Classification of Abnormal Conditions: A Data-driven Aid for the Selection of Abnormal Operating Procedures in NPPs

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Abstract: Abnormal Operating Procedures (AOPs) are provided in nuclear power plants (NPPs), which are procedures that specify operator actions to restore normal operating conditions following a transient or abnormalities. The selection of the appropriate AOPs is decided by the combination of multiple alarms which need to be analyzed by the NPP operator to identify the actual abnormality that occurred. However, multiple alarms from multiple systems often occur at the same time during an incident, making it difficult for the operator to select a correct response efficiently in a time-critical situation. Furthermore, quick system recovery to normal condition before the trip is important since any delay may result to a condition that will degenerate to the emergency situation thereby leading to the unwanted shutdown of the plant. Therefore, considering the fact that plant recovery to normal condition before reactor trip occurs is paramount and the operator's state of condition in time-critical situations in case of multiple alarms analysis, the benefits of an aid to assist operator in knowing the actual plant condition in time thereby selecting the appropriate response procedures cannot be overemphasized. In addition, owing to the fact that operator depends only on the alarm systems in selecting AOPs, the symptoms from process parameters are also significant in selecting proper AOPs. In this regards, we proposed a data-driven based pattern detection and classification method that concatenates the symptoms from the process sensors (analog signals) and the alarm signals (digital signals) together for effective identification and classification of abnormities in the event of abnormal situations in NPP. The proposed method is validated using simulation analog data from the Multi-dimensional Analysis for Reactor Safety (MARS-KS) simulator and artificially generated alarm digital data for the case of abnormalities concerning steam generator tube in NPP. The proposed method employing four classification models, Linear Discriminant Analysis (LDA), Classification and Regression Tree (CART), Support Vector Machine (SVM), and Random Forest (RF), are trained, and their performance are evaluated on the test set. The proposed method utilizing RF model performed excellently with 100% performance on the test set over the proposed method utilizing other classification models. The excellent results obtained from the case study suggest that the proposed model is a promising approach for aiding the selection of AOPs in the event of abnormal conditions and minimizing the operators' burden in identifying the actual plant status during abnormal situations.

Keyword: AOPs, Alarm's digital signals, Symptom's analog signals, Abnormality Classification, NPP

1 Introduction

In nuclear power plants (NPPs), operational safety is the topmost priority since the release of radioactive materials can result in financial losses, environmental pollution and even loss of life. Abnormal Operating Procedures (AOPs) [1] are provided, which are procedures that specify operator actions for restoring an operating variable to its normal controlled value when it departs from its normal range or to restore normal operating conditions of the plant following a transient. The entire safety of an NPP is controlled by a certain number of safety related plant parameters, called "symptoms". As long as all symptoms are within pre-determined limits, the plant safety is maintained. If any symptoms exceed limits, operators have to initiate actions in accordance with the appropriate procedure in order to return the plant to normal conditions. There are many symptoms listed in each AOP. These symptoms are used to diagnose the systems through alarms to select a proper AOP.

In NPPs, alarm systems, which monitor all important plant systems and inform operators when abnormal situations occur [2], are the main source that operators depend upon for detecting abnormal situations. Multiple alarms from multiple systems often occur at the same time during an incident, making it difficult for the operator to select a correct response efficiently. In the work of Kim *et al* [3], an alarm and diagnosis-integrated operator support (ADIOS) system has been used to prevent too many alarms from influencing the operator's judgment. Too much information and alarms imposes a heavy burden on operators in a time-critical condition, and that will make it difficult for the operators to comprehend what is real situation in the plant which resulted in the difficulty to conduct a thorough assessment of each individual symptom in a short time. However, the entry point and type of AOPs is decided by the combination of multiple alarms. The operator's quick response to the abnormal situation that resulted in multiple alarms which do not require reactor trip is paramount since any delay may result to a condition that will degenerate to the emergency situation thereby leading to the unwanted shutdown of the plant. Considering the fact that plant recovery to normal condition before reactor trip occurs is necessary and the operator's state of condition in time-critical situations in case of multiple alarms analysis, the benefits of an aid to assist operator in knowing the actual plant condition in time thereby selecting the appropriate response procedures cannot be overemphasized.

Moreover, the symptoms, which are analog signals, from process parameters are also significant in selecting the proper AOPs. Although many research works [4][5][6][7] have been carried out in detecting and identifying accident and transient conditions in NPP, almost all of these works depends only on the process analog signal parameters. The alarm systems signal status have not been integrated or analyzed alongside with the process analog signals.

Therefore, in the sight foregoing, we developed and proposed a data-driven method that is capable of integrating and concatenating multiple alarm digital signals and the symptom process analog signals for analysis in order to have an effective diagnostic aid for early detection of abnormal situations in NPP so that, operator can reliably select appropriate AOP to restore the plant's abnormalities to normal condition as quickly as possible. This has the benefits of overcoming the challenges of the AOP selection during abnormal situation in NPPs and minimizing unwanted shutdown of the plant. In order to achieve these objectives, we first developed a method of encoding the alarm digital signals as well as transforming the symptom analog signals into the space of encoded alarm signals, and then concatenated them together for analysis. The concatenated result is then fed to the detection and classification model which identifies and classifies the abnormal conditions associated with the abnormal input vector.

To validate the proposed aid, a demonstration with simulation data generated from the Multi-dimensional Analysis for Reactor Safety (MARS-KS) code and artificially generated alarm digital data for the case of abnormalities concerning steam generator tube in NPP is performed. Due to unavailability of the digital alarm signals from the MARS-KS code, an artificially generated alarm digital data is used. The proposed method employing four classification models, Linear Discriminant Analysis (LDA), Classification and Regression Tree (CART), Support Vector Machine (SVM), and Random Forest (RF), are trained, and their performance are evaluated on the test set. The proposed method utilizing RF model performed excellently on the test set over the proposed method utilizing other classification models. The results of verification indicated that the developed platform performs the intended functions, and can be used as an effective tool to minimize the operators' burden in identifying the actual abnormality during abnormal situations thereby aiding in selecting the proper AOPs in time.

The remainder of this paper is as follows: section 2 discussed all the methods and approaches used in developing an aid for the selection of AOPs as well as the model validation approach used in this work. The results of validations and their discussions are presented in section 3. And finally, section 4 presented the summary and the concluding remarks.

2 Methodology

The approaches used in this research are summarized and depicted in Fig. 1. The entire flow of the procedures is divided into two paths: training path and test/execution path.

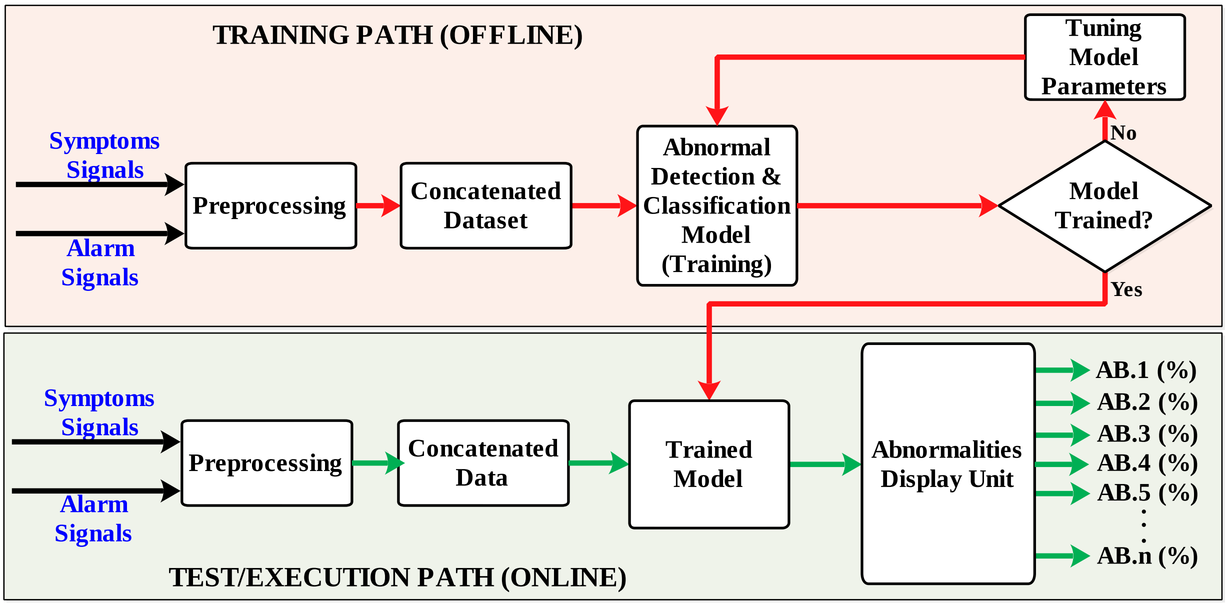

Fig.1 Framework of the proposed model.

The training path is the offline path which consists of the preprocessing unit where the symptom signals from the process sensors and the alarm signals from the alarm systems are preprocessed and concatenated (discussed in details in section 2.1); and the training unit where the concatenated data output from the preprocessing unit is used as the input to train an abnormal detection and classification model. The training process continues by tuning some specified model parameters until the model is well trained. The test/execution path is the online path which consists of the preprocessing unit that performs similar functions as that of preprocessing unit in the training path; the trained model unit which contain the outcomes of the training path, takes in the preprocessed and concatenated online data as input and produces an associated abnormal condition of the plant as output; and the abnormalities display unit where abnormal conditions (AB) with their respective percentage of the detection probabilities are display and provide to the operator. The abnormality that has the highest probability is classified to be the abnormal condition associated with the abnormal input vector. The value of the percentage probability determines how well the model distinguishes the actual abnormality from the rest of the abnormalities if correctly predicted. Hence if the probability of correct prediction is close to or equal 100%, it means that the model is 100% sure that the abnormality is actually associated with the input vector.

2.1 Data Preprocessing and Integration

In order to integrate symptom signals and alarm signals together for further analysis, we encoded the alarm signal in such a way that the continuous signals of the symptoms can be transformed to the space of the encoded alarm signals. Since the sensor variables are continuous signals, there is need to preprocess the continuous data and to come up with the procedure to encode the alarm signals for suitability of the diagnostic models.

It is generally known that at a particular period of time, a single alarm signal parameter has two states: Alarm (activated) and No-alarm (Deactivated). In this work, the alarm signal is encoded as shown in Fig. 2.

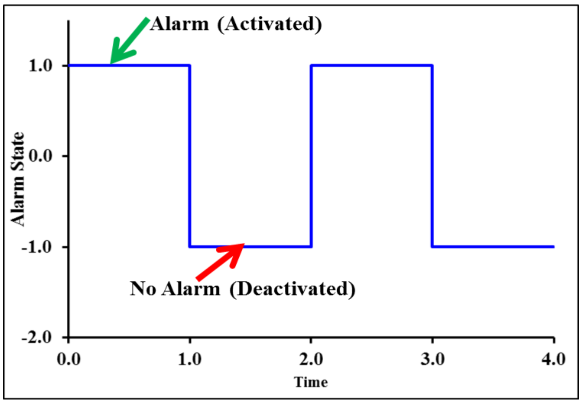

Fig.2 Alarm signal encoding.

If we assume there is a k number of the alarm signal parameters that are activated during a particular abnormal situation in the plant and m number of times at which this particular abnormal condition occurred and observed, the alarm data can be represented in matrix form as

$$\mathbf{AS} = \begin{bmatrix} as_{1,1} & as_{1,2} & \cdots & as_{1,k} \\ as_{2,1} & as_{2,2} & \cdots & as_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ as_{m,1} & as_{m,2} & \ldots & as_{m,k} \end{bmatrix}$$

where $\mathbf{AS} \in \mathbb{R}^{m \times k}$ is a k-dimensional alarm variable signals with m number of observations, and $as_{i,j}$ represents the *ith* alarm state of the *jth* alarm variable. Thus, the encoded form of the above alarm signals is obtained as

$$\mathbf{A} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,k} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \ldots & a_{m,k} \end{bmatrix}$$

where

$$a_{i,j} = \begin{cases} +1, & if\ as_{i,j}\ is\ activated \\ -1, & if\ as_{i,j}\ is\ deactivated \end{cases}. \qquad (1)$$

The value $a_{i,j}$ represents the *ith* encoded alarm of the *jth* alarm variable.

Also, suppose the corresponding continuous symptom signals from the process sensors of that particular abnormal condition are represented as a matrix **S**, where $s_{i,j}$ is the *ith* observation of the *jth* variable associated with a symptom. $\mathbf{S} \in \mathbb{R}^{m \times p}$ is a p-dimensional symptom variable from process parameters which represent abnormal condition from sensor signals.

$$\mathbf{S} = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,p} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,p} \\ \vdots & \vdots & \ddots & \vdots \\ s_{m,1} & s_{m,2} & \ldots & s_{m,p} \end{bmatrix}$$

The continuous symptom data **S** is scaled using feature scaling technique. The technique used in this work is min-max feature scaling heuristic method. Feature scaling is a method used to standardize the range of variables or features of data. In data processing, it is also known as data normalization and generally performed during the data preprocessing step. In order to transform the continuous data to the space of the alarm data for integration, the continuous data is scaled to the range $\{-1, 1\}$. The transformed symptom signal is obtained using min-max feature scaling method given in Equation (2).

$$s'_{i,j} = \frac{2s_{i,j} - \max_j(\boldsymbol{s_j}) - \min_j(\boldsymbol{s_j})}{\max_j(\boldsymbol{s_j}) - \min_j(\boldsymbol{s_j})}. \qquad (2)$$

The resulting datasets **A** and **S’** are then concatenated as follows.

$$\mathbf{Z} = [\mathbf{S}' \quad \oplus \quad \mathbf{A}] \qquad (3)$$

The symbol $\oplus$ in Equation (3) is used to represent *concatenation* in the context of this research work. This means that the concatenation of the *ith* row vector of **S’** to the *ith* row vector of **A** is performed as

$$[s'_{i,1} \quad s'_{i,2} \quad \cdots \quad s'_{i,p}] \oplus [a_{i,1} \quad a_{i,2} \quad \cdots \quad a_{i,k}]$$
$$= [s'_{i,1} \quad s'_{i,2} \quad \cdots \quad s'_{i,p} \quad a_{i,1} \quad a_{i,2} \quad \cdots \quad a_{i,k}]$$

Hence, Equation (3) becomes the preprocessed and integrated data that will be used to train the model, which is given as

$$\mathbf{Z} = \begin{bmatrix} s'_{1,1} & s'_{1,2} & \cdots & s'_{1,p} & a_{1,1} & a_{1,2} & \cdots & a_{1,k} \\ s'_{2,1} & s'_{2,2} & \cdots & s'_{2,p} & a_{2,1} & s_{2,2} & \cdots & a_{2,k} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ s'_{m,1} & s'_{m,2} & \ldots & s'_{m,p} & a_{m,1} & a_{m,2} & \ldots & a_{m,k} \end{bmatrix}$$

where $\mathbf{Z} \in \mathbb{R}^{m \times (p+k)}$ is the integrated outcomes of the concatenation with a *(p+k)*-dimensional variables, m is the total number of time-series observational samples, p is the total number of the sensor signal parameters associated with a symptom, and k is the total number of the alarm signal parameters that are activated during abnormal situations.

When an online abnormal data (symptom signals and alarm signals) comes in, it undergoes the same preprocessing techniques described above but its sequence of the executional flow is as shown in Fig. 3.

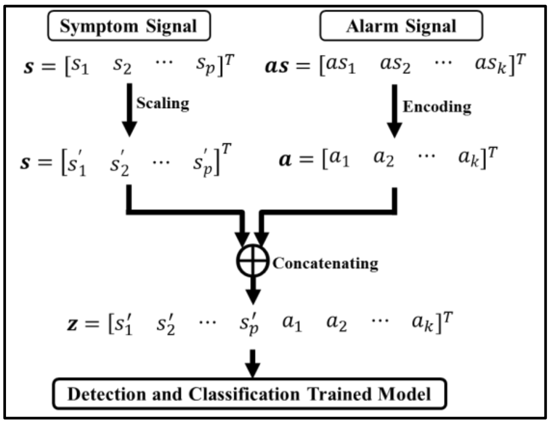

Fig.3 Sequence of executions of preprocessing in online path.

2.2 Detection and Classification Models

In this work, different classification models were investigated in order to choose the best model for the purpose of this work. The classification models selected for investigation are Linear Discriminant Analysis (LDA), Classification and Regression Tree (CART), Support Vector Machine (SVM) with Radial Basis Function Kernel, and Random Forest (RF). The brief introduction of these models is presented in this section. All of these models were trained on the training set, and their performance were evaluated on the test set and compared. The performance metrics used to evaluate each of these models are: confusion matrix, sensitivity, specificity, and accuracy which are also briefly described in this section.

2.2.1 Linear Discriminant Analysis

LDA is a supervised learning algorithm that tries to preserve as much of the class discriminatory information as possible while projecting high dimensional data into a lower dimensional space[8]. In addition, the optimal transformation matrix in LDA is obtained by minimizing the within-class distance and maximizing the between-class distance simultaneously, thereby achieving maximum class discrimination. It is a generalization of Fisher's linear discriminant, a method used in machine learning to find a linear combination of features that characterizes or separates two or more classes of objects. Details of the LDA algorithms can be found in [8].

2.2.2 Classification and Regression Trees

CART is a classification method based on decision trees and uses binary recursive partitioning. It was introduced by [9] in the mid 1980s. First, the overall dataset including all training datasets is split into two subsets by using the best predictor of the output. This binary partitioning is recursively applied to the derived subsets until no further significant partitioning is found. This technique grows a large tree and then prunes the tree to a size that has the lowest cross-validation estimate of error. It is believed that decision trees are more closely mirror human decision-making than do the other classification algorithms [10].

2.2.3 Support Vector Machine

SVM maps the input vectors into the high-dimensional feature space through some nonlinear mapping, where it finds a hyperplane that separates the data by class using support vectors. In summary, an SVM is an algorithm that works as follows [11]:

- It uses a nonlinear mapping to transform the original training data into a higher dimension.
- Within this new dimension, it searches for the linear optimal separating hyperplane (i.e., a "decision boundary" separating the data of one class from another).
- With an appropriate nonlinear mapping to a sufficiently high dimension, data from two classes can always be separated by a hyperplane.
- The SVM finds this hyperplane using support vectors and margins (defined by the support vectors).

The details of the SVM algorithms are available and described in [11][12][13].

2.2.4 Random Forest

RF is an ensemble classifier that consists of a collection of decision trees, which was proposed by Breiman [14]. It combines Breiman's bagging idea and the random selection of features [15]. Generally, decision trees do not have the same level of accuracy as some other classification methods. However, by aggregating many decision trees, using RF, the predictive performance of trees can be substantially improved [10]. In RF, the individual decision trees are generated using a random selection of attributes at each node to determine the split. More formally, each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. During classification, each tree votes and the most popular class is returned. RF is suitable for high dimensional data [10], hence it can be used to resolve the curse of dimensionality.

2.2.5 Performance Metrics

In order to evaluate and select the best suitable classification model for the proposed method, the following performance metrics are used to measure the performance of the classification models described in sections 2.2.1, 2.2.2, 2.2.3, and 2.2.4 on the test dataset:

(a) Confusion matrix
The confusion matrix is a useful tool for analyzing how well the classifier can recognize abnormalities of different classes. Given n number of abnormalities (where $n \geq 2$),a confusion matrix is a table of at least size n by n. For a classifier to have good accuracy, ideally most of the input vector associated with the abnormalities would be represented along the diagonal of the confusion matrix, with the rest of the entries being zero or close to zero.

(b) Sensitivity
Sensitivity is a true positive rate, i.e., the proportion of data points that do belong to an abnormality that are correctly identified. That is, given that the input vector is truly associated with a particular abnormality, sensitivity is the probability that the classifier will predict that abnormality correctly. Sensitivity is the same as *recall*, another classifier performance metric which is calculated using Equation (4).

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{4}$$

where TP is the true positive and it is the total number of the correctly classified data points in an abnormality, FN is the false negative and it is the total number of the misclassified data points in an abnormality to another class.

(c) Specificity
Specificity is a true negative rate, i.e., the proportion of the data points that do not belong to an abnormality that are correctly identified. That is, given that the input vector is truly not associated with a particular abnormality, specificity is the probability that the classifier will predict correctly that the abnormality do not occur. Specificity is calculated by Equation (5).

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{5}$$

where TN is the true negative and it is the total number of the correctly classified data points that are not in a particular abnormality, FP is the false positive and it is the total number of the misclassified data points to an abnormality which in reality do not belong to that abnormality.

(d) Accuracy
The accuracy of a classifier is the percentage of the data points that are correctly classified by the classifier, and it is calculated using Equation (6).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

2.3 Model Validations

The validation of the proposed approaches is performed using simulation data collected from MARS-KS code for the case of abnormalities concerning steam generator tube in NPP. We used the *caret* package [16] in R programing language environment to implement the four classification models described in section 2.2.

The abnormal situations simulated are steam generator tube leakages. Three sets of data with different severity of fracture failure of the tube were collected. The severities of the three sets of data in ascending order are labeled as abnormalities AB.1, AB.2, and AB.3 respectively. After thorough analysis of the collected datasets, 21 sensor signals were selected, which leads to a symptom dataset, **S** of 21-dimensional variables for each abnormalities. The degree of correlation between the 21 continuous sensor signals of AB.1 is depicted in Fig.4.

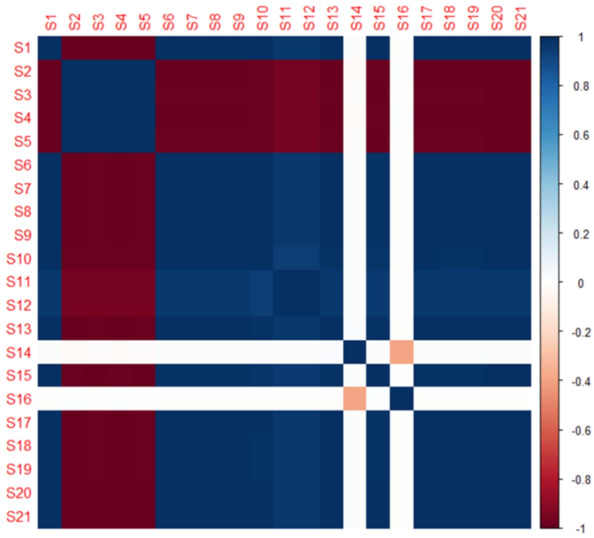

Fig.4 Degree of correlation between the sensors signals of AB.1 tube leak condition.

The number of time series observations in each AB.1 and AB.2 datasets is 5000 (i.e. m=5000 and p=21). The datasets of the three abnormalities are as follows:

AB.1 dataset: $\mathbf{S}_1 \in \mathbb{R}^{5000\times21}$

AB.2 dataset: $\mathbf{S}_2 \in \mathbb{R}^{5000\times21}$

AB.3 dataset: $\mathbf{S}_3 \in \mathbb{R}^{2800\times21}$.

Due to unavailability of the alarm signals from MARS-KS during simulation, the alarm signal is artificially generated. It is discovered that almost 20 alarm variables are activated during any steam generated tube leak. Therefore, based on this, we assumed 20 alarm variables in this work. For every time step in the continuous sensor signals, 20-dimensional alarm signals vector is generated with assumption that at least 90% of alarm variables can be randomly activated during each of these abnormalities. The encoded alarm dataset generated for each abnormalities are as follows:

AB.1 alarm dataset: $\mathbf{A}_1 \in \mathbb{R}^{5000\times20}$

AB.2 alarm dataset: $\mathbf{A}_2 \in \mathbb{R}^{5000\times20}$

AB.3 alarm dataset: $\mathbf{A}_3 \in \mathbb{R}^{2800\times20}$.

The resulted alarm signals is then concatenated with the scaled sensor signals, which led to:

AB.1 concatenated dataset: $\mathbf{Z}_1 \in \mathbb{R}^{5000\times41}$

AB.2 concatenated dataset: $\mathbf{Z}_2 \in \mathbb{R}^{5000\times41}$

AB.3 concatenated dataset: $\mathbf{Z}_3 \in \mathbb{R}^{2800\times41}$.

Each of these three concatenated datasets is partitioned into 80% and 20% for training and test sets respectively. Since the dataset is a time-series data, the splitting is performed using systematic random sampling that preserves the distribution of outcomes in the training and test sets. For example, if we consider $\mathbf{Z}_1$ which has 5000 time-series observations with t_i where $1 \le i \le 5000$), the number of observations in the test set, which is 20% of $\mathbf{Z}_1$, is equal to 1000 (0.2x5000). Then the selection of 1000 observations from 5000 observations is performed such that for every 5 (5000/1000) time steps in $\mathbf{Z}_1$, 1 is randomly sampled. This approach is used to partition each of the three sets into training and test sets. The results of the split of each of the three sets for training sets and for test sets are combined to form the following:

Training dataset: $\mathbf{Z}_{train} \in \mathbb{R}^{10240\times41}$

Test dataset: $\mathbf{Z}_{test} \in \mathbb{R}^{2560\times41}$.

These datasets are then used to train and test the proposed method. The results and discussion are presented in section 3.

3 Results and Discussion

The results of the validation of the proposed model are shown and presented in Fig.5 and Table 1 through Table 4. Table 1 shows the prediction probabilities of the 12 selected test cases from RF results, which are shown as examples of how the results will be displayed to the operator after detection and classification of the abnormalities. With this, the operator can easily know the particular abnormality that occurred, and then select the appropriate corresponding procedures to restore the plant to normal condition within the shortest possible time.

The confusion matrix of the four evaluated models on the test set, which allows visualization of the performance of the proposed model, is shown in Fig.5. The figure contains four confusion matrices, Fig.5 (a) to (d), one for each model. All the correct predictions and classifications are located in the diagonal of the matrix, so it is easy to visually inspect the matrix for errors, since they are represented by values outside the diagonal. In Fig.5 (a), out of 2560 test samples, LDA model misclassified 19 samples of which 2 samples that is actually belong to AB.1 are misclassified to be AB.2 and 17 samples that is actually belong to AB.2, 9 samples and 8 samples are misclassified to AB.1 and AB.3 respectively. In Fig.5 (b), the samples that are misclassified by CART are far more than that of LDA which amount to 460 out of 2560, while in Fig.5 (c), SVM misclassification of sample numbers is only 14 which is a bit smaller compare to that of LDA. In Fig.5 (d), RF has no any misclassification result and correctly identified and classified all samples in the test set associated with each abnormality.

The sensitivity, specificity, and accuracy of the four evaluated models on test set are shown in Table 2, Table 3, and Table 4 respectively. In all of these metrics, RF has demonstrated 100% capability to distinguish between the three simulated abnormal conditions with 100% accuracy. Hence, RF has the best performance follows by SVM, LDA, and CART.

Table 1 Probability from RF on the 12 cases of test set

Cases	Abnormal state prediction probability			Correctly Classified
	AB.1	AB.2	AB.3	
1	100%	0%	0%	AB.1(100%)
2	100%	0%	0%	AB.1(100%)
3	83.2%	16.8%	0%	AB.1(83.2%)
4	100%	0%	0%	AB.1(100%)
5	0%	100%	0%	AB.2(100%)
6	0%	71.4%	28.6%	AB.2(71.4%)
7	0%	99.8%	0.2%	AB.2(99.8%)
8	0.4%	99.6%	0%	AB.2(99.6%)
9	0%	0%	100%	AB.3(100%)
10	0%	0.6%	99.4%	AB.3(99.4%)
11	0%	2.8%	97.2%	AB.3(97.2%)
12	0%	1.2%	98.8%	AB.3(98.8%)

Predicted Abnormal State	Actual Abnormal State		
	AB.1	AB.2	AB.3
AB.1	**998**	9	0
AB.2	2	**983**	0
AB.3	0	8	**560**

(a) Linear Discriminant Analysis

Predicted Abnormal State	Actual Abnormal State		
	AB.1	AB.2	AB.3
AB.1	**999**	65	0
AB.2	1	**930**	389
AB.3	0	5	**171**

(b) Classification and Regression Tree

Predicted Abnormal State	Actual Abnormal State		
	AB.1	AB.2	AB.3
AB.1	**995**	0	0
AB.2	5	**991**	0
AB.3	0	9	**560**

(c) Support Vector Machine

Predicted Abnormal State	Actual Abnormal State		
	AB.1	AB.2	AB.3
AB.1	**1000**	0	0
AB.2	0	**1000**	0
AB.3	0	0	**560**

(d) Random Forest

Fig.5 Confusion matrix of all the models on the test set.

Table 2 Sensitivity of the four models on the test set

Model	Abnormal States		
	AB.1	AB.2	AB.3
LDA	99.8%	98.3%	100%
CART	99.9%	93.0%	30.5%
SVM	99.5%	99.1%	100%
RF	100%	100%	100%

Table 3 Specificity of the four models on the test set

Model	Abnormal States		
	AB.1	AB.2	AB.3
LDA	99.4%	99.9%	99.6%
CART	95.8%	75.0%	99.8%
SVM	100%	99.7%	99.6%
RF	100%	100%	100%

Table 4 Accuracy on the test set

Model	LDA	CART	SVM	RF
Accuracy	99.26%	82.03%	99.45%	100%

4 Conclusions

In this work, a data-driven-based aid for the detection and classification of the abnormalities in NPP is developed and proposed to assist operator in identifying the actual abnormality as quickly as possible during abnormal situations, which in turn, facilitate his/her decision in selecting appropriate AOPs to restore plant to its normal operating condition. The proposed approaches first developed a preprocessing method that encodes the alarm signals, scales the symptom sensor signals, and concatenates the encoded alarm digital signals and the scaled symptom analog signals together. The concatenated signals output is then used as the input to the classification model which predicts the plant abnormality condition and alongside its detection probability. To validate the proposed model, simulation data collected from the MAR-KS simulator for the case of abnormalities concerning steam generator tube in NPP is used as symptom analog signals and artificially generated alarm digital signals are used for alarm signals. Four classification models, LDA, CART, SVM, and RF are trained, and their performance are evaluated on the test set. The proposed method utilizing RF model outperformed the proposed method utilizing other classification models, with 100% performance on test set. The excellent results obtained from the case study, suggest that the proposed model is a promising approach for aiding the selection of AOPs in the event of abnormal conditions.

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