Application of Dynamic Neuro-Fuzzy Network to Nuclear Power Plant Accident Diagnosis including Wrong Signal Detection

Seung Jun Lee, Poong Hyun Seong
Nuclear & Quantum Engineering, Korea Advanced Institute of Science and Technology, 373-1 Guseong-dong, Yuseong-gu Daejeon, Korea 305-701, sjlee@niclab.kaist.ac.kr, phseong@kaist.ac.kr

1. Introduction

The main control room (MCR) operators in a nuclear power plant (NPP) have a supervisory role in terms of information gathering, planning, and decision making. During abnormal conditions or situations in which an accident has occurred, the operator's task is to comprehend a malfunction in real time by analyzing alarms, values or trends of multiple instruments, and so on. For a correct and prompt diagnosis of current plant status, operators should perform diagnostic tasks by observing instruments that clearly show the current state. In a NPP, there are many instruments that indicate the status of the plant. While an analysis of all instruments is the best way to ensure a correct diagnosis, the number of instruments makes it impossible for operators to look at each one individually. An accident diagnosis system is a kind of operator support system. The objective of an accident diagnosis system is to make the task of accident diagnosis easier, to reduce errors, and to ease the workload of operators by quickly suggesting likely accidents based on the highest probability of their occurrence. During the first few minutes after an accident occurrence, operators in a MCR must perform highly mentally workloaded activities. The operators may be overworked and disorder may result. Information overload and stress may severely affect the operators' decision-making ability just when it is required most [1]. In such situations, using an accident diagnosis system for the early detection of problems will be very helpful in that it will enhance operators' decision-making ability and reduce their workload. In fact, this kind of operator support system has already been developed [1,2,3].

2. Accident Diagnosis using Dynamic Neuro-Fuzzy Network

One of the critical issues for accident diagnosis systems is their level of reliability because, without a high level of reliability, operators will not trust their accident diagnosis system. When an accident diagnosis system gets the wrong inputs because of failed instruments or devices, undesirable outputs could be generated. If operators must always consider such misdiagnoses, the accident diagnosis system is meaningless. In fact, in accident diagnosis systems already developed, wrong signals affect results and sometimes lead to misdiagnoses. The accident diagnosis system proposed in this work suggests a possible accident list with the probability for each accident in the list to the operator. Also it identifies instruments which are estimated to be failed and warns them to the operator.

2.1 Dynamic Neuro-Fuzzy Network

The neuro-fuzzy network has the learning capacity of neural networks and the inference capacity of fuzzy methods [4]. One special feature of the neuro-fuzzy network is that important variables of rules and fuzzy functions are determined by trainings. The structure of the neuro-fuzzy network is shown in Figure 1. The neuro-fuzzy network consists of three layers: a fuzzifier layer, a fuzzy function layer, and a defuzzifier layer. Inputs are transformed into fuzzy variables according to rules in the fuzzifier layer. In the fuzzy function layer, outputs are calculated with the transformed variables and fuzzy functions. The results of fuzzy functions are defuzzified and final results are generated in the defuzzifier layer.

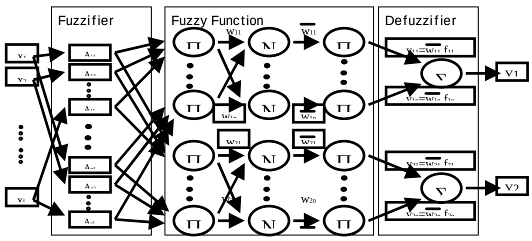

Figure 1. Structure of the Neuro-Fuzzy Network

The dynamic neuro-fuzzy network (DNFN) is used to identify accidents. The DNFN analyzes dynamic processes [5,6]. Feedbacks at the previous step are used for part of the inputs at the current step. The DNFN contains four layers as shown in Figure 2: an input layer, a fuzzification layer, a fuzzy function layer, and a defuzzification layer. Basically, the DNFN is based on the neuro-fuzzy network, so the equations used in the DNFN and the calculation processes are the same as those of the neuro-fuzzy network. In the DNFN, variables used in the neuro-fuzzy network are converted into time functions, and equations for the feedbacks are added.

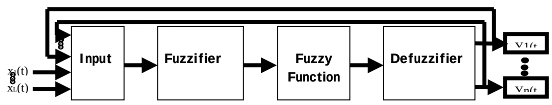

Figure 2. Structure of the DNFN

2.2 Wrong Signal Detection using Reversed Neural Networks

For accident diagnosis, wrong signals which are caused by failed instruments or by some other reasons could be main reasons of misdiagnosis. Such wrong signals may cause incorrect situation assessment. Even if inputs include wrong signals, the system proposed here is able to perform diagnosis but with less accuracy. If there is a function to detect and give warning on the wrong signals, it will be very useful for preventing operators' wrong situation assessment.

In this work, the function for detecting wrong signals was implemented using the DNFN reversely. The reversed neural networks are trained by the same data as those of the DNFN. One different thing is that the outputs of the DNFN are used as inputs in reversed networks and the inputs of the DNFN are used as outputs in reversed neural networks in the neural network training stage. Plant parameters are used as the inputs of the DNFN. The results of diagnosis for the current situation are generated as the outputs. On the other hand, in reversed neural networks, the results of the DNFN are used as inputs and the estimated plant parameters for the current situation are generated as results. Wrong signals can be detected by comparing these results with the actual plant parameters of the current situation. The concept of the reversed neural network is shown in Figure 3. After obtaining predicted plant parameters, each output of the reversed neural networks is compared with actual plant parameter of the current situation. Then the reliability of the output is calculated according to the difference in values of the two variables.

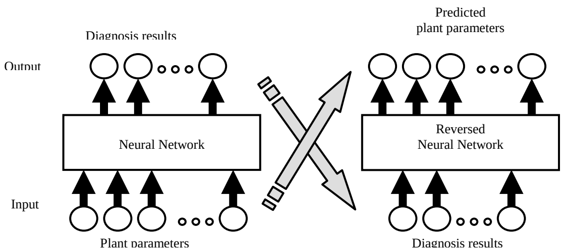

Figure 3. Reversed Neural Network

3. Conclusion

In this work, an accident diagnosis system including a wrong signal detection function is developed. For accident diagnosis, wrong signals which are caused by failed instruments or by some other reasons could be main reasons of misdiagnosis and they may cause incorrect situation assessment. The system proposed here identifies accidents using the DNFN, and detects wrong signals by reversed neural networks. In reversed neural networks, the results of the accident diagnosis are used as inputs, and estimated plant parameters for the current situation are generated as results. Wrong signals could be detected by comparison the results with actual plant parameters of the current situation. The wrong signal detection function can reduce operators' failure in situation assessment by detecting wrong signals and informing them to the operator.

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