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*Neural Networks and their Application to Nuclear Power Plant Diagnosis

by

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NEURAL NETWORKS AND THEIR APPLICATION TO NUCLEAR POWER PLANT DIAGNOSIS

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ABSTRACT

We present a survey of artificial neural network-based computer systems that have been proposed over the last decade for the detection and identification of component faults in thermal-hydraulic systems of nuclear power plants. The capabilities and advantages of applying neural networks as decision support systems for nuclear power plant operators and their inherent characteristics are discussed along with their limitations and drawbacks. The types of neural network structures used and their applications are described and the issues of process diagnosis and neural network-based diagnostic systems are identified. A total of thirty-four publications are reviewed.

I. INTRODUCTION

Since the early 90's a plethora of computer systems based on artificial neural networks (NNs) have been proposed for nuclear power plant diagnostics [1-34]. However, only a couple of early review articles by Uhrig [1,2] discuss the potential application of this technology to the operation of nuclear power plants. Furthermore, at the time of publication (1991), limited NN research was underway in the nuclear industry and just three applications in plant diagnostics had been reported at that time.

The objective of this study is to provide a more comprehensive survey of computer-based diagnostic systems using NNs that have been proposed for the nuclear industry. Due to the overwhelming number of proposed systems, our review is limited to systems designed for the detection and identification of *component* faults (sensor faults are not discussed) in thermal-hydraulic systems, articles published in English since 1990 that appeared mainly in journals published by the American Nuclear Society and conferences held in the U.S., and systems proposed specifically for the nuclear industry.

The main tasks of the diagnostic systems discussed in this paper are the detection and identification of plant component faults based on the response of monitored thermal-hydraulic signals, such as pressure, flow, temperature, and level. Fault detection establishes the occurrence of a plant anomaly and it is usually accomplished by comparing monitored and expected values of thermal-hydraulic signals. Deviations above a specified threshold indicate the occurrence of an anomaly. Once detected, the identification of faulty plant components can be performed by correlating the deviating signals both in time and space and matching the correlations with patterns of component faults.

The rest of the paper is organized as follows. Section II provides a brief description of neural networks followed by discussions in Section III of the advantages and drawbacks of using this technology for nuclear power plant diagnostics. Section IV presents the types of network structures and the types of applications that have been proposed for diagnosis, followed by a description of the major diagnostic issues in Section V. Finally, in Section VI we provide the conclusions.

II. BRIEF INTRODUCTION TO NEURAL NETWORKS

Artificial neural networks can be defined as nonlinear modeling systems consisting of a number of interconnected processing units or neurons. How the inter-neuron connections are arranged and the nature of the connections determine the structure of the network. How the strengths of the connections, known as the network weights, are obtained during the training phase to achieve a desired overall behavior of the network is governed by the training algorithm. There are many different types of network structures and for each structure type there are a large number of training algorithms.

The most widely used type of network structure, both for nuclear power plant diagnostics and other applications, is the feedforward multilayer network (also known as the multilayer perceptron) with the backpropagation algorithm used as the training method. In a multilayer feedforward network, the neurons are arranged in layers and the information signals flow via unidirectional connections from the input layer to the output layer through hidden layers. Feedforward multilayer networks have been classified as universal approximators since mathematical proofs have been derived [35] that show that this type of network structure, using arbitrary squashing functions for mapping the network neurons can approximate virtually any function of interest to any desired degree of accuracy, provided sufficiently many neurons are represented in the hidden layers of the network. The standard backpropagation training algorithm [7,30] is based on gradient descent where the network weights are iterativelly updated such that the difference between the network predicted and target values is minimized.

Most of the applications of NNs for diagnostics use the feedforward network structure with some variation of the backpropagation training algorithm [3-9,11-12,14-18,21-22,24,26-33]. Among the other types of network structures proposed for diagnostics are the Kohonen self-organizing network [8-9,13], the perceptron-like network [10], the temporal network [25], the probabilistic network [19], the Boltzman machine [20], and radial basis function network [23]. For a detailed description of most of these network structures and associated training algorithms the reader should refer to any NN book.

III. ADVANTAGES AND DRAWBACKS

Inherent in the neural networks methodology and their application to plant component diagnostics are noticeable advantages and drawbacks. Among the most noticeable advantages and capabilities, we may include their general purpose nature which allows for a wide range of applications, their capability to provide real-time responses once trained, their ability to generalize from trained examples, and their ability to recognize faulty component patterns even when the information comprising these patterns is noisy, sparse or incomplete. It is the generalization capability of NNs that enable them to correctly classify pattern containing noise [18]. Also, the non-algorithmic nature of NN simulations makes it possible to model complex system when only data of system inputs and outputs are available [8].

Among the most noticeable limitations and drawbacks, we may include the fact that the training process is time consuming and requires large amounts of training data the quality of which strongly affects the success of the approach. When used for transient classification, it is necessary to *anticipate* all possible transient scenarios and use them for training. Scale-up to include additional transient scenarios cannot, in general, be performed incrementally and involves the modification of the network architecture and retraining of the entire system from scratch. Neural nets also lack explanation facilities and cannot explain the decision path of the underlying knowledge base. Also, the advantage of NNs to generalize from trained examples and perform inferences when the input data are beyond the scope of their knowledge can have negative consequences. For instance, a feedforward network might incorrectly give a classification answer with high confidence for a new type of transient on which it has never been trained [19].

IV. STRUCTURES AND APPLICATIONS.

Many different types of network structures have been proposed for various applications in the detection and identification of plant component faults. In addition to stand-alone NN-based systems, numerous diagnostic systems have involved the use of two or more networks and the combination of NNs with other computational tools in the development of hybrid diagnostic systems. In this section we present the types of network structures that have been proposed for diagnostics and discuss the types of applications used within each structure type. We also present the various diagnostic system architectures involving the use of multiple networks and hybrids of NNs with other computational tools.

The vast majority of the proposed systems use the feedforward network architecture [3-9,11-12,14-18,21-22,24,26-33] with different variations of the backpropagation training algorithm. Variations of the standard backpropagation algorithm were suggested to eliminate the excessively long training time required to obtain acceptable errors [22,28-31], the selection of training parameters [29-31], the occurrence of premature saturation of the network output neurons [28-31], and the selection of the number of neurons in the hidden layer [16-18]. Feedforward networks have been used primarily as a transient classification tool to detect and identify a set of prespecified component failures [5-9,11-12,14-18,22,24,26-33]. Given data representing the values of a set of sensor measurements (the input to the network), the network classifies the data into one or more transient classes (the output of the network) learned during the network training phase.

A couple of other applications of feedforward networks have also been proposed. For instance, in addition to transient detection and identification, Jeong et al. [32] applied this type of network to estimate the severity level of the transients. Lin et al. [21] and Hines et al. [3-4] independently proposed the use of feedforward networks exclusively for fault detection (not identification). Neural networks were used to classify the discrepancy or residue between measured plant signals and expected behavior calculated by reference simulation models.

Among the other types of network structures we may include the Kohonen self-organizing network proposed by Guo and Uhrigh [8-9] to pre-process transient data and classify the time-dependencies into clusters. The properties of the clusters were then used as diagnostic features for transient classification. Kohonen nets were also used by Furukawa et al. [13] for transient feature selection. Xing and Okrent [24] used an unsupervised clustering network to pre-process transient data of anticipated transients without scram in boiling water reactors. Ragheb and Campos [10] used perceptron-like networks for classifying pipe break sizes, and Uluyol and Ragheb [25] applied temporal networks to recognize time-dependent patterns of transients. Bartal et al. [19] proposed the use of probabilistic nets to classify unknown transient events as "don't know." Marseguerra and Zio [20] proposed the use of the Boltzman machine for transient classification and Renders et al. [23] used radial basis function networks to predict the values of variables that were not measured from directly measured variables, which were then used to detect plant anomalies.

In addition to stand-alone network architectures, multi-level hierarchical structures of NNs and modules of double networks arranged in series and in parallel have also been proposed. For instance, Guo and Uhrig [8-9] used a self-organizing network to pre-process the original transient data and reduce the number of training patterns, followed by a modular structure of modified feedforward networks that eliminate the difficulty of training the networks with many transients [8]. A similar approach was suggested by Xing and Okrent [24] through a two-level hierarchical structure. At the first level, a clustering network was used to pre-process the data which was then provided to a feedforward networks, at the second level, for transient classification. Jeong et al. [15] used modules of double feedforward nets arranged in parallel with feedback from one net to the other to discriminate between two transients with similar pattern signatures. Basu and Bartlett [18] proposed a two-level hierarchical structure of two feedforward networks to reduce the size of the classification problem and Reifman et al. [26-27] suggested a multi-level array of feedforward networks that use the thermal-hydraulic characteristics of the plant components during normal operation to discriminate among possible faulty component candidates. At the first level, networks would be used to separate out different component types that perform equivalent functions, e.g., open valves and pumps, and at the lower levels, networks would be used to separate out different specific components of the same type, e.g., gate valve vs. globe valve, and gate valve 1 vs. gate valve 2.

To alleviate some of the limitations of NNs for component diagnostics, hybrid diagnostic systems involving the combination of NNs and other computational tools have been suggested. For example, the combination of NNs and expert systems in a two-level hierarchical architecture has been reported by different researchers. Reifman et al. [26-27] suggested the use of an expert system followed by an array of NNs where the purpose of the expert system is to generate hypothesis about the possible failures which are then tested by an array of networks to identify the faulty component from the hypothesized candidates. In contrast, Ohga and Seki [6] suggested the use of feedforward networks at the first level, followed by an expert system. In the first level, the network receives analog data and hypothesizes about the possible component faults and in the second level, the expert system with a heuristically constructed knowledge base receives the network diagnosis and confirms the results using digital data of the plant status. Hybrids of numerical simulation programs and NNs have been proposed for transient detection [3-4,21]. In this approach, simulation programs are used to represent reference models and NNs are used to classify the residue between measured plant signals and expected behavior calculated by the reference simulation models.

V. DIAGNOSTIC ISSUES

The diagnostics of component faults in nuclear power plant systems is a very complex process due most prominently to the possible occurrence of multiple faults, limited amount of instrumentation, transient dynamics, and noise in the measured signals. In addition to these issues inherent in plant diagnostics, new issues arise as diagnostic methodologies are coded into software in the development of computer-based diagnostic systems [3-4]. The main issues of plant diagnostics and NN-based diagnostic systems are summarized below.

Multiple Component Faults. The occurrence of multiple component faults closely spaced in time and space is difficult to detect and identify because of the possibility of one component fault partially or completely canceling out the effect of another on the measured plant signals. Furthermore, because each transient event needs to be explicitly represented when NNs are used for transient classification, it may become impractical to use NNs for the diagnosis of multiple component faults due to the large number of possible fault combinations that need to be represented. To circumvent this combinatorial explosion, some NN approaches have attempted to diagnose multiple faults based solely on the representation of single component faults [7,22].

Transient Dynamics. Since transient events evolve in time, the diagnostic procedure needs to account for the thermal-hydraulic time constants of the plant systems [34]. For the types of NN structures proposed so far for plant diagnostics, temporal information needs to be explicitly represented in one of two approaches. In one approach, a few snapshots in time are employed to represent the entire history of each transient event in the training database [6,16-18,24,30-31,33] where the number of necessary snapshots is sometimes obtained in an iterative fashion [16-18,33]. As long as care is taken to select snapshots representative of the entire transient, this approach should be adequate to handle the transient dynamics. In another approach, the entire time history of the transient is employed [8,10,12,15,22,25,32] which increases the already time-consuming process of NN training.

Corrupted Signal Observation. Advisory systems are expected to operate under real plant conditions where the plant signals are corrupted with noise. The intrinsic ability of NNs to filter noisy data while preserving its structure and detail is perhaps one of the major advantages of using NNs for fault detection and identification. The majority of the reviewed articles discuss the diagnosis performance of NNs with noise added to the data [5-7,10-12,15-18,20,22,24-25,32] and concluded that NNs can successfully classify transient events when a 10% noise (equivalent to approximately 3 standard deviations) is present in the data. The results also indicate that NNs trained with input noise appear to become less sensitive to input noise in the test data [12,17].

Verification & Validation (V&V). Verification is the process of determining whether or not the system is working as designed and validation is the process of evaluating whether or not the system performs its intended function, i.e., arrives at the correct answer. Incorrect inferences made by software systems during a plant emergency condition could confuse and mislead operators with the potential to produce catastrophic consequences. This possibility is perhaps greater with NN-based software than with conventional simulation programs since NN-based systems will provide answers even if the question is beyond the scope of their knowledge [19]. Clearly, one of the V&V challenges of NN-based advisory systems is to be able to delineate the boundaries and determine the functional correctness and completeness of their knowledge. However, except for the work of Kim and Bartlett [33], no other efforts have been made in the nuclear community to study the V&V issues of NNs.

VI. CONCLUSIONS

Neural networks were initially applied in the diagnosis of component faults in nuclear power plant systems as a classification tool for the direct mapping of plant signals into component faults. Due to the need to anticipate the possible fault scenarios and the availability of the associated transient data for training purposes, this use of neural networks is undesirable when applied to complex plant systems composed of a large number of components each of which having different failure modes. More recently, neural networks have been applied to the characterization of normal operating plant conditions and transient data pre-processing, and have been combined with other computational tools in the development of hierarchical multi-level diagnostic systems. The synergism of hybrid computer systems combining neural networks with other computational tools have the potential of addressing some of the major challenges in nuclear power plant diagnostics Future research should concentrate in the development of V&V methodologies to delineate the boundaries of the knowledge base of neural networks and to provide error bounds for their inferences.

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