation is designed to address the plant-level diagnostics question of whether the malfunction is a mass or a momentum imbalance. The method of component characteristics discussed in Section 2.2 is used to give curves 1-3 in $w_1, w_{II}$ space with each curve corresponding to a certain set of malfunctions. Details are available in [6]. The $w_1$ flow is the charging pump discharge header flow and the flow $w_{II}$ is the pump seal injection flow. Figure 3 shows the actual data from the set of testing transients as dots. It can be seen that the group of dots do actually congregate around the set of three curves in $w_1, w_{II}$ space. The fact that the transient data does group around the predicted three curves shows that the method of component characteristics is a valid one. ANNs trained to associate particular mass or momentum failures in various flow segments with curves 1-3 were tested for various transients. In every case, the correct diagnosis was provided.

5. PROMANA MODULE

PROMANA, the transient management module within the IGENPRO system, is a logical extension of the PRODIAG module. Once PRODIAG has identified a fault in a process system, the same first-principles approach is applied to that process system to identify corrective actions that will mitigate the fault situation. Most, if not all, advisory systems that have been developed, or are under development, are designed for a specific plant system. PROMANA is intended to be a generic code that can be applied to many different plants without the need for major revisions of the computer code and the associated requirements for verification and validation of the modified code. Specific plant operating parameters and configurations are contained in a separate database that is linked to the main body of the code.

To determine the set of operator actions needed for T-H system realignment in response to a component malfunction requires an alternate flow-path search through the T-H system loops. A primary goal of the PROMANA module is to not restrict the solution to a predefined set of alternate flow paths which is based on an assumed fault. The PROMANA approach is to consider all possible ways to interconnect various segments of a system or even multiple, connected systems. After studying representative system flow diagrams, it became clear that the only approach consistent with this goal was to base the solution on a junction-segment description of the system. PROMANA thus assumes that any system can be described by a series of interconnected flow segments, each defined by one inlet and one outlet junction. Each junction

![Graph](image)

FIG. 3. Test of ANN Representations for CVCS Seal Loop Malfunctions.
can have a number of segments attached to it (a current limit of three is imposed for development purposes). The relationships between the junctions and segments are stored in one of several database files used by the program.

The following steps outline the general solution approach taken in the PROMANA module after a failed component is identified.

- identify all safety-related components affected by the failure (forward search);
- develop a list of possible replacement flow paths made up of flow segments containing the replacement components (reverse search);
- search for replacement components (mass, momentum, energy function) that can provide the required source or sink of mass, momentum or energy to the safety-related components within the possible replacement paths;
- prioritize the possible replacement options based on calculated thermal-hydraulic parameters for these solutions; and
- verify that all high-level safety function requirements are met by the new configuration.

When a given component is identified as faulted, the segment containing that component is identified from the database. The search program is invoked in a forward-search mode, starting at the outlet junction of the failed segment. Following normal flow paths, all segments that are serviced (i.e., receive flow from) by the failed segment are located and stored in a table. Each of these loops is examined to see if it contains any safety-related components. These components are defined as those whose function is critical and must be maintained if the process or plant is to remain on-line, or whose function is necessary for the safety of the system. Starting from the inlet junction of any segment containing a safety-related component, PROMANA is then run in reverse-search mode to construct either (a) all loops than can deliver flow to the important component or (b) all loops that can function as a bypass around the failed segment. During this search, normally closed valves may be opened and segments whose flow may be reversed are included in potential paths. These are examples of the first-principles PRD rules and CCD T-H component generic attributes which are used in PROMANA. The same first-principles approach to the knowledge base structuring is taken in PROMANA as in PRODIAG but there are differences in the knowledge. The thermal-hydraulic parameters associated with each segment of the constructed paths are examined to see if they match or exceed those necessary to meet the requirements of the safety-related components. If the new path meets those requirements, it is added to a table of recommended alternate paths. Thermal-hydraulic calculations based on first-principle rules are used to prioritize the list of solutions, which is presented to the system operator as a guide to corrective actions.

6. CONCLUSIONS/SUMMARY

A knowledge base structure for the IGENPRO approach to knowledge-based digital systems for process transient diagnostics and management has been developed with the potential for generic T-H system independence. It is first-principles T-H function and T-H component-characteristics based and does not require preknowledge of the faulted event data. It is therefore not event based. Analogous to the approach taken for the numerical simulator codes such as RELAP and TRAC, the only plant and T-H system specific knowledge that is required is the connectivity information of the PID and the normal operating component characteristics. In this manner, V&V should become simpler with comprehensive generic knowledge and relatively small knowledge bases. On an application dependent basis, V&V should only be required for code input and not for the code itself.
This knowledge structure based on the combined use of a first-principles T-H function ES and T-H component-characteristic ANNs has been constructed for the PRODIAG diagnostic module. Implementation in the PRODIAG code has been completed for a laboratory proof-of-concept system. A set of first-principles qualitative physics-based ES rules and a supervisory flow logic which are plant and T-H system independent have been developed. While ANN training has to be T-H system specific, a set of ANN representations which could be derived by a plant- and T-H system-independent automated reasoning program, has also been developed. ES diagnostics proceed through a three-step mapping process, where trends in T-H variables are mapped into trends in imbalances of mass, energy, and momentum, which are then mapped into generic faulty components and next mapped into specific faulty components. The mapping from T-H variables to imbalances in the conservation equations is performed through qualitative physics-based rules. Unlike prior work describing the use of qualitative physics-based rules, the approach here is generic, with no need to customize the rules as a function of the process to be diagnosed. The proposed approach is T-H system-independent and can be applied to different processes and plants, with the provision of the appropriate process-specific piping and instrumentation diagram. Promising proof-of-concept testing results have been obtained with PRODIAG using CVCS transient test data provided by the Braidwood PWR full scope operator training simulator. The objective of generic portability appears to be feasible.

Given the progress made with PRODIAG diagnostics module, development of the knowledge base structure for the transient management module PROMANA has proceeded along similar lines. The three ES databases, the PRD, CCD and PID utilized by PRODIAG, are also used by PROMANA but there are differences in the knowledge which is required. To determine the set of operator actions needed for T-H system realignment in response to a component malfunction requires an alternate pathway search through the T-H system loops. This is the basic goal of the PROMANA module. To perform this search with a generic T-H system independent method requires that the PROMANA knowledge-base structuring be at a very basic level, component-level structuring and not at a higher level, system-level structuring. This necessitates the usage of the generic component-level classification dictionary, the CCD and obviates the usage of a generic system-level classification dictionary, the SCD. This basic level classification is required because a system could simultaneously have any of the three T-H functions, mass, momentum or energy. In contrast it is simpler to classify the T-H function on a component level. Using the CCD structure puts the PROMANA on the same footing as PRODIAG. As with PRODIAG, in addition to T-H function, PROMANA also uses T-H characteristics (attributes both qualitative and quantitative). There are, however, differences in that the T-H attributes useful for transient management are not exactly the same as those useful for T-H diagnostics. There are also differences in the PRD rules. But in general, both PROMANA and PRODIAG use the first-principles IGENPRO T-H function/T-H characteristics approach derived for the knowledge-base structuring. The PROMANA code system has been developed to the point where it is now possible to automatically construct all possible flow paths leading from a failed component, examine those paths for the presence of important components, then automatically search the system for all potential flow paths to restore the function of the failed component.

Work is continuing on performing a blind-blind test of PRODIAG with simulator data for the Braidwood Component Cooling Water System. Effort is proceeding on the PROMANA module with the focus also on the Braidwood CVCS. PROMANA will interface with a simulator code to meet quantitative limits from technical specifications and a probabilistic risk assessment code to provide risk and reliability screening criteria. Proof-of-concept-testing will involve comparisons with the CVCS Abnormal Operating Procedures. Braidwood CVCS operating plant data is being used to both develop and test the PROTREN module. Fuzzy logic will be used. Achievement of the IGENPRO R&D goals should contribute to the acceptance of knowledge-based digital systems for plant transient diagnostics and management. Since these goals include T-H system and plant independence this R&D effort would be ideally suited for international
collaboration across national reactor plant lines. An international collaborative project à la the NRC ICAP program for RELAP-5 and TRAC, but at an earlier project stage than ICAP, would be promising if focused on the shared development of first-principles T-H knowledge bases using the unique experiences of the worldwide community of reactor safety analysts and engineers.

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