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NUCLEAR POWER PLANT DIAGNOSTICS STUDY AT THE MIDLAND TRAINING SIMULATOR

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INTRODUCTION

Training simulators provide a real world environment for testing advanced diagnostic and control systems as an aid to nuclear power plant operators. The simulators not only duplicate the hardware in the actual control room, allowing for analysis of man-machine interface, but also represent the dynamic behavior of the reference plant in real-time, in a realistic manner. Training simulators provide the means to representing the reference plant operations in a wide range of operation conditions including off-normal and emergency conditions. Transient events with very low probability of occurrence can then be represented and used to test the capabilities of advanced diagnostic and control systems. For these reasons, full-scope operator training simulators have been used as a test bed for a number of advanced diagnostic concepts.[1,2]

The University of Michigan and Consumers Power Company have been collaborating in a program devoted to the development and study of advanced concepts for automatic diagnostics and control of nuclear power plants. The program has been focused on the use of the full-scope operator training Midland Nuclear Power Plant Unit 2 (MNP-2) Simulator for development, testing, and verification of advanced diagnostics concepts. In our current efforts, we have developed two artificial intelligent (AI) diagnostic concepts that have been applied to the MNP-2 Simulator: the systematic generation and updating of a rule-based knowledge system for nuclear power plant diagnostics[3,4] and a nonlinear parameter estimation algorithm called the simulation filter.[5] The two concepts correspond to two different levels of the knowledge base, shallow and deep, of a transient diagnostic expert system. For the first concept, systematic generation and updating of a shallow knowledge base, the MNP-2 Simulator is used to generate a database of transient events from which diagnostic rules are inductively learned. The generation of the shallow knowledge is obtained by grouping transient events of similar characteristics, i.e., forming patterns, which are then cast in the form of "if ... then ..." production rules. The second concept, the simulation filter, uses an extended Kalman Filter algorithm to optimally estimate or adjust, as necessary, selected system parameters in the simulation models representing a nuclear power plant. Through the systematic adjustment of key system parameters and use of plant data, the simulation filter provides the means for improving the fidelity of low-order, fast simulation models. The simulation filter algorithm is used with the MNP-2 Simulator to improve the simulation of the Three Mile Island Unit 2 (TMI-2) accident.

THE DIAGNOSTICS PROCEDURE AND THE MIDLAND SIMULATOR

The diagnostics procedure for identifying malfunctions in nuclear power plants using the two previously described advanced concepts is illustrated in Figure 1. Once signals have been validated and an anomaly in plant behavior has been detected, the knowledge base of the diagnostics expert system is applied to identify the malfunction through a two-step process. In the first step, rule-based knowledge, obtained through a systematic pattern recognition technique or through known cause-effect relations, are used to narrow down the possible causes of the anomaly to a few hypotheses. In the second step, model-based knowledge in the form of computer simulation programs, representing the dynamic reactor systems, are then called to simulate each of the hypotheses generated. By comparison of each hypothesized and simulated malfunction with plant data, the inference engine of the expert system identifies the malfunction according to which hypothesis best accounts for the actual behavior of the plant. In our current studies, the MNP-2 Simulator is used for systematic generation of the rule-based knowledge using statistical pattern recognition and for testing the simulation filter as a tool to improve simulation results. The development and incorporation of diagnostics AI concepts to the MNP-2 Simulator allow us to study the possible use of a full-scope simulator as a plant diagnostic tool. A full-scope simulator and AI concepts could be, eventually, implemented as a package to aid reactor operators in the diagnostics and control of nuclear plants.

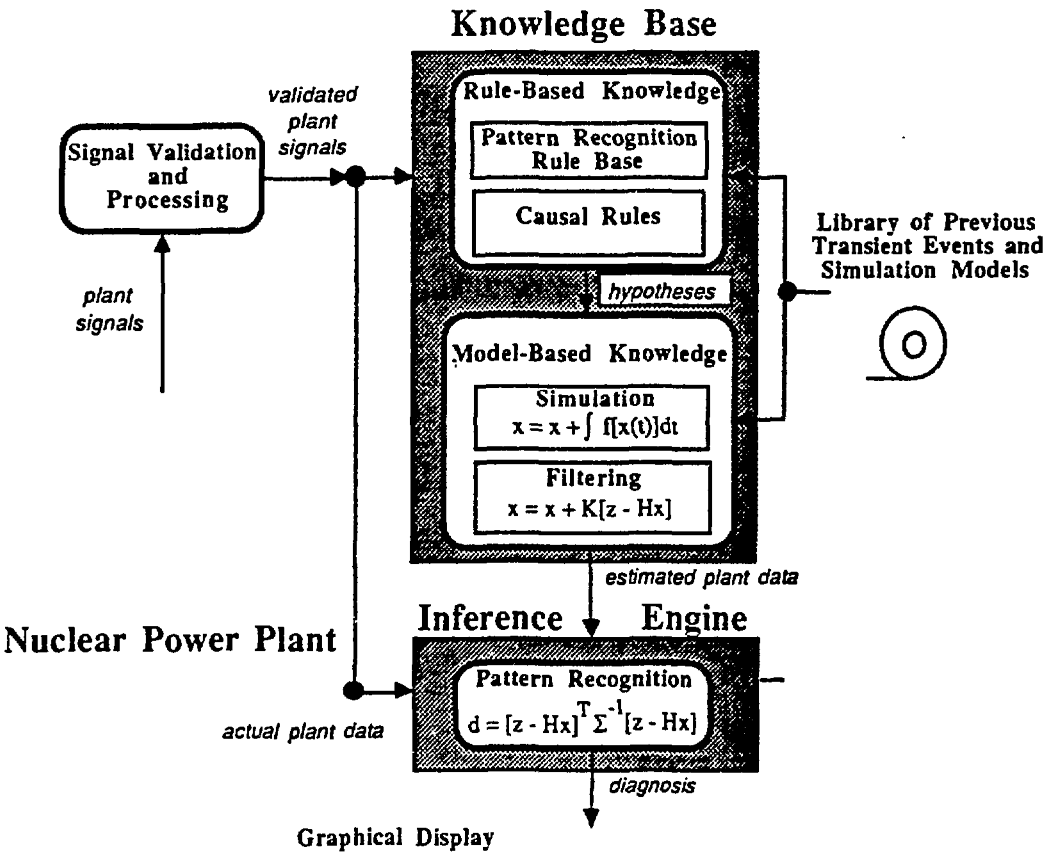

Figure1. A Two-Step Approach for Nuclear Power Plant Diagnosis.

The MNP-2 Simulator is a full-scope operator training simulator modeled after a Babcock and Wilcox PWR of the 2452 MWt class. The Simulator represents, in real time, all major systems of the plant and simulates a wide range of operating conditions including off-normal and emergency conditions. From a library of more than 300 transient events, up to 17 non-conflicting malfunctions can be selected at different severity levels and introduced at any time. The Simulator can be initialized to any one of more than 50 possible initial conditions corresponding to different combinations of power level, core burnup, soluble boron concentration, etc.

In the systematic generation of the shallow or rule-based knowledge the MNP-2 Simulator is used to construct a database of 144 transients corresponding to 12 event types. To generate the database of transients, we simulate each one of the 12 events occurring separately, i.e., assuming single failures, a dozen times. For each one to the 12 simulations of an event, a different combination of failure severity and initial conditions is used. The Simulator is crucial in the representation of a realistic and broad database which allows for the inductive generation of context-independent rules; where the same event may be correctly diagnosed under different failure extent and operating conditions of the power plant. Studies are under way to characterize multiple failures represented by the MNP-2 Simulator.

The MNP-2 Simulator was used to model the TMI-2 accident scenario and provided an excellent test for the simulation filter. The MNP-2 Simulator consists of a large number of crude computer modules so that every component of the plant is modeled in real time. It was thus possible to test, in a real world environment, the ability of the simulation filter to improve the quality of the simulation involving a complex sequence of events. We are currently extending the simulation filter into a generic module that can be applied to improve simulation results of any module of the Simulator.

GENERATION OF SHALLOW KNOWLEDGE

A statistical pattern recognition algorithm was developed and incorporated as the Rg code,[3,4] at the University of Michigan, to systematically generate and update diagnostic rules for nuclear power plants. Given a database of M transient events with each transient having one of the K distinct event types E_k, $(k = 1,...,K)$, and M associated values for each of the N selected features F_n, $(n = 1,...,N')$, the Rg code generates diagnostic rules by modeling, through statistical patterns, the relationships between the events E_k and the features F_n of the transient database. The statistical modeling process consists of two sequential steps: feature selection and pattern recognition. In the first step, feature selection, multivariate statistical analysis techniques[3] are used to retain a subset of N salient features, e.g., plant parameters, from an original set of N' features. This step corresponds to the fact that during the operation of nuclear power plants hundreds of signals are monitored, but when the plant goes into an upset condition only a few of these signals or features are important in the characterization of the transient. In the second step, pattern discovery, an entropy minimax algorithm[6] is used to search the possible feature space formed by the N selected features and discover sub-spaces or patterns that partition the database of transient events into clusters of events of similar characteristics. Once the N most significant features have been automatically selected by the Rg code, with $N << N'$, an N-dimensional feature space populated with the M events can be constructed to discover a set of optimal discriminatory patterns. The discovery of patterns is illustrated for N=2, K=3, and M=34 in Figure 2. Optimal patterns are discovered by populating the two-dimensional feature space with the 34 events of 3 possible types E_k, $(k=8,9,10)$, and then searching for a partition of the feature space into I patterns C_i, $(i=1,...,I)$, corresponding to the minimum of entropy $S(E|C)$[6]

$$S(E|C) = \sum_{i=1}^{I} P(C_i)\, S(E|C_i) = \sum_{i=1}^{I} P(C_i) \sum_{k=1}^{K=3} \{-P(E_k|C_i) \ln P(E_k|C_i)\}. \quad (1)$$

Here $P(C_i)$ is the probability that any of the events are located in C_i. The conditional entropy $S(E|C_i)$ for cluster C_i is the average over K event types of information $-\ln P(E_k|C_i)$ weighted by the conditional probability $P(E_k|C_i)$ of E_k being located in C_i. The probabilities $P(E_k|C_i)$ and $P(C_i)$ are calculated as Bayes' estimators[7] with least biased prior distribution, i.e., that corresponding to maximum entropy.[8] The minimum entropy criterion agrees with our intuitive notion that the feature space should be partitioned in such a way that events in the same pattern tend to be of the same type. Entropy $S(E|C)$ would attain its minimum value, i.e., $S(E|C)=0$, for the limiting case in which for all patterns C_i, $(i=1,\dots,I)$, $P(E_k|C_i)=1$ for a particular event E_k and zero for all other events. This corresponds to the case where all events are perfectly clustered and each cluster has events of one type only.

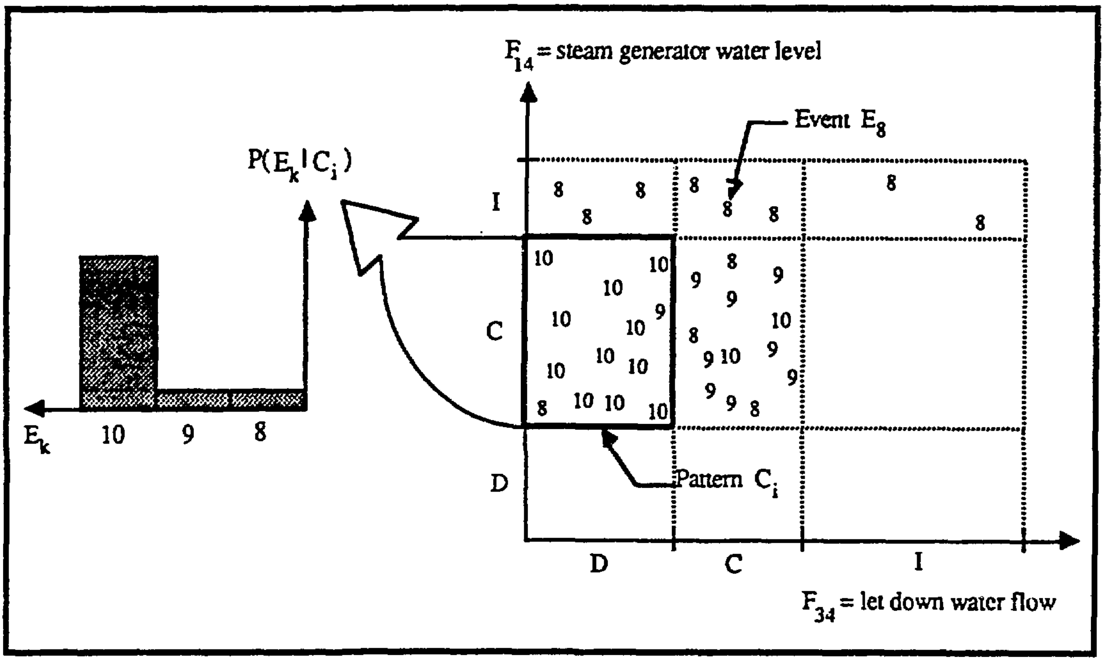

Figure 2. Pattern Recognition in a Two-Dimensional Feature Space.

The patterns discovered in the two-dimentional feature space can be used to represent diagnostic rules in the form of "if (condition) then (consequence) with certainty <x>." The condition part is specified by the location of cluster Ci in the feature space while the consequence part is given in terms of event E_k, with the conditional probability $P(E_k|C_i)$ providing a measure <x> of the certainty of occurrence of the events. To handle the large dimensionality of the feature space additional algorithms have been developed to decompose the N-dimentional partitioning problem and approximate the simultaneous discovery of the most discriminatory set of I patterns into I sequential discovery of patterns one at a time. The Rg code also allows for the updating of the rules, in an incremental fashion, to incorporate the information content of a new event in a systematic and computationally efficient manner. An incremental learning approach[3,4] within the context of the entropy minimax algorithm has been developed to incorporate the new event without restructuring the entire rule base.

The MNP-2 Simulator was used to construct a transient database of 144 single-failure events of 12 distinct types, where 40 features, F_1, F_2, ..., F_{40}, from various plant modules, were recorded for each simulation of an event. The Rg code used the database to automatically generate 25 production rules in a two-level hierarchical knowledge structure for the anti-core melt safety function.[9] All of the rules are represented by a small number of features and are consistent with our physical understanding of the behavior of the plant systems. For instance, rule R_{14} corresponding to a leak in the primary side letdown line E_{10} with 94% probability is defined by:

IF { (F_{14}= steam generator water level is constant) and
(F_{34}= letdown water flow is decreasing) },

THEN { $P(E_8) = 0.03$, $P(E_9) = 0.03$, $P(E_{10}) = 0.94$ },

where E_8 and E_9 correspond to leaks in the steam generator tube and in the reactor coolant system, respectively. Rule R_{14} expresses the fact that the occurrence of E_{10} has no affect in the secondary side steam generator water level F_{14} and causes a decrease in the downstream primary side letdown water flow F_{34}. Rule R_{14} is also graphically represented in Figure 2 where F_{14} and F_{34} are segmented into three intervals, representing decreasing (D), constant (C), and increasing (I) trends, respectively, in the feature variables.

The remaining 24 diagnostic rules and the two-level hierarchical knowledge base structure are described in detail in references 3 and 4. The accuracy and time-dependent diagnostic ability of the generated twenty-five rules were validated through an on-line diagnostics test. Nine out of eleven randomly selected transient events were correctly diagnosed throughout the transient. The other two events escaped diagnosis because some of their features did not match all of the features associated with the corresponding classification patterns.

IMPROVING SIMULATION RESULTS WITH THE SIMULATION FILTER

The use of power plant simulation models to represent deep-knowledge requires that the models are both accurate and fast-running. The simulation models should represent the reference plant in details and with high accuracy, such that simulated transients provide a good agreement with plant data. The models should be fast-running such that the various hypothesized malfunctions can be tested faster than real time. These two requirements impose, however, conflicting objectives in the simulation models. Simulation models that represent the reference plant in detail and provide accurate simulation results are inherently slow. To resolve the two conflicting objectives, we use an extended Kalman filter[10] algorithm, the simulation filter,[5] to adjust key parameters in the simulation model. With the simulation filter providing improved agreement with the actual plant data, it is then possible to use low-order, fast simulation models, such as the ones used in the MNP-2

Simulator, for diagnostic purposes. For example, to accurately simulate a leak out of a power-operated relief valve (PORV) in the pressurizer of the MNP-2 Simulator, the relief flow is adjusted so that other simulated plant parameters such as pressurizer pressure and water level match measured plant data.

The Kalman filter provides an optimal estimate of a system state $\mathbf{x}(k|k)$, given measurements of the system $\mathbf{y}(k)$ along with a set of linear equations that describe the dynamics of the system. The state estimates are optimal in the sense that they yield minimum square error. To apply the Kalman filter to nonlinear system equations, such as nuclear reactor dynamics, the system equations are linearized at frequent time intervals. Once the system equations have been linearized, the recursive Kalman filter algorithm computes the optimal state estimate $\mathbf{x}(k|k)$ through two steps. In the first step, the extrapolated state estimate $\mathbf{x}(k|k-1)$ is obtained from the previous time step $\mathbf{x}(k-1|k-1)$ using the linearized model equations

$$\mathbf{x}(k|k-1) = \mathbf{\Phi}(k-1)\, \mathbf{x}(k-1|k-1) + \mathbf{F}(k-1), \tag{2}$$

where $\mathbf{\Phi}(k-1) = \exp(\mathbf{A}\Delta t_{k-1})$ is the state transition matrix, $\mathbf{A} = (\partial \mathbf{f}/\partial \mathbf{x})$, and $\mathbf{F}(k-1)$ is a constant of integration. Then, in the second step, the optimal state estimate $\mathbf{x}(k|k)$ is obtained by updating the extrapolated state estimate based on the new measurement $\mathbf{y}(k)$ and the Kalman filter gain matrix $\mathbf{K}(k)$

$$\mathbf{x}(k|k) = \mathbf{x}(k|k-1) + \mathbf{K}(k)\, [\mathbf{y}(k) - \mathbf{H}(k)\, \mathbf{x}(k|k-1)], \tag{3}$$

where $\mathbf{H}$ is the state-space to measurement-space transition matrix.

Two sources of modeling errors are introduced by linearizing the state equations.[5] The first is in the computation of the extrapolated state estimate $\mathbf{x}(k|k-1)$, and the second is in the computation of the state transition matrix $\mathbf{\Phi}(k-1)$; which is indirectly used to calculate the Kalman gain $\mathbf{K}(k)$ and hence the optimal state estimate $\mathbf{x}(k|k)$. To handle these problems, an implicit Kalman filter algorithm called the simulation filter has been developed.[5] The simulation filter replaces the linearized system model of the Kalman filter with actual nonlinear simulation program results. The state extrapolation x(k|k-1) is obtained directly from simulation and the state transition matrix $\Phi(k-1)$ is obtained by solving Eq. (2) for $\Phi(k-1)$.[5]

In our earlier attempt to test the simulation filter algorithm on the MNP-2 Simulator[11] the filter was applied only to the pressurizer module. In our current efforts we are rewriting the simulation filter algorithm in a highly modular and general purpose structure so that the filter can be linked, with minimum manual intervention, with any component module of the Simulator. The implementation of the general purpose filter algorithm at the MNP-2 will provide the first step in the evaluation of the use of full-scope simulators as an actual plant diagnostic tool. The filter module would be used as a parameter estimation algorithm to bring the Simulator results in agreement with the actual plant data which could than be used for diagnostics and control purposes.

The schematic diagram representing the interaction of the general purpose simulation filter with the MNP-2 Simulator is illustrated in Figure 3. After each simulation routine representing a plant component module is used by the Midland Simulator, the Simulator calls the simulation filter routine and provides it with the extrapolated state estimate z(k|k-1). At the first stage of the filter routine, the state variables x(k|k-1) corresponding to the current component module are fetched from the full state extrapolation vector z(k|k-1), which contains the state variables for all modules. Next, the filter algorithm is used to provide an updated estimate of the system state x(k|k) based on x(k|k-1) and noise corrupted measurements y(k). The filter algorithm also requires the initialization of various covariance matrices which must be provided by the user. Finally, the updated vector z(k|k) is obtained by replacing x(k|k-1) with the corresponding updated state vector x(k|k). The full updated state vector z(k|k) is then send back to the Simulator. Since some of the updated state variables are recalculated in other modules during the same time step, is is necessary to consistently propagate the updated variables through the other modules such that additional calculations in the Simulator would reflect the updated state variables.

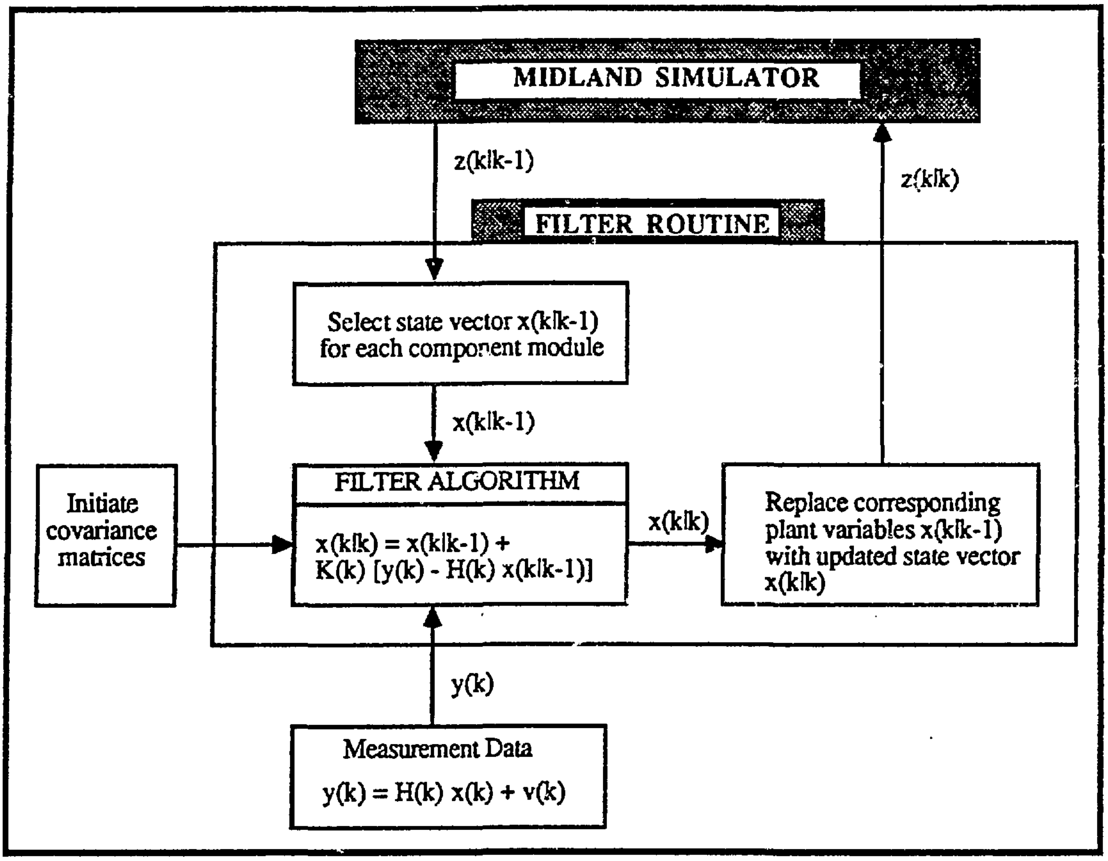

Figure 3. Flowchart of the Simulation Filter Routine and the Midland Simulator.

The TMI-2 accident scenario was chosen as our preliminary test case for the simulation filter on the MNP-2 Simulator. The TMI-2 accident consisted of a loss of feedwater flow followed by a stuck open pressurizer PORV. The pressurizer model in the MNP-2 Simulator is a low-order, two-region model primarily based on the conservation of mass and energy. All pressurizer components are represented, including the heaters, spray lines, surge line, and relief valves. Six state variables were chosen for our test case: mass and specific enthalpy of the liquid and vapor regions in the pressurizer, overall pressurizer pressure and PORV relief flow. Figure 4 shows the improvement obtained with the simulation filter applied to the TMI-2 simulation on the MNP-2 Simulator. The filtered pressurizer pressure and pressurizer level are significantly closer to the TMI-2 data than the unfiltered results. The filter also adjusts one unmeasurable parameter, relief flow, to provide a more accurate estimate than the unfiltered case. In fact, this estimation of PORV relief flow plays a key role in the improvements observed in Figure 4. The fluctuations in the filtered results appear to be due to the crudeness of the Simulator model.

SUMMARY AND FUTURE EFFORTS

This paper presents the results of our initial studies in the application of two diagnostic AI techniques to the Midland full-scope simulator. For systematic construction of a diagnostic rule base, the pattern recognition Rg code was applied to a comprehensive database of simulated transients obtained from the MNP-2 Simulator. A set of context-independent rules capable of diagnosing single-failure transient events was obtained and successfully validated through an on-line diagnostics test. Through our successful implementation of the simulation filter in the MNP-2 Simulator, we have also shown that the simulation quality of complex power plant simulators can be improved by the parameter estimation technique. The filtered simulation results can then be used effectively as deep knowledge to evaluate diagnostic hypotheses generated by the shallow knowledge.

Our current efforts involve the implementation of the general purpose simulation filter routine to the MNP-2 Simulator. For the implementation of this task we are considering the use of a stand-alone workstation for efficient parallel execution of the filter algorithm. We are also investigating the possibility of using the Rg code to characterize multiple-failures simulated by the MNP-2 Simulator. Our current and future efforts should provide the means for analyzing the use of full-scope simulators integrated with AI advanced concepts as a plant diagnostic tool.

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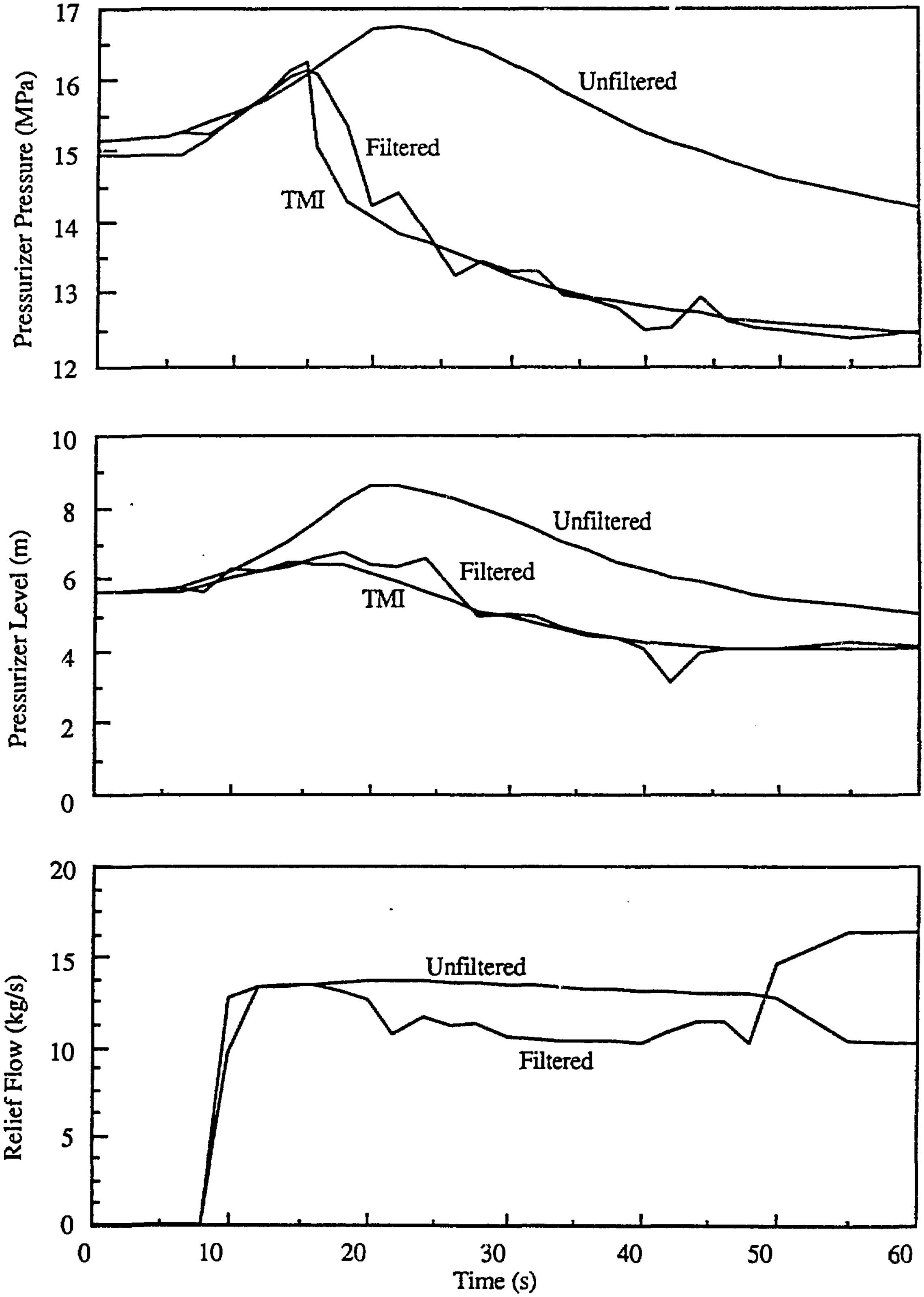

Figure 4. Comparison of Filtered and Unfiltered Variables with TMI-2 Data.