Suggestion of a RNN-based Plant Diagnosis System for Extreme Situations in Nuclear Power Plants

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Abstract: The safe operation of nuclear power plants (NPPs) is a common goal for all nuclear industries. NPPs sometimes face with tiny events or rarely encounter accidents which are more severe than events. But events and accidents will not largely spread by well-activating safety systems and by correctly diagnosing and controlling the plants by the operators. Nevertheless, accidents including severe accidents have occurred only once in a while which caused by combining problems of human errors, natural disaster, failure of systems, etc. Therefore, the researches of preventing and mitigating those accidents have to keep going on future.

In this paper, we focused on diagnosing the initiating events or accidents in order to help main control room (MCR) operators and technical support center (TSC) members. In addition, we considered not only diagnosing the initiating events or accident but also giving the information about malfunctioning instrumentations in real time by comparing signal trends of each instrumentation to MCR operators and TSC members. We designed the recurrent neural network (RNN)-based plant diagnosis system for giving information to MCR operators and TSC members and also we conducted the case study to verify the suggested system. Moreover, we compared the suggested RNN-based system with traditional rule-based expert system.

Keyword: Recurrent neural network, Operator support system, extreme situation, severe accident

1 Introduction

The safe operation of NPPs is a common goal for all nuclear industries[1]. Many research areas including not only nuclear engineering but also mechanical engineering, electrical engineering, physics, etc. have been studied to make NPPs safe. Nevertheless, lots of events and small accidents have occurred consistently since NPPs were started to generate the electricity. Moreover, severe accidents have occurred three times in the history even though NPPs have been safely constructed, cautiously maintained, and securely operated. Hence events and accidents may occur inevitably from small events to severe accidents.

Operators follow abnormal operating procedure (AOP) or emergency operating procedure (EOP) respectively depending on the situation. But if EOP couldn't prevent and mitigate the accident, the core may be damaged. From that time, the responsibility is shifted from EOP to severe accident management guideline (SAMG). Decision-making procedure is necessarily required at this time to establish strategies step by step because SAMG doesn't give the accurately correct answer to mitigate the core like EOP.

Because of the weakness of SAMG, several approaches have been studied. JH Moon and CS Kang (1999) suggested fuzzy based decision making support system[2]. Not only the fuzzy based system but also expert systems such as SAMOS (Vayssier et al., 2003), ADAM (Zavisca et al., 2002), SAMEX (KAERI, 2010) have been suggested to support the operators to mitigate the severe accident[3]. These are quite good systems but they are rule-based system. They also have strong points to mitigate the accident by following rules but accident scenario designers have to input all accident sequences and each symptom directly into their database. It is impossible to cover the infinite scenarios and to put the all scenarios because all severe accidents are beyond design based accident.

Decision making support systems which are also called accident management support tools

(AMSTs) are composed of three steps: tracker, predictor, and decision making support[4]. In this paper, we focused on the tracker step which main tasks are discerning the accident initiators, speculating size of postulated breaks, detecting the location of postulated breaks and failures, etc. If we want to bisect accident's sequence in NPPs, the first step is to prevent core damage and the next step is to mitigate the accident sequence. Researches about event identification, fault detection, plant diagnosis, etc. are closer to the preventive step. These researches have been conducted from early 90s but they have been focused on the accident of the transient progress. Diagnosing plant status, detecting initiating event, etc. may be more important in the prevention domain but this process is also needed in the mitigation domain. According to Man Gyun Na, it is important for operators and technical staffs to find out what an initiating event of a severe accident is by observing initial short time trends of major parameters in order to effectively accomplish severe accident management strategies[5]. And since plant operators are provided with only partial information so it is very difficult for operators and TSC members to predict the progression of the events by staring at temporal trends of some parameters on large display panels in the MCR and TSC[5]. In addition, potential wrong diagnosis of the initial accident in preventive domain can be possible[6].

Not only diagnosing initiating event but also recognizing the state of each instrumentation is also important. If the accident caused by extreme hazard occurs, it will arise multiple hardware failures that can affect equipment to malfunctioning[7]. Therefore, providing the information about state of each instrumentation for operators and TSC members is also very helpful to mitigate the accident in the extreme situation.

In this paper, we are going to discuss about RNN-based plant diagnosis system for extreme conditions. First, we will deal with RNN in detail. Next, we will do the case study with constructed RNN based model and we will compare between a developed RNN-based system and traditional expert-based systems for diagnosis plant status.

2 Comparing rule-based system with neural network-based system

2.1 Neural network

Neural network was firstly introduced by Warren McCulloch and Walter Pitts in 1943[8]. After that suggestion, lots of neural network related researches were conducted for several decades. However, neural network related researches have critical problems they cannot have been demonstrated because the lowness of computer performance and the lack of data. So neural network related researches just have been laid the theoretical study. After early 2010, these researches began to study vibrantly because of the improving of the computer GPU performance and generating tremendous data called big data.

The simple structure of three layers neural network is represented in figure 1. Neural network is composed of input layers, hidden layers and output layers. Each layer is connected with edge respectively. Neural network can find the optimal output through iterating of feedforward networks and backpropagation. All edges have their own weights respectively. The weight of each edge is calculated by applying its activation function to a weighted sum of the values of its input nodes.

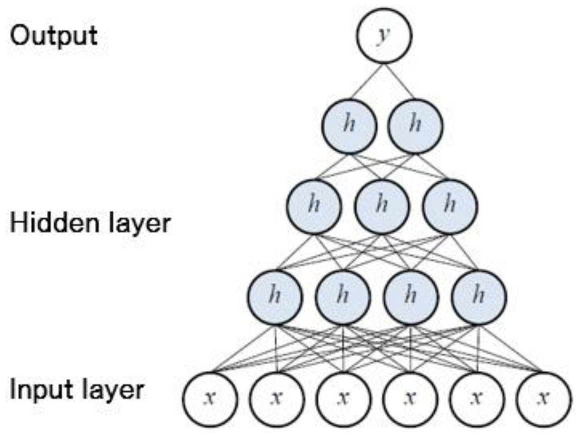

Fig. 1 A structure of three layers neural network.

Then, this neural network shows calculated value through output nodes. This process is called feedforward networks. Backpropagation is the process of updating the weights on each edge respectively. It uses the chain rule to calculate the derivative of the loss function with respect to each parameter in the network. The weights are then adjusted by gradient descent.

There are lots of gradient descent methods for error backpropagation to minimize a loss function such as stochastic gradient descent, momentum, adaptive gradient, and adaptive gradient, etc. Anyway, the main purpose of feed forward neural network is to calculate with some functions using input data and find the output value through hidden layer. And the purpose of the backpropagation is to update the weights of each edge in order to make more precisely.

2.2 Recurrent neural network

In a conventional neural network that all inputs and outputs are independent of each other. But some tasks, sequential information, are not appropriate for training with conventional neural network. However, RNNs can be useful for dealing with sequential information. They perform the same task for every element of a sequence, with the output being depended on the previous computations. They have a 'memory' which captures information about what has been calculated so far.

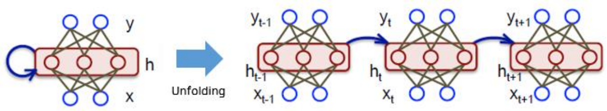

Fig. 2 A simple structure of RNN.

However, conventional RNNs have a critical problem which is a vanishing gradient problem. It is a difficulty found in training neural networks with gradient-based methods and backpropagation. As it was explained in section 2.1, each of the edge weight receives an update proportional to the gradient of the error function with respect to the current weight in each iteration of training. It has the effect of multiplying n of these small numbers to compute gradients. So the gradient decreases exponentially with number of itneration while the front layers' train very slowly.

To overcome the problem of vanishing gradients, Long Short-Term Memory (LSTM) was introduced by Hochreiter and Schmidhuber in 1997[9]. The LSTM model resembles a standard RNN with a hidden layer, but each node in the hidden layer is replaced by a memory cell. Each cell ($\mathrm{h_t}$) takes as input the previous state $\mathrm{h_{t-1}}$ and current x_t. These cells internally decide what to keep in or what to erase from memory. Then they combine the previous state, the current memory, and the input.

2.3 Comparing expert system with neural network based system

Several researches about AMSTs have been studied and developed. As I explained in introduction part, AMST is composed of tracker, predictor, and decision making support. Current AMST tracker is a conventional rule-based expert system. They are based on the premise that expert knowledge can be encapsulated in a set of 'If-Then' type rule. However, adapting these conventional rule-based expert systems to tracker of AMSTs may lead some troubles when the real accidents occur because they have some limitations.

First, people cannot predict all possible accident scenarios. Expert systems can only help to MCR operators and TSC members in the special situation when the saved accident scenario matches up with the real occurred accident. If the apposite accident scenario was not saved in the expert system database, then this AMST would be a useless thing. Therefore, if these are made with sophisticated systems based on tremendous database not saved whole scenarios, expert system may not help having limitations. In addition, predicting the whole BDBA scenarios and then storing these scenarios to the database of expert system is unreasonable.

Second, I&C systems may fail to operate by the impulse caused by the accident. Current AMST tracker cannot help highly depending on the integrity of sensors of instrumentations because they are rule-based expert system. If extreme hazard like Tsunami in Fukushima plant can break the sensors and shuts off the information from sensors, then current AMST's tracker would not notice and provide the correct prospective directions to operators and TSC members and so these tools would not reassure people on that extreme situation. Accidents have infinite accident scenarios and some of them may lead operators and TSC members to panic. Rule-based expert systems have limits to help them to manage the unexpected accident sequences.

However, neural network-based systems are very flexible. These systems make decisions by using a set of mathmatical process rather than searching related rule. So they are more rapid and precise than previous system[10]. Moreover, neural network-based systems are tolerance to noise, dynamical adjustment of changes in the environment, ability to generalize, and ability to discover new relations between variables may be significant benefits[10]. Expecially, accidents including extreme hazard may incur the detriments of instrumentations. As I explained before, if the input data to AMSTs' tracker from the instrumentation were wrong, the output of the rule-based expert system would lead operators and TSC members wrong way even though these systems have been perfectly designed. However, neural-network based systems have robustness of thes tolerances so we expect these systems can operate well even in the extreme situation.

3 Case study

3.1 Model construction

The event identification system has been constructed with the neural network based model. Among of the neural network, we selected RNN and we selected LSTM model among the RNN. The reason why we selected LSTM-RNN model among the whole neural network models is our simulation data is sequential data. The accident sequences in NPPs always follow time-sequential process. RNN model which can show splendid performance for sequential data and has been used for stock market, weather forecasting, natural language processing was chosen for this research. Surely, there are lots of architectures of RNN models such as simple recurrent model, echo state model, Bi-directional RNN, LSTM, etc. Each architecture has advantages and disadvantages respectively. Especially, the major advantage of LSTM architecture has no vanishing gradient problem which is the very splendid trait for iterating the feedforward network and backpropagation. Therefore, we selected the LSTM architecture through the whole RNN model. We gained input data from the compact nuclear simulator (CNS). The simulator uses reference plants as Westinghouse pressurized water reactor (PWR). The plant modeled in the CNS is a three loop Westinghouse PWR. The primary system and the primary side of steam generators are described using advanced SMABRE code with two phases capability. We can gain several hundred of measured instrumentation parameters from the CNS. We also take more than hundreds of initiating events by the CNS. In this lab-scale case-study, we used a hundred instrumentation parameters and five initiating events including normal operating condition. The instrumentation parameters are composed of binary parameters expressed only 0 (closed) or 1(open) such as valve's state and numerate parameters expressed continuous number such as pressurizer pressure, steam generator level, reactor average temperature, etc.

So, this RNN based plant diagnosis system is composed of one hundred inputs which are instrumentation parameters and used LSTM double layer model with one thousands of hidden nodes per each layer. This model is described in figure 3. The reason why we designed LSTM-RNN double layer model and used one thousands of hidden nodes in each layer is that model was showed the highest performance through the trial and error approach. Trial and error approach is an

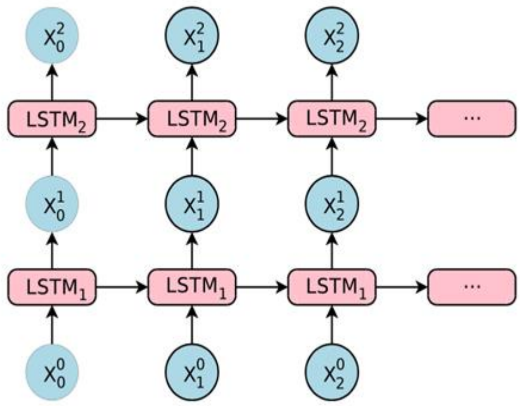

Fig. 3 A structure of the constructed model.

almost unique method to make the proper model because neural network has a non-convex optimization problem. Finding the global minimum is quite difficult in non-convex optimization as you can see in figure 4.

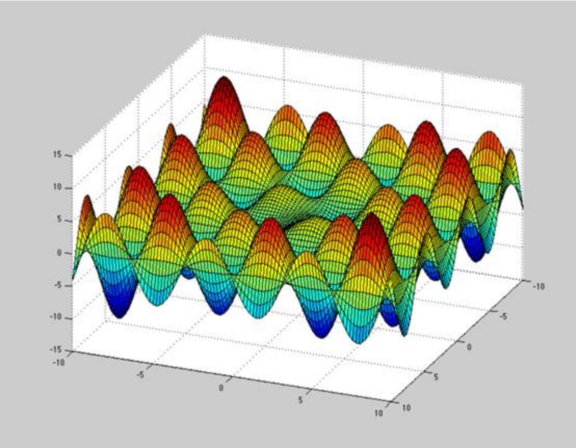

Fig. 4 An example graph of non-convex optimization.

3.2 Results comparing rule-based expert system and RNN-based system

As I explained in the previous section, we were supposed to deal with a normal operating scenario and four accident scenarios – 'normal sequence', 'drop of all control rods in CBA', 'Rod bank uncontrolled in', 'pressurize (PRZ) PORV stuck open', and 'PRZ spray valve open, 'fails to close or jammed shut'. The form of each scenario is time-series sequential data which express parameters measured by instrumentations. And we assumed that the 'PRZ PORV stuck open', one of the five scenarios, occurred in this case study.

3.2.1 Traditional rule-based plant diagnosis system

Rule-based expert system has to follow the rule. Therefore, making rules are necessary to operate this system. We brought the CNS procedure firstly to make rules which interprets symptoms of each accident scenario, and checked relevant sequences of our five scenarios. We checked the critical instrumentations which can classify those five scenarios. Critical instrumentations are backup heater, PRZ level, PRZ pressure, etc. Second, we decided the probability of each accident can happen and so the probability was assumed 0.0001 of each scenario. Third, sensor-error probabilities are also assumed to 0.0001 for fail-high and fail-low and 0.0008 for stuck at steady. Last, we took the Bayes' rule to calculate the probability that this rule-based expert system has to follow up. Summarizing rules of a rule-based expert system:

Rule 1. Four accident scenarios and one normal operation scenario can happen.

Rule 2. The probability of occurring each accident scenario is 0.01%.

Rule 3. The probability of each sensor error is 0.01% (for fail-high, fail low)

Rule 4. The probability of each sensor error is 0.08% (for stuck at steady)

Rule 5. The calculation has to be followed by Bayes' rule.

The result is represented in Table 1. If we assumed that PRZ PORV stuck open accident happened, then traditional rule-based expert system can

Table 1 Result of rule-based plant diagnosis system

Symptoms	Normal scenario	Drop of all control rods in CBA	Rod bank uncontrolled in	PRZ PORV stuck open	PRZ spray valve open, fails to close or jammed shut
Initial condition	9.9960E-01	1.0000E-04	1.0000E-04	1.0000E-04	1.0000E-04
Rx trip sign on	2.5009E-01	2.4997E-01	2.4997E-01	2.4997E-01	2.4997E-01
Turbine trip on	3.5732E-02	3.2142E-01	3.2142E-01	3.2142E-01	3.2142E-01
Backup heater on	3.7089E-06	3.3333E-01	3.3333E-01	3.3333E-01	3.3333E-01
PRZ level decrease	3.7122E-10	3.3333E-01	3.3333E-01	3.3333E-01	3.3363E-05
PRZ level increase	1.1145E-13	1.0007E-04	1.0007E-04	9.9980E-01	1.0007E-04
PRZ pressure decrease	1.1155E-17	1.0007E-04	1.0007E-04	9.9980E-01	1.0007E-04
PRT temperature increase	1.1167E-21	1.0018E-08	1.0018E-08	1.0000E+00	1.0018E-08

Table 2 Result of rule-based plant diagnosis system with malfunctioning of instrumentation for PRT temperature

Symptoms	Normal scenario	Drop of all control rods in CBA	Rod bank uncontrolled in	PRZ PORV stuck open	PRZ spray valve open, fails to close or jammed shut
Initial condition	9.9960E-01	1.0000E-04	1.0000E-04	1.0000E-04	1.0000E-04
Rx trip sign on	2.5009E-01	2.4997E-01	2.4997E-01	2.4997E-01	2.4997E-01
Turbine trip on	3.5732E-02	3.2142E-01	3.2142E-01	3.2142E-01	3.2142E-01
Backup heater on	3.7089E-06	3.3333E-01	3.3333E-01	3.3333E-01	3.3333E-01
PRZ level decrease	3.7122E-10	3.3333E-01	3.3333E-01	3.3333E-01	3.3363E-05
PRZ level increase	1.1145E-13	1.0007E-04	1.0007E-04	9.9980E-01	1.0007E-04
PRZ pressure decrease	1.1155E-17	1.0007E-04	1.0007E-04	9.9980E-01	1.0007E-04
PRT temperature steady	1.0138E-14	9.0955E-02	9.0955E-02	7.2713E-01	9.0955E-02

detect the correct accident through the fixed rules. This rule based system can alert to MCR operators and TSC members that PRZ PORV stuck open accident happened with 100%.

However, we cannot be assured all instrumentations can normally operate if the accident occurred. Therefore, it is needed to check if one or more instrumentations were failed caused by the accident, how the calculated result would be changed. In this case, we intentionally broke the instrumentation of measuring of PRT temperature which was increased in real but indicated steady to operators because of malfunctioning. Then, the probability of detecting that accident reduced from 100% to 72.71% in the Table 2. It means rule-based expert system has to be affected the condition of the instrumentations. If accidents make several critical instrumentations malfunctioning, then correct diagnosis of the accident may be impossible by the rule-based plant diagnosis system.

3.2.2 RNN-based plant diagnosis system

The RNN-based plant diagnosis system doesn't need to have any rules. Designer just makes up the algorithm and sets up the architecture. Then computer keeps self-learning by iterating feedforward network and backpropagation to optimize given works what designer delineated. The architecture what we used in this case study is double layer LSTM-RNN model as it was described previous part. And we trained this RNN-based model with the CNS time-sequential data.

We also assumed PRZ PORV stuck open accident scenario occurred the same as previous rule-based system assumed. Before the training the model, the system couldn't classify the all accidents when we put each accident. However, after self-training by using designed algorithm, the system can classify all accident scenarios with high confident level. The predictive probability of occurring of PRZ PORV stuck open accident of RNN-based system is 99.58%. Surely, the probability of occurring the same accident as 100% which rule-based system showed is higher than the RNN-based system did. But the result of the RNN-based system, 99.58%, is also said quite accurate system.

We also checked the situation of malfunctioning PRT temperature instrumentation which we did using rule-based system. We were supposed to the effect of malfunctioning instrumentations in the RNN-based system is lower than in the rule-based system because the trait of neural network. When the measuring PRT temperature instrumentation was failed, the probability was also the same as 99.58%. We cannot believe the result of changing nothing. Therefore, we made one more instrumentation which is measuring PRZ pressure malfunctioning. Then the system provided the probability to us that the system speculated accident sequence is also PRZ PORV open accident as 88.03%. The probability was decreased when two instrumentations were malfunctioning but it could detect the correct accident scenario. In summarizing, the result was not changed when one instrumentation was malfunctioning and slightly decreased when two instrumentations were concurrently malfunctioning. It shows that this constructed system has higher robustness of the sensor failures than traditional rule-based systems.

Not only identifying and classifying the initiating accidents but also detecting the failed sensors can be possible for this RNN-based plant diagnosis system. Detecting failed sensor and providing that information to MCR operators and TSC members are helpful and necessary to diagnose the plant state and mitigate the accident. If unknown accident occurs, this system analyses and classifies the correct accident scenarios by comparing the changes of the trend which provided each instrumentation. After diagnosing the proper accident, comparing each trend of parameter provided by each sensor and stored in the database can be possible. If the sensor provided trend of each instrumentation are not as similar as expected stored trend in the scenario, this system shows and alerts to MCR operators and TSC members that sensor might be failed. Then MCR operators and TSC members can perceive the possibility of sensor failure.

In summary, RNN-based plant diagnosis system showed better performance than traditional rule-based system. It has high robustness of sensor malfunctioning so it can more properly operate in the extreme situation caused by accidents. In addition, this system can provide instrumentations' condition which are well-functioning or malfunctioning to the MCR operators and TSC members. Knowing each instrumentation's condition is important and very useful to mitigate the accident, especially for SAMG domain.

4 Conclusion

Lots of researches have been conducted for making NPPs safe. Events and accidents may occur with even very low possibility by these researches. In this regard, operators have to diagnose the plant abnormal state as swiftly and accurately as possible when the events or accidents occurred. Only if operators did, operators control precisely and interrupt the ongoing accident sequence. Therefore, diagnosing initiating events is important step in the transient to EOP domain so most researches have been focused on this step. However, plant state diagnosing is also needed in the SAMG domain. Because there is possibility that operators diagnosed the accident incorrectly in previous domain so the accident became severe accident or the accident may occur largely and pacy with short time which operators may not correctly diagnose and control the plant before core damage. So the RNN-based plant diagnosis system was developed considering about these characteristics.

This system is designed of neural network. So it has high robustness of sensor-malfunctioning and although unknown accident which scenario was not stored database occurs, it can correctly classify the accident. In addition, MCR operators and TSC members can check the sensor malfunctioning of each instrumentation from the system and the system also provides graphical trend information of instrumentations' parameters. Being served graphical trend of parameters of each instrumentation and each instrumentation's condition for MCR operators and TSC members are quite helpful to mitigate the accident.

References

[1] "Operational safety performance in indicators for nuclear power plants", IAEA, 2000. [IN CASE OF REPORT]

[2] Joo Hyun Moon and Chang Sun Kang, "Use of fuzzy set theory in the aggregation of expert judgements", Annals of Nuclear Energy, 1999. [IN CASE OF PAPER IN THE JOURNAL]

[3] Soo-Yong Park and Kwang-il Ahn, "SAMEX: SEVERE ACCIDENT MANAGEMENT SUPPORT EXPERT", Annals of Nuclear Energy, 2010. [IN CASE OF PAPER IN THE JOURNAL]

[4] Mahdi Saghafi and Mohammad B.Ghofrani, "Accident management support tools in nuclear power plants: A post-Fukushima review", Progress in Nuclear Energy, 2016. [IN CASE OF PAPER IN THE JOURNAL]

[5] Man Gyun Na, Sun Ho Shin, Sun Mi Lee, Dong Won Jung, Soong Pyung Kim, Ji Hwan Jeong, Byung Chul Lee, "Prediction of Major Transient Scenarios for Severe Accident of Nuclear Power Plants, IEEE transactions on nuclear science, Vol. 52, No. 2, April, 2004. [IN CASE OF PAPER IN THE JOURNAL]

[6] M. Andreeva, M.P. Pavlova, P.P. Groudev, "Overview of plant specific severe accident

management strategies for Kozloduy nuclear power plant, WWER-1000/320, Annals of Nuclear Energy 35, pp. 555-564, 2008. [IN CASE OF PAPER IN THE JOURNAL

[7] "Severe accident management programmes for nuclear power plants", IAEA, 2009. [IN THE CASE OF REPORT]

[8] McCulloch, Warren and Walter Pitts, "A logical calculus of ideas immanent in nervous activity", Bulletin of Mathematical Biophysics, Vol. 5, N0. 4, pp. 115-133, 1943. [IN CASE OF PAPER IN THE JOURNAL]

[9] Sepp Hochreiter and Jurgen Schmidhuber, "Long Short-Term Memory", Neural Computation Vol. 9, No. 8, pp. 1735-1780, 1997. [IN CASE OF PAPER IN THE JOURNAL]

[10] Se Woo Cheon and Soon Heung Chang, "Application of neural networks to a connectionist expert system for transient identification in nuclear power plants", Nuclear technology, Vol. 102, pp. 177-191, 1993. [IN CASE OF PAPER IN THE JOURNAL]