DEVELOPMENT AND IMPLEMENTATION OF INTELLIGENT CONDITION MONITORING SYSTEM FOR STEAM TURBINE TRIPS

Firas B. Ismail Alnaimi, Rahmat Izaizi B. Ismail and Pin Jern Ker
Power Generation Research Centre, College of Engineering, Universiti Tenaga Nasional, Putrajaya Campus, Jalan, Selangor, Malaysia
E-Mail: Firas@uniten.edu.my

ABSTRACT

Sustainable initiatives are increasingly getting attention from the research community and one of the aspects in achieving sustainable development is to enhance the efficiency and optimize the technology used to generate and utilize energy. Fault detection and diagnosis is a critical optimization factor in power generation sector. Early faults detection ensures that correct mitigation measures can be taken, whilst false alarms should be eschewed to avoid unnecessary cost of operation, interruption and downtime. Pure Intelligent Condition Monitoring System (ICMS) represented by artificial neural network (ANN), developed by training the network with real operational data, may be proven to be useful for real-time monitoring of a power plant. In this work, an integrated data preparation method has been proposed and the development of ANN models to detect steam turbine trip for Malaysia MNJ power station will be presented. Two models adopting feed forward with back propagation ANN were trained with real data from the MNJ station. The developed models were capable of detecting the specific trip within a period of 32 minutes before the actual trip occurrence, which is considered to provide good and satisfactory early fault detection.

Keywords: artificial neural networks, condition monitoring system, steam turbine.

INTRODUCTION

Driven by the advancement in various industries, the demand for energy has grown rapidly for the past few decades. This increasing need of power and energy can only be satisfied with the construction of additional power plant or by optimizing and increasing the efficiency of existing plant. The later actions are more beneficial considering the cost of establishing a new plant is massive and it involves many stakeholders. One pervasive factor that decreases the efficiency of a power plant is the forced outages or unplanned equipment downtime. Forced outages typically involve losses up to millions of USD and at least 5% of the total power generation availability. For power generation industry, the hidden cost of downtime can represent 5–10% of the annual revenue and potentially 30–40% of annual profits [1]. Predictive maintenance as one of optimization action has emerged to provide condition-based early warning. In power generation industry, it provides early warning of asset failure such as combustion turbines, steam turbines, boiler feed water pumps and cooling water pumps.

One of the most important elements in a power plant is its steam turbine. Steam turbine trip can lead to entire plant shutdown, thus it is very critical to ensure that the turbine is at normal operation. By developing an intelligent condition monitoring systems (ICMS) for steam turbine trips, the causes of turbine trips can be identified and mitigation steps can be taken to maintain the normal and safe operating condition of the turbine. The operational data of steam turbine need to be studied and measured to detect the tripping trends which will be used to drive the algorithm used in the ICMS.

A detailed data preparation procedure for steam boiler fault detection and diagnosis (FDD) analysis was presented by Firas B. Ismail Alnaimi *et al.* [2], where real data of steam boiler were captured, identified, clustered, and sampled. After plant data preparation, parameters selection phase began, where the data were tested, checked, and normalized. The boiler behaviour was studied, and the most influencing parameters were decided. For fault detection and diagnosis neural network (FDDNN) model training-validation phase, feed-forward neural networks were used. The FDDNN model could detect and diagnose the super heater low temperature quickly and accurately.

ANN modelling of all the major combined heat and power (CHP) plant components was possible as demonstrated by M. Fast and Thomas Palmé [5]. The described ANN models are plant specific; however, the method is general, and thereby applicable to other power plants and configurations. The pros and cons of ANN monitoring approaches were also summarized. The pros of ANN were no detailed physical in-formation are needed, only operational data is required, ANN calculation is fast and can be used online, and ANN can establish relationships between performance parameters and operational conditions that are difficult to model. The cons of ANN monitoring were summarized as, data covering the entire operation range is needed for training and any new operational condition changes require a retraining.

A solution for sensor fault detection, isolation, and accommodation by employing ANN as a classifier was presented by Thomas Palmé *et al.* [6]. Nonlinear Principal Component Analysis (PCA) for early warning of gas turbine failure implemented through the use of Auto-Associative Neural Network (AANN) was also demonstrated by Thomas Palmé *et al*. [7]. In this work, the use of AANNs for early detection of abnormal engine behaviour could warn the operator a few days prior to full failure. A comparison is made between the nonlinear PCA with AANNs and a standard PCA model. The result showed that the AANN could provide a more reliable detection of failure by a higher residual generation during failure mode, as well as fewer false indications prior to the failure.

Table-1. Summary of previous researches on ANN application in power generation industries.

Authors	Training algorithm	Activation function	Type of data	Coding	Performance indicator	Application area
Firas B. Ismail Alnaimi *et al.,* 2011 [2]	Rprop, BFGS quasi-Newton, SCG, Levenberg Marquardt	logistic, hyperbolic tangent, linear summation	real data	MATLAB	RMSE	Steam Boiler
M. Fast and Thomas Palmé, 2010 [5]	gradient descent	hyperbolic tangent	real data	-	MSE	combined heat and power plant
Thomas Palmé *et al.*, 2011 [6]	SCG	nonlinear transfer functions, linear transfer function	simulation data	-	MSE	Gas turbine
Thomas Palmé *et al.*, 2011 [7]	SCG	-	real data	-	MSE	Gas turbine
Thomas Palmé *et al.*, 2011 [8]	SCG	-	real data	MATLAB	MSE	Gas turbine
Raza Abdulla Saeed and Loay Edwar George, 2012 [9]	back propagation	-	simulation data	MATLAB	MSE	Francis turbine runners
K. P. Kumar *et al.* , 2012 [10]	-	-	simulation data	MATLAB	-	Steam turbine
M. Saberi *et al.* [11]	-	-	real data	MATLAB	-	Centrifugal Pump

BFGS: Broyden–Fletcher–Goldfarb–Shanno, **SCG:** Scaled Conjugate Gradient,
RMSE: Root Mean Squared Error, **MSE:** Mean Squared Error

A Multi-Layer Perceptron (MLP) Neural Network (NN) model to develop a base-line model of a gas turbine was developed by Thomas Palmé *et al.* [8]. MLP based NN model is used for baseline development of two different gas turbine (GT) types, and for several different units of each type. An ANN based vibration analysis for steam turbine was proposed by K. P. Kumar *et al.* [10]. The simulation results using actual data from operating power plants showed the data detection method could be applied to identify the fault presence with less intervention of a human expert. The same technique can be used to classify all the faults of the turbo generator by training with different fault conditions data.

The performance and robustness of SVM and ANN for fault diagnosis in a centrifugal pump were compared by M. Saberi *et al.* [11]. The SVMs method with Gaussian and linear functions are superior due to better performance, robustness in noisy environments, and its simplicity. Table-1 summarizes the methodologies and ANN topologies consideration of the previous researches.

In this work, an integrated data preparation method has been proposed. This paper also presents the development of two ICMS to diagnose turbine trip. Both are using a feed-forward with back propagation ANN. The first model uses only a hidden layer (1HL) and the second model uses 2 hidden layers (2HL). Various ANN topologies were considered and the data to train these ANN were taken from MNJ power station which is a coal-fired power plant located on a man-made reclaimed island off the coast of Perak, Malaysia. Turbine trip data and operational data with 1 minute interval for a period of 1 year (2008) were provided by the plant owner. 70% of these data were used for ANN training, 15% were used for cross validation and the remaining 15% were used for testing. The input variables were selected initially according to research scope and plant operator experience.

Brief description of the plant

A brief description of MNJ coal-fired power plant will be discussed in this section. It is located about 10 km south of the nearest town Lumut, approximately 288 km north of Kuala Lumpur and near to the tourism island of Pangkor. The power blocks scheme of the plant are identical unit of 3 x 700 MW. The type of boilers for the three units is drum type and controlled circulation tangential firing. They are equipped with economiser, superheater, reheater and low NO_x burners. The boilers are designed to burn imported international coals as main fuel on base load. Light fuel oil will be used for ignition and for sustaining the flame at low load. The turbine generator sets have a rated output corresponding to a nominal net power of 700MW and have a rotating speed of 3000 rpm. The turbine is of axial flow design with all the turbine and generator rotors are directly coupled in tandem. The turbine consists of a high pressure (HP) turbine, an intermediate pressure (IP) turbine and two double flow low pressure (LP) turbines. Table-2 shows the parameter for both the boiler and turbine.

The generator is a two-pole hydrogen and water cooled machine of the "Gigatop" type. The rotor winding and the stator core are hydrogen cooled. The stator winding and the terminals are directly water cooled. The machine is fitted with the seal oil, gas cooling and stator water cooling systems. Its excitation is provided by a static excitation connected to the slip ring unit. The circulating water system takes cooling water from the sea to the three condensers by means of six 50 % duty concrete volute type main cooling water pumps. The feedwater heating plant includes four LP heaters arranged in series, with LP1 & 2 located in the condenser neck, one feedwater tank equipped with a de-aerator and three HP heaters [12-13].

Table-2. Boiler and steam generator parameters.

Boiler parameters	
Life steam flow	2390 t/h
Life steam pressure	175 bars abs.
Life steam temperature	539°C
Feedwater temperature	277°C
Fuel	Coal
Ignition fuel	Light oil
Steam generator parameters	
Nominal rating	943MVA
Power factor	0.85
Voltage	23 kV
Frequency	50Hz
Short circuit ratio	0.51
Efficiency	98.9%
H2 pressure	4 bar gauge
Excitation	Static

Artificial neural network (Ann) – Brief theory

Artificial Neural Network (ANN) is a fast-growing soft computing method, which has been used in different type of industries recently. ANN is a computational model inspired by natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron. When the signals received are strong enough to surpass a certain threshold, the neuron is activated and will emit signals through the axon. This signal might be sent to another synapse, and might also activate other neurons.

ANN imitates the characteristic of a natural neurons by several functions, namely inputs (like synapses), which are multiplied by weights (strength of signals) and then computed by mathematical function, determining the activation of neuron. Another function will compute the output, which will sometime depend on a certain threshold. A neural network model is made up of interconnected artificial units (neurons). Neurons are arranged in different layers, including input layer, hidden layer(s), and output layer. The number of neurons and layers depends on the type of problems need to be solved and the complexity of the system to be modelled.

ANNs learn the relation between the inputs and outputs of the system through a process called training. Each input into the neuron possessed its own associated weight. Weights are adjustable numbers, which are also determined during the training process of the network. Figure-1 shows a simple structure of a typical ANN with 4 inputs, first hidden layer with 5 neurons, second hidden layer with 3 neurons, and one output.

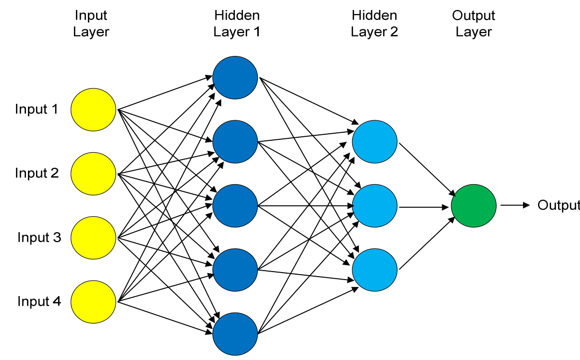

Figure-1. Simple ANN structure.

METHODOLOGY

Turbine trip identification

One of the main causes of forced outages in a thermal power plant is turbine trip. The plant operator's experience was fully utilized to determine the type of turbine trip which will be analyzed in the work. The turbine trip chosen, which is a steam temperature fall turbine trip is one of the most influential trips occurred in MNJ station. The details of the trip are shown in Table-3.

Table-3. Trip details.

Plant	MNJ
Unit	Unit 3
Month	June
Start	05/06/2008 06:30
End	05/06/2008 08:26
Description	Turbine tripped on HP steam temperature fall rate alarm activated due to Final Superheater temperature suddenly dropped to 521°C from 571°C due to Superheater 2nd stage spray water valve jammed at 28%.

Plant data preparation

Data preparation is about constructing a dataset from one or more data sources to be used for analysis and modelling. Good data preparation is a key prerequisite to successful neural networks training. Data preparation is often a time consuming process and heavily prone to

VOL. 11, NO. 24, DECEMBER 2016 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

errors. In practice, it has been generally found that data cleaning and preparation takes approximately 80% of the total data engineering effort. The quality of the prepared data to be used as input for the ICMS may strongly influence the system performance [14]. The data preparation phase could be divided into three execution phases as shown in Figure-2.

Identification of data is when the turbine operational variables were identified and acquired for the specific turbine trip. Initially, 1800 observations (actuator and sensor signals) were identified from on-line plant control system. The number of observation was reduced by a process shown in Figure-3. Only observations related to turbine were considered and the numbers of variables

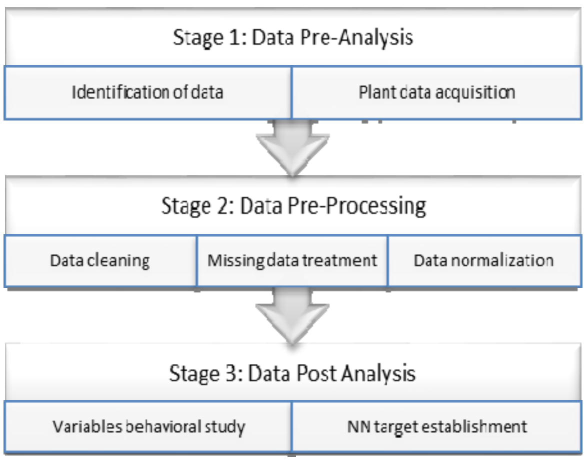

Figure-2. Plant data preparation stages.

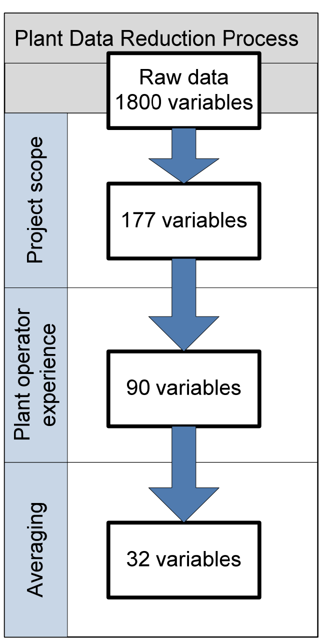

Figure-3. Plant data reduction process.

were reduced from 1800 to 177. Taking into account the advice from plant operator, the 177 observations were further reduced to 90 by neglecting non-effective factors on the trip scenarios. Some of the observations were from the same sensors and by comparing the sensor serial number, the observation were reduced from 90 to 69. Most observations were measured by multi sensors so an averaging approach was adopted to further reduce the number of variables. Finally, 32 influential turbine operation variables, as listed in Table-4, formed the final set of the training data.

Data pre-processing

Data pre-processing stage consists of 3 main steps; which are data cleaning, missing data treatment and data normalization. Data cleaning is about dealing with noise values or error in the observed values. For MNJ station, the common concerns about noise in the data were duplicate records. It was found that some of the readings from the actuators and sensors were duplicated several times in the data storage. This noise could be detected and removed by analyzing the sensors/actuators serial number and with visual cleaning. The noise could also be removed by creating an automated graphical tool that could detect duplicates and remove them accordingly.

Table-4. Influential operation variables.

Variables	Description	Unit
v1	Steam flow	t/h
v2	FW flow	t/h
v3	drum pressure	Barg
v4	SH steam pressure	Barg
v5	SH steam temperature	°C
v6	E inlet temperature	°C
v7	HT Re-heater outlet temperature	°C
v8	HT SH exchange metal temperature	°C
v9	SH exchange metal (A) temperature	°C
v10	HT SH inlet header metal temperature	°C
v11	Final SH outlet temperature	°C
v12	SH steam (control) pressure	bar
v13	FW valve station flow	t/h
v14	FW control valve position	%
v15	E inlet pressure	bar
v16	Drum level corrected	mm
v17	Drum level compensated	mm
v18	E outlet temperature	°C
v19	FW flow transmitter	%
v20	Boiler circulation pump1 pressure	bar
v21	Boiler circulation pump 2 pressure	bar
v22	LT SH left wall outlet temperature	°C
v23	LT SH right wall outlet temperature	°C
v24	LT SH left wall temperature	°C
v25	LT SH right wall exchange metal temp.	°C
v26	SH exchange metal (B) temperature	°C
v27	Intermediate SH outlet temperature	°C
v28	Intermediate SH outlet header metal temp.	°C
v29	HT SH outlet header metal temperature	°C
v30	HT Re-heater outlet steam pressure	bar
v31	Superheated steam pressure	bar
v32	SH water injection flow	ton/hr

removed by analyzing the sensors/actuators serial number and with visual cleaning. The noise could also be removed by creating an automated graphical tool that could detect duplicates and remove them accordingly.

Missing data usually are the missed observation values or information losses. If the missing data percentage is high the record must be neglected. For cases where the missing data occurrences are limited, the missed values can be replaced with mathematical forecasting methods: the most common mathematical forecasting methods are: extrapolation and interpolation.

Data normalization is important for treating multi-scale data. Non scaled data could be bias or interfere with the training process and lead to an unstable operation of the ICMS. The ICMS performs better with numerical data scaled between 0 and 1. The normalization techniques used in the project is the Min-Max normalization [15]. Min-Max formula shown in Equation. (1) is applicable when minimum and maximum values for an occurrence are known.

$$\text{New value} = \frac{(\text{original value} - \text{oldMin})}{(\text{oldMax} - \text{oldMin})} \qquad (1), [15]$$

Data post analysis

Data post analysis stage consists of two main steps; behavior analysis of the turbine operation variables and the establishment of NN targets. After thorough analysis of the operational variables, the targets for the ICMS will be set accordingly with the specific trip. The methods of target matrix establishment were repeated by assuming the faulty data with ±5, ±10, ±15, ±20 and ±25 minutes. The analysis has shown that the ±20 minutes provided optimum training performance of the ANN system, where RMSE change compared to the ±25 is negligible; i.e., the steady state convergence was achieved. It was decided that the fault target interval was within 20 minutes before and 20 minutes after reaching "1". Hence all the other values are assumed non-faulty values and they are tagged as "0" in the normalization format.

DESIGN AND MODELLING OF ICMS

The design and modelling of the proposed ICMS were developed with the help of MATLAB codes. The development procedures are highlighted and discussed in this section. The type of intelligent system used was a feed-forward ANN. Choosing a good topology is a crucial task for the success of any ANN modelling. The topology selection influences the learning process, time, and its classification. The selection criteria in this work are based on its impact towards the network performance. The main NN topologies include; training algorithms, learning rate, momentum coefficient, activation functions, the number of hidden layers, and the number of hidden layer neurons. The best structure for the ANN is the one that can predict the behavior of the system as accurately as possible and the method used in this works was by adopting Root Mean Square Error (RMSE) as performance indicator. The formula is shown in Equation. (2)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \qquad (2)$$

Where the (yi)ˆis the predicted value and yi is the observed value.

Three different types of training algorithms were considered based on their computational time and performance. The characteristic of each training algorithm based on MATLAB help description are as follows:

i. Scaled conjugate gradient backpropagation (trainscg): Backpropagation is used to calculate derivatives of performance with respect to the weight and bias variables. It uses less memory.
ii. Levenberg-Marquardt backpropagation (trainlm): The fastest backpropagation algorithm in MATLAB toolbox, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms.
iii. Bayesian regulation backpropagation (trainbr): Minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. Takes longer time but may be better for challenging problems.

The learning rate (α) value (commonly between 0.1 and 0.9) must be determine by the neural network user and usually reflects the rate of learning of the network. Values that are too large might produce instability in the network and unsatisfactory learning. On the other hand, values that are too small might result in excessively slow learning. The learning rate for the proposed ICMS was fixed at the value rate of 0.5.Three different types of activation functions were considered based on their suitability with normalized data. The type of activation functions are:

i. Linear summation function (P).
ii. Sigmoid logistic function (L).
iii. Hyperbolic tangent (T).

RESULT & DISCUSSION

Two ICMS were proposed to diagnose the turbine trips. Both are using a feed-forward ANN. The first model uses only a hidden layer (1HL) and another one uses 2 hidden layers (2HL). The two systems were coded in MATLAB. The outcomes of the developed ICMS are presented in this section. The discussion was focused on determining the best NN topology combination based on RMSE as the performance indicator. To get the results, several NN topologies were trained for both one hidden layer (1HL) model and the two hidden layers (2HL) model. Different numbers of neurons for each hidden layer ranging from one to ten were tested.

Table-5 summarizes the outcomes of ICMS with one hidden layer. Based on the result, it was proven that trainlm was the fastest training algorithm with only 5 iterations to achieve the performance goal. From observation, the average computation time for trainbr was the slowest and some of the training reaches the maximum

VOL. 11, NO. 24, DECEMBER 2016 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

epoch (10,000 iterations) but it produces the best RMSE of 0.0346.

Table-5. Result summary for 1HL NN.

Training Algorithm	Architecture	Activation Function	RMSE	Number of iteration
trainscg	6HL1*	T+T	0.1594	27
trainlm	4HL1	P+T	0.1353	5
trainbr	2HL1	T+P	0.0346	18

*6HL1: 6 neuron in the 1st Hidden layer

Table-6 summarizes the outcomes of ICMS with two hidden layer. Based from the result, it was shown that trainlm was still the fastest training algorithm; with only 12 iterations to achieve the performance goal. From observation, it was noticed that 2HL ICMS with trainbr training algorithm performs really well with plenty of very low error results. The best performance achieved was 1HL1-2HL2 ICMS using trainbr training algorithm with RMSE of 0.0200. In general, ANN with two hidden layer have better performance compared to one hidden layer.

Table-6. Result summary for 2HL NN.

Training Algorithm	Architecture	Activation Function	RMSE	Number of iteration
trainscg	7HL1-10HL2	P+T+T	0.1404	21
trainlm	1HL1-5HL2	T+P+T	0.1114	12
trainbr	1HL1-2HL2	T+T+T	0.0200	13

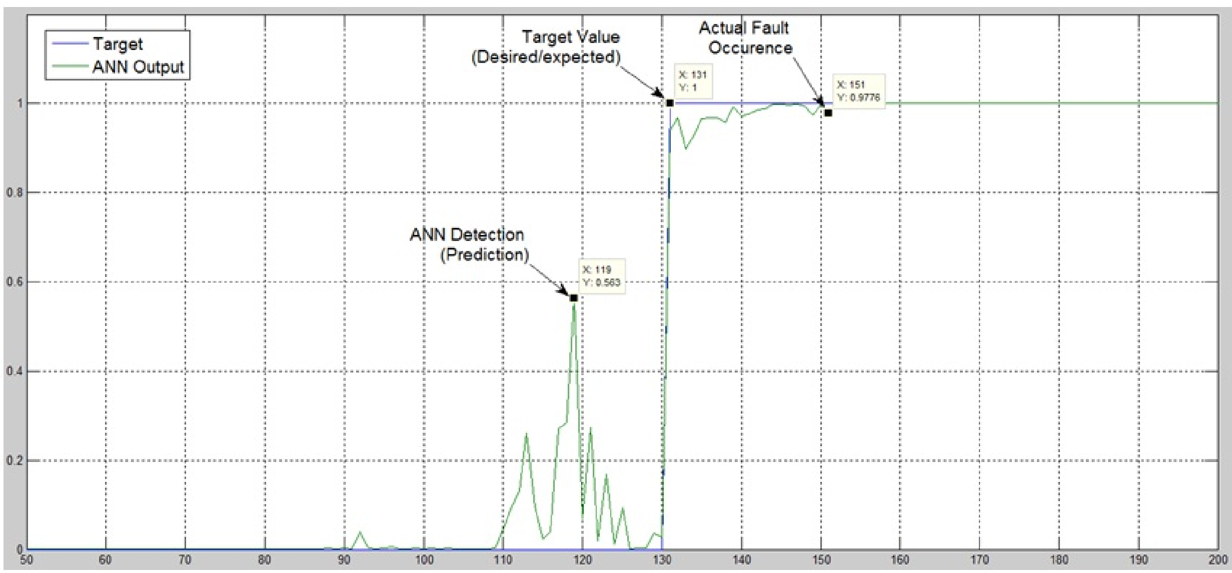

Figure-4. Optimal 2HL ICMS output – trainbr.

Figure-4 shows the output of the optimal 2 HL ICMS using trainbr training algorithm. In the study, the data from MNJTPP steam turbine operational history was normalized between 0 – 1. By analyzing the operational parameter behavior, the operational thresholds were calculated. The normal operation was determined as below 0.3, low alarm warning was between. 0.3 – 0.6, and high alarm warning was above 0.6. The sensor reading was taken in one minute interval and the fault happens at the 151st interval. The intelligent system detects the fault at the 119th interval (which is 32 minutes before the plant monitoring system). The output is 0.56, which is considered as a low alarm warning. In brief, all six proposed ICMS configuration using 1HL and 2HL were capable of detecting the specific thermal power plant trip within a period of around 20 to 30 minutes before the trip occurrence. This time period is considered satisfactory.

CONCLUSIONS

The main objective of this work was to develop an ICMS to detect steam temperature fall turbine trip by ANN application. An important advantage to highlight is that the ICMS can be developed with operational data without the need of a detailed model of the plant system. Trial and error approach was adopted to find the most suitable ANN topology for the specific turbine trip. The ANN topology considerations in this work are training algorithm, learning rate, activation function, and number of hidden layer and their neurons.

In both one hidden layer and two hidden layer ANN, the highest performance are with Bayesian regularization back propagation training algorithm. It is known that this training algorithm takes longer computational time compared to other algorithm but it is the most suitable for complex problem. It is found that once the correct number of neurons and activation function are matched through trial and error, the ANN model will produce good performance within acceptable time.

The best performance for the model is found to be a two hidden layer ANN using Bayesian regularization back propagation training algorithm with 1 neuron in the first hidden layer, 2 neurons in the second hidden layer and hyperbolic tangent activation function in all the layers. The ANN model is found to have good prediction accuracy with only 0.0200 errors. The model predicted the fault 32 minutes before the existing plant monitoring system. With earlier fault detection, the plant operator can implement mitigation measures and bring the plant back online faster which in turn reduce the downtime cost for unscheduled shutdown. It must be clarified that if any changes occur in the system, a retraining of the ANN is required.

For future work, the ICMS can also be trained to detect other types of turbine trips. A retraining with the new type of trips data would be required. The ICMS also could be improved by adopting optimization methods such as genetic algorithm.

ACKNOWLEDGEMENTS

The authors would like to express acknowledgement to Universiti Tenaga Nasional (UNITEN) and Ministry of Higher Education (MOHE), Malaysia for the opportunity and sponsorship of this corresponding research under the FRGS research fund.

REFERENCES

[1] Bell, David, "The Hidden Cost of Downtime: A Strategy for Improving Return on Assets", Maintenance Technology, Volume 14, Number 7, July/August 2001, page 28

[2] Firas B. Ismail Alnaimi and Hussain H. AL-Kayiem, "Artificial Intelligent System for Steam Boiler Diagnosis Based On Superheater Monitoring", Journal of Applied Science 11 (9): 1566 – 1572, 2011.

[3] Alnaimi, F. B. I., & H. H. Al-Kayiem. (2010), "Multidimensional Minimization Training Algorithms for Steam Boiler Drum Level Trip using Artificial Intelligent (AI) Monitoring System", Intelligent and Advanced Systems, 2010 International Conference on Intelligent and Advanced System (ICIAS): 1 – 6.

[4] FB Ismail, HH Al-Kayiem, "Multidimensional minimization training algorithms for steam boiler high temperature superheater trip using artificial intelligence monitoring system", Control Automation Robotics & Vision (ICARCV), 2010

[5] M. Fast, T. Palme´, Application of artificial neural network to the condition monitoring and diagnosis of a combined heat and power plant, Energy 35 (2010) 1114–1120.

[6] Thomas Palmé, Magnus Fast and Marcus Thern, Gas turbine sensor validation through classification with artificial neural networks, Applied Energy 88 (2011) 3898–3904.

[7] Thomas Palmé, Peter Breuhaus, Mohsen Assadi, Albert Klein, Minkyo Kim, "Early Warning Of Gas Turbine Failure By Nonlinear Feature Extraction Using An Auto-Associative Neural Network Approach", Proceedings of ASME Turbo Expo 2011.

[8] Thomas Palmé, Peter Breuhaus, Mohsen Assadi, Albert Klein, Minkyo Kim, New Alstom Monitoring Systems Leveraging Artificial Neural Network Technologies, Proceedings of ASME Turbo Expo 2011.

[9] Raza Abdulla Saeed, Loay Edwar George, Apply Pruning Algorithm for Optimizing Feed Forward Neural Networks for Crack Identifications in Francis Turbine Runner, International Journal of Soft Computing and Engineering (IJSCE), 2012.

[10] K. P. Kumar, K.V.N.S. Rao, K.R. Krishna, B. Theja, Neural network based vibration analysis with novelty in data detection for a large steam turbine, Shock and Vibration 19 (2012) 25–35.

[11] M. Saberi, A. Azadeh, A. Nourmohammadzadeh, and P. Pazhoheshfar, Comparing performance and robustness of SVM and ANN for fault diagnosis in a centrifugal pump, 19th International Congress on Modelling and Simulation, Perth, Australia, 12–16 December 2011.

[12] ALSTOM Power, "Manjung Malaysia, Coal-Fired Steam Power Plant - Technology in harmony with nature", 2009 PT-PE/BPROB/MJGTPP09/eng/PPS/01.09/FR/4474

[13] ALSTOM Power, "MANJUNG 3x700MW Thermal Power Plant, Malaysia", 2000 PWER / BPROB / MJGTPP03 / eng / PPB / 06.03 / FR / 4474

[14] Shichao Zhang, Chengqi Zhang, Qiang Yang, Data Preparation For Data Mining, Applied Artificial Intelligence, 17:375–381, 2003

[15] R. Roiger and M. W. Geatz, Data Mining: A Tutorial-Based Primer. Addison Wesley Boston, 2003.

[16] A. Azadeh, M. Saberi, A. Kazem, V. Ebrahimipour, A. Nourmohammadzadeh, Z. Saberi, A flexible algorithm for fault diagnosis in a centrifugal pump with corrupted data and noise based on ANN and support vector machine with hyper-parameters optimization, Applied Soft Computing 13 (2013) 1478–1485

[17] Karim Salahshoor, Mojtaba Kordestani, Majid S. Khoshro, Fault detection and diagnosis of an industrial steam turbine using fusion of SVM (support vector machine) and ANFIS (adaptive neuro-fuzzy inference system) classifiers, Energy 35 (2010) 5472e5482.

[18] Karim Salahshoor, Majid Soleimani Khoshro, Mojtaba Kordestani, Fault detection and diagnosis of an industrial steam turbine using a distributed configuration of adaptive neuro-fuzzy inference systems, Simulation Modelling Practice and Theory 19 (2011) 1280–1293.

[19] Karim Salahshoor, Mojtaba Kordestani, Design of an active fault tolerant control system for a simulated industrial steam turbine, Applied Mathematical Modelling 38 (2014) 1753–1774.

[20] C.M. Bartolini, F. Caresana, G. Comodi, L. Pelagalli, M. Renzi, S. Vagni, Application of artificial neural networks to micro gas turbines, Energy Conversion and Management 52 (2011) 781–788.

[21] Nong Nurnie Binti Mohd Nistah, Yudi Samyudia, Foad Motalebi, Firas Basim Ismail Alnaimi. Intelligent monitoring interfaces for coal-fired power plant boiler trips: a review. 7th CUTSE (Engineering Goes Green) Conference 2012.

[22] Hamid Asgari, XiaoQi Chen, Raazesh Sainudiin. Modelling and simulation of gas turbines. Int. J. of Modelling, Identification and Control, 2013 Vol.20, No.3, pp.253 - 270.

[23] Lee, Y. K., Mavris, D. N., Volovoi, V. V., Yuan, M. and Fisher, T. A Fault Diagnosis Method for Industrial Gas Turbines Using Bayesian Data Analysis. Journal of Engineering for Gas Turbines and Power, APRIL 2010, Vol. 132 / 041602-1.

[24] Keem Siah Yap, Chee Peng Lim, and Mau Teng Au. Improved GART Neural Network Model for Pattern Classification and Rule Extraction with Application to Power Systems. IEEE transactions on neural networks, VOL. 22, NO. 12, December 2011.

[25] Firas B. Ismail, Vinesh Thiruchelvam. Back Propagation Artificial Neural Network and Its Application in Fault Detection of Condenser Failure in Thermo Plant. 4th International Conference on Energy and Environment 2013 (ICEE2013).

[26] Purva Deshpande, Nilima Warke, Prakash Khandare, Vijay Deshpande. Thermal Power Plant Analysis Using Artificial Neural Network. 2012 nirma university international conference on engineering, NUiCONE-2012, 06-08 December, 2012.

[27] Paulo C. Fritzen, Ghendy Cardoso Jr, João M. Zauk, Adriano P. de Morais, Ubiratan H. Bezerra and Joaquim A. P. Beck. Alarm Processing and Fault Diagnosis in Power Systems Using Artificial Neural Networks and Genetic Algorithms. 2010 IEEE International Conference on Industrial Technology (ICIT).

[28] Yann-Chang Huang, Chao-Ming Huang, Huo-Ching Sun, Yi-Shi Liao. Fault Diagnosis Using Hybrid Artificial Intelligent Methods. 2010 5th IEEE Conference on Industrial Electronics and Application.

[29] TANG Jia-li, CAI Qiu-ru, LIU Yi-jun. Gear Fault Diagnosis with Neural Network based on Niche Genetic Algorithm. 2010 International Conference on Machine Vision and Human-machine Interface.

[30] Hou Guolian, Jiang Pan, Wang Zhentao, Zhang Jianhua. Research on Fault Diagnosis of Wind Turbine Control System Based on Artificial Neural Network. Proceedings of the 8th World Congress on Intelligent Control and Automation, July 6-9 2010, Jinan, China.

[31] Zhixin Yang, Wui Ian Hoi, Jianhua Zhong. Gearbox Fault Diagnosis based on Artificial Neural Network and Genetic Algorithms. Proceedings of 2011 International Conference on System Science and Engineering, Macau, China - June 2011.

[32] LIU Xiao-qin. A Method for Fault Diagnosis in Chemical Reactor with Hybrid Neural Network and Genetic Algorithm. 2011 International Conference on Electronic & Mechanical Engineering and Information Technology.

[33] Huo-Ching Sun, Yann-Chang Huang. Fault Diagnosis of Steam Turbine-Generator Sets Using Evolutionary Based Support Vector Machine. 2012 International Symposium on Computer, Consumer and Control.

[34] Homam Nikpey, Mohsen Assadi, Peter Breuhaus. Development of an Artificial Neural Network Model for Combined Heat and Power Micro Gas Turbines. 2012 International Symposium on Innovations in Intelligent Systems and Applications (INISTA).

[35] YUAN Gui-li, QIN Shi-wei, GAN Mi. Motor Fault Diagnosis of RBF Neural Network based on Immune Genetic Algorithm. 2013 25th Chinese Control and Decision Conference (CCDC).

[36] Hasni M., Hamdani S., Taïbi. Z.M., Touhami O., Ibtiouen R., Rezzoug A. Faults Diagnosis of Induction Machine by Using Feed-Forward Neural Networks and Genetic Algorithms. 2013 9th Asian Control Conference (ASCC).

[37] Maria Puig-Arnavat, J. Alfredo Herna´ndez, Joan Carles Bruno, Alberto Coronas. Artificial neural network models for biomass gasification in fluidized bed gasifiers. Biomass and bioenergy 49 (2013) 279-289.

[38] J.A. Hernández, D. Colorado, O. Cortés-Aburto, Y. El Hamzaoui, V. Velazquez, B. Alonso. Inverse neural network for optimal performance in polygeneration systems. Applied Thermal Engineering 50 (2013) 1399 - 1406.

[39] Arash Jamali, Pouria Ahmadi, Mohammad Nazri Mohd Jaafar. Optimization of a novel carbon dioxide cogeneration system using artificial neural network and multi-objective genetic algorithm. Applied Thermal Engineering 64 (2014) 293 - 306.

[40] Y.El. Hamzaoui, J.A. Rodríguez, J.A. Hernandez, Victor Salazar. Optimization of operating conditions for steam turbine using an artificial neural network inverse. Applied Thermal Engineering 75 (2015) 648 - 657.

[41] A. Sagbas, T. Karamanlıoğlu. The Application of Artificial Neural Networks in the Estimation of Wind Speed: A case study. 6th International Advanced Technologies Symposium (IATS'11), 16-18 May 2011, Elazığ, Turkey.

[42] Hamid Asgari, XiaoQi Chen, Raazesh Sainudiin, "Applications of Artificial Neural Networks (ANNs) to Rotating Equipment", 3rd Conference on Rotating Equipment in Oil & Power Industries, Tehran Iran, 2011.

[43] Benazzouz, Djamel; Benammar, Samir; Adjerid, Smail, Fault Detection and Isolation Based on Neural Networks Case Study: Steam Turbine, Energy and Power Engineering, 2011, 3, 513-516.