Monitoring the Status of Safety Functions using LSTM

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Abstract: Human errors is one of the major factor for events that can aggravate the plant safety. Therefore, in case of abnormal or emergent situation, monitoring safety functions or diagnosis of Nuclear Power Plant (NPP) states are burdensome in spite of necessity. This study attempts to develop algorithms for monitoring the status of safety functions and diagnosis of accident. Therefore, it is expected that this approach can be applied to diagnose the overall NPP states.

Keyword: Long Short-Term Memory, Monitoring, Diagnosis

1 Introduction

Monitoring the state of current nuclear power plants (NPPs) is performed under the judgment of operators considering indicators and alarms based on the procedures. Safety functions which are critical for the NPP integrity should be monitored repeatedly and periodically while performing procedures. In case of abnormal or emergency situation, continuous monitoring of safety functions may be a mentally burdensome task for operators, because they should try to identify possible success paths at the same time [1]. In addition, diagnostic activities in emergency situations may cause not only delay of effective responses, but also occurrence of serious consequences due to selecting an inadequate procedure (i.e. wrong diagnosis) [2].
According to the Operational Performance Information System (OPIS) [3], the human error is one of the major factors for unexpected reactor trips. From 2000 to 2016, about 17% of events (i.e., 47 of 274) were caused by human errors.

Early detection of anomalies and accurate diagnosis are very crucial for the safety of NPPs. In that sense, this study attempts to develop an algorithm for the on-line monitoring of the status of safety functions and the diagnosis of accidents. This study applies two approaches. First, a rule-based algorithm is suggested for monitoring safety parameters. Then, Long Short Term Memory (LSTM), which is one of the Recurrent Neural Networks (RNNs) is suggested for the diagnosis of accident.

2 On-line monitoring of safety functions

2.1 Parameters for monitoring of safety functions

For developing an on-line monitoring algorithm for the safety functions of NPPs, this study selects safety parameters. A power plant of Westinghouse 900 MWe with three loops has been used as a reference plant. Six critical safety functions (CSFs) will be monitored, i.e., subcriticality, corecooling, heat sink, RCS integrity, containment integrity and RCS inventory. Fig.1 shows the hierarchy of CSFs. Total 29 parameters are selected for monitoring of six CSFs. Table 1 shows the selected parameters by function.

2.2 Rule based expert system

To monitor parameters related with CSFs, a rule-based expert system has been developed. A rule-based expert system mimics the reasoning of human expert based on rules as the knowledge. Therefore, it can provide a way to code expert knowledge for narrow areas. By using assertion sets and a set of rules that designate how assertions work such as a set of if-then statements (i.e., IF-THEN rules), rule based expert systems can be created [5].

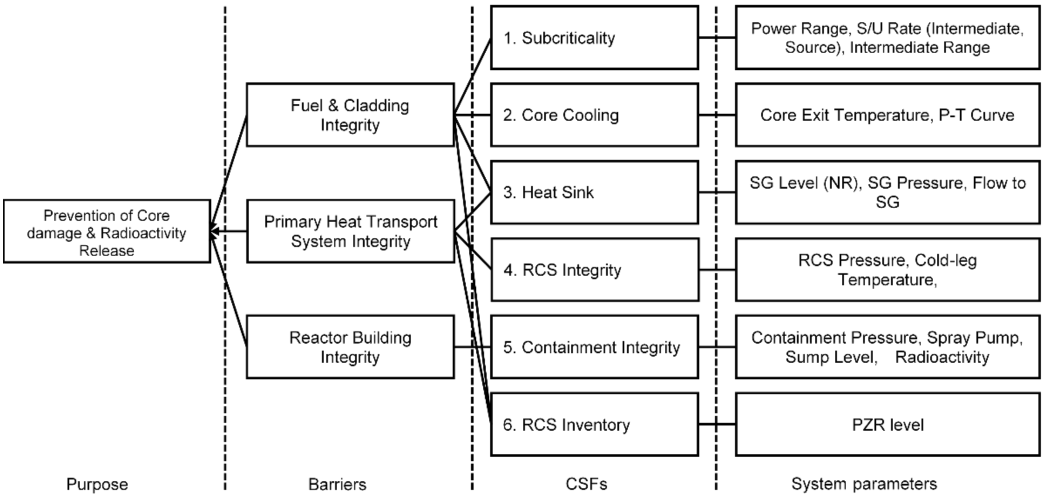

Fig.1 The hierarchy of critical safety functions in Westinghouse PWR

Table 1 Selected parameters

CSF	Parameters	Number
Subcriticality	Power range, Intermediate range, start-up rate (source , intermediate)	4
Corecooling	Core exit temperature, hotleg temperature, RCS pressure	5
Heat sink	SG narrow range lvl and pressure, feedwater and aux feedwater flow	12
RCS integrity	RCS average temp	3
Containment integrity	Containment pressure, spray pump operation, sump lvl,	4
RCS inventory	Pressurizer water lvl	1
	Total	**29**

The rule base has been developed based on CSF tree of emergency operating procedure. Fig. 2 shows an example of CSF tree for heat sink. The integrity of heat sink function can be determined by the narrow range level and pressure of steam generators and total feedwater flow. Depending on the severity, the status of CSF are classified into 1 to 4 levels, i.e., the normal condition, abnormal state, risk-significant and extreme threat. The on-line monitoring algorithm using the rule base was implemented with Python 3.5.3. Fig. 3 shows a part of Python code for the on-line monitoring for the heat sink function.

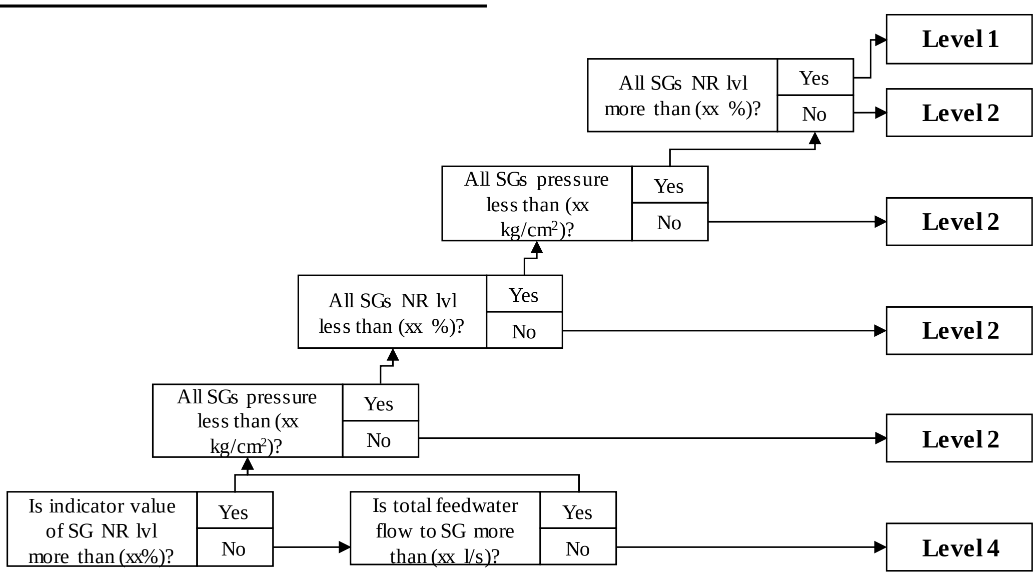

Fig. 2 An example of CSF tree for heat sink

Fig.3 An example algorithm for heat sink on python

2.3 Test

The on-line monitoring algorithms for six CSFs have been tested by using the Compact Nuclear Simulator (CNS). For the demonstration of algorithm, a Loss of Coolant Accident (LOCA) scenario with the size of 200 square centimeters in loop 1 hot-leg was used. The malfunction to the CNS simulator is injected after 30 seconds. The total simulation time is 2,265 seconds. There are no control or additional interventions. Fig. 4 and 5 show the test results for monitoring the safety functions of heat sink and reactor coolant system (RCS) integrity. X-axis and Y-axis represents the time and levels of CSFs, respectively.

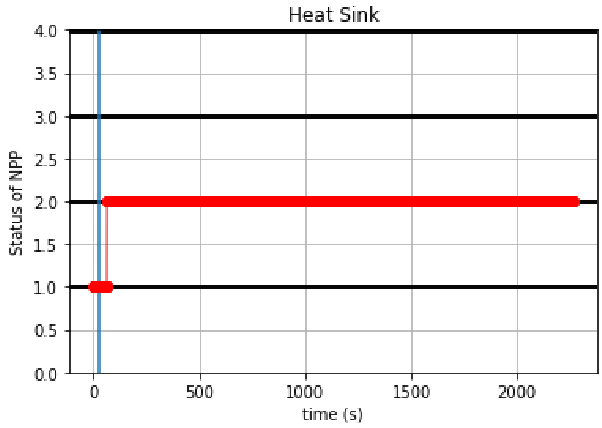

Fig.4 Heat sink status monitoring result

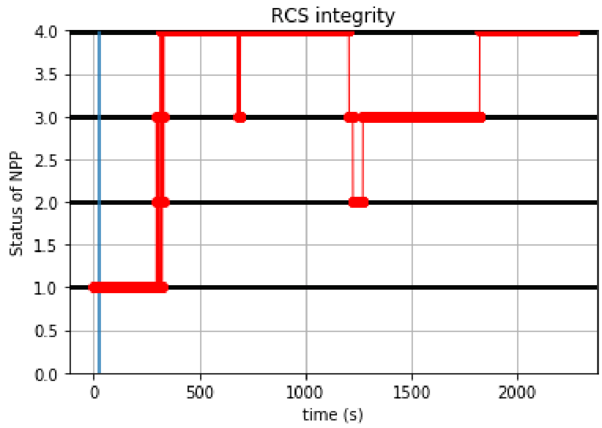

Fig.5 RCS integrity status monitoring result

3 Accident diagnosis

3.1 LSTM

This paper suggests the accident diagnosis algorithm using Long Short-Term Memory (LSTM). LSTM is an improved Recurrent Neural Network (RNNs). In case of original RNN, it tracks past values and goes back in time (i.e., back propagation). However, too much back propagation by long time causes vanishing gradients problem [6]. To improve RNN for this problem, LSTM is introduced for sequence learning. The modern LSTM design of cell has remained close to the original with forget gate and peep-hole connection [7].

As other LSTM models, in this study, each LSTM cell adjusts the output value using the input gate, the forgetting gate, and the output gate while maintaining the cell state. The input gate determines capacity of the input value. The forgetting gate determines how much to forget the degree of previous cell state, and the output gate determines how much to output. The following Equations (1) to (4) stand for each gate denoted by i, o and f respectively. g means the input node and has a $tanh$ activation function denoted by ϕ. Also, σ stands for a sigmoid function.

$$g_l^{(t)} = \phi(W_l^{gx} h_{l-1}^{(t)} + W_l^{gh} h_l^{(t-1)} + b_l^g) \quad (1)$$
$$i_l^{(t)} = \phi(W_l^{ix} h_{l-1}^{(t)} + W_l^{ih} h_l^{(t-1)} + b_l^i) \quad (2)$$
$$f_l^{(t)} = \phi(W_l^{fx} h_{l-1}^{(t)} + W_l^{fh} h_l^{(t-1)} + b_l^f) \quad (3)$$
$$o_l^{(t)} = \phi(W_l^{ox} h_{l-1}^{(t)} + W_l^{oh} h_l^{(t-1)} + b_l^o) \quad (4)$$

These equations give the update for a layer of memory cells $h_l^{(t)}$ where $h_{l-1}^{(t)}$ stands for the previous layer at the same sequence step and $h_{l-1}^{(t)}$ stands for the same layer at the previous sequence step. As output, a fully connected layer at the highest LSTM layer, because our problem is multi-label [7]. Fig.6 shows a simple LSTM model for multi-label classification that is applied in this study. At the end of model, softmax function layer shown in Fig.7 was used for deciding the order of accident probabilities.

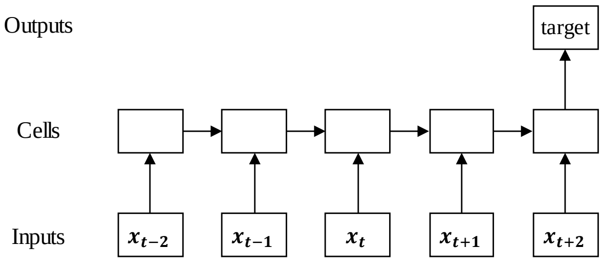

Fig. 6 A simple LSTM model for multi-label classification

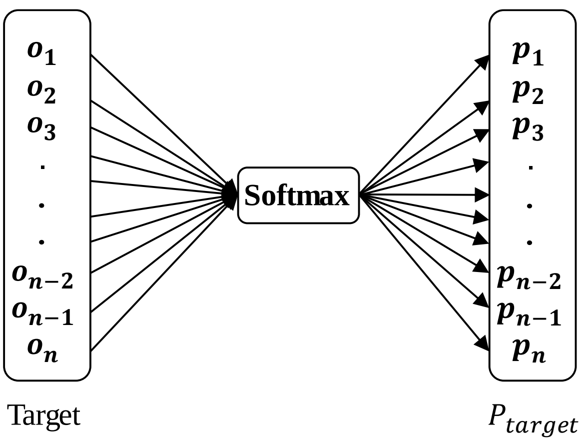

Fig.7 An example of softmax function layer

Same as monitoring, the coding of algorithm was implemented with Python 3.5.3. A total of 168 parameters were selected based on procedures, CSFs, and by importance for control of NPP operation. In addition, 112 scenarios (i.e., 122,609 datasets with 168 variables) were used for training. Learning rate and iteration sets are 0.001 and 2,000 respectively. Also, hidden layers are 3. These hyper parameters are set by manual search (i.e. trial and error learning).

3.2 Test

The designed LSTM model was examined with some test scenarios. Fig. 7 shows an example for a LOCA with the size of 10 square centimeters in loop1 cold-leg.

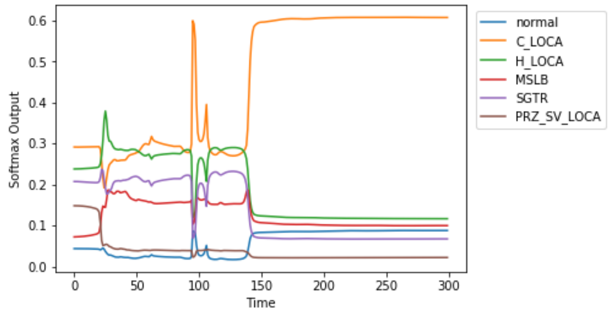

Fig.8 Loop1 Cold-leg LOCA ($10cm^2$)

Not only this case but also most cases, accidents are usually diagnosed within 200seconds. Fig. 9 to 10 show some examples of diagnosis results.

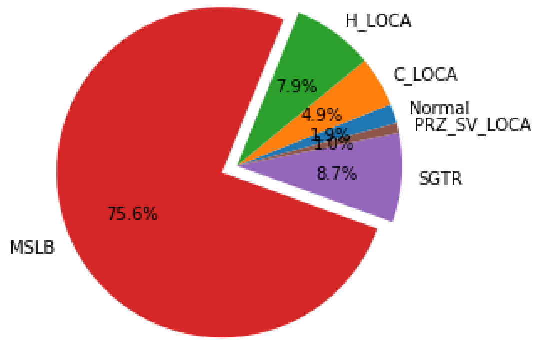

Fig.9 A result for diagnosis of MSLB

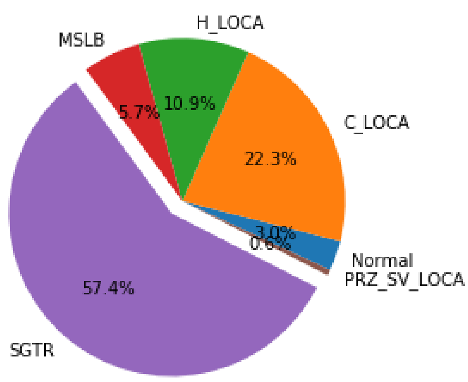

Fig.10 A result for diagnosis of SGTR

5 Conclusion

5.1 Discussion

In case of accident diagnosis algorithm, if unknown events or untrained events are given, it cannot classify accidents by itself. Though untrained events can be overcome by gathering more data, to cope with unknown events, it needs specific standards (e.g., probability standards). Also, monitoring results can be applied to classify accidents after pretreatment with Python.

5.2 Conclusion

The goal of this study is to develop algorithms for monitoring CSFs in NPP and accident diagnosis to unload operator's task in abnormal or emergent situation for safety. It is expected that this approach can be applied to not only the performance monitoring, but also the diagnosis of NPP states.

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