Proceedings of the Korean Nuclear Society Spring Meeting
Gyeongju, Korea, 2004

Development of an Accident Diagnosis System using a Dynamic Neural Network for Nuclear Power Plants

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Abstract

In this work, an accident diagnosis system using the dynamic neural network is developed. In order to help the plant operators to quickly identify the problem, perform diagnosis and initiate recovery actions ensuring the safety of the plant, many operator support system and accident diagnosis systems have been developed. Neural networks have been recognized as a good method to implement an accident diagnosis system. However, conventional accident diagnosis systems that used neural networks did not consider a time factor sufficiently. If the neural network could be trained according to time, it is possible to perform more efficient and detailed accidents analysis. Therefore, this work suggests a dynamic neural network which has different features from existing dynamic neural networks. And a simple accident diagnosis system is implemented in order to validate the dynamic neural network. After training of the prototype, several accident diagnoses were performed. The results show that the prototype can detect the accidents correctly with good performances.

1. Introduction

A nuclear power plant (NPP) is a complex engineering system consisting of several interdependent processes. A typical main control room (MCR) of a NPP has more than a thousand of alarms which are a major information source used to detect a process deviation. The role of operators is a supervisory task of information gathering, planning and decision making. During an abnormal or accident condition, the information overload and stress on the operator may severely affect the decision-making ability, when it is required most. In emergency situations such as a loss of coolant accident (LOCA) and a steam generator tube rupture (SGTR), hundreds of lights turn on or off within the first minute. In such emergency situations, the operator's task is to comprehend a malfunction in real time by analyzing alarms turned on, values or trend of many instruments, and so on [1]. Since many alarms which turn on and off repeatedly can cause operators' confusion, an operator support system can be useful for the operators' accident management. In order to help the plant operators to quickly identify the problem, perform diagnosis and initiate recovery actions ensuring the safety of the plant, many operator support system and diagnosis systems have been developed.

2. Accident Diagnosis System

An accident diagnosis system is a kind of operator support systems. The objective of an accident diagnosis system is to make operators' accident diagnosis task easier and to reduce errors and workload of operators by quickly suggesting an accident which has highest occurrence probability. During first a few minutes, after accident occurrence, operators in a MCR should perform high mental workloaded activities such as monitoring plant status, diagnosing the accident and finding the causes of the accident. Operators in a MCR may get high workload and sometimes fall into disorder. In such situations, it becomes difficult task to analyze the current situation and to find causes of the accident. Therefore, the early detection by accident diagnosis systems can be very helpful to operators' decision making and workload reduction.

In fact, many accident diagnosis systems have been already developed [1],[2],[3],[4]. The systems can be categorized largely into two systems; knowledge-based systems and neural network-based systems. For the former systems, it is important to construct knowledge base about all possible faults in a NPP. For instance, these systems may not generate correct results, if unexpected faults occur. On the other hand, the latter accident diagnosis systems are trained by examples, so knowledge data are not necessary. These systems have an ability to handle unexpected faults.

The neural network can be an efficient method not only for inference engine in the accident diagnosis systems, but also for pattern matching. The neural network has an ability to learn from actual results without requiring explicit rules and extensive human efforts, and an ability to function with slightly different inputs or noisy inputs. The operator's task of comprehending a malfunction can be viewed as a form of pattern recognition. In addition, in order to develop diagnosis accidents, unexpected possible cases should be considered. Therefore, the neural network is regarded as a power tool, since it is good at pattern matching and informal input handling.

However, conventional accident diagnosis systems did not consider a time factor sufficiently. The outputs of conventional accident diagnosis systems are updated every time step, because input of the networks are changed every time step. In this case, the systems always repeat same calculations, because time factor are not considered in these systems. These systems can diagnose accidents roughly, but they cannot perform detailed analysis. That is, these systems can give the information to operators what this accident is such as LOCA or SGTR, but detailed information like the rupture size or position cannot be obtained by these systems. Therefore, this work proposes the accident diagnosis system in order to make up for the weak points in these accident diagnosis systems.

3. Dynamic Neural Network

Neural networks which have a good capability for alarm pattern analysis can be a good method to implement an accident diagnosis system, since almost all accidents have their own alarm patterns. For example, hot leg LOCA, cold leg LOCA, and SGTR have quite different alarm patterns. The accidents also have much different alarm patterns according to their size.

Therefore, neural networks could be an efficient method in an accident diagnosis system because of their capability for alarm pattern analysis. However, there are some problems to implement an accident diagnosis system using existing neural networks.

Basically, neural networks are useful especially when the rules of knowledge base are inaccurate, informal, too large, and complex, since such rules are not necessary in neural networks. Typical neural networks such as Perceptron and Hopfield network have weak points for solving dynamic and complex problem, since they are just used for static situations. It means that it is difficult to apply typical neural networks to dynamic situations. Therefore, a neural network which has an ability to handle continuously varying situations is needed to implement an accident diagnosis system.

If the neural network is trained according to time, more efficient and detailed accidents analysis can be performed using same inputs. Since each accident has its own feature such as different sequences and different occurrence time. Also an ability to handle wrong inputs or noisy signals can be enhanced.

Dynamic neural networks are proposed to solve the problems of typical neural networks related to the dynamic aspects. Generally, the dynamic neural networks are used for prediction of next or future states as a solution of optimal controls of nonlinear problems [5]. Dynamic neural networks usually have time-varying weight factors and use feedbacks of previous step’s outputs to handle nonlinear problems with large network sizes and long training times. Dynamic neural networks can be also modified, depending on the objectives.

4. Dynamic Neural Network for Accident Diagnosis

In this work, a modified dynamic neural network is proposed for an accident diagnosis system.

There are some problems to implement an accident diagnosis system using existing dynamic neural networks. The most important problem is that existing dynamic neural networks use the feedbacks of outputs at the previous time step for the inputs at the current or the next time step. If an incorrect output is generated at a certain time step, it may affect the calculation of outputs at the next time step and make incorrect results again.

In the accident diagnosis system, even if small deviation of inputs may propagate and eventually cause incorrect results because many accidents have very similar input patterns. Therefore, in order to implement an accident diagnosis system, we need a modified dynamic neural network which can compensate the deviations.

Basically, the dynamic neural network suggested in this work is based on the multi-layer perceptron. The network has three distinguishable features; time-varying weight factors and offsets, the final output layer, and the calculation method to obtain outputs. The structure of the dynamic neural network is shown in Fig.1.(a).

Firstly, in the dynamic neural network, all weight factors and offsets are the functions of time which have different values at each time step. That is, the dynamic neural network can be regarded as an assembly of many static neural networks for each time step as shown in Fig.1.(b). The values of weight factors and offsets are independent of values at other time steps.

Secondly, the dynamic neural network has one additional layer to the multi-layer perceptron, that is, final output layer. The units in hidden layer and output layer have the time functions for offsets and the units in final output layer have offset values. While the analysis for each time step is performed in the former two layers, the final decision is made regardless of time step in the latter layer. If one or more alarm signals are generated wrong at some time steps, the output values probably become wrong. These undesirable values can propagate through the iterative process, and finally cause an inaccurate result. These wrong values can affect the final output values, so a wrong decision will be generated. To prevent it, the consistency of values of the output layer should be considered in final output. This dynamic neural network uses an average of normalized output values.

Lastly, in the dynamic neural network, the output of current time step is obtained considering networks of not only the current time step, but also the previous and the next time step. An input of training scenarios will not be same as that of real accidents at exactly same time step. Time deviations about alarm occurrences will probably exist, so the dynamic neural network should consider the deviations. Therefore, in the dynamic neural network, for obtaining an output, networks of previous and next time steps are also used.

The calculation process is shown in Fig.2. Outputs of these networks are calculated by sigmoid function which is to give relative importances to the outputs, and finally maximum value is selected.

The equation (1) represents the sigmoid function used in this system.
x: difference between a current time step and a target time step
w: considering range

$$f(x) = \frac{1}{1 + \exp\left(10 \times \left(\frac{2x}{w} - 1\right)\right)} \quad \text{--} \ (1)$$

5. Prototype

A prototype for an accident diagnosis system was implemented using the dynamic neural network. And the prototype is trained and validated using a simulator. Firstly, the dynamic neural network in the prototype was trained by accident scenarios obtained using the simulator. Four accidents were selected for training: LOCA, SGTR, SLB, and FLB. The dynamic neural network of the prototype was trained by 44 accident scenarios as below. We can set accident size for each accident. For example, LOCA has 10 sizes from 1 to 10. The network in this system is trained for only accidents which have even number sizes, because we can validate this system by results of simulations for accidents about odd number sizes.

The prototype has 45 inputs and 44 outputs, and is trained by 44 training cases.

- 45 inputs
  - 19 alarms
  - 26 trip parameters

- 44 outputs
  - Hot leg LOCA – Loop A and B, size 2, 4, 6, 8, and 10: 10 cases
  - Cold leg LOCA – Loop A and B, size 2, 4, 6, 8, and 10: 10 cases
  - SGTR – Loop A and B, size 2, 4, and 6: 6 cases
  - SLB – Loop A, B, and Header, size 2, 4, 6, 8: 12 cases
  - FLB – Loop A and B, size 2, 4, 6: 6 cases

- 44 training cases
  - Hot leg LOCA – Loop A and B, size 2, 4, 6, 8, and 10: 10 cases
  - Cold leg LOCA – Loop A and B, size 2, 4, 6, 8, and 10: 10 cases

- SGTR – Loop A and B, size 2, 4, and 6: 6 cases
- SLB – Loop A, B, and Header, size 2, 4, 6, 8: 12 cases
- FLB – Loop A and B, size 2, 4, 6: 6 cases

After training, five accident diagnoses were performed. First three accidents include the even size of ruptures, and last two accidents include the odd size of ruptures. The results of the accident diagnoses are shown in followings;

Accident 1: Hot leg LOCA, Loop A, size 10
- Hot leg LOCA, Loop A, size 10: 0.924
- Hot leg LOCA, Loop A, size 8: 0.462
- Hot leg LOCA, Loop B, size 10: 0.342
- Hot leg LOCA, Loop B, size 8: 0.323
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Accident 2: SLB, Loop A, size 4
- SLB, Loop A, size 4: 0.943
- SLB, Loop A, size 2: 0.629
- SLB, Loop B, size 4: 0.376
- SLB, Loop A, size 6: 0.365

Accident 3: FLB, Loop B, size 6
- FLB, Loop B, size 6: 0.937
- FLB, Loop B, size 4: 0.569
- FLB, Loop A, size 6: 0.465
- FLB, Loop A, size 4: 0.399

Accident 4: Cold leg LOCA, Loop B, size 7
- Cold leg LOCA, Loop B, size 8: 0.756
- Cold leg LOCA, Loop B, size 6: 0.721
- Cold leg LOCA, Loop B, size 10: 0.582
- Cold leg LOCA, Loop A, size 8: 0.539

Accident 5: SLB, Loop B, size 7
- SLB, Loop B, size 8: 0.772
- SLB, Loop B, size 6: 0.734
- SLB, Loop A, size 8: 0.579
- SLB, Loop B, size 4: 0.491

As shown in above results, this prototype showed quite good performances in first three simulations, since for the first three accidents, the sizes of accidents in the tests are identical to those of the training scenarios. In other two tests, the odd size of accidents, this prototype showed reasonable results, even if the size of accidents in the tests were not previously trained.

6. Conclusions

This work suggested the dynamic neural network for more efficient accident diagnosis systems.

Conventional accident diagnosis systems do not consider a time factor sufficiently, so these systems cannot perform detailed analysis. The accident diagnosis system proposed in this work is to cope with the weak points in these accident diagnosis systems. If the neural network is trained according to time, more efficient and detailed accidents analysis can be performed using same inputs. Therefore, we modified the dynamic neural network to be suitable for the accident diagnosis and applied it to accident diagnosis. The dynamic neural network used in this work has different distinguishable features; time-varying weight factors and offsets, the final output layer, and the calculation method to obtain outputs.

If the dynamic neural network in an accident diagnosis system is trained by scenarios of various accidents according to their sizes and accident occurrence positions, the accident diagnosis system can perform detailed accident analysis by real-time and show the accident with highest probability at current time step as far as the scenarios of the accidents are in training scenarios.

A simple accident diagnosis system was implemented using the dynamic neural network for the feasibility study. After training of the prototype, five accident diagnoses for some accidents were performed. In the simulations, the prototype was able to detect the correct accidents with good performances. This accident diagnosis system is close to multiple alarm processing system. Because this system is just a prototype, its input patterns for analyzing accidents consist of only alarms and trip parameters. In order to make more reliable and efficient accident diagnosis system, much more variables such as values and trend of instruments should be considered.

7. References

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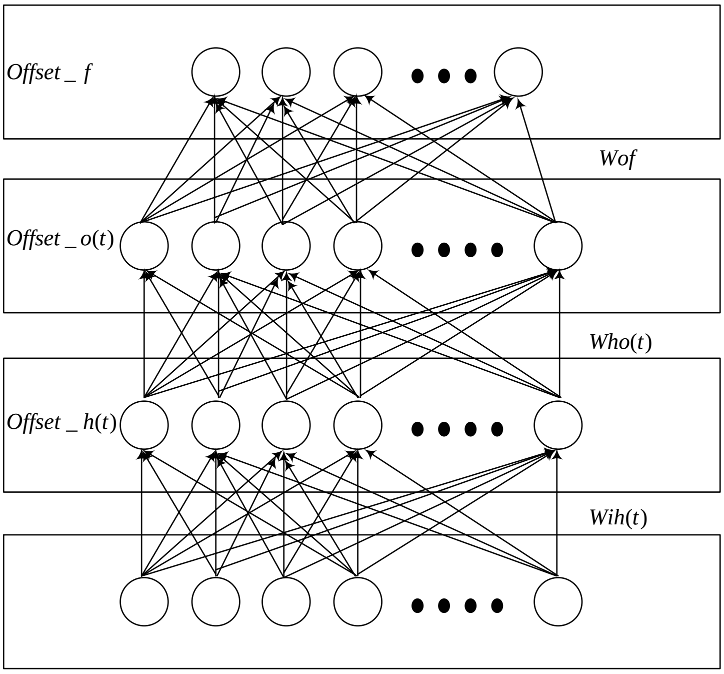
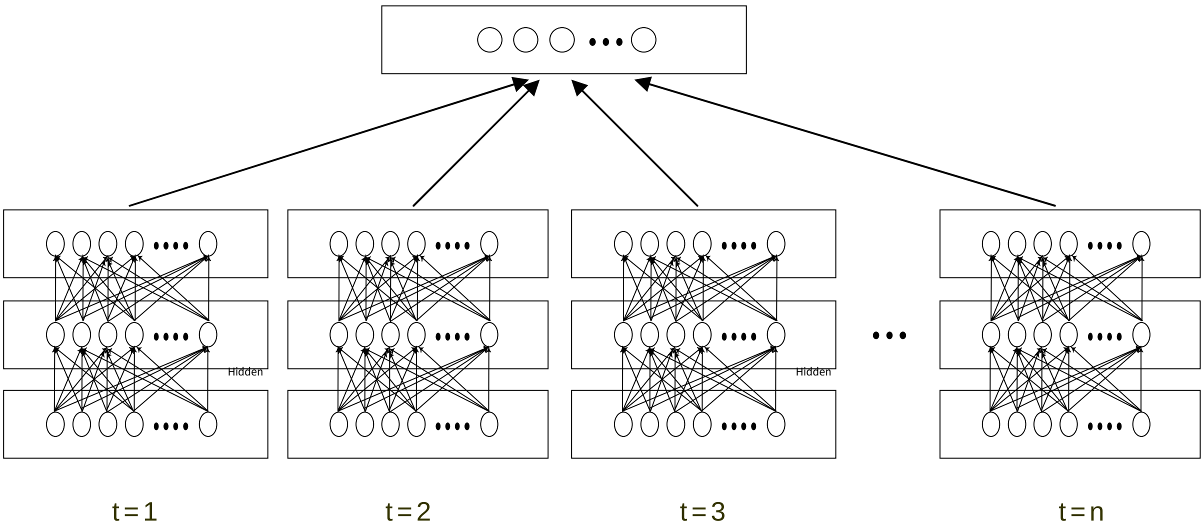


(a)



(b)

Fig.1. The structure of the dynamic neural network

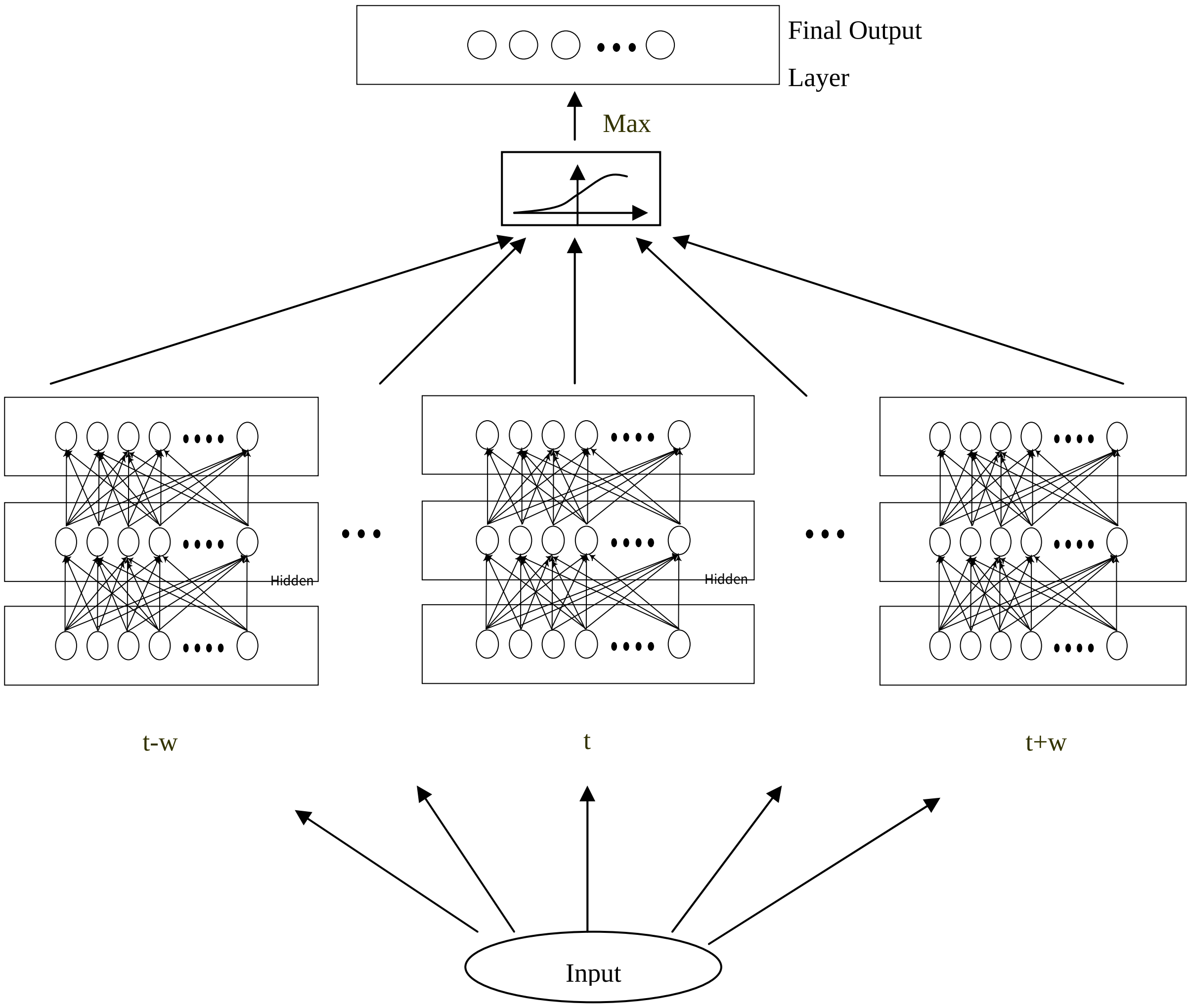


Fig.2. An output calculation at time step ‘t’