[UCI]I804:24011-200000267261

2019년 2월

석사학위 논문

Development of an Accident Diagnosis Algorithm based on LSTM during NPP Full Power Operation and Startup Operation

조선대학교 대학원

원 자 력 공 학 과

양 재 민

Development of an Accident Diagnosis Algorithm based on LSTM during NPP Full Power Operation and Startup Operation

장단기 메모리를 기반으로 한 원자력 발전소의 전출력
운전과 기동 운전 시의 사고진단 알고리즘 개발

2019년 2월

조선대학교 대학원

원 자 력 공 학 과

양 재 민

Development of an Accident Diagnosis Algorithm based on LSTM during NPP Full Power Operation and Startup Operation

지도교수 김 종 현

이 논문을 공학 석사학위신청 논문으로 제출함

2019년 2월

조선대학교 대학원

원 자 력 공 학 과

양 재 민

양재민의 석사학위논문을 인준함

위원장 조선대학교 교수 나 만 균 (인)

위 원 조선대학교 교수 송 종 순 (인)

위 원 조선대학교 교수 김 종 현 (인)

2019년 2월

조선대학교 대학원

CONTENTS

List of Tables

List of Figures

ABSTRACT

Development of Accident Diagnosis Algorithm based on LSTM during NPP Full Power Operation and Startup Operation

Yang Jaemin
Advisor : Prof. Kim Jonghyun, Ph.D.
Department of Nuclear Engineering
Graduate School of Chosun University

Currently running nuclear power plants (NPPs) are managed under the goal of electricity power generation with safety. According to the safety purpose of NPPs, any action (e.g., control of components, maintenance, monitoring) taken at the plant are carried out based on procedures. Hence, in order to ensure the safety of NPP, operators must follow procedures and any other requirements described in the technical specification. However, in case of emergency operation, it requires that the appropriate accident diagnosis must be done first so that operators are possible to cope with the situation properly, nevertheless, it is the extremely strenuous task, which can give rise to the probability of operator errors. Furthermore, there are various operation modes. Concerning the issue of such diagnostic activities, a variety of operator supporting systems and diagnostic algorithms have been introduced to reduce the burden of operators. Owing to nuclear power plant data characteristics such as nonlinear, time sequential and multivariate, in this light, this thesis aims at proposing an accident diagnosis algorithm for the diagnosis of accidents considering the characteristics of NPP startup operation and full power operation based on LSTM. It is expected that the safety of NPP during startup operation can be improved by application of algorithm for diagnosis of accidents.

I. Introduction

Currently running nuclear power plants (NPPs) are managed under the goal of electricity power generation with safety. Most of them utilize fission energy to produce water vapor by boiling water, which is used for operating the turbine and produce electricity. It is the same as thermal power generation in the perspective of water boiling to produce water vapor, however, it has comparatively few greenhouse gas emissions and has radioactive risks [1]. Even though the benefit from economic feasibility and eco-friendly characteristic of NPP are rather substantial than other energy sources, in case of a nuclear power plant accident, the damage is unpredictable to estimate that even if the utility and related organizations are careful enough to manage it, thus, the social anxiety about the accident is considerably sizable. Therefore, to generate electricity and to ensure the safety of the public from the consequences of postulated accidents and potential risks are two overall goals of NPP [2].

According to the safety purpose of NPPs, any action (e.g., control of components, maintenance, monitoring) taken at the plant are carried out based on procedures. These procedures are documents, which describe safety regulations that must be followed during operation to ensure safety of NPPs. Operators should not take any actions based on personal experience or functional skill, but they must perform actions as described in the procedure for avoiding human error, improving operation quality, and ensuring compliance with regulatory requirements. Hence, in order to ensure the safety of NPP, operators must continuously check and monitor by complying with the safety limits, safety system operation setup values, operating limits and any other requirements described in the technical specification. In addition, if unexpected behavior of NPPs occur such as transients or accidents, operators should take appropriate responding action based on assigned procedures such as alarm response procedure, abnormal operating procedure and emergency operating procedure depending on the severity of anomalies [3].

In case of emergency operation, it requires that the appropriate accident diagnosis must be done first so that operators are possible to cope with the situation properly, however, it is the extremely strenuous task to them. In order to diagnose the accident correctly, the diagnostic activity is performed by using the state of plant behaviors and satisfaction of the critical safety functions based on the procedures. In addition, the corresponding response of the operator is essential under the situation that cause excessive stress such as fixed time, rapid fluctuating parameters, and numerous systems changing instantaneously. Under this demanding circumstance to operators, it needs a lot of cognitive demands in order to respond correctly, which can give rise to the probability of operator errors. In addition, on account of these features, not only a delay in effective response but also more severe consequences can happen from wrong selection of procedure [4-9].

Furthermore, there are various operation modes such as plant startup, shutdown as well as general power operation, and under these diverse operation modes, not only plant behaviors (e.g., criticality, power level, average reactor coolant temperature) but also operability of systems or components are different with full power operation. Due to those different characteristics of operations, even if there are assigned procedures depending on specific situations, it is probable that operators may not recognize the accident in required time. Moreover, the availability of components and systems (e.g., bypass of safety injection, availability of steam dump system) are different so that they cannot be operable when it is necessary to respond. In addition, during this period, there may be a lot of maintenance activities that can foster a decrease of safety from the weakening of the defense in depth concept and lack or risk management Thus, even if a same accident occurs under startup operation, operators may have difficulty in responding correctly [10, 11].

Concerning the issue of such diagnostic activities, a variety of operator supporting systems and diagnostic algorithms have been introduced to reduce the burden of operators. Various approaches are currently being made not only in NPPs but also in various fields for diagnostics tasks. Among them, approaches that utilize artificial intelligence, which are highlighted through the fourth industrial revolution, are increasing noticeably. Some of them based on such artificial intelligence techniques (e.g., artificial neural networks (ANNs), fuzzy logic, the hidden Markov model, support vector machine) show noticeable performance. Representatively, ANNs are regarded as one of the most promising approaches because in case of pattern recognition problems and nonlinear problems they have shown remarkable achievement as useful tools. In that sense, several studies have suggested ANNs to develop algorithms for diagnostic tasks in NPPs and some of them give potential applicability of ANNs [12-17].

Numerous methods applied ANNs have been suggested, however owing to nuclear power plant data characteristics such as nonlinear, time sequential and multivariate, this study apply recurrent neural networks (RNNs) as a development tool for accident diagnosis. RNNs are specified method to deal with time-series data, that is, it is a suitable one to reflect dynamic characteristic of NPPs and also it is a prominent network from which the information feature related to the dynamic system [18]. Despite good characteristics of it, there are two well-known limitations related with weight control of networks that are come from back-propagated error. Blowing-up and vanishing gradients, the former one can cause the oscillation of weights, whereas, the other can lead weights to be zero. Hence, these can result in a prohibitive duration for learning or even the trained one may not work well (i.e., poor performance). To deal with this problem of RNN, long short-term memory (LSTM) has been proposed to improve potentially inherent defects of it [19]. Although it is based on same RNN architecture, it can cover long temporal sequences of data as well as varying-length sequential data. In addition, lots of recent studies based on LSTM show the applicability and contentable performance in various fields (e.g., natural language processing, image captioning, handwriting recognition, genomic analysis) [20-27].

In this light, this thesis aims at proposing an accident diagnosis algorithm for the diagnosis of accidents considering the characteristics of NPP startup operation and full power operation based on LSTM. The first part of thesis will be concerned with operational modes of NPP and an approach to reflect those characteristics for the suggesting algorithm, based on a Westinghouse 930MWe pressurized water reactor with three loops as shown in Fig. 1 [28].

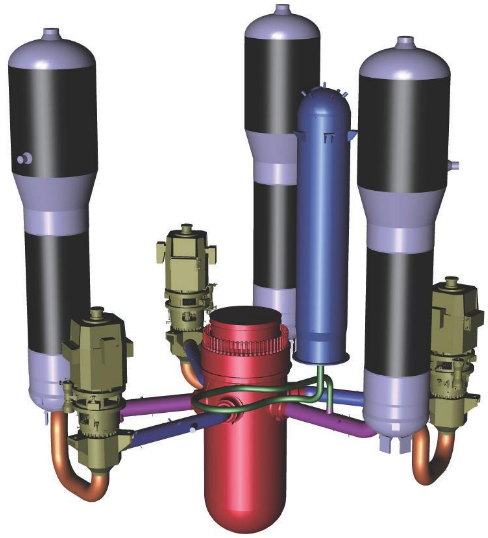

Fig. 1. Typical reactor coolant system (RCS) used in PWR with three loops

Then, the accident diagnosis algorithm on the basis of LSTM is introduced and results are shown to demonstrate its effectiveness during full power operation and startup operation using compact nuclear simulator (CNS) , which is developed by the Korea Atomic Energy Research Institute (KAERI). The reference plant is implemented in this simulator [29].

II. Operational Modes of Nuclear Power Plant

Generally, operational modes of the reference plant can be divided by several conditions such as reactor criticality (Keff), rated thermal power (RTP), average reactor coolant temperature (Tavg), coldleg reactor coolant temperature(Tcold), and so on. In case of operational modes of target plant for this study is divided into six modes considering several plant parameters and major cooling source during plant heat-up, as following table 1 [30, 31].

Table 1. Westinghouse 3-loop NPP operation modes

Mode	Name	Major cooling source during plant heat-up [31]	K_{eff}	RTP (%)	T_{avg} (℃)
1	Power Operation	Steam generator	≥0.99	>5	-
2	Startup	Steam generator	≥0.99	≤5	-
3	Hot Standby	Steam generator	<0.99	-	≥177
4	Hot Shutdown	Residual heat removal system to steam generator	<0.99	-	$177>T_{avg}>93$
5	Cold Shutdown	Residual heat removal system	<0.99	-	≤93
6	Refueling	-	-	-	-

According to the table 1, such major plant behaviors are changed variously depending on the mode. In addition, major cooling source during plant heat-up and operable systems or components are different respectively by the operation mode, also due to various initial conditions, the behavior of the power plant can be different even if the same accident occurs. Therefore, those different features should be considered for developing accident diagnosis algorithm to reflect different plant conditions which might aggravate accuracy of diagnosis result.

A. Operation Modes

To formalize different characteristics of operation mode, this section will deal with operational features of full power operation and startup operation. The full power operation in this section represents a normal state of the NPP, whereas, in case of startup operation, it is described in a range of operation modes from cold shutdown (i.e.,mode 5) to power operation (i.e., mode 1) during plant heat up.

1. Full power operation

During the full power operation, thermal energy is generated by fission. This energy is transferred from the core to the steam generator (SG) via the hot-leg of the reactor coolant system. The heat exchanged coolant is forcibly circulated to the reactor by the reactor coolant pump (RCP). Energy is transferred from the reactor coolant through the U-tube of the SG to the feedwater of the steam generator in the secondary system. The transferred energy causes a phase change of the feedwater to the steam state. The generated steam is supplied to the turbine through the main steam system to work and produce electrical output from the generator. The pressurizer pressurizes the coolant above the saturation pressure to prevent the hot coolant from boiling, and the pressure is controlled by the heater in the pressurizer and the pressurizer spray water supplied from the outlet of the RCP.

Most of plant parameters represented from the indicators are steady state during full power operation. Table 2 shows the specification of reference plant during full power operation. In case of the reference plant, it is kept in steady state during this period. Due to stable condition of NPP, if any anomalies or accidents occur, operators can recognize relatively easier than other operation modes from unusual plant behaviors. Also, many studies have dealt with this issue [10, 32-34].

Table 2. Specification of reference plant during full power operation

Reference plant	Westinghouse PWR
Electrical output	930 MWe (100%)
NSSS Power, megawatt thermal	2800 MWth
RCS Pressure	160Kg/㎠
Number of loops	3 loops
Hot-leg / cold-leg temperature	325℃/290℃
RCS average temperature	308℃
Steam generator average pressure	64.4Kg/㎠

2. Startup operation

For the purpose of plant startup, the temperature and pressure of the reactor coolant must be increased to the designed no load level. Since the reactor reaches the critical point and before producing the thermal output, the frictional heat generated by the continuous operation of the RCP increases the temperature of the reactor coolant by providing initial heat with the decay heat of the core. The pressurizer, acting as a buffer for the reactor coolant, accommodates the volumetric expansion due to the temperature increase of the reactor coolant and regulates the pressure to keep the coolant under supercooled condition. The measuring instrumentation related to the temperature and pressure of the RCS indicates to the operator the relevant operating parameters so that the plant can maintain heating, cooling, pressurization and decompression within a certain range.

When the startup of NPP, systems used for pressure regulation and temperature control might be changed, and some safety systems may be bypassed and unusable. For example, in case of cold shutdown operation mode, when starting RCPs to heat up the RCS, the

RCS pressure should be maintained at 28kg/㎠ via chemical and volume control system (CVCS). In this case, when the pressurizer water level is 100%, the pressure of the RCS is regulated by adjusting the flow rate of the charging pump and the flow rate of the low pressure discharging pipe, which are the connection path from the residual heat removal system (RHR) to CVCS. In addition, when the temperature and pressure of the RCS reach 146℃ and 28kg/cm2 respectively, the valves are aligned to isolate the RHR from the RCS and to perform the function of low pressure safety injection as an engineering safety feature (ESF). At temperatures and pressures above this point, the role of the heat sink is changed from RHR to steam generator. That is, the heating rate of the RCS can be controlled by using steam generators and the related system. Thus, during startup operation, available systems, systems, and operating variables are varied widely.

B. Classification of Operational States

Fig. 2. Classification of plant states

The framework for classification of operational states was developed considering both the complex NPP characteristics and dynamic states under startup operation. In case of accident diagnosis under startup operation, operation modes are different so that initial conditions under accident or anomaly are different by mode. In addition, even if the operation mode is same, the availability of components or systems can be different depending on the time of occurrence. To deal with these dynamic characteristic and complexity of startup operation, in order to develop the accident diagnosis algorithm which can be applied for both startup operation and full power operation, this study proposes an approach to classify operation modes.

Plant states are classified as shown in Fig. 2. A module is created for each mode of the power plant, and each module is composed of plant states which are selected based on specific criteria (i.e., the step which can affect the change of control mode “auto/manual”, the step that can affect the availability of safety systems, the step that use different systems to control). then, the appropriate classifier for the plant condition will be activated and output diagnosis results. Based on procedures for operating CNS during plant startup operation from cold shutdown mode to startup mode, 14 steps are selected and principal changes are shown in table 3. According to these selected steps, plant states (PSs) are classified before and after the step, as a result, total 15 plant states are identified.

Table 3. Principal changes after performing selected steps

No.	Principal changes
1	PV-145 “Manual” -> “Auto”
2	Charging control, PZR heaters / sprays “Manual” to “Auto”
3	Isolation of RHR, RHR pump stop, Safety injection is available
4	Shutdown control rods assembly drawn out
5	Accumulator isolation valve (HV39) open
6	Block Automatic opening of the PORV
7	PORV block clear: HV-6 available
8	P-12 status light-out
9	Steam dump to control: available
10	Source range trip block
11	Reactor trip on RCS flow, PZR low pressure, PZR high level is possible
12	Expanding of feedwater flow path
13	Steam Pressure setpoint control is changed to “Auto”
14	Reactor trip on low flow in a single loop is possible

For example, following Fig. 3 and Fig. 4 show the plant parameters during PS under accident, before and after the selected step No.11 and No.12. The blue line shows the plant behavior when an accident occurs in the condition before the step, and the orange line shows the plant behavior when the accident occurs after the step. In case of Fig.3, under pilot operated safety and relief valve (POSRV) stuck open situation which can be classified as LOCA, the reactor trip of plant is faster in PS-2 that the interlock is disappeared, so there are some differences in core exit temperature (CET), subcooled temperature margin, and SG levels in wide range. In addition, Fig.4 shows plant parameters under steam generator tube rupture (SGTR) 12㎠. Due to these differences, if only one algorithm is used for learning for startup operation, the difference of plant behaviors can degrade the performance of it or increase the possibility of wrong diagnosis.

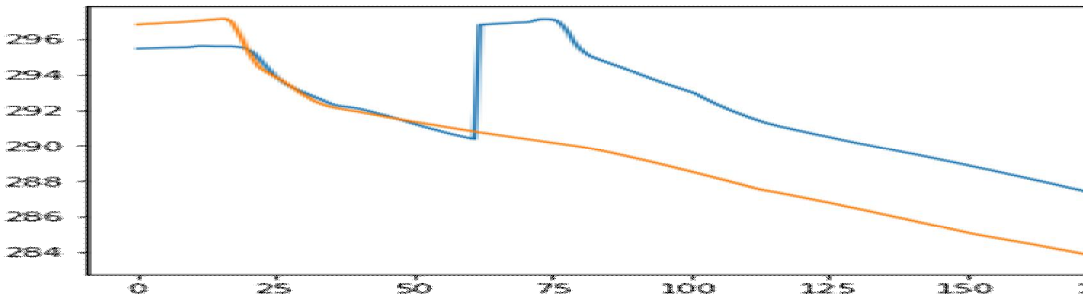

Fig. 3. Plant parameters before and after the selected step No.11
(accident: POSRV stuck open, left:CET, right: Subcooled temperature margin)

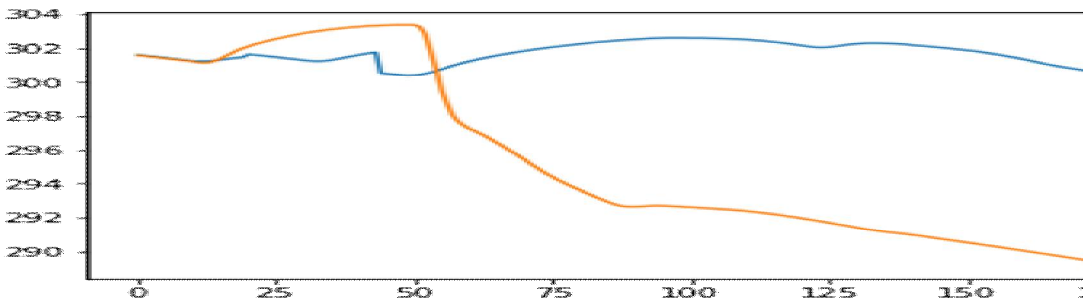

Fig. 4. Plant parameters before and after the selected step No.12
(accident: SGTR, left:CET, right: Subcooled temperature margin)

III. Accident Diagnosis Algorithms

This chapter introduces accident diagnosis algorithm considering the plant dynamics and operational mode. To reflect the time-series characteristics, the LSTM network structure is applied to develop the algorithm. The algorithm is trained with the data obtained from the CNS. The validation of network is performed with several test datasets.

A. Long Short-Term Memory (LSTM)

This study applies the LSTM network for the on-line accidents diagnosis algorithm of NPP. LSTM is an advanced version of RNN which is also an approach of ANN. ANN is a widely used statistical learning algorithm in machine learning, which was inspired by the biological neural network (i.e., brain). This model has a problem-solving ability due to artificial neurons (nodes) that form a network of synaptic connections and convert the synaptic bond strength through learning. Representatively, it can be branched into three paradigms of learning (i.e., based on whether supervised or not, and reinforcement learning) depending upon a particular type of learning task. In the case of supervised learning such as LSTM, it is optimized for the problem by calibrating implied data with the correctly labeled answers. Thus, it is generally used for guessing and approximating a veiled function. In other words, it is appropriate for analyzing tasks (i.e., pattern recognition, regression, and sequential data). Generally, accident diagnosis could be classified as a type of pattern recognition problems. It is widely known that ANNs show great performance in solving pattern recognitions. This section presents a brief introduction to RNN and LSTM.

1. RNN

Although numerous ANNs have been suggested, RNN is selected to model the accident diagnosis algorithm because it shows a good performance in analyzing time-series data. In contrast with other ANNs, it assumes that input and output are not separate of each other.

Namely, it can deal with sequential information as input data. The same calculation process is applied to every element of one sequence, and the result (i.e., output) is affected by the previous computation result. According to this assumption, because it utilizes the same calculation process, the structure of vanilla (i.e., the state is composed of a single hidden vector, h) RNN seems a circulating shape as shown in Fig. 5.

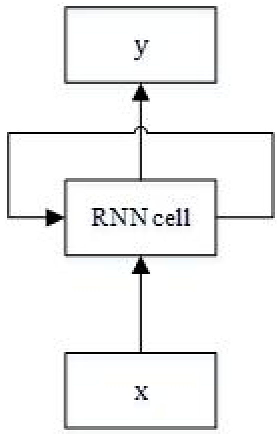

Fig. 5. Structure of vanilla RNN

It is a kind of ANN that the hidden node is linked to the directional edge to structure a circulating structure. Because of this structure, unlike common ANNs with distinctive parameters for each layer, they all share the same parameters. A sequence of vectors, x, is processed by utilizing recurrence formulas, Equations (1) to (3), at every time step. Fig. 6 shows the internal operational process in a single RNN time step [6, 9, 13, 14 ,17].

$$h_t = f_w(h_{t-1}, x_t) \tag{1}$$

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b_n) \tag{2}$$

$$y_t = W_{hy}h_t \tag{3}$$

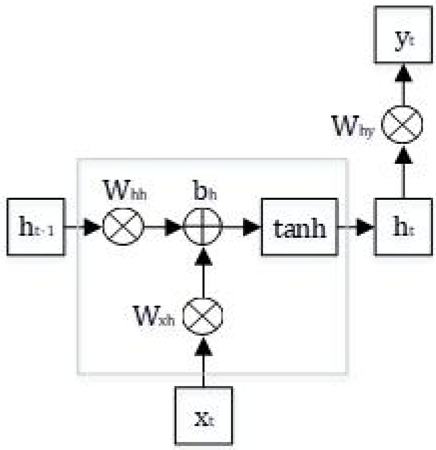

Fig. 6. Internal operational process in a single RNN time step

Because of this structure, the same task is performed to every element of one sequence and, also the output is affected by the computation results of prior calculations; hence, it is called "recurrent". In other words, RNN has memory information concerning the results computed so far. Thus, the preceding information can be applied to deal with the current problem. Therefore, this algorithm is the most appropriate method of solving a series of events or problems.

Furthermore, in the case of training, RNN does not regulate the weights by merely carrying the errors occurred at the current moment to the lower layer as original error backpropagation that is the learning algorithm of conventional ANNs. The conventional backpropagation updates each hyperparameter (i.e., weight and bias) by returning to the neural network and considering the proportion of error ascribed to the output stage. However, RNN learns this from the backpropagation through time (BPTT) algorithm, which delivers the errors occurring at the current point to the past. In this case, because each layer has the equal weight in the RNN, all the derivative errors associating with the weight at the equivalent position are augmented, and the weight is updated by obtaining numerical mean. Thus, RNN learns the error occurring in the current step by transmitting the error to the past state.

Because of these characteristics from BPTT, in the case of the NPP field, RNN is used for wide range of sequential data analysis, such as fault or anomaly detection, system health management, and accident diagnosis. The neuro-expert system was suggested for the combination of RNN and multilayer perceptron (MLP) including simple rules. In order to detect anomalies in the beginning stages and to give alarms about wrong signals occurring, neural networks such as RNN or MLP are applied. In parallel with neural networks, diagnostic activities based on the alarm information and inference of the causing factor have been performed through the expert system. Also, it can be applied to analyze dynamic cases solely (e.g., high-temperature gas cooling reactor, bearing damage) [18, 35-37].

The conventional RNN tracks past values back through time. However, too much backpropagation over a long period brings about a vanishing gradient problem due to the weight being multiplied repeatedly during the process of learning thus far into the past. The definition of a gradient is simply a measurement of the rate of change of y with variations in x. By applying it to the neural network, the relationship among all weights and errors of the neural network could be obtained; that is, adjusting the value of a neural network allows the resulting change of error to be determined. If the gradient could not be obtained precisely, the relationship between the measurement and the error is not clear; hence, learning cannot be achieved accurately. During the back-tracking of RNN in time, because the neural network is composed of multiplication operations, multiplying a very tiny value several times ultimately results in a considerably large value (i.e., vanishing gradient, blowing up), like compound interest charged by banks [38].

2. LSTM

LSTM is suggested for sequential data learning to deal with RNN regarding this vanishing gradient problem. LSTM is a type of neural network RNN based architecture for processing long temporal sequences of data. Time-series data can also be dealt with by other sequence models such as conditional random fields, Markov models, and Kalman filters. However, only LSTM is feasible to learn long-range dependencies. It may be hard to say that LSTM has a divergent structure from RNN; however, it utilizes a different equation to compute the hidden state. LSTM utilizes a structure which is called a memory cell in place of a RNN neuron. It integrates fast training with effectual learning on the tasks, which require time-series short-term memory storage for lots of time-steps during a trial. By enforcing special units that are called the memory cell, LSTM could learn to span minimal time lags more than 1000 discrete time steps. It determines whether the previous memory value should be altered, and calculates the value to be stored in the current memory based on the current state and the input value of the memory cell. This structure is highly efficient in storing long sequences. Moreover, alternative models (e.g., conditional random fields, Markov models, and Kalman filters) require domain knowledge or feature engineering, offering less chance for unexpected discovery, whereas LSTM can learn representations and discover unforeseen structures [35, 39, 40].

As with other LSTM models, in this study, each LSTM cell adjusts the output value using the several gates (i.e., input gate, forgetting gate, and output gate) while maintaining the cell state. Information in the cell state is consistent, and information can be added or removed through each gate. Furthermore, because the operation of each gate is comprised with an addition operation attached to the cell state, it can avoid the vanishing gradient problem.

The input gate adjusts the capacity of the input value. Also, the forgetting gate adjusts the degree to which the prior cell state is forgotten, and the output gate adjusts how much to output. Equation (4), denoted by g, represents the input node and has a tanh activation function denoted by ϕ; Equations (5), (6), and (7) represent the gates denoted by i, f, and o, respectively; σ represents a sigmoid function. Fig. 7 shows the architecture of the LSTM cell applied in this study.

$$g_l^{(t)} = \phi(W_g \cdot [h_{t-1}, x_t] + b^{g_l}) \tag{4}$$

$$i_l^{(t)} = \sigma(W_i \cdot [h_{t-1}, x_t] + b_l^i) \tag{5}$$

$$f_l^{(t)} = \sigma(W_f \cdot [h_{t-1}, x_t] + b_l^f) \tag{6}$$

$$o_l^{(t)} = \sigma(W_o \cdot [h_{t-1}, x_t] + b_l^o) \tag{7}$$

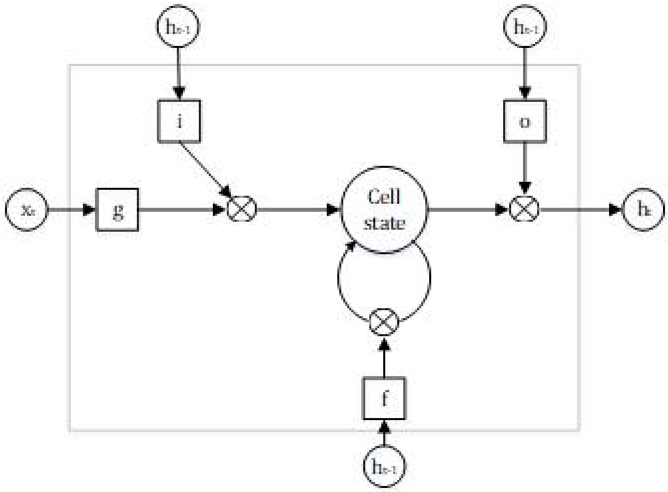

Fig. 7. Architecture of the LSTM cell

As shown in Fig. 7, the LSTM unit is composed of a cell with several gates attached. These gates can update the layers of memory cells $h_l^{(t)}$, where $h_{l-1}^{(t)}$ represents the prior layer at the simultaneous sequence step (i.e., a prior LSTM layer), and $h_l^{(t-1)}$ means the same layer at the prior sequence step.

This study utilizes the conventional LSTM structure. To model the optimized LSTM network without change of LSTM unit, it is necessary to decide the appropriate hyperparameters to design the algorithm (e.g., the number of input sequence or hidden layers). This is the reason why the objective of learning through the neural network is to decide the weight and value of bias that minimize the cost function. However, to get the expected level without the overfitting or underfitting problem, the optimization of hyperparameters should be required.

As well as the learning rates or iteration counts of training, the input sequence could be a kind of hyperparameters which represents the sequential length of the input data that LSTM uses to calculate the output. According to the length of input sequence, the performance of network is changed. In addition, the hidden layer is the hyperparameter which is needed to transform the inputs into a usable form for the output layer. Basically, each layer in the neural network gets the input for analysis farther from the original raw data that is closer to the goal. Therefore, the performance of the model could be affected by the number of hidden layers.

Four approaches (i.e., manual, grid, random search, and Bayesian optimization) are widely utilized in hyperparameter optimization. The manual search is a method of approximating optimal parameters and observing the results on the basis of the designer's intuition or experience. In a large frame, the grid search has significant big difference from manual search and is theoretically similar; however, it is analyzed utilizing a priori knowledge, and the scope of the hyperparameter is determined. Thereafter, the point at a certain amount of interval in the range is set and the points individually to decide the optimal value is tested. Following this, on the basis of the estimated optimal values, the new optimal value is searched by subdividing it. Like as the grid search, the random search utilizes a priori knowledge to decide the range of hyperparameters. Then, in place of identifying at regular intervals, an operation to search the optimal value proceeds. This may not seem to be different to a grid search, but if the result must be produced within a specific time-frame, random search tends perform better [41]. Since the basic principle of Bayesian optimization utilizes prior knowledge, the key to this method is on the basis of determining the direction of the next search after developing a statistical model on the basis of the experiment results thus far. It tends to find optimal values within a shorter time than using random or grid search [42]. Unfortunately, there is no golden rule so far, and much of it is dependent upon the experience and intuition of the designer.

B. Development of Accident Diagnosis Algorithms

Accident diagnosis algorithms based on LSTM used in this thesis are introduced in this part. The accident diagnosis is performed with the NPP datasets on the basis of trained classifier. During the training stage, the classifier is trained based on training datasets which are answer-labeled and also having a specific pattern for each accident. After sufficient training, it is validated with the test dataset and then used for real cases. Fig. 8 describes an overview of the process for accident diagnosis using LSTM.

To model the algorithm, a desktop computer with following hardware configurations is used: NVIDIA GeForce GTX 1080 8GB GPU, Intel 4.00GHz CPU, Samsung 850 PRO

512GB MZ-7KE512B SSD, and 24GB memory. Python 3.6.3 is used for coding language that is one of the most widely used computer language for machine learning and deep learning. The libraries developed to design the algorithm based on machine and deep learning (e.g., Tensorflow, Keras and scikit-learn) were used.

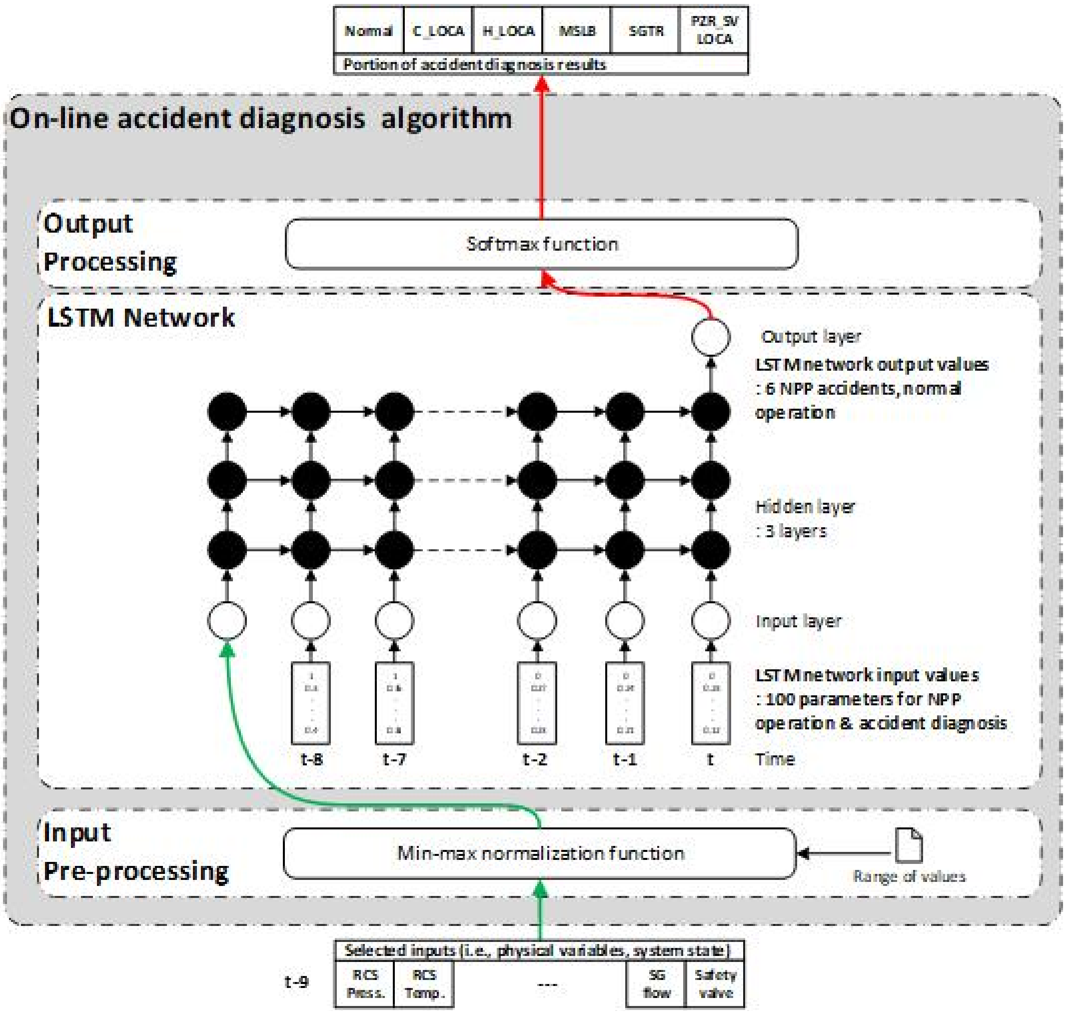

Fig. 8. Overview of process of accident diagnosis

1. LSTM network modeling for accident diagnosis

The model for accident diagnosis is designed for multi-labeled classification, because diagnoses may not be mutually exclusive. To identify an accident, the sequential trend of variables is needed as using inputs. Thus, it is applied a many-to-one structure to design the model. Fig. 9 illustrates a simple LSTM model for multi-label classification that is the base model applied in this study. According to the certain number of NPP input data sequences, the designed model can diagnose the plant state by capturing the pattern, that is, NPP trend.

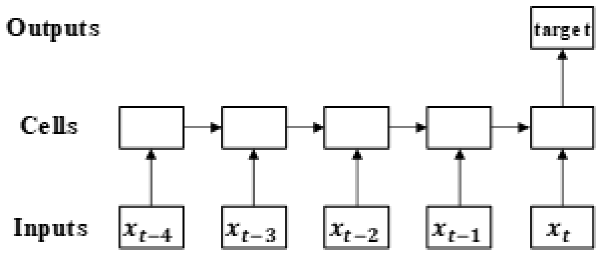

Fig. 9. Simple LSTM model for multi-label classification

2. Preprocessing and postprocessing

Preprocessing of the input values is implemented to the LSTM input layer. For the purpose of LSTM network training, all the values of input in the network should be fitted by normalizing value from the raw NPP data. This is because normalization can help to reduce the opportunity of getting stuck in local minima, which is not global minima among the some minimum points of error during the learning process, due to different scales of variables (e.g., RCS temperature: 300 ℃, Valve State: 0 or 1). The min-max scaling method is applied to calibrate the input values. The minimum and maximum of values are decided within the collected data (e.g., not real minimum or maximum of plant variables). Using the min-max scaling method, normalization performs a linear transformation of the raw data, and via the equation (8), the datasets are scaled within range from zero to one.

$$X_{norm} = (X - X_{\min}) / (X_{\max} - X_{\min}) \tag{8}$$

As a post-processing for the output of LSTM network, the softmax function layer shown in Fig. 10 is utilized to decide the ranking of accident probability.

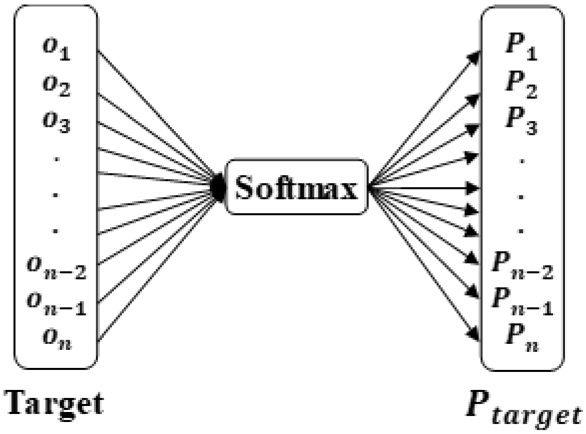

Fig. 10. Example of softmax function layer

The softmax function is an activation function commonly used in the output layer of the deep learning model; the purpose of it is to classify more than three classes [43]. Therefore, this study utilizes the softmax function for post-processing since there are six classes in the training. Softmax is a function which exponentially increases the importance by an exponential function; it also rises the deviation among the values, and then normalizes. It normalizes the input value to the output value within zero and one via the equation (9), and the sum of the output values should be always one.

$$S(y_i) = e^{y_i} / \sum e^{y_i} \tag{9}$$

Fig. 11 shows an example of an application of the softmax layer to transform output values to probabilities. Even if it is transformed, the magnitude relation of each output value does not change, and the output from softmax can be analyzed in terms of probability [44, 45]; thus, it enables stochastic analysis for multi-label classification.

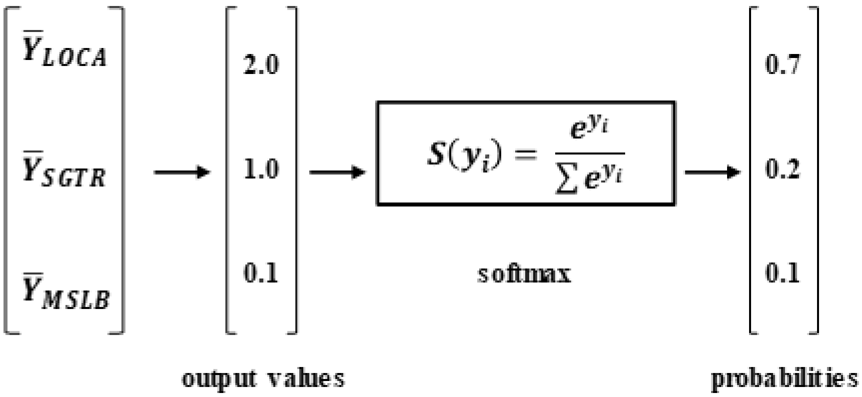

Fig. 11. Example of transformation from outputs to probabilities

3. Network training and optimization

The network is trained and implemented using the CNS, which implements the Westinghouse 3-loop, 930 MWe PWR. Fig. 12 shows the LSTM model for multi-label classification that is applied in this study.

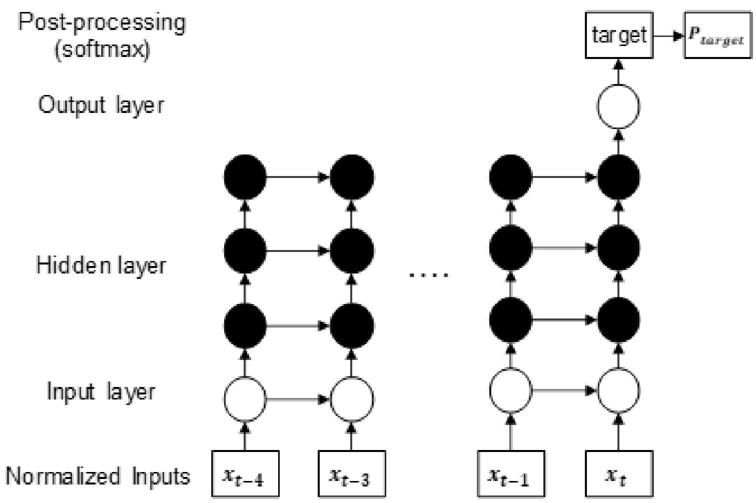

Fig. 12. LSTM model for multi-label classification

The coding of algorithm was implemented with Python 3.6.3. In case of full power operation, a total of 168 parameters are selected on the basis of critical safety functions, emergency operating procedures, and importance of the control for safe NPP operation; finally, input pre-processing is applied to choose 100 parameters. A total of 112 scenarios with 122,609 datasets (i.e., 122,609 seconds of data including 100 plant variables in each time step) are utilized for training, as shown in Table 4. The scenarios includes manual actuations followed by procedures and automatic actuations of systems and components. The learning rate and number of iteration sets are 0.005 and 3,000, respectively.

Table 4. Scenarios used for network training (Full power)

Initiating Events	**Number**
LOCA in Cold-leg	29
LOCA in Hot-leg	29
PZR safety valve opening (malfunction)	5
SGTR	17
Main steam line break (MSLB)	32
Total	112

In case of startup operation, a total of 51 parameters were selected based on procedures and by importance for control of NPP operation. Up to date, 65 scenarios (i.e., 11,571 seconds of data including 51 plant variable values in each time step) were used for training. Table 5 shows the scenarios used for training (2% power).

Table 5. Scenarios used for network training (2% power)

Initiating Events	**Number**
LOCA	32
MSLB inside containment	12
MSLB outside containment	12
SGTR	9
Total	65

To optimize the model, the manual search method has been applied by changing the hyperparameters and choosing appropriate input variables. Table 6 shows an accuracy comparison results of the different structures of networks. Input sequence lengths of five and ten, and two or three hidden layers are tested.

Table 6. Accuracy comparison between networks

Number of sequence	**Layers**	**Accuracy**	
		168 inputs	**100 inputs**
10	2	0.784	0.854
5	2	0.609	0.839
10	3	0.795	0.859
5	3	0.620	0.833

To evaluate the performance of the networks, the accuracy of the diagnosis results is considered. The accuracy is defined as Equation (10).

$$Accuracy = \frac{Correct\ results}{Diagnosis\ results} \tag{10}$$

This study only considered the accuracy as an optimization parameter. This is because the data for training and validation cannot be false positive or false negative unless false positive or false negative data are made artificially. Based on the performance comparison results, an input sequence length of ten and three layers is selected as the optimal LSTM network.

IV. Application of Accident Diagnosis Algorithms

The suggested algorithm has been tested with three scenarios, such as LOCA, SGTR, and MSLB, which are not used scenarios in the training session.

A. Test Results for Full Power Operation

Fig. 13 shows the test results for LOCA with sizes of 10 and 100 cm2 in Loop 1 cold-leg. Each line represents the accident or normal state of NPP. The malfunction is injected at 30 s for every test scenario. The X-axis and Y-axis represent the time and diagnosed result from the model with post-processing, respectively. The graphical results show that the accident is diagnosed constantly (i.e., the oscillation range is under 0.02) after approximately 150 s.

(a) 10㎠ LOCA in Loop 1 cold-leg

(b) 100㎠ LOCA in Loop 1 cold-leg

Fig. 13. Accident diagnosis results of LOCA

Figs. 14 and 15 also show the diagnosis correctly right after the malfunction is injected (i.e., 30 s) with suggested algorithm for SGTR and MSLB accidents. The reason why the diagnosis of LOCA takes longer time than SGTR and MSLB is that three different LOCAs were trained in the LSTM network (i.e., cold-leg LOCA, hot-leg LOCA, pressurizer safety valve LOCA). Even though the location is different in those LOCA, the plant behaviors are akin and then the LSTM takes a little bit long time to produce the steady result. In addition, the diagnose results for small and large LOCAs take akin length of time. However, the result of large LOCA shows the distinguished softmax output compared with the other accidents than the result of small LOCA does.

Fig. 14. Accident diagnosis result of 40㎠ SGTR in loop2

Fig. 15. Accident diagnosis result of 200㎠ MSLB in loop2

B. Test Results for Startup Operation

The designed accident diagnosis algorithm has been tested with two test scenarios (i.e., SGTR and LOCA) in the startup operation at 2% power. The malfunction is injected at 10 seconds. The solid line means the actual value of test data. The dotted line means the diagnosis result of algorithm. The X-axis represents the time and Y-axis represents diagnosed result, respectively. In addition, each line represents the accident or normal state of NPP.

Fig. 16 shows the diagnosis result for SGTR with size of 10 cm2 in loop 1. The results show that the accident is diagnosed right after the injection of malfunction.

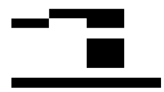

Fig. 16. Accident diagnosis result of 10㎠ SGTR in loop1

Also, the Fig. 17 shows the diagnosis result for LOCA with size of 40 cm2 in loop2 cold-leg. After approximately 20 seconds, its diagnoses constantly converge to almost 1.

Fig. 17. Accident diagnosis result of 40㎠ LOCA in loop2 cold-leg

V. Conclusion

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, this study shows the implementation of suggested accident diagnosis algorithm for full power operation and startup operation. There is still room for improvement to implement other modes considering availability of components or systems. In addition, the trained algorithm can be improved by hyperparameter tuning.

This study suggests an algorithm for accident diagnosis during startup operation to unload operator's task in abnormal or emergent situation for safety. As a result of accident diagnosis, it is expected that the safety of NPP during startup operation can be improved by application of algorithm for diagnosis of accidents.

REFERENCES

[1] Cometto, M., & Keppler, J. H. (2012). Nuclear energy and renewables: system effects in low-carbon electricity systems. Paris Dauphine University, Tech. Rep.

[2] Commission, U. S. N. R. (2012). NUREG-0711 Human Factors Engineering Program Review Model Revision 3. Washington, DC: United States Nuclear Regulatory Commission.

[3] Commission, U. N. R. (1981). Guidelines for preparing emergency procedures for nuclear power plants USNRC. Retrieved from

[4] Woods, D. D. (1988). Coping with complexity: the psychology of human behaviour in complex systems. Paper presented at the Tasks, errors, and mental models.

[5] Meister, D. (1995). Cognitive behavior of nuclear reactor operators. International journal of industrial ergonomics, 16(2), 109-122.

[6] Kontogiannis, T. (1996). Stress and operator decision making in coping with emergencies. International Journal of Human-Computer Studies, 45(1), 75-104.

[7] Vaurio, J. K. (1998). Safety-related decision making at a nuclear power plant. Nuclear engineering and design, 185(2-3), 335-345.

[8] Park, J., & Jung, W. (2004). A study on the systematic framework to develop effective diagnosis procedures of nuclear power plants. Reliability Engineering & System Safety, 84(3), 319-335.

[9] Yang, J., & Kim, J. (2018). An accident diagnosis algorithm using long short-term memory. Nuclear Engineering and Technology, 50(4), 582-588.

[10] Jang, S. C., Kang, H. G., Lim, H. G., Park, J. H., Eom, H. S., Kim, T. W., & Ha, J. J. (2005). Development of Risk Assessment Technology for Low Power, Shutdown and Digital I and C Systems. Retrieved from

[11] Yang, J., Lee, D., & Kim, J. (2018). Accident Diagnosis and Autonomous Control of Safety Functions During the Startup Operation of Nuclear Power Plants Using LSTM. Paper presented at the International Conference on Applied Human Factors

and Ergonomics.

[12] Fantoni, P., & Mazzola, A. (1996). A pattern recognition-artificial neural networks based model for signal validation in nuclear power plants. Annals of Nuclear Energy, 23(13), 1069-1076.

[13] Embrechts, M. J., & Benedek, S. (2004). Hybrid identification of nuclear power plant transients with artificial neural networks. IEEE Transactions on Industrial Electronics, 51(3), 686-693.

[14] Uhrig, R. E., & Hines, J. (2005). Computational intelligence in nuclear engineering. Nuclear Engineering and Technology, 37(2), 127-138.

[15] Lee, S. J., & Seong, P. H. (2005). A dynamic neural network based accident diagnosis advisory system for nuclear power plants. Progress in Nuclear Energy, 46(3-4), 268-281.

[16] Mo, K., Lee, S. J., & Seong, P. H. (2007). A dynamic neural network aggregation model for transient diagnosis in nuclear power plants. Progress in Nuclear Energy, 49(3), 262-272.

[17] Moshkbar-Bakhshayesh, K., & Ghofrani, M. B. (2013). Transient identification in nuclear power plants: A review. Progress in Nuclear Energy, 67, 23-32.

[18] Nabeshima, K., Suzudo, T., Seker, S., Ayaz, E., Barutcu, B., Türkcan, E., . . . Kudo, K. (2003). On-line neuro-expert monitoring system for borssele nuclear power plant. Progress in Nuclear Energy, 43(1-4), 397-404.

[19] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural computation, 9(8), 1735-1780.

[20] Vohradsky, J. (2001). Neural network model of gene expression. the FASEB journal, 15(3), 846-854.

[21] Pollastri, G., Przybylski, D., Rost, B., & Baldi, P. (2002). Improving the prediction of protein secondary structure in three and eight classes using recurrent neural networks and profiles. Proteins: Structure, Function, and Bioinformatics, 47(2), 228-235.

[22] Xu, R., Wunsch II, D., & Frank, R. (2007). Inference of genetic regulatory

networks with recurrent neural network models using particle swarm optimization. IEEE/ACM Transactions on Computational Biology and Bioinformatics, 4(4), 681-692.

[23] Liwicki, M., Graves, A., Fernàndez, S., Bunke, H., & Schmidhuber, J. (2007). A novel approach to on-line handwriting recognition based on bidirectional long short-term memory networks. Paper presented at the Proceedings of the 9th International Conference on Document Analysis and Recognition, ICDAR 2007.

[24] Auli, M., Galley, M., Quirk, C., & Zweig, G. (2013). Joint language and translation modeling with recurrent neural networks.

[25] Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. Paper presented at the Advances in neural information processing systems.

[26] Vinyals, O., Toshev, A., Bengio, S., & Erhan, D. (2015). Show and tell: A neural image caption generator. Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.

[27] Karpathy, A., & Fei-Fei, L. (2015). Deep visual-semantic alignments for generating image descriptions. Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.

[28] Xing, J., Song, D., & Wu, Y. (2016). HPR1000: advanced pressurized water reactor with active and passive safety. Engineering, 2(1), 79-87. Han, S. J., Park, J. H., & Jang, S. C. (2003). Identification of initiating events using the master logic diagram in low-power and shutdown PSA for nuclear power plant. Retrieved from

[29] Korea Atomic Energy Research Institute. (1990). Advanced compact nuclear simulator textbook.

[30] NRC, U. (2012). Standard Technical Specifications Westinghouse Plants. NUREG-1431, 1, 2.

[31] Masche, G. (1971). Systems summary of a Westinghouse pressurized water reactor nuclear power plant: Westinghouse Nuclear Energy Systems.

[32] Park, J. H., Kim, T. W., Han, S. J., Jang, S. C., & Lim, H. G. (2003). Event data collection and database development during plant shutdown and low power operations at domestic and foreign reactors. Retrieved from

[33] Han, S. J., Park, J. H., & Jang, S. C. (2003). Identification of initiating events using the master logic diagram in low-power and shutdown PSA for nuclear power plant. Retrieved from

[34] Jang, S., Park, J., Kim, T., Lim, H., & Son, Y. S. (2004). Detailed thermal-hydraulic analysis for Korea standard nuclear power plant during low power/shutdown operation. Retrieved from

[35] Şeker, S., Ayaz, E., & Türkcan, E. (2003). Elman's recurrent neural network applications to condition monitoring in nuclear power plant and rotating machinery. Engineering Applications of Artificial Intelligence, 16(7-8), 647-656.

[36] Subekti, M., Kudo, K., & Nabeshima, K. (2006). The development of anomaly diagnosis method using neuro-expert for PWR monitoring system. Paper presented at the International Conference on Advanced in Nuclear Science and Engineering (ICANSE2007).

[37] Ayodeji, A., Liu, Y.-k., & Xia, H. (2018). Knowledge base operator support system for nuclear power plant fault diagnosis. Progress in Nuclear Energy, 105, 42-50.

[38] Hochreiter, S., & Schmidhuber, J. (1996). Bridging long time lags by weight guessing and "Long Short-Term Memory". Spatiotemporal models in biological and artificial systems, 37, 65-72.

[39] Monner, D., & Reggia, J. A. (2012). A generalized LSTM-like training algorithm for second-order recurrent neural networks. Neural Networks, 25, 70-83.

[40] Lipton, Z. C., Kale, D. C., Elkan, C., & Wetzel, R. (2015). Learning to diagnose with LSTM recurrent neural networks. arXiv preprint arXiv:1511.03677.

[41] Bergstra, J., & Bengio, Y. (2012). Random search for hyper-parameter optimization. Journal of Machine Learning Research, 13(Feb), 281-305.

[42] Snoek, J., Larochelle, H., & Adams, R. P. (2012). Practical bayesian optimization

of machine learning algorithms. Paper presented at the Advances in neural information processing systems.

[43] Nasrabadi, N. M. (2007). Pattern recognition and machine learning. Journal of electronic imaging, 16(4), 049901.

[44] Lei, Y., Jia, F., Lin, J., Xing, S., & Ding, S. X. (2016). An intelligent fault diagnosis method using unsupervised feature learning towards mechanical big data. IEEE Transactions on Industrial Electronics, 63(5), 3137-3147.

[45] Tao, S., Zhang, T., Yang, J., Wang, X., & Lu, W. (2015). Bearing fault diagnosis method based on stacked autoencoder and softmax regression. Paper presented at the Control Conference (CCC), 2015 34th Chinese.