Conceptual Development of Non-Conventional Steam Turbine of Thermal Power Plant

Amar kumar shrivastava
Department of Mechanical Engineering
Rewa Institute of Technology

Pushpraj Singh
Department of Mechanical Engineering
Rewa Institute of Technology

Abstract

Steam turbine is the main system of a steam power plant and critical for power generation. Therefore, there is urgency for maintaining the reliability and availability of a steam turbine. A fast and accurate fault detection and diagnosis (FDD) system should be developed as an integral part to prevent a system from catastrophic disaster due to unhandled failures. Many previous studies applied model-based methods to build the FDD system. However, using those approaches required prior knowledge of the system. The power plant is a complex system, where comprehensive process knowledge is a real challenge. On the other hand, power plants have implemented condition monitoring which resulted in process monitoring data. Therefore, this study proposed a data-driven FDD system in a steam turbine of thermal power plant. The study used the process monitoring data from an Indonesian government owned steam power plant. A neural network based classifier was constructed to detect and diagnose faults as well as normal operating condition based on three scenarios. The result showed that the last two scenarios, with and without PCA approach, outperformed the first scenario which only used selected process parameters. The study demonstrated the superiority of data driven approach in the fault detection and diagnosis area.

Keywords- Data Driven Approach, Fault Detection and Diagnosis, Neural Network, Power Plant, Steam Turbine

I. INTRODUCTION

Fault detection and diagnosis (FDD) has a significant role in achieving the cost efficiency in production and safe production, References [1] and [2] has elaborated some examples of some significant impacts of negligence the safety and security in the complex industries, from material losses to life-threatening impact. According to International Federation of Automatic Control (IFAC) SAFEPROCESS Technical Committee, as in [3], i.e., the fault is “an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable/usual/standard condition.” Fault detection means the determination of fault occurrence in a system, while fault diagnosis is a determination of type, location and time of occurred fault [3].

From early literature, many FDD systems were developed using model based approach [4]. As the industrial process has become more complex, the model based approach is no longer suitable to detect and diagnose faults. This approach required a thorough understanding of the system. In this big data era, when automatic process monitoring is conducted continuously and generate a data stream, data driven approach has become more popular approach in FDD system [5].

A steam turbine is the main system of a steam power plant. It has a complex and dynamic structure in generating power. Maintaining its normal operating condition is essential for maintaining power generation. Distributed control system (DCS) has been implemented to monitor the process in power generation, real time and continuously. This study aims to develop data-driven FDD system of the steam turbine using DCS data with Neural Network (NN) mechanism. Real time monitoring data from Muara Karang Steam Power Plants unit 4 and five were collected for this study. The Muara Karang has been serving since 1980’s and provided around 26% of peak electricity demand for Jakarta greater area.

The paper sections are organized as follow. Section II presents the criticality of a steam turbine and the importance of steam turbine FDD system. Section III describes how the study was conducted by applying NN classifying approach on three scenarios. It outlines the NN approach and its superiority, proposed FDD study, data preprocessing, and finally the data processing using BPNN mechanism. Section IV presents the results and analysis of previous data processing. Finally, the paper is concluded in Section V.

II. STEAM TURBINES

A. Steam Turbine Mechanism

The steam turbine is a type of heat engine which alters heat into mechanical energy and is used in industry for several critical purposes: to generate electricity by driving an electric generator and supported equipment such as compressors, fans, and pumps [6]. The turbine makes use of the fact that steam when passing through a small opening, attains a high velocity. The velocity attained during expansion depends on the initial and final heat content of the steam. This difference in heat content represents the heat energy converted into kinetic energy during the process. In term of design, steam turbine generator sets consist of mechanical, electrical, hydraulic, heating and related accessorial units, even hundreds of components in the mechanical unit, i.e., blades, rotor

shaft and bearings, casing and seals, pressure sections of the turbine, and steam flow control [7]. Fig. 1 shows steam turbine configuration which consists of HP, IP and LP turbine.

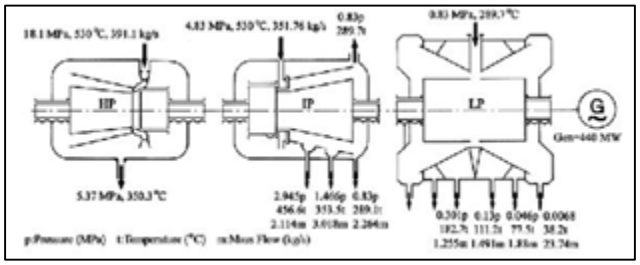

Fig. 1: Steam Turbine Configuration [8]

As in Fig.1, a typical compound turbine, the steam turbine of 200 MW Muara Karang steam power plant consists of high pressure (HP), intermediate pressure (IP) and low pressure (LP) sections. The process in a steam turbine is started with superheated high-pressure steam entering through a stage nozzle, which was intended to increase the steam velocity. The pressure of steam is then reduced after rotating the turbine, and it is reheated in boiler [6]. After reheating, the steam enters the intermediate and low-pressure turbines which have a more complex design. Multiple extractions are employed to enhance the thermal efficiency of the turbine.

B. Steam Turbine Faults

However, only some fault types were researched in this study based on classification by [12] as on Fig. 2. There were two factors considered for determining which fault types will be examined in this study: (1) availability of related process parameters to a certain fault type, and (2) availability of historical data regarding the fault. There are 140 process parameters of the steam turbine which monitored continuously during operation in every second, which mainly cover temperature, pressure, flow, and vibration. Only fault types which were related to process parameters were considered. From the selected fault types, only some have historical data. This process was confirmed through in depth discussion with experts in the power plant. This step resulted in four types of fault: misalignment, rotor bowing, blade erosion and cracking case.

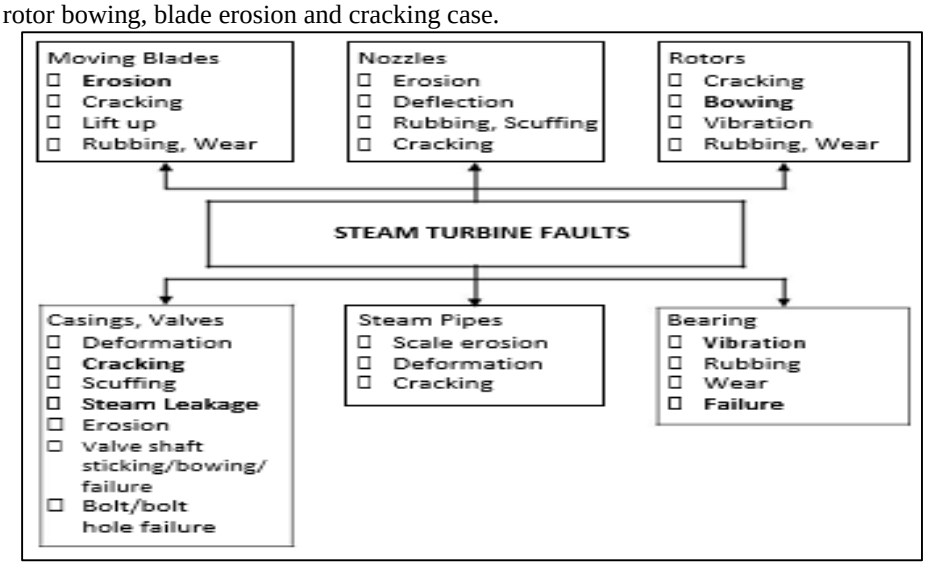

Fig. 2: Degradation, Damages, and Failure Modes of Steam Turbine Components, adapted from [12]

Misalignment is a condition where the center lines of coupled shafts do not coincide. There are two types of misalignment: parallel and angular misalignment. Whatever misalignment is developing, the high vibration of two consecutive bearings indicates this development. The limit of high bearing vibration is 0.125 mm. However, the vibration value around 0.04 – 0.05 mm mm from two consecutive bearings show the indication of misalignment. The raising temperature of the bearing is also a sign for misalignment. Misalignment data were grabbed from January 30, 2017.

The second type of fault is rotor bowing. Rotor and shaft have a similar meaning. The rotor is the rotating part inside the engine, while the shaft is the rest of rotating part outside the engine. Rotor bowing is initiating due to unavailable space for rotor expansion. The raising vibration of all bearings indicates that rotor bowing is developing. From data grabbed on July 15 2014, all bearings experienced increasing of vibration around 0.04 until 0.3 mm, while the limit is 0.125 mm. Abnormality in differential expansion and casing expansion are also signs of rotor bowing.

Blade erosion, as the third type of fault, is indicated by an abnormality of condenser absolute pressure. The pressure of condenser is vacuum under the atmospheric pressure. It was measured below atmospheric pressure. The smaller condenser absolute pressure means more wet steam in the blade than permissible amount. Actually, the development of wet steam is allowable for the

last blade in LP turbine due to condensation and reheat process from previous HP and IP turbines. However, the maximum permissible wet steam is around 10% off the limit [10]. Blade erosion fault data were gathered from December 19, 2016, when condenser absolute pressure dropped from the normal operating condition.

The last type of fault is cracking case, the third type of fault, is demonstrated by the high-temperature difference of upper and lower casing of steam turbine. Even though it will need further investigation due to a warning from the intelligent system that cracked is developing, early detection of this symptoms is beneficial. An indication of the cracked case can be gathered from data on November 23, 2015. Allowable limit of HP-IP upper and lower casing temperature is -42 to 42 degrees Celsius. Those four fault types and normal operating condition were simulated in this FDD system study using data driven approach.

III. STEAM TURBINE FAULT DETECTION AND DIAGNOSIS SYSTEM USING NEURAL NETWORK APPROACH

There has been the wide application of NN in fault detection, including in power plants, such as in [13-16]. NN is a method in machine learning which has been popular due to its capability of handling nonlinear and complex problems. NN comprises of interconnected s which represent knowledge with their assigned weights [17] as on Fig. 3. A typical NN used is multilayer perceptron, which consists of input layer, hidden layer and output layer. The number of inputs (x1, x2 ,…,xn) represents the number of features in the process. Then, each input neuron is connected to each hidden neuron in the hidden layer. Finally, each hidden neuron is connected to each output neuron (y1, y2,…,ym). The strength of each connection is known as weight, i.e. vij for connection between each input neuron and each hidden neuron, and wjt for connection between each hidden neuron and each output neuron. These weights were modified to ensure that the output is consistent with the anticipated output [18]. The activation function applied for this study is sigmoid.

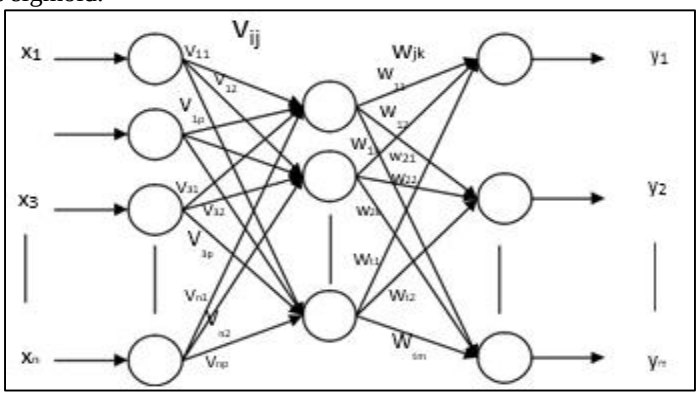

Fig. 3: Neural Network Architecture

Backpropagation NN (BPNN) was selected as machine learning mechanism in this study. BPNN is the most popular technique in the neural network (NN). It consists of iterative gradient algorithm to minimize the mean square error (MSE) between the output of multilayer feedforward perceptron and the data output. In addition to feed forward computation, BPNN adds backpropagation to the output layer, back propagation to the hidden layer and the weight updates. When the value of error function is sufficiently small as expected, then the iteration should be stopped. BPNN automatically detected and diagnosed fault type.

Three scenarios were proposed for studying FDD system. Scenario 1 used 19 selected process parameters as inputs. Scenario 2 used 140 process parameters as inputs. Scenario 3 applied PCA to 140 process parameters prior BPNN. Fig. 4. below, illustrates the proposed scenarios of FDD system. The inputs represent process parameters of the steam turbine, while the outputs represent fault types.

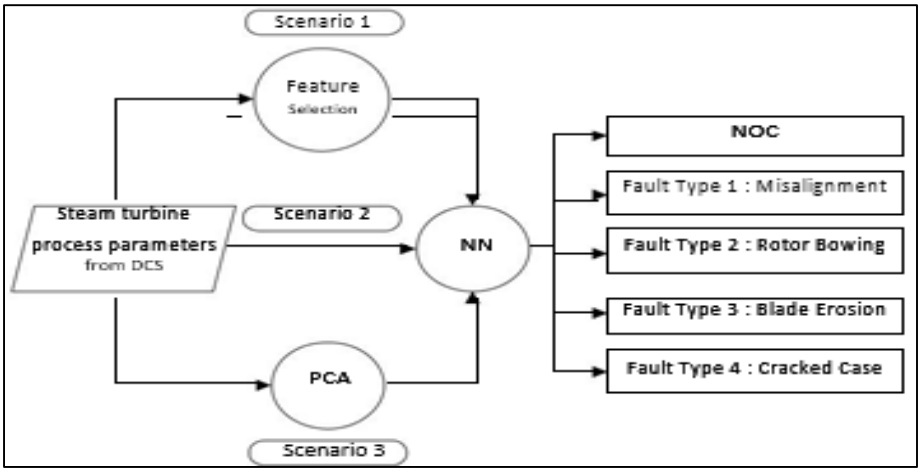

Fig. 4: Proposed Scenarios of FDD system

The scenario 1 actually described the current situation, where inputs used for fault event were limited to certain process parameters which were selected based on in depth discussion with the experts in the power plant. In this scenario, feature selection was applied. Meanwhile, in the scenario 2, all process parameters data were processed as features using BPNN after data scaling. Scenario 3, feature extraction was conducted before data processing. The objective of conducting feature selection and extraction is to reduce feature dimensions to simplify the model in terms of model complexity and computation time.

A. Data Preprocessing

Data preprocessing consists of data scaling and dimensional reduction, i.e. feature selection and extraction. Data cleaning and scaling were applied to all scenarios. In the meanwhile, feature selection was only applied to scenario 1, and feature extraction using principal component analysis (PCA) was only applied to scenario 3. The following sub sections elaborate each stage in the data processing.

1) Data Cleaning and Scaling

The first step followed data acquisition was data cleaning. Data for processing were limited to data which were related to those four fault events and data of normal operating condition. The length of data used in this study was 1500 for five classifications, NOC and four faults. 300 data points represented each fault type and NOC.

The next step was data scaling. This data scaling was conducted to avoid bigger scale domination over smaller scale data. Min-max formula was applied to get scaled data. The formula is as follow:

$$x_{i\,new} = \left[\left(\frac{x_i - \min(x)}{\max(x) - \min(x)}\right) * 2\right] - 1 \qquad (1)$$

The result of the data scaling min-max formula as on (1) above is the value between -1 to 1 for each feature or attribute.

2) Feature Selection

The feature selection applied in the scenario 1 was conducted based on previous knowledge of experts and basic theory of process parameters to certain fault type relation. It was confirmed that only 19 process parameters of steam turbine were related to those faults. They are eccentricity, casing expansion, differential expansion, bearing drain temperature (for bearing 1 until 7), bearing vibration (for bearing 1 until 7), HP-IP upper/lower casing temperature and condenser absolute pressure.

The following are some definitions regarding selected features. Eccentricity is the measurement rotor bow at slow-roll which is usually due to any combination of fixed mechanical bow, temporary thermal bow and gravity bow. Differential Expansion on a turbine is the relative measurement of the rotor's axial thermal growth with respect to the case, i.e, casing expansion. Absolute values of turbine-shaft expansion and turbine-casing expansion are measured using a linear variable differential transformer (LVDT) at movable end of the turbine. Hence, differential expansion is the difference between these two expansions. Those process parameters are related to rotor bowing.

Turbine bearing vibration (from bearing 1 until bearing 7) are related to misalignment and rotor bowing. The turbine bearing drain temperature (bearing 1 until 7) should rise when the vibration rises. HP-IP Upper/Lower casing temperature measure the temperature difference of upper casing and a lower casing which is related to the casing distortion. The upper casing usually has a higher temperature than the lower casing. Hence, it may cause a crack in the casing. As explained in the previous section, condenser absolute pressure is related to the blade erosion. Hence, the BPNN used features from the selected 19 process parameters to detect NOC and faults.

3) Feature Extraction

Scenario 3 applied to feature extraction using PCA before data were processed using BPNN. Feature extraction was used to reduce feature dimension into orthogonal principal components while still described the maximum variability (essence) of the data. Principal Component Analysis (PCA) aims to find the most meaningful redefined features to express data sets [19]. Let x=[x1, x2,…,xm] ^{T} represent a random vector of observations on m process parameters with sample covariance matrix A. By using singular value decomposition (SVD) below:

$$ä = Q^T A Q \qquad (2)$$

Where Q is the loading matrix, consists of eigenvectors in each column, corresponding to ä, a diagonal eigenvalues matrix. Each eigenvalue represents component variance which has been captured by each principal component (PC). Q is orthonormal eigenvectors such that $QQ^T=Q^TQ=I$.

PCA transforms m correlated variables (process parameters) into new m uncorrelated variables (PCs) using the following formula on Eq3.

$$Z = Q^T|x - \bar{x}| \qquad (3)$$

The decision about the appropriate number of retained PCs could be subjective. In this study, using ratio which explained at least 90% of the variance, the 140 original process parameters of steam turbine process parameters were reduced into 4 PCs.

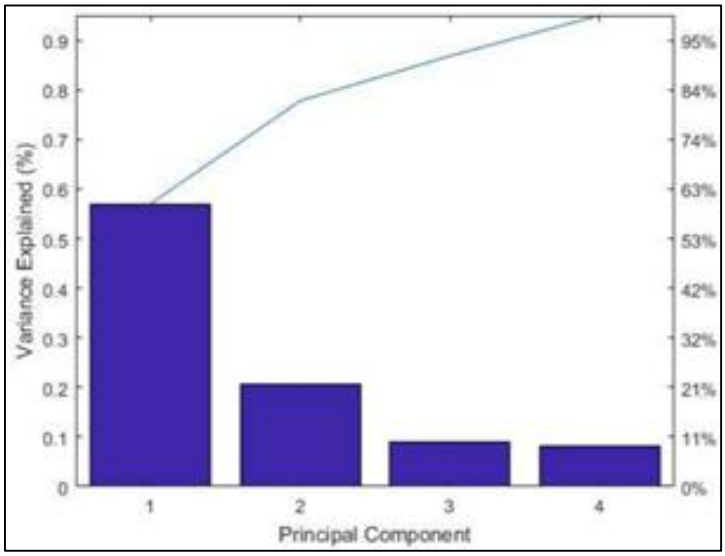

Fig. 5: Scree Plot

Based on the scree plot on Fig. 5. Above, the first principal component (PC) explains around 57.07 % variability of data, while it drops significantly on the second PC. The second PC explains 20.75%, the third PC explains around 9.02% and the fourth PC only 8.18%. By retaining the four PCs, 95.03% variability of data can be explained.

B. Faults Classification using BPNN

The BPNN architecture used was multilayer perceptron, which consists of one input layer, one hidden layer and one output layer. There are 140 process parameters for monitoring steam turbine operation. The number of hidden neurons was determined based on rule of thumb. The optimal size of hidden neurons is commonly between input and output sizes. Furthermore, one can expect good performance using the mean of input and output neurons. In this study, the number of hidden neurons was 75 for Scenario 1, 25 for Scenario 2 and 7 for the Scenario 3.

Data were then split into training data and testing data with ratio 1: 5. Therefore, there were 50 training data (16, 67%) and 250 testing data (83.33%) for each class. Some combinations of learning rate (Ţ) and momentum were selected based on trial and error to find the best result. The value was tested from 0.1 until 0.3 for Ţ, and from 0.1 until 0.8 for momentum. The limit of iterations: (1) SSE should be lower than 0.01 and (2) epoch number should be 1000 at maximum.

IV. EXPERIMENTAL SETUP, RESULTS AND DISCUSSION

Performance of each scenario was measured by using detection rate (accuracy) and computation time. From all scenarios, the accuracy of fault detection and diagnosis shows satisfying results. Even though the results were varied, but they were closed to 100% accuracy. It may be due to the power plant Operational condition. During its operation, a steam turbine in a power plant has steady process parameter. Even though there is a change in the production load, to maintain the stability of the process, the remaining process parameters will stay the same. The results of each scenario are detailed in the following sub sections.

A. Scenario 1: Feature Selection

Scenario 1 only used 19 process parameters as explained in the previous sub section as inputs to the back propagation learning mechanism. Table I listed all the results from learning rate (Ţ) 0.1 and momentum 0.2.

Table 1: BPNN Results with 19 Process Parameters

Epoch	*Accuracy of Training (%)*	*Accuracy of Training (%)*	*Time (second)*
541	*100*	*88*	*10.56*
538	*100*	*88*	*10.46*
541	*100*	*88*	*10.15*
551	*100*	*88*	*10.11*
547	*100*	*88*	*10.05*
529	*100*	*88*	*9.71*
550	*100*	*88*	*10.12*
537	*100*	*88*	*9.88*
541	*100*	*88*	*9.98*
534	*100*	*88*	*9.81*

All the ten times computations resulted in the recognition rate of 100% for training data and only 88% for testing data. The source of lower recognition rate of testing data due to an error in recognition of type 2 fault, i.e., rotor bowing. The rotor bowing

phenomenon was developed when all bearings vibration increased. By using only 19 inputs, the recognition rate of this fault dropped into 40%. It seems that more variables should be related to this fault type. Fig. 6. Below described the error of recognition of type 2 Fault based on real output value.

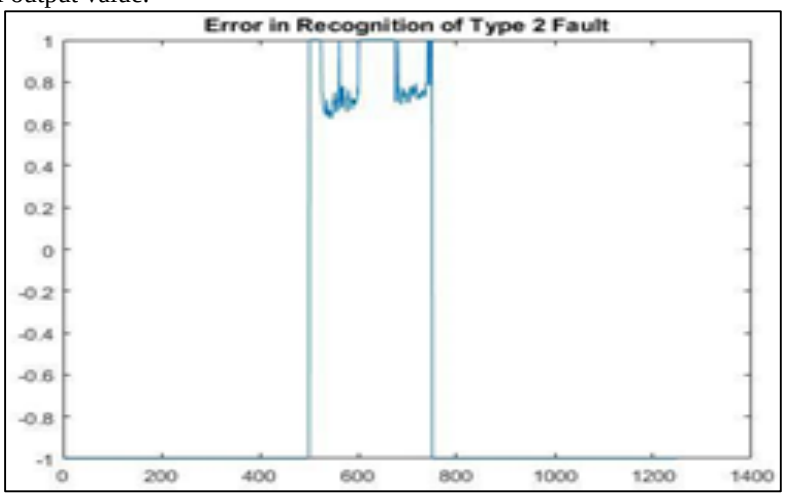

Fig. 6: Error in recognition of Type 2 Fault: Rotor Bowing

B. Scenario 2: BPNN using All Process Parameters

Using the original process parameters, 140, Table II shows the results of BPNN using learning rate (Ţ) 0.1 and momentum 0.1. Other combinations of learning rate (from 0.1 to 0.2) and momentum (from 0.1 to 0.6) were tried. Other combination of learning rate (Ţ) 0.2 and momentum 0.1 demonstrated the lowest computation time, however the slope of SSE versus epoch show less smooth learning process.

All combinations show consistent results with 100% of accuracy, both training and testing data. For a combination of Ţ 0.1 and momentum 0.1, the mean of computation time is 8.97 second to get MSSE 3.98x10-5. The epoch range is from 133 to 139.

Therefore this approach demonstrated a satisfactory result in detecting faults. The accuracy of data processing was significantly higher than the previous scenario which limited 19 process parameters as features. Table II below describes the result of each computation.

Table 2: BPNN with 140 Process Parameters

Epoch	*Accuracy of Training (%)*	*Accuracy of Testing (%)*	*Time (second)*
136	*100*	*100*	*9.03*
136	*100*	*100*	*9.76*
135	*100*	*100*	*8.80*
137	*100*	*100*	*8.98*
136	*100*	*100*	*8.93*
134	*100*	*100*	*8.74*
136	*100*	*100*	*8.87*
139	*100*	*100*	*9.07*
135	*100*	*100*	*8.82*
133	*100*	*100*	*8.66*

C. Scenario 3: PCA and BPNN

After trial and error of learning rate and momentum combination, the highest average of accuracy was gained from learning rate (Ţ) 0.3 and momentum 0.3. Using four PCs as inputs in this back propagation learning mechanism, Table III shows the recognition rate of training as well as testing data along with epoch and computation time. The stopping criteria for the iteration was SSE < 0.01 (MSSE <0.00004).

Table 3: PCA and BPNN Results

Epoch	*Accuracy of Training (%)*	*Accuracy of Testing (%)*	*Time (second)*
419	*100*	*100*	*10.80*
481	*100*	*100*	*13.10*
480	*100*	*100*	*12.54*
466	*100*	*100*	*12.18*
496	*100*	*100*	*12.93*
452	*100*	*100*	*11.81*
459	*100*	*100*	*12.19*
507	*100*	*92.40*	*13.20*
416	*100*	*93.76*	*10.87*
449	*100*	*100*	*11.75*

From ten computation trial, only the eight and the ninth did not show 100% of the recognition rate. Sources the error in the recognition was NOC, which was misclassified into type 1 fault. It may compensate unexplained variability from the selected four PCs. However, the accuracy is still high, above 90%. Even though PCA show promising results, if the interpretation of feature cause is important, then PCA is not preferable to be applied in dimension reduction.

V. CONCLUSION

Based on this study results, we conclude that application of data driven FDD system in the steam turbine of a thermal power plant shows superior results. Almost all scenarios demonstrated high accuracy results. However, scenario 2 and 3 outperformed results compared to scenario 1. It depicts that the ability of NN approach in FDD system is promising.

Scenario 2 and 3 which considered more features than scenario 1, demonstrated better accuracy. Scenario 1 only considers smaller input process parameters, limited to experts' knowledge of the process. The data driven approach in FDD overcomes the limitation of human being in constructing features which contribute more in the fault occurrences. More structured methods in feature selection, such as decision tree and correlation analysis should be applied in the future research to recognize the most contributing features.

Moreover, application of feature extraction using PCA in scenario 3 presented satisfying result. Other derivation of PCA method should be tried in the next study.

The limitation of this study is the type of faults detected. In the real time, more type of faults should be detected. However, only limited previous fault data available. Therefore, for the next research, we should consider the other possibility of fault that can be gathered from the real data or simulated data to challenge the BPNN to detect and diagnose faults.

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