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Original Article

Transient Diagnosis and Prognosis for Secondary System in Nuclear Power Plants

Sangjun Park [a], *Jinkyun Park* [b], *and Gyunyoung Heo* [c,*]

[a] *IInstrumentation and Control/Human Factors Research Division, Korea Atomic Energy Research Institute, 989-111, Daedeok-daero, Yuseong-gu, Daejeon, 34057, South Korea*

[b] *Integrated Safety Assessment Division, Korea Atomic Energy Research Institute, 989-111, Daedeok-daero, Yuseong-gu, Daejeon, 34057, South Korea*

[c] *Department of Nuclear Engineering, Kyung Hee University, Yongin-si, Gyeonggi-do, 17104, South Korea*

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A B S T R A C T

This paper introduces the development of a transient monitoring system to detect the early stage of a transient, to identify the type of the transient scenario, and to inform an operator with the remaining time to turbine trip when there is no operator's relevant control. This study focused on the transients originating from a secondary system in nuclear power plants (NPPs), because the secondary system was recognized to be a more dominant factor to make unplanned turbine-generator trips which can ultimately result in reactor trips. In order to make the proposed methodology practical forward, all the transient scenarios registered in a simulator of a 1,000 MWe pressurized water reactor were archived in the transient pattern database. The transient patterns show plant behavior until turbine-generator trip when there is no operator's intervention. Meanwhile, the operating data periodically captured from a plant computer is compared with an individual transient pattern in the database and a highly matched section among the transient patterns enables isolation of the type of transient and prediction of the expected remaining time to trip. The transient pattern database consists of hundreds of variables, so it is difficult to speedily compare patterns and to draw a conclusion in a timely manner. The transient pattern database and the operating data are, therefore, converted into a smaller dimension using the principal component analysis (PCA). This paper describes the process of constructing the transient pattern database, dealing with principal components, and optimizing similarity measures.

1. Introduction

Nuclear power plants (NPPs) are increasing the capacity and progressing with much more reliable systems for safety. However, an operator's role should never be underestimated, since the most significant cause of unexpected shutdowns is still human error. Many human errors are induced by an operator's inability to diagnose the transient pattern at its

* *Corresponding author.*
E-mail address: gheo@khu.ac.kr (G. Heo).
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initiation [1,2]. Human errors can be reduced by training with qualified procedures, but these may be graded depending on variation in individuals. Information technology can compensate this differentiation, and it is expected ultimately to improve safety and availability of NPPs [3]. Through interviews, most of the operators could not recognize well what type of transient occurred after a transient state, but they recognized an abnormal state. Therefore, this study started from the following hypothesis: it is possible that operators take proper action to cope with transients at an initial state by recognizing what the transient scenario is and how much time remains until reactor or turbine trip. Consequentially, this is effective for increasing the time to cope with the transient state because operators can reduce the time to diagnosis. The proposed idea is to collect the transient pattern database from a plant simulator and to compare a plant state with the transient pattern database using a pattern matching algorithm [4,5]. The transients in this study were focused on those from the secondary system in NPPs. According to statistics, many unexpected shutdowns result from the secondary system rather than the primary system due to the complexity in terms of operation and maintenance [6]. That is, inspection and maintenance activities are more prone to result in human errors [7,8]. Investigations on trip causes from the secondary system have not progressed because safety of the secondary system is relatively less valued than that of the primary system. This paper will explain the three steps: (1) construction of the transient pattern database; (2) signal preprocessing including the dimension compression; and (3) pattern matching methodology and its verification.

2. Materials and methods

In this study, a pattern searching methodology is developed to decide whether a current plant is progressing to a turbine and/or generator trip and it is based on the database acquired at transient states from a simulator. We hypothesized that an early detection and diagnosis for transients would be possible by extracting the characteristic features from the prior patterns. Also, it is expected that the operators are able to get sufficient time for taking actions through the information regarding the remaining time to trip. As a result, the purpose of this study is that those operators properly cope with transients occurring at a secondary system in an NPP by providing the type of transient and remaining time to reactor or turbine trip through the pattern matching technique.

2.1. *Overall framework*

As Fig. 1 shows a whole framework of this study, the purpose of the transient monitoring system is to indicate the remaining time to a turbine trip, and the possibility of the turbine trip is evaluated by comparing with a set of on-line signals and the transient pattern database in a certain time window. The transient database representing the latent abnormal scenarios which occur due to a malfunction in the secondary system is composed by acquiring signals from the simulation of the NPPs. The acquired data go through several steps. One of the most important preprocessing steps is the dimension compression. The reason for the dimension compression is to minimize the time while performing the pattern matching algorithm [9–12]. Consequently, several hundred variables are reduced in size without losing much information therein. This study performs principal component analysis (PCA) for the dimension compression [13]. Operating data is acquired through a real-time database or data collection system (DCS). The dimension of the operating data is suppressed by the PCA as well. After then, the pattern matching system will start to search the most similar pattern among the stored patterns in the transient database with the operating data. One important factor in this process is to utilize the reasonable similarity measurements. In this study, the feasibility of various similarity measures for the pattern matching was verified and a cosine measure was finally selected. When a certain pattern is detected and interpreted as the departure of a transient

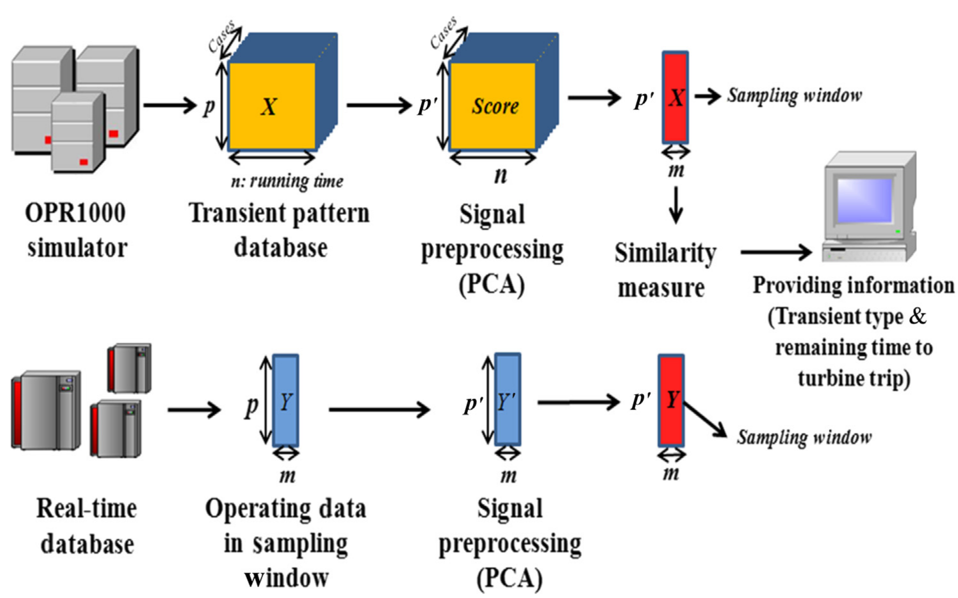

Fig. 1 – Framework of transient monitoring system. PCA, principal component analysis.

phenomenon, this is characterized by diagnosis. After this, it is possible to inform the operator of the type of transient scenario and the remaining time to turbine trip, which belongs to prognostics. The prognosis usually means the remaining useful lifetime. Therefore, from the point of view of an operator, the remaining time to trip is regarded as the prognosis because our methodology aims to provide the remaining time to trip.

2.2. *Transient pattern database*

This study aimed at accumulating the transient database for the secondary system in operating NPPs. The transient scenarios could be taken from the operator training simulation for a 1,000 MWe pressurized water reactor, which is the most common in South Korea, and all scenarios were collected under a certain malfunction without intervention of operators after initiation. Transient scenarios were selected by analyzing the whole list of about 200 cases loaded on the simulator, and then dividing them into the primary system and secondary system. Finally, we selected a total of 54 scenarios that would preferentially have an effect on turbine or generator trips. Next, we triggered a scenario by intentionally inputting the malfunction at the operator's panel. The transient patterns were acquired by applying various initial conditions to consider the fact that a plant behavior is subjected to the initial conditions even for an identical malfunction.

Table 1 shows a part of the lists of the transient pattern database. The severity level means the magnitude of accident and it affects a variable of electric output. Thus, we should consider the severity level to observe the electric output and physical behavior. For example, if incident or accident at severity 5% occurred, the output of electric changed little and stabilized, because this is the level that largely cannot affect the incident or accident. However, if it occurred at severity 50%, the electric output largely changed and a reactor or turbine trip happened, because this is the level at which the incident or accident occurred. In other words, the severity level is the factor that can give a change of physical behavior and electric output. From Table 1, we can recognize that the results are different depending on the initial conditions within a single initiating event. For example, electric output was changed a little when a steam generator downcomer pipe rupture happened at severity level 5%. However, it reaches the trip in a decreasing trend when the initial condition was severity level 50~100%. The time required until trip was also different, but scenarios generally finished within 600 seconds. To take the pattern features by the point of trip, signals were collected under different initial conditions, so each transient scenario was repetitively simulated for two to three cases by increasing the severity. All of the process variables indicating the behavior of the secondary system and reactor/turbine trip were selected as the fields for the transient pattern database and there were ~550. This was the maximum number of parameters that authors could log in from the simulator. However, the dimension of the transient pattern database was too big for monitoring in a timely manner, so we considered a smaller database which resulted in an equivalent solution within a few seconds. In order to achieve this strategy, the acquired data from both signal sources go through signal preprocessing steps. One of the most significant preprocessing steps is performed by the PCA. The purpose of the PCA is to minimize the time while performing the pattern matching algorithm by compressing the dimension of signals. At the same time, the PCA can remove a noise component in the signals so it is easy to identify the dominant direction of signals' variance. The comparison of two patterns is conducted in a specific internal size of time, referred to as a sampling window. For example, if the size of a sampling window is m seconds, an operating data is accumulated during m seconds and this data will be compared with the transient patterns which are bounded by the same size with the sampling window. Finally, the determination of an expected transient pattern is based on the calculation results using similarity measures.

Fig. 2 explains how to generate alarms when a transient is detected and how to provide the remaining time to trip. All of the patterns have the signal for representing a generator output. If we are successful in finding out an expected transient pattern at m as shown in Fig. 2, the remaining time to a trip is supposed to be the interval

Table 1 – Several cases in transient pattern database.

Initiating event	Initial condition	Results
Steam generator downcomer pipe rupture	(1) Severity = 5%	(1) Power decreased & stabilized
	(2) Severity = 50%	(2) Reactor stop (after 1.5 min)
	(3) Severity = 100%	(3) Reactor stop (after 1.0 min)
Main steam pipe safety valve malfunction opening stage	(1) Severity = 1%	(1) Little or no change
	(2) Severity = 5%	(2) Recognition of opening safety valve
Atmospheric dump valve failure open	(1) Severity = 5%	(1) No change in power
	(2) Severity = 10%	(2) Little change in power
	(3) Severity = 50%	(3) Reactor stop (after 40 s)
Condenser vacuum failure	(1) Severity = 10%	(1) Reactor stop (after 2 min)
	(2) Severity = 100%	(2) Reactor stop (after 40 s)
Feedwater common header rupture	(1) Severity = 5%	(1) No change in power
	(2) Severity = 20%	(2) Little change in power
	(3) Severity = 40%	(3) Reactor stop (after 6 min)
Steam generator blowdown pipe rupture	(1) Severity = 10%	(1) Little change in power
	(2) Severity = 30%	(2) Power decreased
	(3) Severity = 50%	(3) Reactor stop (after 2 min)

between T_m and the end of scenario T_n, which is zero generator output. This process is repeated every second. If there is no any matched pattern, then it is regarded as a normal condition; if there is, it means that the turbine trip annunciator should be able to provide both the type of transient pattern and its initial conditions as long as the pattern's uniqueness can be guaranteed.

2.3. Dimension compression

The transient pattern database contains 54 scenarios and each scenario has two to three cases depending on initial conditions. Considering the number of variables for the scenario, it is a massive quantity. We expected that the transient monitoring would only be meaningful when the whole process should be over within a few seconds. This study proposes a size reduction of massive data through the dimension compression. Furthermore, the dimension compression can have another benefit of decreasing the noise in the signals. The PCA used in this study is a dimension compression method reducing the number of variables where the data of variables interconnecting each other is linearly converted to their independent principal components. The PCA is applied to the transient pattern database as well as operating data in a time through the following steps. The transient pattern database matrix X is expressed in the following manner:

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & x_{ij} & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix} \tag{1}$$

where X is the matrix for an individual case, n is the number of observations, and p is the number of variables.

The matrix X indicates all of the raw data collected from the simulator for each case. Because the collected variables can include the digital type or constant variables, these kinds of variables should be removed due to their abnormal contribution on pattern matching. Another point to be checked is that the transient pattern database has difference units and normal range, so the similarity calculation can be corrupted. To prevent these troubles, the PCA is implemented after normalizing the variables:

$$x_j^{max} = \max_j \{x_{1j}, x_{2j}, \cdots, x_{nj}\} \tag{2}$$

where x_j^{max} is the maximum value of j^{th} variable.

The normalized matrix Z is made by dividing all of the values in a single vector by x_j^{max}:

$$Z = \begin{pmatrix} z_{11} & \cdots & z_{1p} \\ \vdots & z_{ij} & \vdots \\ z_{n1} & \cdots & z_{np} \end{pmatrix} \tag{3}$$

where Z is the normalization matrix and $z_{ij} = x_{ij}/x_j^{max}$.

Before conducting the PCA, we sliced the matrix Z such that the length of sliced matrix is equal to the sampling window explained in Fig. 1. If the size of a sampling window is m, then the sliced subset of the matrix Z is represented by Eq. (4). For preliminary tests, the sampling window size was decided as 10 seconds:

$$Z^l = \begin{pmatrix} z_{l-m,1} & \cdots & z_{l-m,p} \\ \vdots & \ddots & \vdots \\ z_{l1} & \cdots & z_{lp} \end{pmatrix} \tag{4}$$

where l can vary from $m+1$ to n. Subscript l means the latest value.

The score matrix S_z is obtained by multiplying the covariance matrix and the original matrix:

$$S_z = Z \cdot \Sigma_z \tag{5}$$

where S_z is the score matrix.

The principal components consisting of the score matrix can explain the degree of capability to capture the variance of the data. In other words, the principal component corresponding to a larger eigenvalue can have more information than other principal components. In order to take this benefit, we will use the principal components as a weighting factor in calculating similarity. When a score matrix has the eigenvalue λ_i, the weighting factor for j^{th} principal component is as follows:

$$Q_j = \frac{\lambda_j}{\sum_{i=1}^{p} \lambda_i} \tag{6}$$

where Q_j is the weighting factor and p is the total number of principal components.

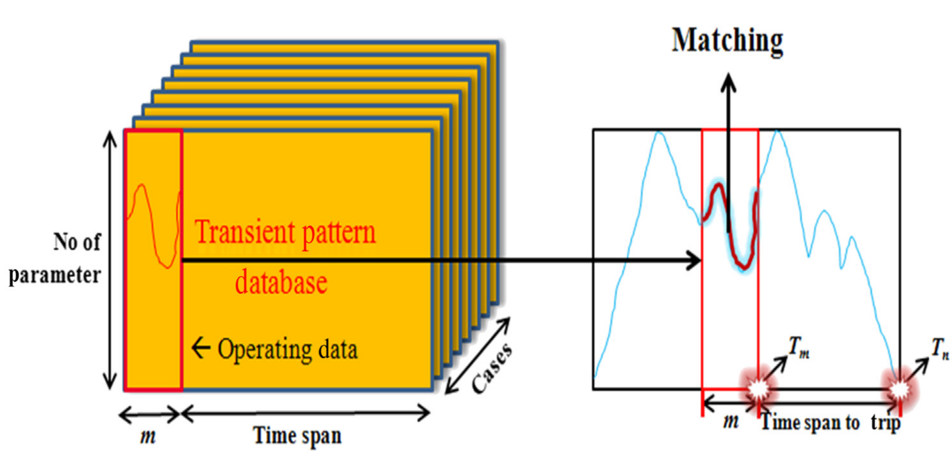

Fig. 2 – Method to generate alarms and provide remaining time to trip.

The eigenvalue λ is obtained by unit matrix I:

$$(S_z - \lambda I) = 0 \quad (7)$$

where λ is an eigenvalue and I is a unit matrix.

The required number of principal components was decided such that over 99.9% of variance of the entire data can be captured. In this study, the number of principal components was decided as 10. This is approximately under 4% of the original number of variables, which means it is possible to improve the matching speed by over 25 times. The transient pattern database is re-stored by considering the weighting factors. Other transient data corresponding out of the 10 largest principal components are trimmed in the database. So the final score matrix is given by:

$$S_{z'} = \begin{pmatrix} z'_{11} & \cdots & z'_{1p'} \\ \vdots & \ddots & \vdots \\ z'_{n1} & \cdots & z'_{np'} \end{pmatrix} \quad (8)$$

The operating data has to be processed by the PCA and compared with the transient pattern database. Since all the processes are the same, the final result, $S_{t'}$ can be expressed as follows:

$$S_{t'} = \begin{pmatrix} t'_{11} & \cdots & t'_{1p'} \\ \vdots & \ddots & \vdots \\ t'_{m1} & \cdots & t'_{mp'} \end{pmatrix} \quad (9)$$

2.4. Similarity measures

To compare operating data with the transient pattern database, similarity measures are necessary. In the study, Euclidean distance, cosine distance, and Manhattan distance were relatively tested as similarity measures. The similarity is the concept of distance between two points in the N dimension. When to perform similarity calculation, $S_{t'}$ is usually much shorter than $S_{z'}$ in terms of the number of data ($n > m$). Therefore, $S_{t'}$ is trimmed from a certain start point to the next m^{th} point for each similarity calculation. The start point is taken as the first position of the transient pattern database and then moved to the next one for each time. This iteration continues when the start point reaches the $n - m + 1^{th}$ position. The Manhattan distance is defined as:

$$d(z\prime, t\prime) = \sum_{j=1}^{p'} \left[Q_j \times \sum_{i=1}^{m} \left| z'_{ij} - t'_{ij} \right| \right] \quad (10)$$

Euclidean distance formula is defined as:

$$d(z\prime, t\prime) = \sum_{j=1}^{p'} \left[Q_j \times \sqrt{\sum_{i=1}^{m} \left(z'_{ij} - t'_{ij} \right)^2} \right] \quad (11)$$

A cosine measure is calculated by using the inner product of two vectors. The cosine measure formula is defined as:

$$d(z\prime, t\prime) = \sum_{j=1}^{p'} \left[Q_j \times \cos^{-1} \frac{z'_j \cdot t'_j}{\left\| z'_j \right\| \cdot \left\| t'_j \right\|} \right] \quad (12)$$

In the case of Euclidean and Manhattan distance, a calculated result should be closer to zero when two patterns are similar. In the case of cosine measure, the result approaches one when two patterns are matched.

3. Results

The purpose of this section is to check the preliminary validity of the proposed algorithm for developing a full scope turbine trip annunciator. To achieve this purpose, we have to use actual transient data, but the number of such cases is rare and limited to be released, so it was not proper to validate the performance of the proposed algorithm. As a contingency plan, we decided to use hypothetically generated operating data to see the feasibility of the proposed idea. We assumed that the operating database and database acquired from the simulator is almost similar because all of the operators working in NPPs periodically get training in simulators and the training knowledge is using real work. Although operating data and simulator data are a bit different, we expect the difference to be within noise level. We analyzed the effect of various type of noise added in the simulation data. Randomly taking signals by using a sampling window from the normalized transient pattern database, the matrix Z, we intentionally corrupted it by adding various noises and regarded this as operating data.

Fig. 3 explains the creation process of hypothetical operating data and Fig. 4 shows the patterns of noises. The patterns of noises correspond to the variation for different initial conditions, different severity, and general random noise. Noises we considered were: (1) Pattern 1: a uniformly distributed noise with maximum ± 1% which is for assuming a general random noise; (2) Pattern 2: a parallel shift with maximum ± 5% which means a bias due to different starting points of operation; and (3) Pattern 3: a gradual increase or decrease which explains the effect caused by different severity. In this test, the same type of noise was applied to all of the parameters. Next, we performed the trend analysis to observe how to change the trend of database applied to the PCA.

Fig. 5 shows the trend which analyzed a case of 'Steam generator downcomer pipe rupture' of severity at 1% and 10%. The vertical axis indicates the magnitude of principle components and the horizontal axis indicates time. In a trend of severity at 1%, Pattern 1, applied uniformly distributed noise, shows a similar trend and a fine vibration was found, but it was not shifted. Pattern 2, applied parallel shift, shows a similar trend and a very small shift, and Pattern 3, applied a rate increase or decrease, shows a similar trend, but a small shift. In a trend of severity at 10%, Pattern 1 shows a similar trend of principle components and a little vibration, but no shift. Pattern 2 shows a similar trend and shifted. Pattern 3 shows a similar trend but a clear shift. Therefore, we can conclude that the pattern applied uniformly distribution noise of severity at 1% and 10% indicates a similar trend of principle components. But other patterns show the outstanding aspect that an initial condition in the same scenarios indicates a similar trend of principle components, but different severity in the same scenarios shows a clear shift and an inclined trend of principle components. Furthermore, each of the different scenarios has different principle components. This analysis indicates that the severity with a magnitude that can trigger a trip has intrinsic physical characteristics and pattern. In other words, if we have multiple transient data which have

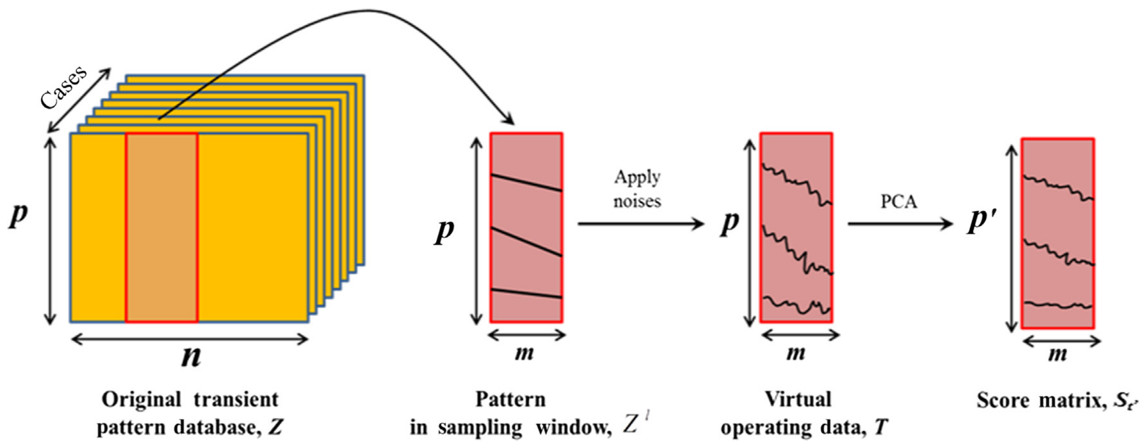

Fig. 3 – Creation of a hypothetical operating data. PCA, principal component analysis.

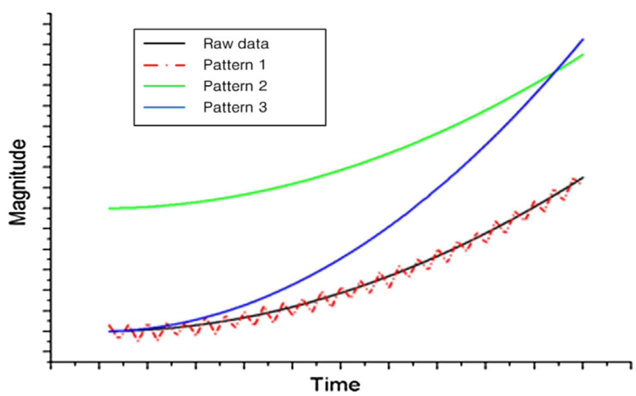

Fig. 4 – Pattern examples for validation.

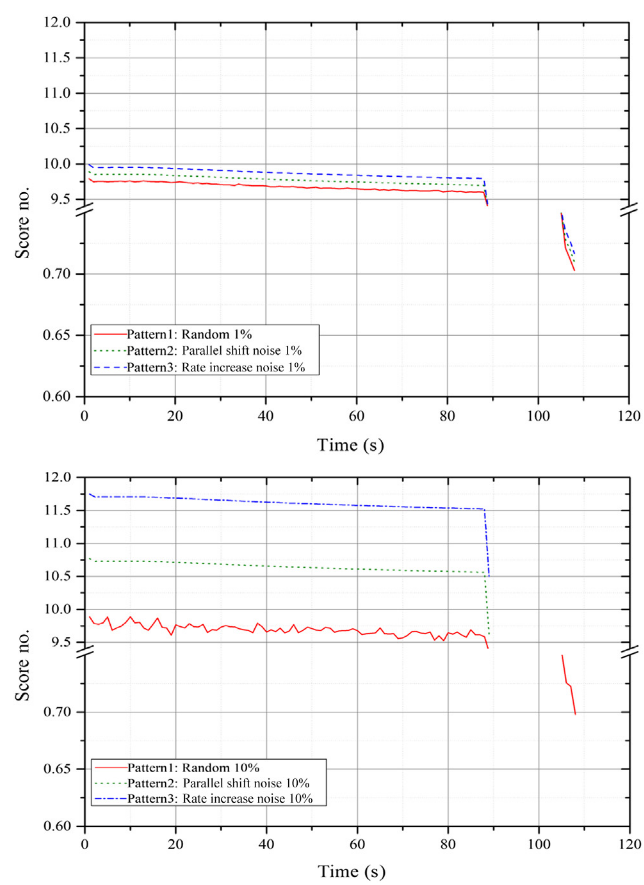

Fig. 5 – Trend comparison of principal components at 1% severity and the trend comparison of three cases at 10%.

different characteristics, it is possible to distinguish them by observing the behavior of principle components.

As a next step, we performed similarity measures in the manner of one of the pattern matching techniques to find the matching point between the transient database and the hypothetical database as considering real operating data. In this study, we compared and finally decided the performance of individual measures such as Manhattan distance measure, Euclidean distance measure, and Cosine distance measure. In order to show the feasibility of preprocessing, the results from pure time domain analysis, those from PCA without a weighting factor in Eq. (6), and those from PCA with a weighting factor are shown in parallel and compared. Tables 2–4 indicate the entire results.

The verification results are summarized in Tables 2–4. Table 2 shows the similarity comparison performed in a time domain, Table 3 shows the results for dimension compression, and Table 4 shows when a dimension compression is performed with weighting factors. A total of 26 operating data were randomly extracted from the transient patter database and used as a raw data. We assigned ‘OO’ when the successful matching probability is > 90%, ‘O’ for > 70%, ‘Δ’ for > 50%, and ‘X’ for < 50%. For evaluating the speed of pattern matching or

Table 2 – Similarity measures in time domain.

	Raw data	Pattern 1	Pattern 2	Pattern 3	Speed
Manhattan	OO	OO	OO	X	1.0
Euclidean	OO	OO	OO	X	1.0
Cosine	OO	X	X	OO	0.4

Table 3 – Similarity measures without weighting in principal component domain.

	Raw data	Pattern 1	Pattern 2	Pattern 3	Speed
Manhattan	OO	O	O	X	0.3
Euclidean	OO	O	O	X	0.3
Cosine	OO	O	O	OO	0.2

Table 4 – Similarity measures with weighting in principal component domain.

	Raw data	Pattern 1	Pattern 2	Pattern 3	Speed
Manhattan	OO	OO	OO	X	0.3
Euclidean	OO	OO	OO	X	0.3
Cosine	OO	OO	OO	OO	0.2

computing time, the time required for finishing the calculation of Manhattan distance without dimension compression was considered as a reference, unity. In Table 2, the result of similarity measures in a time domain represents the performance without dimension compression. The matching probabilities of Manhattan distance and Euclidean distance for similarity measures are in good agreement for most of the cases except for Pattern 3, where the raw data was multiplied with uniform rate in a time domain. By contrast, the results of cosine similarity measure are different from the reference while it was observed to have a higher matching speed. For observing the degree of improvement in the aspects of accuracy and computing time, we implemented identical verification tests by utilizing the PCA. Table 3 shows the performance of the similarity measures without weighting factors being applied in a principle component domain. This result shows that the cosine measure has a high matching probability. It is true that the data processing was faster due to reduction of the quantity of data. The similarity measures in a time domain are likely to mislead a result because there is no method to remove the noise portions by themselves. The pattern matching in a principal component domain is able to more or less reduce the noise portions. The results in Table 3 are satisfactory in terms of computing time, but need to be improved in terms of accuracy. Since the coverage of each principal component is different, we had to verify its feasibility in the pattern matching process. Table 4 shows the results of similarity measures with the weighting factors applied to variables in a principle component domain. The matching probability has generally increased. However, no difference is found in matching time. The performance of the cosine measure is worth noticing. While the computing time of the cosine measure had no benefit, it was found that its matching probability was > 90%. However, Manhattan distance and Euclidean distance were not good at Pattern 3. From these results, the cosine measure was decided as the best measure of matching in the aspects of computing time and accuracy. It should be noted that all similarity measures are evaluated for a limited number of noise patterns, so, for increasing the reliability, more calculations need to be performed for various cases, particularly by utilizing real-time data from NPPs.

4. Conclusion

This paper was focused on analyzing the physical behavior of NPPs under transient states through the pattern matching. The pattern matching is a technique to increase the detection probability by applying various similarity measures to the data acquired from a simulator of NPPs after signal preprocessing, such as normalization, dimension compression, and weighting factors. Various similarity measures were investigated and the cosine measure was determined as the best in the aspects of accuracy and computation time. Therefore, it is possible to prognose and diagnose a transient state which occurred from a secondary system in an NPP and prevent a turbine trip by using a pattern matching technique. Also, in this study we focused on the calculation of the remaining time to reactor trip and finding out the type of transient. However, this methodology can be applied to detect the system failure in NPPs, if it is possible to make grouping databases related with incidents or accidents of system failure and each time of system failure can be decreased and increased depending on the initial conditions. We expect that this study contributes to help as a countermeasure that can reduce the magnitude of an accident by providing the coming accident information when operators encounter the unexpected situation.

Conflicts of interest

All authors have no conflicts of interest to declare.

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