

# **DEVELOPMENT OF A HYBRID INTELLIGENT SYSTEM FOR ON-LINE MONITORING OF NUCLEAR POWER PLANT OPERATIONS**

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## **ABSTRACT**

Nuclear power plant operation is a complex task which requests high reliability, highly skilled operators and advanced analytical tools. Because of system complexity, operators and system managers have difficulty to analyze the great quantity of collected data to formalize correct and timely decisions, which is very important, either in normal operation or at emergency situations. Artificial intelligence has been introduced to solve nuclear power plant operation complexity in equipment health monitoring for systems, structures, and components, *SSC*, in the nuclear power plants, *npp*. The purpose of monitoring is to relate the relevant features to a set of variables, which define the current health state of the *SSC*. The real-time fault diagnosis, and decision making tasks become cumbersome due to complexity and high load of monitored data. This paper introduces a hybrid intelligent system as a solution to address the difficulty of these tasks. The developed methodology combines several artificial intelligence techniques, as Bayesian networks, influence diagrams, neural networks and fuzzy logic. Two modules, expert system module and the neural network module, are incorporated into the complete system. The proposed hybrid architecture has desirable properties inherited from both fields of numeric neural networks and symbolic expert systems. The expert system module of the hybrid system has been completed and validated on the bearing system of horizontal charging pumps in nuclear power plants. The neural network module is in development stage.

## **KEYWORDS**

Intelligent system, fault diagnosis, nuclear systems-structures-components, predictive maintenance, Bayesian networks, influence diagrams, neural networks, hybrid systems

## **1. INTRODUCTION**

Different features of several systems, structures, and components, *SSC*, in the nuclear power plants are continuously monitored. The purpose of the monitoring is to relate the relevant features to a set of variables, which define the current health state of the *SSC*. During the monitoring task, large amounts of data are to be processed and rapid response to various phenomena and critical decision making is very necessary in nuclear power plant operations.

This vast amount of alarms on the monitored variables is available to the human experts in the nuclear power plants. However, the human expert can only observe and analyze a small set of the variables or alarms at a time. This is a concern in the situations when timely and critical decisions are necessary during on-line operation of the power plants. Therefore, having to manage large amount of information for real-time diagnosis and monitoring of the nuclear power plant *SSC* is a big problem to the plant operators and system engineers. Our objective is to bring a solution to this perplexity, to help the operators and system engineers take timely and appropriate decisions. The predictive real-time monitoring systems, which are designed via artificial intelligence techniques, are one of the best candidates as a solution to this problem. However, no single method in artificial intelligence can successfully address all the complexities of systems in the scale of nuclear power plants. Hence, we develop and implement a hybrid strategy, which integrates relevant artificial intelligence techniques and carries the merits of the included techniques. The techniques involve the knowledge based expert systems, as well as purely numeric based models in the machine learning field. In this strategy, the system performs better than the case where the individual techniques would be implemented alone in the monitoring domain. Our methodology provides prediction and explanations for non-linear relations between the input signals and the future malfunctions, support in beneficial advice for maintenance actions and for complex decisions, prediction of the results of its own actions in the nuclear power plants. The system becomes to have the cognition that is concerned with reasoning and decision making on actions, which must be undertaken to achieve specific goals. In order to accomplish this, the method has to model either the physical component to which it is being applied, or the human expert who is observing the physical component within its domain. The key challenges in such a design include the reasoning under uncertainty, the planning for the action, and learning from the events, in a computationally efficient algorithm. The various combinations of different methods and strategies in artificial intelligence underlie the solutions to these key challenges with different nature in different domains. In our work, the techniques that involve the knowledge based expert systems, as well as purely numeric based models in the machine learning field, are chosen to develop the hybrid intelligent system.

Our project is focusing on application at future nuclear power plants that could come on-line. However, the methodology is also flexible enough to be retrofitted on present nuclear power plants and can be applied to other types of industrial applications.

In this paper, the role of artificial intelligence in real-time fault diagnosis and decision support is introduced in Section 2. The architecture and development of the hybrid intelligent system in our work are presented in Section 3. An example case on the bearing system of the high energy horizontal pumps, for the validation of the intelligent system, is given in Section 4. The current conclusions and the planned future work are dictated in Section 5.

## **2. REAL-TIME AI FOR FAULT DIAGNOSIS AND DECISION MAKING IN COMPLEX SYSTEMS**

### ***2.1 Real-time applications***

Real-time systems require more than just fast hardware to be successful. This is particularly true for very complex applications with dynamic environments and huge volumes of data, such as nuclear

power plant operations, where timely response is as important as a correct response. The issues that should be addressed which are pertinent to the important real-time considerations are as follows (Schwuttke & Gasser, 1991): interface to the external environment to gather data, integration with procedural programs, continuous operation, adaptability to the changing facts, reasoning about past, present and future events, data management, and uncertain or missing data.

Real-time fault diagnosis deals with the timely detection and diagnosis of abnormal operating conditions. Abnormal operating situations can cause high amount of economic loss and endanger the safety in the nuclear power plants. Thus, fault diagnosis and decision making are very important aspects of safe and optimal operation of nuclear power plants.

The predictive real-time monitoring systems, which are designed via artificial intelligence techniques, are one of the best candidates as a solution to this problem. These techniques give information for the identification of potential future failures and their causes. They analyze the relations between items of data coming from vital components of a power plant, thereby making it possible to perform preventive maintenance. However, no single method in artificial intelligence can successfully address all the complexities of systems in the scale of nuclear power plants. Hybrid strategies, when designed carefully, perform better than the individual components of the methodology on health monitoring of complex systems.

In addition to the hybrid strategy, it is important to push diagnosis and monitoring down to component level, and to send processed health monitoring data, instead of raw data back to the man machine interface, which is at the control room in the nuclear power plants, to make the information easier for the operator to manage.

## ***2.2 Selected AI techniques appropriate for real-time fault diagnosis and decision making***

Knowledge-based systems, or expert systems, *ES*, offer the opportunity to let computers solve problems which are normally thought to require human expertise. Such systems are able to provide valid ranges for variables, to predict future abnormal situations from these values, using the knowledge of domain experts, to explain failures and decision and to indicate the reasons of the findings.

Bayesian networks, *BN*, filled a void in expert system technology with their ability to coordinate bidirectional inferences and have emerged as a general representation scheme for uncertain knowledge. Bayesian networks are directed acyclic graphs, *DAG*, in which the chance nodes represent the variables of interest (e.g., the temperature of a device, a failure mode of a component, the occurrence of an event) and the directed links represent informational or causal dependencies among the variables (Jensen, 2001). The strength of a dependency is represented by conditional probabilities that are attached to each pair of nodes in the network. The most distinctive feature of Bayesian networks, stemming largely from their causal organization, is their ability to represent and adapt to changing configurations. The ability to handle uncertainty in the modeled domain is another valuable feature of Bayesian networks.

Influence diagrams, *ID*, were originally invented as a compact representation of decision trees for symmetric decision scenarios. They are now seen more as a decision tool extending Bayesian networks. An influence diagram consists of a directed acyclic graph over chance variables, decision variables, and utility functions. The structure comprises of a directed path over the decision variables, and utility functions.

In order to reduce the dependence of a final ES on the knowledge-acquisition phase, some machine learning techniques have also been applied in the real-time monitoring field. The study of neural networks is the study of information processing in networks of elementary numerical processors. The emphasis is on accounting for intelligence via the statistical and dynamic regularities of highly interconnected, large-scale networks. The use of neural networks, *NN*, is a good approach to predictive control systems because of the existence of the highly non-linear relationships between the data and the

abnormal situations and their computational efficiency, which is important to real-time on-line monitoring purposes.

### **3. HYBRID METHODOLOGY: INTEGRATION OF BAYESIAN NETWORKS AND NEURAL NETWORKS**

#### ***3.1 Architecture of the hybrid intelligent health monitoring system***

The intelligent system that is in our project adopts modeling the physical domain, which is characterized by uncertainties. The causal relations modeling of the monitored SSC is done by using Bayesian probability theory, decision theory. These theories are combined with the directed acyclic graphs to complete the models in Bayesian networks, and influence diagrams. The models are solved with expert system shell software. These expert systems provide the prediction of the failure progression and diagnosis, as well as the advice concerning maintenance actions for the monitored system. The information, which makes the foundation of the expert systems, has been elicited subjectively from domain experts. The knowledge elicited from the experts, namely the *knowledge base* of the expert systems, is necessary in defining the behavior of the system under all possible conditions within the operational domain. However, in order to apply this methodology real-time on large-scale systems, the algorithms must be computationally efficient, in addition to the other requirements for preference. The solution to BN and ID models become computationally expensive when the models get large in scale, in spite of their great ability to reason under uncertainty, to explain the findings, and to provide decision support. The computation time for results of a single feature input gets longer than the required period between data collection for the monitored features. For such cases, we combine the expert system and the neural network models, where the NN model has a functional structure as a duplicate of the BN model in neural network framework. The NN model is computationally more appropriate for real-time monitoring of complex, large systems. Therefore, we propose to do the on-line diagnostic process by running a neural network model with the relevant input from the observed features. Due to lack of recorded data, which match the feature signals to the fault conditions in the nuclear power plant SSC, it is not possible to train the NN with appropriately reliable accuracy by using only the insufficient recorded data. The BN based expert system diagnostic model is appropriate to be used to produce the data, which is necessary for training of the NN model in signal-fault domain. However, the NN model lacks the explanatory property, and decision making capability. Hence, the BN and ID models are kept for the purposes of explanation and decision support. This important set of information is extracted from the BN and ID based expert systems by running them with the same input externally, i.e., not real-time. In this way, when required, the user is provided by reasoning and explanation for the results that are obtained by the NN model, which are parallel to those of the BN model. This combination removes the “black-box” repute of NN models in front of the user. The ID model is an advisory expert system model that is kept for decision making purposes and is run with the same relevant input externally.

The sensor signals, which are collected in the first stage monitoring, are converted to feature intervals with fuzzy logic algorithms to obtain the likelihood values versus the measured values of the relevant signals.

Figure-1 shows the structure and interactions between the structural elements in the proposed hybrid intelligent monitoring system:

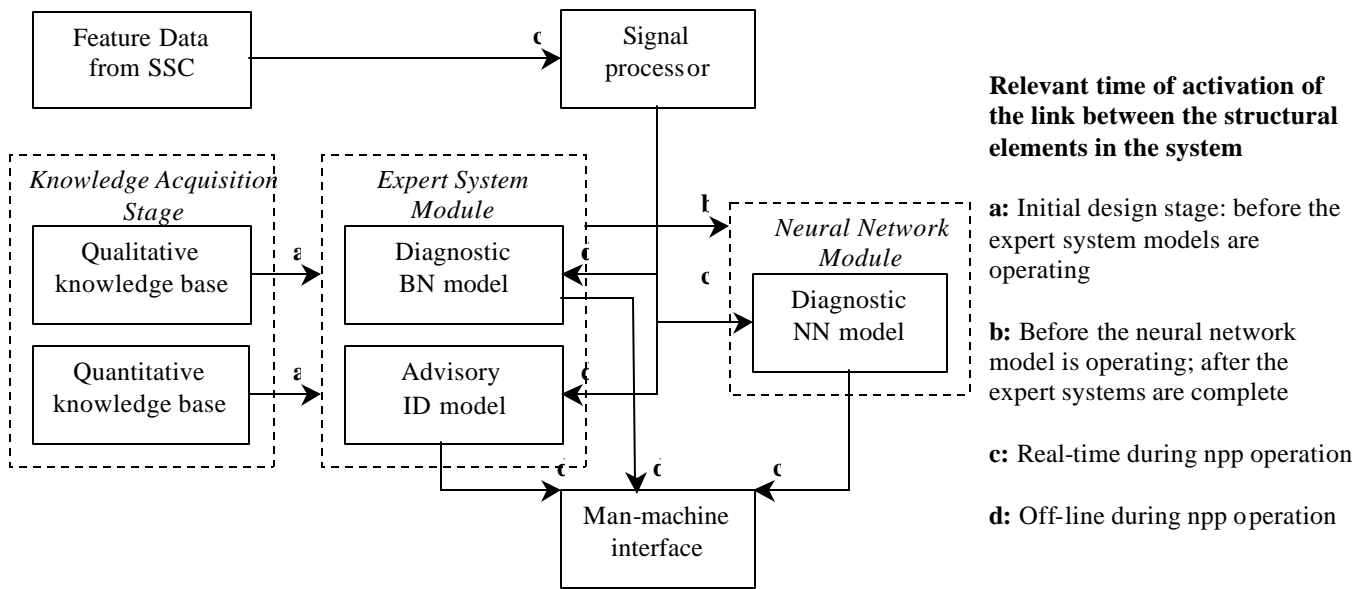


Figure 1: Structure for the proposed hybrid intelligent monitoring system

### 3.2 Construction of the expert system, ES, module – diagnostic and advisory models

#### 3.2.1 ES module knowledge base and reasoning paradigm

The information necessary for the knowledge base of the ES module is elicited from the domain experts by interviews and by numerical data extraction. The knowledge base of the ES module is structured with three major elements: (1) First is constructing the functional hierarchy and the causal relations in the system. As the complexity in the power plants is high, the modeling started at the SSC level with the help of the fault trees which we have constructed. This systematic functional hierarchy in the system makes the modeling task more efficient. The second (2) is possible set of action decisions. The third (3) is the conditional probability values for the causal links, and the utility functions for the actions and state changes. The third element is necessary in supporting for decision making. These modules, altogether, define the behavior of the SSC under all defined sequences of operation. The elements (1) and (2) make the qualitative information in the knowledge base. The module (3) represents the quantitative information in the technical information database. Hence, the elements (1) and (2) comprise the *qualitative knowledge base*, and (3) comprises the *quantitative knowledge base* (Yildiz & Golay, 2001)

The domain knowledge representation in the ES module is in two ways. The qualitative knowledge base adopts the graph representation. The *directed acyclic graphs* and the *influence diagrams* are used in the diagnostic and advisory models of the ES module, respectively, as the graph representation. The quantitative knowledge base is made up of the conditional probability values linked to each causal relationship between the variables of the physical system. The conditional probability values define the strength associated with the casual links.

The reasoning under uncertainty is handled by using the Bayesian theory and the decision theory, as the probabilistic models, for the analytical solution. The states of the variables are defined probabilistically. The probabilities over the unobserved variables, given the setting of the observed variables (i.e. evidence) are computed by the expert system. This is *diagnostic reasoning* task, where effects are made known and the causes are inferred (Yildiz & Golay, 2001). The computations involved

in this inference are spent on making the relevant pieces of gathered information explicit. In our application, this refers to starting with the measured features, and inferring to the possible fault or failure modes, which would be the causes to the changes in the feature readings. This is the propagation in the opposite direction of the causal arrows.

### *3.2.2 Diagnostic and advisory models*

The diagnostic module is for determining the root cause of failures and for diagnosis. It consists of the fault/failure mode, and feature variables related to the SSC of concern. These variables are fit in a hierarchical breakdown, which also considers the causal relations between the variables. Within the model, these variables are represented by discrete chance nodes. The causal relations between the variables are represented by directed links. The states of the variables are the severity of the fault condition, as well as the normal – healthy – operating condition of the variable. Therefore the diagnostic model gives indication for the healthy operation as well as the severity level of the operation of the SSC in a probabilistic description.

The advisory module is for deciding what actions to take for having the highest benefit given the circumstances, and for predicting the outcome of the possible actions. Advisory model consists, in addition to the variables in the diagnostic module, decision and utility variables. The decision variables are based on the possible actions relevant to a fault/failure mode. This set includes the no action, on-line maintenance and off-line maintenance options. The utility variables are the functions which mathematically describe the benefit or cost of taking a decision given the current operating conditions.

### *3.3 Construction of the neural network, NN, module – diagnostic model*

Due to strict regulatory rules in nuclear power plant operations, the reliability of an on-line monitoring method to be applied must be high. For this reason, the probability of predicting the failures correctly – the accuracy – must be high. The size of the training set depends, by the *probably approximately correct (PAC)* model (Mitchell, 1997), on the value of the required accuracy, the error bound of the prediction, the uncertainties and the complexity measure of the machine learning algorithm that is to be used for the task of fault diagnosis and prediction in this methodology. All such dependencies indicate the requirement for large training data sets on the feature-fault condition pairs. The data collected in monitoring the SSC in the nuclear power plants are not available in a well recorded manner. That is to say, the recorded data is not sufficient in quantity to train a neural network with high reliability, i.e., with high accuracy, for fault diagnosis and prediction in any of the commercially operating nuclear power plants. This is equivalent mathematically to a small available training set size and low accuracy.

When training sets of only insufficient size is available, the solution we advise is producing the required data reliably. Theoretically, this can be done in two ways: First way is by initiating all the fault conditions in the real system itself. This can be very risky, destructive and expensive to be employed for systems in the nuclear power plants. Second way is by initiating the same fault conditions in a software model of the real system/equipment. This software can be a deterministic or a probabilistic model which simulates the behavior of the SSC. We chose the probabilistic model for efficiency and explanatory property concerns. The probabilistic model that we propose to use is the ES module, which is already developed and validated. This gives the opportunity to produce as many as required data for the training data set for the NN module. The network for such a classification problem will have input units, hidden layer units, and output units. Each input unit will be associated with one range of the signal from the sensor readings. Each output unit will be associated with one type of SSC operating/fault condition.

The performance and accuracy of the neural network module of the hybrid intelligent system must be tested and validated, too. This will be done by running the module on a test data set. The test data set will be produced in the same manner as the training data set.

### 3.4 Signal processor algorithm

The signal processor element of the health monitoring structure consists of an algorithm which maps the measured signal values to a set of likelihood values. The set of likelihood values define the probability of the relevant feature to be in the low, normal, or high region of observation, given the measurement value. This mapping is accomplished by producing a set of rules and membership functions. This computation involves a fuzzy logic method. The rules are composed of a set of ancestors and consequences. The ancestors are the boundary values of the measurements between the low, normal-medium, and high regions. The consequences are the states of the features. The likelihood values are computed by assigning linear membership functions to the set of rules, in a normalized manner. The likelihood values that are obtained from the signal processor are the inputs to the NN diagnostic, BN diagnostic, and ID advisory models.

## 4. AN APPLICATION EXAMPLE: FAULT DIAGNOSIS IN BEARING SYSTEM OF HIGH ENERGY HORIZONTAL CHARGING PUMP

The first stage application of this methodology is being done on the bearing system of high energy horizontal charging pump, which are important in safe operation of nuclear power plants. The ES module of our methodology is completed and this module is validated on the bearing system mock-up, which is at the Applied Research Laboratory at PennState University. The ES module knowledge base has been prepared with the concept described in Section 3.2, by interviews and file transfer with the domain human experts. The design of the module has undergone much iteration during the development stage. The two models, the diagnostic BN and the advisory ID models, have been finalized. A failure mode of the bearing system, within the advisory model, is shown as an example to dictate the thought concept in this modeling. The complete system structure is very tedious to show in this paper.

Different scenarios for abnormal operating conditions have been prepared. The scenarios involved either single fault conditions, or multiple fault conditions which appear at different locations in the ES structure. These scenarios have been implemented externally on the ES module. The diagnostic model can predict the abnormal condition, specify the place where it starts and point out the initial reasons, and also differentiate between several faulty conditions. The advisory model provides the set of most beneficial actions given the circumstances, and predicts the consequences of its own actions. Both of the models have given the results, as the probabilistic description for the fault states, root causes, the beneficial actions, future state conditions, all consistent with the expectations of the domain experts, and in a much faster and clearer fashion.

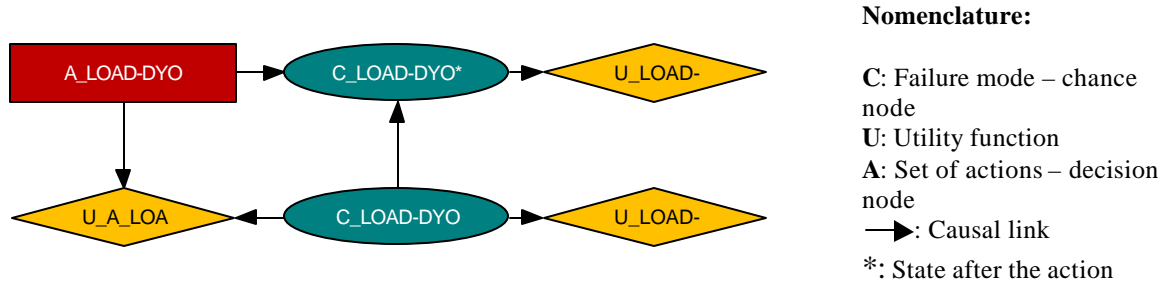


Figure 2: The influence diagram structure in the advisory model – example: Dynamic load failure mode

## 5. CONCLUSION AND FUTURE WORK

In this work, the methodology for a hybrid intelligent system has been developed to forecast future faults and failures, to provide fault diagnosis, and to aid in timely and correct decisions in nuclear power plant operations. The methodology combines selected techniques from the science of artificial intelligence in the hybrid system. The hybrid system holds the desired properties of each individual technique. It performs better than the individual techniques if they were to be implemented alone for this task. The main reason for this is that the hybrid system approach overcomes the limitation of each individual technique, as no technique, by itself, is appropriately applicable to the many sub-problems that occur in the task of real-time fault diagnosis and decision support in complex systems, as in nuclear power plant operations.

We have proposed to combine the knowledge based expert system technology with numerical neural networks, in two parts: ES module and the NN module. The experts systems have the capability to have reasoning and explain the findings to the user, which is a very important aspect that the nuclear power plant operators expect. The techniques we adopt in the ES modules are the Bayesian networks and the influence diagrams. The reason for the choice of Bayesian networks are mainly the valuable features of reasoning under uncertainty, handling both statistical and subjective information, adapting to the changes in the domain and graphically clear representation. The ID helps for decision support as extensions of BN. However, due to computational expense of BN and ID models in large scale systems, we propose to do the real-time diagnostic process within a neural network framework which are computationally efficient and can very well model the non-linear dynamic relations in the physical systems. However, the sufficient size of training data set, in the feature-fault domain, is not available from the currently operating nuclear power plants. The problem of training the NN module is overcome by using the ES module to produce enough data for a high-accuracy diagnostic NN model. Finally, the NN module is computationally more appropriate for use in real-time monitoring of complex systems. The ES module is kept off-line for reasoning and decision making under the same conditions.

This project is an on-going work, initially being applied to the bearing system of a high energy horizontal centrifugal pump for validation. The ES module is completed and validated on the mock-up, which is located in the Applied Research Laboratory at PennState University. The ES module of this work contributes to the USDOE-NERI project Smart Equipment and System Design for Improving the Safety in Future Nuclear Power Plants. The NN module is in development stage and designed at Nuclear Engineering Department at MIT, separately from the NERI project. Our future work will focus on completing the design of the NN module, integrating all the elements in the hybrid structure and validate the complete system. The final model is very promising to remove the burden of analyzing the vast amount of data in nuclear power plant operations, for predictive maintenance and decision making. We acknowledge the NERI Smart Core Management Team for their valuable support in this work.

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