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Original Article

Abnormality diagnosis model for nuclear power plants using two-stage gated recurrent units

Jae Min Kim, Gyumin Lee, Changyong Lee**, Seung Jun Lee*

Ulsan National Institute of Science and Technology, 50, UNIST-gil, Ulsan, 44919, Republic of Korea

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A B S T R A C T

A nuclear power plant is a large complex system with tens of thousands of components. To ensure plant safety, the early and accurate diagnosis of abnormal situations is an important factor. To prevent misdiagnosis, operating procedures provide the anticipated symptoms of abnormal situations. While the more severe emergency situations total less than ten cases and can be diagnosed by dozens of key plant parameters, abnormal situations on the other hand include hundreds of cases and a multitude of parameters that should be considered for diagnosis. The tasks required of operators to select the appropriate operating procedure by monitoring large amounts of information within a limited amount of time can burden operators. This paper aims to develop a system that can, in a short time and with high accuracy, select the appropriate operating procedure and sub-procedure in an abnormal situation. Correspondingly, the proposed model has two levels of prediction to determine the procedure level and the detailed cause of an event. Simulations were conducted to evaluate the developed model, with results demonstrating high levels of performance. The model is expected to reduce the workload of operators in abnormal situations by providing the appropriate procedure to ultimately improve plant safety.

1. Introduction

Nuclear power plants (NPPs) are subject to strict safety standards to prevent any harmful effects on their surroundings, especially when severe accidents occur. Since human errors such as misdiagnoses and wrong manipulations can cause undesired negative effects on plant safety, detailed operating procedures should be followed by operators to diagnose the NPP and perform corrective actions in abnormal situations. In general, there are two types of operating procedures for abnormal events: abnormal operating procedures (AOPs) and emergency operating procedures (EOPs). When faced with an abnormal situation, operators must identify the causes of the current situation and perform corrective actions based on the corresponding AOP to return the plant to a normal condition [1]. Response timing in this case is critical: if the situation is not successfully mitigated in the proper amount of time and becomes too severe for the AOPs to cope with, the situation becomes an emergency situation (or accident). This requires the reactor to be shut down and mitigation actions performed to manage plant safety based on the appropriate EOP.

In the case of the Advanced Power Reactor 1400 (APR-1400), which is the target NPP of this study, when an accident causing reactor trip occurs, operators must perform the standard post-trip action procedure including urgent actions to maintain plant safety, and then perform the diagnostic action procedure to identify the appropriate EOP from among seven total EOPs. It takes several minutes to identify the appropriate EOP through a symptom-based flowchart provided in the diagnostic action procedure. In contrast, the first action of the operators in an abnormal situation is to identify the appropriate AOP from among 82 AOPs with 224 total sub-procedures. This large number of AOPs as well as the number of plant parameters to be considered for diagnosis make identifying the appropriate AOP difficult. In practice, it is not possible to compare current plant parameters and alarms with all the entry conditions of the more than 200 AOPs, and thus operators tend to make decisions based on their knowledge and experience.

Each entry condition described in an AOP includes around 10 symptoms of expected alarms and plant parameter changes. There are hundreds of alarms when a specific plant parameter goes above or below the pre-defined set points, with alarms having different occurrence times for given abnormal situations. For example, in case of a pipe leakage of the charging system, if the leakage size is

* Corresponding author.
** Corresponding author.
E-mail addresses: changyong@unist.ac.kr (C. Lee), sjlee420@unist.ac.kr (S.J. Lee).

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large, it only takes a couple of minutes for operators to confirm the related alarms and changes of the related plant parameters. However, if the leakage size is small, it takes several minutes for the first alarm to even initiate, and tens of minutes to confirm the multiple alarms and parameter changes in order to identify the abnormal event. In this way, depending on the severity of an abnormal event, symptoms may not be clear enough for operators to detect the event in its early stages, thereby causing operators to spend more time for diagnosis [2,6].

It can be seen that abnormal situations require both an early and accurate diagnosis. More time for operators to conduct corrective actions and more reliable diagnoses of abnormal situations will be helpful for reducing human errors.

As means of support, there have been several attempts to develop a system that can diagnose NPP states on behalf of the operators [3–15]. Although these approaches have achieved useful methods to diagnose transient states, most of the studies focused on severe events that result in reactor trips. In addition, when selecting input variables, previous works generally rely on expert judgement, which limits the number of variables and the scope of the target systems. Further, most are static models that give a diagnosis result in a fixed time. Previous methods therefore have practical limitations to handle large amounts of cases, such as abnormal operation conditions, and require expert judgement to obtain the features of the data.

To solve these problems, this work aims to develop a system that can handle all monitorable parameters with two judgement processes employing an algorithm that has strength in time-series data analysis. The principal component analysis (PCA) method is first used to extract features and reduce the dimensionality of abnormal operating data from a simulator. These preprocessed data are then used for training and testing the diagnosis model. The model structure comprises two levels considering possible cases that can occur: the algorithm in the main level determines the appropriate AOP corresponding to the event occurring, and the sub-level determines the detailed cause of the event. Gated recurrent unit (GRU) algorithms are used to handle the preprocessed dataset. As an application, 10 AOPs are selected as abnormal scenarios with 1004 variables that can be monitored in the NPP simulator. It was observed in the results that the developed model—by considering only plant parameters rather than the simultaneous examination of alarms and symptoms as required by operators—was able to identify the appropriate AOP in less than 1 min after event occurrence at a high level of accuracy.

The remainder of this paper is organized as follows. Section II introduces related research and describes a general AOP. Section III covers model development with related techniques. Sections IV and V present the application settings and results, and Sections VI and VII provide discussions and conclusions.

2. Background

2.1. Related works

Over the past few decades, there have been attempts to identify abnormal situations in NPPs through data-driven analysis. Rather than the model-driven approach, the research focus of abnormality diagnosis has shifted to symptoms [3]. Starting with classifying variable patterns of failures, recent studies have moved to determining abnormal conditions through complex algorithms.

Numerous studies have focused on directly analyzing plant parameters or patterns as a method of diagnosing NPP status. Miller et al. [4] applied a hierarchical classification method to reduce search space to a manageable size in a top-down manner based on the role of the systems. By identifying patterns in the variables of component failures in abnormal situations, failures can be determined when they have a similar pattern. Similarly, Horiguchi et al. [5] used patterns of 49 normalized plant parameters occurring in an abnormal situation. An artificial neural network (ANN) algorithm was trained with these patterns to identify 100 abnormal cases. Santosh et al. [6,7] applied a resilient-back propagation algorithm to solve the pattern recognition problem for NPP transient diagnosis. Rocco et al. [8] employed different support vector machine (SVM) algorithms for identifying unknown anomalies.

For improved pattern recognition, Serker et al. [9] applied Elman's recurrent neural network (RNN) algorithm to predict signals and detect damage on bearings. Zhao et al. [10] employed a local feature-based GRU algorithm for tool wear prediction, gearbox fault diagnosis, and bearing fault detection. Lee et al. [11] and Mo et al. [12] clustered analog and digital data as inputs for two algorithms; in this system, the modified dynamic neural network handles digital inputs such as alarms and valve states, and the dynamic neuro-fuzzy network handles analog inputs indicating continuous changes of plant parameters.

One of the issues for abnormality diagnosis is how much confidence diagnostic models have in their judgements. Embrechts et al. [13] compared the performances of various neural network algorithms and data normalization methods to identify unlabeled data as “don't-know” types of transients. Costa et al. [14] proposed a system that uses artificial neural networks at the first level for transient diagnosis, and fuzzy logic at the second level for analysis of the outputs to determine the cause of a given event.

Such prior research has two limitations in regard to selecting input variables and the number of cases that were handled. Domain knowledge of NPP accidents was considered by experts when selecting input variables. Ayodeji et al. [15] applied PCA in preprocessing to reduce the dimensions of the input dataset and filter noise. Although PCA successfully achieved the anticipated results in this work, only 43 original variables were used in which only some of the primary systems were involved.

In the present work, all variables that can be monitored in an NPP simulator are used as the inputs. Ten AOPs are selected with 18 sub-procedures included. Related systems are chosen to evenly represent an NPP, including both primary and secondary side systems.

2.2. Abnormal operating procedure

Similar to other hazardous industries, the nuclear field has established operating procedures to guarantee a high level of safety in the plants. These procedures are grouped by the operation purpose according to the plant state. Among them, AOPs provide the operators with information to diagnose the plant state and to stabilize the plant after an abnormal event occurs.

When an abnormal event occurs in an NPP, plant parameters begin to fluctuate outside of their normal states, with some parameters reaching a setpoint that generates alarms. Operators should then identify that the NPP is not in a normal state and diagnose the plant condition correctly [16]. After the NPP is diagnosed, the operators should stabilize the plant using the appropriate AOP. Operators are trained to find the appropriate procedure in accordance with the relevant entry condition after diagnosing the plant state. Alarms and symptoms act as the entry conditions provided for in each sub-procedure, which are identifiable in the main control room.

Once the NPP is tripped or a safety injection signal is actuated, the situation is considered as an emergency (i.e., no longer an abnormal situation). In this case, operators must shut down the plant safely by following appropriate EOPs [17]. In order to prevent the situation from becoming an emergency, operators must consider hundreds of combinations of alarms, symptoms, and corresponding entry conditions of the AOPs to accurately judge and mitigate the situation before NPP trip. Therefore, early and accurate diagnosis of an abnormal situation in NPPs is crucial to maintain plant safety.

3. Methodology

Fig. 1 shows the overall model development process, from generating data to training. Data are preprocessed after generation from an NPP simulator. These data are used to train the GRU algorithms in both main and substages.

As one of the methods to reduce the data dimensions, the feature extraction method extracts latent features from original variables. It has an advantage to develop a real-time fault diagnosis system by extracting the key characteristics from the entire dataset. Since the data obtained through an NPP simulator cover a wide range of properties such as pressure, temperature, and flow rate, PCA was chosen as the preprocessing method. Fig. 2 shows a heatmap plot of the correlations for a portion of the data. The horizontal and vertical axes are assigned variables, and the heatmap is drawn to represent variances. Since the number of variables exceeds 1000, correlations are not obvious from the full heatmap on the left; therefore, the extracted heatmap on the right for only 20 variables out of the entire dataset is included to show the high correlation among variables.

Since these datasets reflect an NPP state over time, GRU algorithms are chosen for considering all the information at each point in time. The GRU algorithm is one of the solutions to overcome the vanishing gradient problem by using more sophisticated activations than traditional RNNs [18–20]. Even though symptoms may not appear at the beginning of an abnormal situation, it is possible to identify failures by recognizing any change from the observation point.

This section covers the model structure, PCA method, and GRU algorithm.

3.1. Model structure

One of the difficulties when diagnosing an abnormality of an NPP is the wide range of target systems and corresponding outputs. In response, this work designs a two-stage model (TSM) utilizing GRU algorithms, as shown in Fig. 3.

Rather than processing all cases with one algorithm, the first diagnosing or main stage predicts the AOPs, while the substage predicts the sub-procedures of individual AOPs by their own algorithms. Based on the prediction results of the algorithm at the main stage, the corresponding substage shows the sub-procedure of the AOP.

By dividing the decision process into two stages as such, the opportunity to detect errors increases. In addition, each algorithm in the TSM model considers a smaller number of labels compared to one algorithm that must cover the entire process.

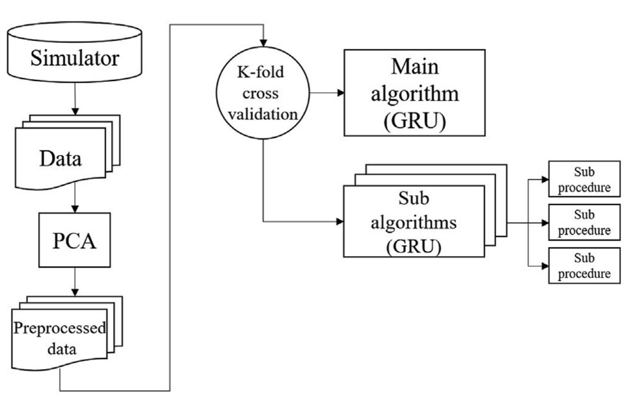

Fig. 1. Process to develop the abnormal state diagnosis model.

3.2. Principal component analysis

Mathematically, unique features of data can be expressed as a total variance. PCA is a method to convert some original data into a dimensionally reduced dataset [21]. To do this, PCA calculates a linear transformation matrix by the following steps.

First, a correlation matrix or covariance matrix of the original data is obtained when normalizing the original data matrix. The maximum-minimum normalization method is used for this work:

$$x^*_{t,i} = \{x_{t,i} - \min(x_i)\} / \{\max(x_i) - \min(x_i)\} \quad (i = 1, 2, \ldots , p), \tag{1}$$

where $x_{t,i}$ is the i-th input variable at time t and $x^*_{t,i}$ is the normalized variable. The maximum and minimum values are extracted from the i-th dataset.

Second, the correlation matrix is decomposed by its eigenvectors and eigenvalues, where the eigenvectors represent the principal components (PCs), and the eigenvalues represent the percentage of variance described by the corresponding eigenvectors. This can be expressed by:

$$\begin{aligned}
\overrightarrow{z_1} &= a_{11}\overrightarrow{x_1} + a_{12}\overrightarrow{x_2} + \ldots + a_{1p}\overrightarrow{x_p} = \overrightarrow{a_1}^T X \\
\overrightarrow{z_2} &= a_{21}\overrightarrow{x_1} + a_{22}\overrightarrow{x_2} + \ldots + a_{2p}\overrightarrow{x_p} = \overrightarrow{a_2}^T X \\
&\cdots \\
\overrightarrow{z_p} &= a_{p1}\overrightarrow{x_1} + a_{p2}\overrightarrow{x_2} + \ldots + a_{pp}\overrightarrow{x_p} = \overrightarrow{a_p}^T X
\end{aligned}$$

$$\boldsymbol{z} = \begin{bmatrix} \overrightarrow{z_1} \\ \overrightarrow{z_2} \\ \cdots \\ \overrightarrow{z_p} \end{bmatrix} = \begin{bmatrix} \overrightarrow{a_1}^T X \\ \overrightarrow{a_2}^T X \\ \cdots \\ \overrightarrow{a_p}^T X \end{bmatrix} = \begin{bmatrix} \overrightarrow{a_1}^T \\ \overrightarrow{a_2}^T \\ \cdots \\ \overrightarrow{a_p}^T \end{bmatrix} X = A^T X, \tag{2}$$

where $\overrightarrow{z_k}$ is the k-th vector of the PCs ($k = 1, 2, \ldots, p$) and A^T is the orthogonal matrix whose k-th column $\overrightarrow{a_k}$, is the k-th eigenvector of the covariance matrix. X is the normalized dataset.

Third, the number of PCs is determined based on the cumulative percentage of variance described. For example, if the sum of the top 10 PCs is 0.90, then these 10 PCs have 90% of the information from the original data.

3.3. Gated recurrent unit

GRU uses two gates: update and reset. The activation h_t, which is a linear interpolation between the previous activation h_{t-1} and the candidate activation $\tilde{h}_t$, is computed by:

$$h_t = z_t h_{t-1} + (1 - z_t)\tilde{h}_t, \tag{3}$$

where update gate z_t determines the extent that the unit updated its activation, or content. The updated gate is computed by:

$$\textit{update gate} \; : z_t = \sigma\left(W^{(z)} x_t + U^{(z)} h_{t-1}\right), \tag{4}$$

where σ is the logistic sigmoid function, and x_t and h_{t-1} are the input at time t and the previous hidden state, respectively. $W^{(r)}$ and $U^{(r)}$ are trained weight matrices. The candidate activation $\tilde{h}_t$ is

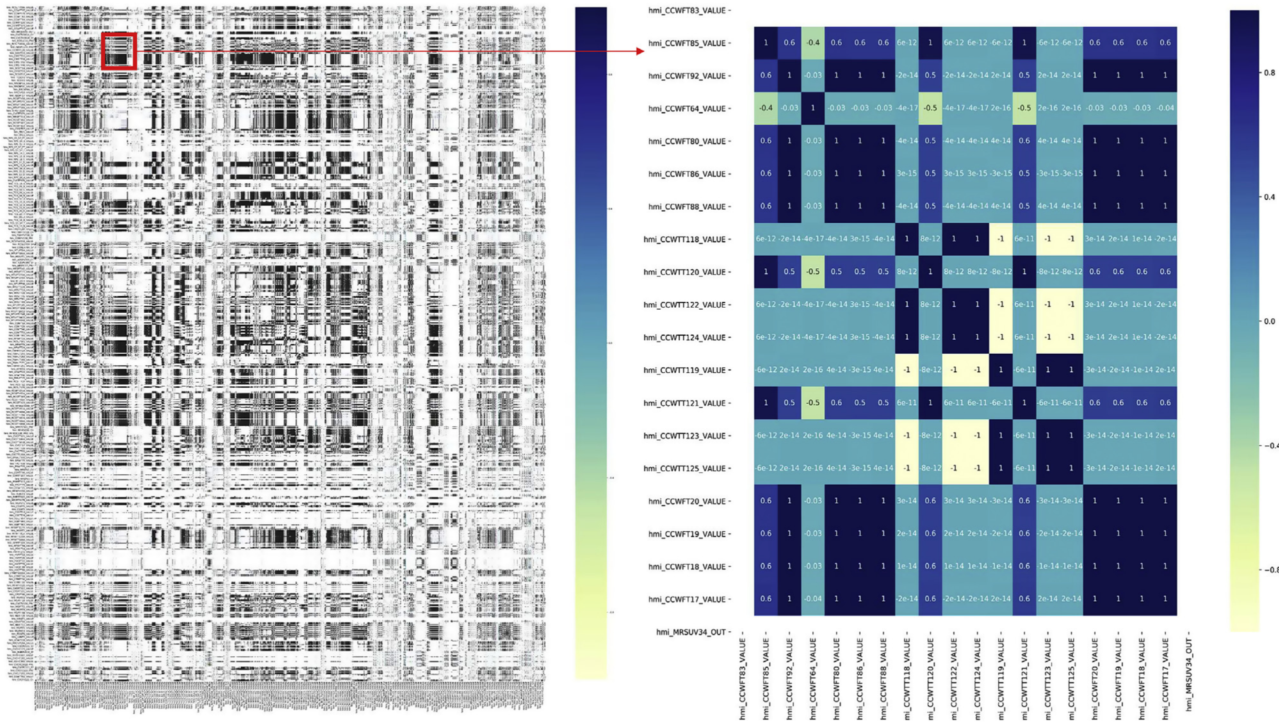

Fig. 2. Heatmap of variances of sample data (dark blue: 1, yellow: −1). The closer a variance is to 1 or closer to −1, the greater a correlation between two variables. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

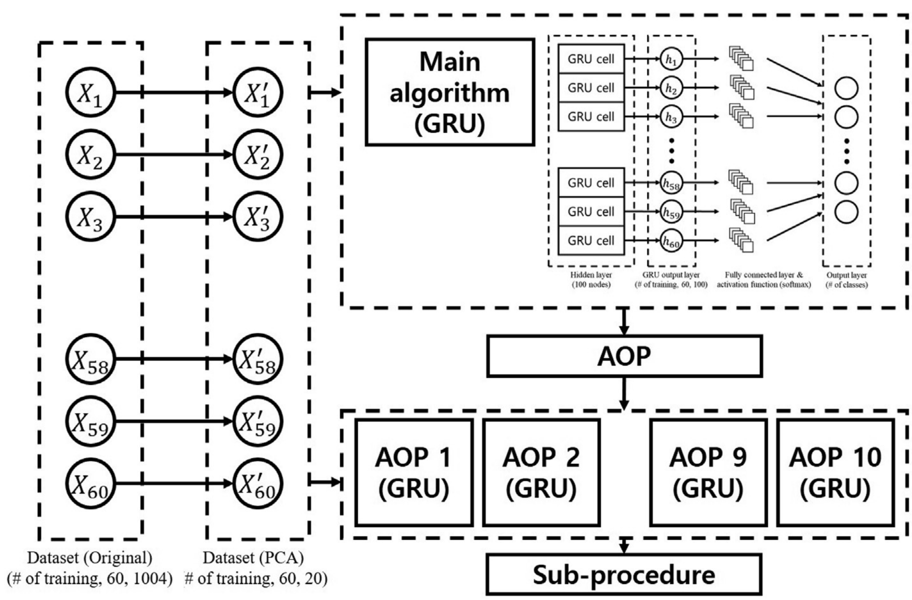

Fig. 3. Determination process of the abnormal state diagnosis model using GRU algorithms in two stages.

computed by:

$$\tilde{h}_t = \tanh(Wx_t + U(r_t \odot h_{t-1})), \tag{5}$$

where r_t is a set of reset gates, and $\odot$ is an element-wise multiplication. Similar to the update gate, the reset gate is computed by:

$$reset\ gate\ : r_t = \sigma\left(W^{(r)}x_t + U^{(r)}h_{t-1}\right), \tag{6}$$

Using these gates, Fig. 4 depicts a GRU algorithm controlling

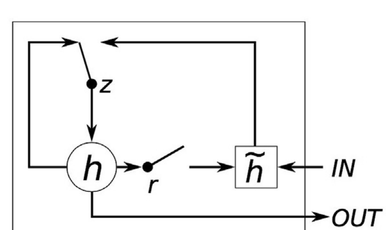

Fig. 4. Schematic diagram of the gated recurrent unit algorithm [19].

how much information that is passed between cells will be reflected in the current state. This allows the GRU to reduce computational complexity, thereby enabling more efficient computation.

4. Experimental settings

4.1. Descriptions of datasets

Owing to the lack of real NPP operation records of abnormal situations, training data needs to be secured through a simulator. In this work, the 3KEYMASTER simulator was used to generate the training data [22]. This simulates a generic 1400 MWe pressurized water reactor similar to the APR-1400. Although the simulator does not perfectly match the APR-1400, abnormal scenarios have been chosen to enable similar abnormal symptoms when implemented in the simulator.

Useful functions include inserting malfunctions into components and running the simulator with a pre-written script. In addition, it can accelerate simulation time to twice as fast as real time for an efficient data production environment. The simulator's ability to produce various scenarios by controlling the degree of malfunction and injection time makes it suitable for the present work.

A total of 10 abnormal scenarios were selected to simulate various situations as listed in Table 1. Scenarios were selected considering the relevance of target systems and the number of sub-procedures in the AOPs. All scenarios had 1 min run times before the reactor or turbine trip condition. It was found in preliminary tests that the algorithm completed its prediction in under 1 min after a malfunction was injected according to the scenario. Steam generator (SG) tube leakage, condenser (CDS) vacuum abnormality, pilot-operated safety relief valve (POSRV) leakage, and main steam isolation valve (MSIV) abnormality each have one sub-procedure. Charging water system (CHRG) abnormality, letdown water system (LTDN) abnormality, reactor makeup water (RMW) tank valve abnormality, and reactor coolant pump (RCP) abnormality have multiple sub-procedures in a single system. Circulating water system (CWS) abnormality and main steam system (MSS) abnormality comprise multiple sub-procedures in multiple systems.

A total of 300 datasets were generated for each sub-procedure, and a total of 5700 datasets were obtained including normal operation.

4.2. Experimental setup

The epoch, which represents one training cycle, was set to 100 for model fitting. Normal-state data were partially duplicated to balance the number of abnormal cases, because the system code continuously produced almost the same results for the same initial condition. The batch size was set to 28.

To evaluate the performance of the developed model, a k-fold cross-validation method was used. Data were exclusively divided into five groups, with 80% of the original raw data randomly selected for training and the remaining 20% used for testing.

Performance evaluating factors are listed as the following descriptions and Eqs. (7)–(10) [23].

- Accuracy: The fraction of the count of correct predictions

$$Accuracy = \frac{\#\ of\ correct\ predictions}{Total\ \#\ of\ samples} \tag{7}$$

- Precision: The ability of the classifier not to label a negative sample as positive

$$Precision = \frac{1}{\sum_{l \in L} |\widehat{y}_l|} \sum_{l \in L} |\widehat{y}_l| \frac{|A \cap B|}{|A|} \tag{8}$$

- Recall: The ability of the classifier to find all the positive samples

$$Recall = \frac{1}{\sum_{l \in L} |\widehat{y}_l|} \sum_{l \in L} |\widehat{y}_l| \frac{|A \cap B|}{|B|} \tag{9}$$

- F1 score: The weighted harmonic mean of precision and recall

$$F1\ score = \frac{1}{\sum_{l \in L} |\widehat{y}_l|} \sum_{l \in L} |\widehat{y}_l| \frac{2{*}Precision{*}Recall}{(Precision + Recall)} \tag{10}$$

where y is the set of predicted (sample, label) pairs, y_l is the subset of y with label l, $\widehat{y}$ is the set of true (sample, label) pairs, $\widehat{y}_l$ is the subset of $\widehat{y}$ with label l, and L is the set of labels.

Table 1
List of selected AOPs.

#	Title of abnormal operating procedures	#	Sub-procedure
1	SG tube leakage (SGTL)	1–1	SG 1,2 tube leakage
2	Charging water system abnormality (CHRG)	2–1	Normal charging pump trip (PM)
		2–2	Charging valve abnormality (VV)
		2–3	Water line leakage (LN)
3	Letdown water system abnormality (LTDN)	3–1	Water line leakage (LN)
		3–2	Letdown valve abnormality (VV)
4	CDS vacuum abnormality (CDS)	4–1	CDS vacuum release
5	POSRV leakage (POSRV)	5–1	POSRV leakage (VV)
6	RMW tank valve abnormality (RMW)	6–1	VCT[a] low level (LL)
		6–2	VCT high level (LH)
7	CWS abnormality (CWS)	7–1	LP[a] condenser tube leakage (LN)
		7–1	IP[a] condenser tube leakage (LN)
		7–1	HP[a] condenser tube leakage (LN)
		7–2	Valve abnormality (VV)
		7–3	Pump trip (PM)
8	MSIV abnormality (MSIV)	8–1	MSIV abnormality
9	RCP abnormality (RCP)	9–1	RCP CCW[a] loss (LC)
		9–2	RCP seal damage (SD)
10	MSS abnormality (MSS)	10–1	SBCS[a] valve abnormality (VV)
		10–2	Main steam leakage (LN)

[a] VCT: volume control tank; LP: low pressure; IP: intermediate pressure; HP: high pressure; CCW: component cooling water; SBCS: steam bypass control system.

Since data were selected randomly, performance evaluating factors were taken from the weighted average of test datasets.

4.3. Comparative analysis

Performance of the TSM was compared with ANN and SVM algorithms to evaluate its competitiveness. All models used the same preprocessed data through PCA and the cross-validation method.

In the TSM, each GRU algorithm in both levels has the same setup with a (60,20) input layer, a hidden layer with 100 nodes, and a (60,100) output layer. Softmax was used as the activation function along with the Adam optimizer.

In the ANN, the size of the hidden layer was 20, with ReLu (rectified linear unit) used as the activation function in this case and again the Adam optimizer. Both of these are typically used functions in deep learning algorithms. For multi-classification, a radial basis function kernel was used for the SVM with a one-vs-one decision function.

5. Results

The data preprocessing and developing models were implemented in a Python 3.6 environment with Keras and scikit-learn modules.

The TSM contains 1 algorithm in its main level and 10 algorithms in its sub-level, one for each abnormal event. For a given abnormal event, the related sub-level algorithm determines the sub-procedure based on the results predicted by the algorithm in the main level. Fig. 5 illustrates this process, where the main-level algorithm determines the title of the AOP, in this case CHRG, and then the sub-level algorithm for CHRG determines the specific sub-procedure, in this case water line leakage (LN, from Table 1). As shown in the graphs, the probability of the predicted label is marked each second.

Here, 20 PCs were conservatively chosen to further increase the accuracy, with more than 99.99% of information conserved. Each algorithm in the TSM was trained with the same training environment. Table 2 shows the performance evaluation factors of the main algorithm of the TSM, ANN, and SVM models, indicating that TSM shows the best performance among the comparative models. Table 3 shows the performance evaluation factors of the TSM sub-algorithms. The sub-layer algorithms predicted with an almost 100% accuracy for the given data. Thus, accurate prediction at the main stage is the key for TSM.

6. Discussion

Analysis of AOPs requires a great amount of time and effort from non-trained NPP operators. In response, PCA allows for the efficient reduction of data dimensionality while maintaining as much information as required. A test was conducted to validate the PCA method for NPP diagnosis, comparing with expert-selected parameters based on an AOP analysis (knowledge-based parameters). The total number of selected parameters was 62, which relate to

Table 2
Performance evaluation metrics for the proposed model and two major models.

Model	TSM (main)	ANN	SVM
Accuracy	**0.9982**	0.9590	0.7563
Precision	**0.9982**	0.9715	0.7610
Recall	**0.9983**	0.9590	0.7563
F1 score	**0.9982**	0.9621	0.7464

Table 3
Performance Evaluation Metrics for 10 Sub algorithms of the Proposed Model.

Model	CDS	CHRG	CWS	LTDN	MSIV
Accuracy	1.0000	0.9917	1.0000	1.0000	0.9983
Precision	1.0000	0.9917	1.0000	1.0000	0.9983
Recall	1.0000	0.9919	1.0000	1.0000	0.9983
F1 score	1.0000	0.9917	1.0000	1.0000	0.9983
Model	MSS	POSRV	RCP	RMW	SGTL
Accuracy	1.0000	0.9983	0.9944	0.9978	1.0000
Precision	1.0000	0.9983	0.9945	0.9978	1.0000
Recall	1.0000	0.9983	0.9944	0.9978	1.0000
F1 score	1.0000	0.9983	0.9944	0.9978	1.0000

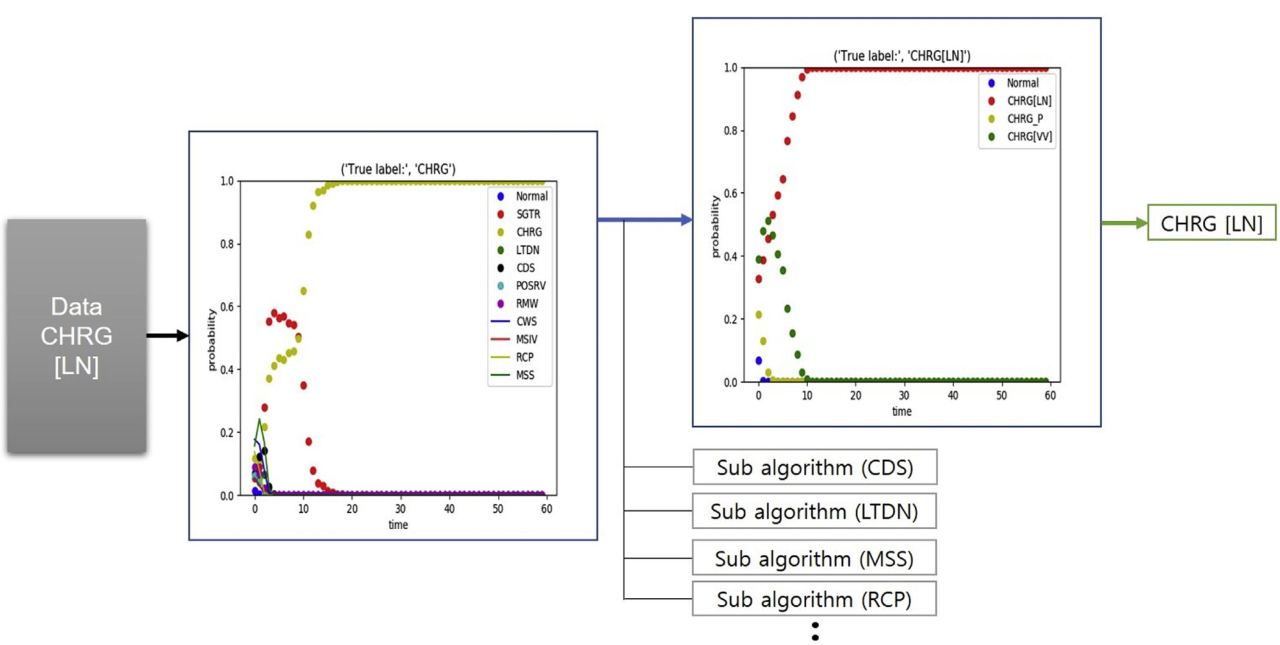

Fig. 5. Prediction process in the two-stage model for a charging water system abnormality with water line leakage.

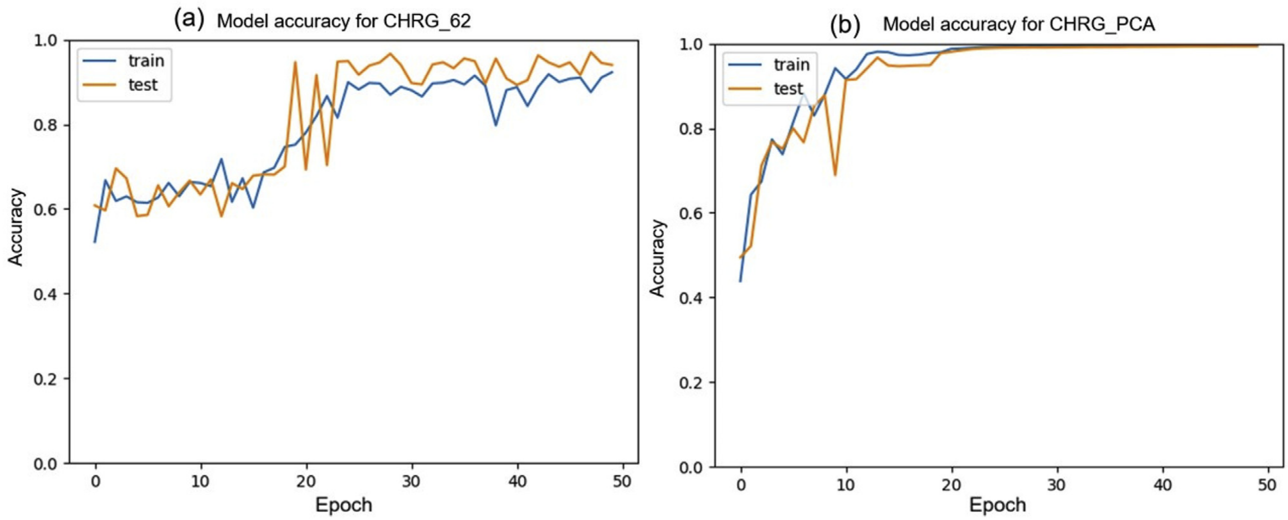

Fig. 6. Model accuracy graphs of (a) knowledge-based parameters and (b) PCA (Epoch: the number of training cycle).

symptoms and alarms in the AOP and include crucial parameters of the primary system such as reactor coolant system pressure. As shown in Fig. 6, the algorithm using 20 PCs achieved convergence on accuracy with smaller epochs compared to the one using knowledge-based parameters.

Because of the high correlation among plant parameters, a relatively small number of PCs sufficiently preserves the information of the original data. For example, in the first test, only 10 PCs were selected that preserved more than 98% of the information. Later, 20 PCs were selected so that the data contained 99% or more of the original information.

With the same training environment, in fact, ANN showed good performance with an accuracy of more than 95%. If the input dataset was not preprocessed though, more than a thousand variables would complicate the diagnostic algorithm and increase the computation time. In addition, this work only used 10 out of 82 AOPs for the APR-1400 as an application; thus, the difference between the models might be greater when they handle the entire set of AOPs. Since this study has identified the possible feasibility of an abnormality diagnosis model, further studies will treat more complex situations by increasing as much as possible the number of scenarios.

If a model has only one algorithm, the model will require new training to update the whole model, including all AOPs and corresponding sub-procedures, whenever new data are generated. The TSM though, on the other hand, will achieve higher efficiency because only the main algorithm is updated to account for the AOPs, while the individual sub-procedures are determined by the algorithms in the sub-level.

With respect to decision time, it is advantageous to be able to directly diagnose changes in NPP status, even in cases where alarms are not actuated. Considering that operators would check symptoms only after being warned, detection of a change in plant status may take a long time if the severity of the related abnormal event is low. Along these lines, it was notably found in preliminary tests that the TSM completed its prediction in under 1 min, even in cases with low severity.

Moreover, the TSM has benefits in solving a given problem in a top-down manner, similar to operator judgment. It is also believed that when a complex accident situation occurs or if judgment is wrong, the multiple steps in the TSM will allow for interim review and mistake identification.

7. Conclusion

In this paper, abnormal diagnosis models for NPPs were suggested. Development consisted of three steps: analyzing the present operating procedures and generating data from a simulator, preprocessing the data to obtain accurate prediction results, and training the deep-learning algorithm with the preprocessed data. The TSM was developed using multiple GRU algorithms to diagnose the plant state with a given dataset of abnormal events. The model showed accurate prediction results at the sub-procedure level. Considering the complicated environment of real NPPs, it will be efficient to train the diagnosis model by dividing training data into AOP- and sub-procedure levels when updating.

It is said that the diagnosis of a single event is possible by operators following the appropriate AOP step-by-step according to the alarms and symptoms; however, the time required for this varies by individual, and multiple abnormal conditions pose a great challenge to operators and support systems. Future systems should therefore be able to consider a greater variety of situations, such as multiple abnormal events. Moreover, since simulator data are calculated by system codes, output variables have smooth curves unlike real plant data. This means the noise not included in the training data could degrade the performance of the model; it is therefore necessary to develop a noise-tolerant diagnosis model to apply the proposed system to an actual NPP. Future work will focus on testing such problems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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