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

www.arpnjournals.com

MODELING AND SENSITIVITY ANALYSIS OF A MULTI-NETS ANNS MODEL FOR REAL-TIME PERFORMANCE-BASED CONDITION MONITORING OF AN INDUSTRIAL GAS TURBINE ENGINE

Mohammadreza Tahan, Umair Sarwar, Masdi Muhammad and Z. A. Abdul Karim
Department of Mechanical Engineering, Universiti Teknologi Petronas, Bandar Seri Iskandar, Perak Darul Ridzuan, Malaysia
E-Mail: masdimuhammad@petronas.com.my

ABSTRACT

The present study aims to investigate the use of Artificial Neural Networks (ANN) for the performance-based condition monitoring of indusrial gas turbine engines. Toward this end, a health assessment tool is presented by developing a Multi-Nets ANN model. A number of key performance parameters that are commonly measurable on the most industrial gas turbines are monitored and their associated neural networks for the healthy condition are trained. Three-layer feed-forward configuaration is chosen to construct the networks, the Levenberg-Marquardt algorithm is used as the training function, and the k-fold cross-validation process is employed to obtain the optimum number of neurons in the hidden layers. The model is developed and tested using the gas path performance data collected from an 18.7 MW twin-shaft industrial gas turbine. A special attention is also devoted to the system theory interpretation in order to evaluate the effect of the input neurons on each output of the Multi-Nets. To that end, the sensitivity analysis is formulated using derivatives based on an interpretation of the neural network's weights.

Keywords: gas turbine, performance-based condition monitoring, diagnostics, multi-networks, artificial neural networks, sensitivity analysis.

INTRODUCTION

Gas turbines are widely being used for providing prime movers in the power plants, petrochemical companies, and oil and gas industry. During the operation and maintenance phase of gas turbines, condition monitoring activities play a decisive role. Various maintenance strategies are usually recommended by manufacturers base on equipment and process condition. Costly run-to-failure and scheduled preventive maintenance methods can be avoided by implementing predictive maintenance, which continuously detects performance problems and makes the user aware of the situation [1]. This method which refers to a condition-based maintenance recommends the maintenance actions based on the information obtained from condition monitoring and can increase maintenance agility and responsiveness, improve operational availability, and reduce life cycle total ownership costs [2]. Condition monitoring can be implemented using different methods and utilize various levels of technology. Gas turbine condition monitoring methods can generally be classified as mechanical-based condition monitoring and performance-based health monitoring. It is well known that performance-based monitoring has a prominent ability in all three steps of gas turbines CM including health assessment, diagnostics, and prognostics. This method is not only able to provide maintenance engineers with gas turbine performance information but also has an outstanding capability to give an effective vision of the gas path component degradation.

Over the last two decades, significant research efforts are conducted on the development of gas turbine performance-based condition monitoring systems. The main idea of all presented approaches is to simulate the healthy gas turbine in various operating conditions and set the output as the accepted healthy references. Then, through the passage of time, the engine is monitored to determine deviation from the reference performance in order to detect an impending failure. However, the selected key performance parameters and the analyzing methods characterize various approaches which can generally be classified into two categories. The first category, known as model-based methods, mainly rely on the mathematical modeling of the engine operation. Gas-path analysis [3], Kalman filter [4] and weighted Least Squares [5] are three main types of these methods which are mostly considered by the gas turbine research community. Typically, these methods promise successful detection of both abrupt and gradual degradation in the engine performance. However, when the modeling uncertainties and the system complexity increase, their monitoring accuracy decrease. The second category, known as data-driven methods, mostly rely on real-time or collected historical data from the engine sensors to learn the behavior of the healthy and unhealthy engine. A wide range of data-driven methods is developed for health assessment, diagnostics and prognostics of gas turbines, as reported in the application of ANNs [6, 7], Genetic Algorithms (GA) [8], Expert Systems (ES) [9] and Fuzzy Logic (FL) [10, 11]. Research results prove that these methods provide a flexible tool to deal with the complexity and non-linearity characteristics of dynamical systems.

In this paper, a Multi-Nets Artificial Neural Networks (M-N AANs) which employs standalone trained ANNs as learners are developed for the purpose of health assessment of an 18.7 MW twin-shaft industrial gas turbine. Each of these networks represents a performance parameter of the engine and can be valuable in monitoring and fault detection of the gas turbine. Levenberg-Marquardt (LM) algorithm is employed to train these

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

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networks and a k-fold cross-validation process is used to obtain the optimum number of neurons in hidden layers. An interpretation of the neural network via examination of the interconnection weights is finally attempted in order to assess the ability of each network in data interpolation and real-time forecasting.

STUDIED GAS TURBINE AND TRAINING DATA

A schematic diagram of the selected gas turbine engine which is of twin-shaft open loop type is shown in Figure-1 and its associated performance at standard condition is listed in Table-1.

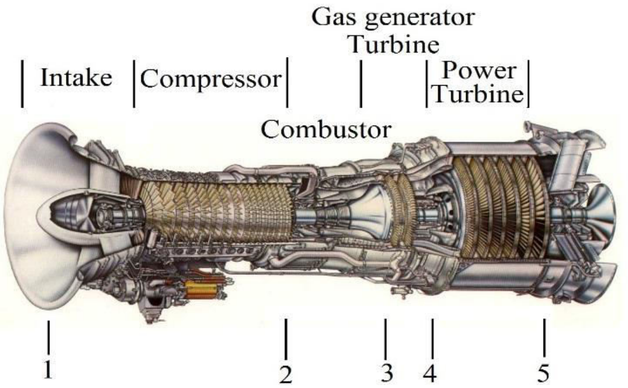


Figure-1. Schematic layout of the case studies gas turbine.

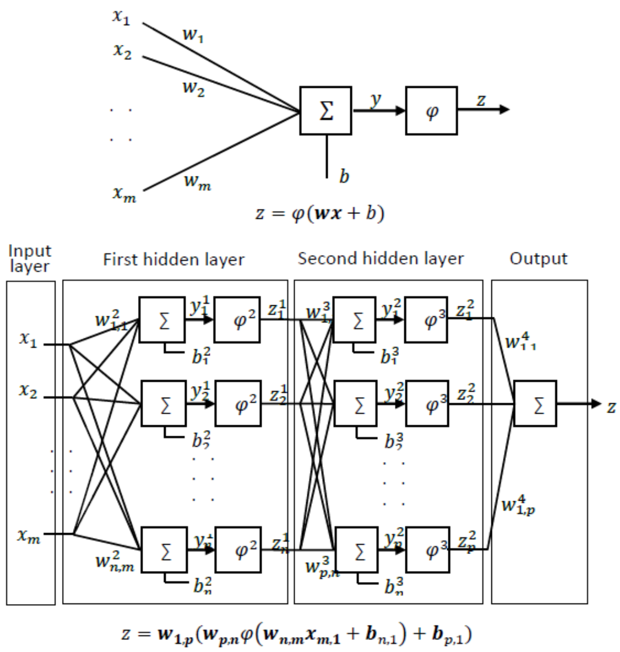
Table-1. The performance of the studied gas turbine at standard condition.

Parameter	Value	Unit
Compressor pressure ratio	17.05	Bar
Compressor outlet temperature	470.82	°C
Gas generator speed	9160	RPM
Output shaft speed	3523	RPM
Air flow	60.51	Kg/s
Output power	18669	KW
Fuel type	Natural gas	-

In using ANNs for condition monitoring and health assessment, it is necessary to train multiple networks in order to learn and represent the dynamic characteristic of the equipment. The multiple networks can then be used to monitor the real-time performance and behavior of the equipment. In order to implement this idea for IGT, a complete set of engine performance data at healthy condition is required. Toward this end, a gas turbine off-design performance simulation model developed and verified previously is used. The ambient condition and operation loads are the input requirements of this model and the pressure and temperature values through the gas path, air and fuel mass flow rates, gas generator speed, the isentropic efficiency of various components, and overall thermal efficiency of the engine are the output parameters. Data collected from the real gas turbine during two months operation indicates that the engine mostly operates in the following condition: 26.5 to 33.5 °C ambient temperature, 1 atm ambient pressure, power load of 10 to 17 MW, and the output rotational speed of 2600 to 3100RPM [12]. Therefore, the engine simulating model has been run in the above-mentioned condition and the output is considered as the data for the training and testing of the networks. 1200 sample points are collected to be applied for network training. In order to improve the learning capability, sample data are shuffled. And to scale data in the same range of values, min-max normalization method is applied for each input feature.

Fundamental of artificial neural network

Neuron structure, network configuration, learning method and stopping criteria characterize the neural network technique. A scheme of the single artificial neuron is shown in Figure-2a. In this neuron, by using the weights, w_i, incoming data, x_i, are linearly combined. Then, the scalar bias b is added to form the net input, y. The bias is much like a weight, except that it has a constant input. Note that w and b are both adjustable scalar parameters of the neuron. Finally, the net input is passed through the activation function φ, which produces the scalar output z. Here, φ is a transfer function, typically a step function or a sigmoid one, which takes the argument y and produces the output z. These three processes are called, respectively, the weight function, the net input function and the activation function and forms the neuron structure.



$$z = \varphi(\boldsymbol{wx} + b)$$

$$z = \boldsymbol{w_{1,p}}(\boldsymbol{w_{p,n}}\varphi(\boldsymbol{w_{n,m}}\boldsymbol{x_{m,1}} + \boldsymbol{b}_{n,1}) + \boldsymbol{b}_{p,1})$$

Figure-2. a) Scheme of the single artificial neuron. b) The architecture of a two- hidden layered feedforward single target neural network.

Single neurons can be combined to build a various neural network. A schematic diagram of a two hidden layered neural network is presented in Figure-2b. The two layer feed forward neural network (FFNN) is of four layer configuration including two hidden layers, i.e. layers 2 and 3, plus one input layer, i.e. layer 1, and one output layer, i.e. layer 4. Each layer has a weight matrix w, a bias vector b, and an output vector y. To distinguish between the

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ARPN Journal of Engineering and Applied Sciences

weight matrices, output vectors, etc., of each layer, the layer number is appended as a superscript to the variable of interest. The network shown above has M^1 inputs and N^1 neurons in the first hidden layer and N^1 inputs and N^2 neurons in the second hidden layer.

ANNs training

Multi-layered feed-forward supervised configuration proved to bear a keen capability to approximate nonlinear mapping. ANN with one hidden layer are widely used in researches and have proven to give satisfactory results. Increasing the number of hidden layers increases the computation time and the danger of overfitting which may cause poor out-of-sample forecasting capability. In ANNs models, the number of neurons in the first and last layers are easily determined using the number of inputs and outputs, respectively. However, the proper selection of neurons in the hidden layer is one of the most important steps in the perceptron network training. If an inadequate number of neurons are used, the network is not able to model complex data, and the fitting result is poor. If too many neurons are used, the training time may become excessively long, and the network may overfit the data. Eventhough there is no ideal solution to this problem, many methods are developed to help in determining the optimum number of hidden layers. In order to specify the number of neurons in hidden layer, K-fold cross-validation method is employed in this research. The summary of this method is as follows.

1. Split training data into k equal-sized parts called folds.
2. Set a candidate number of neurons for hidden layer(s).
3. Train the network k times, in each time use k-1 folds as training data and the kth fold as testing data.
4. Choose the number of neurons whose average testing error over the k trials is lowest.

It is generally accepted that selection of a network that performs suitable learning on the testing set with the least number of hidden neurons is preferred. One should take in mind that during a testing various number of hidden neurons, it is important to keep all other parameters constant. Changing any parameter creates a new neural network with a potentially different error level which would needlessly complicate the selection of the optimum number of neurons.

In this work, hyperbolic tangent sigmoid (1) transfer functions are assigned to a hidden layer.

$$f(x) = (e^x - e^{-x})/(e^x + e^{-x}) \tag{1}$$

Mean Absolute Percentage Error ($MAPE$) also is considered as the error function (4).

$$MAPE = \frac{1}{m}\sum_{j=1}^{m}\left|\frac{T_j - Z_j}{T_j}\right| \tag{2}$$

Where m denotes the number of data patterns, Z is the network output and T is target values. The error function was applied backward into the network to adapt the weights. The weights are promoted in the training process to ensure that the error function is minimum and no overtraining happens. Once the training finished successfully, the synaptic weights will be saved. As discussed by Hagan and Menhaj [13], Levenberg-Marquardt algorithm is one of the best techniques for ANNs training especially when the number of weights increases. Therefore, although it does require more memory than other algorithms, it is highly recommended as the first choice for supervised problems. The weights in a Levenberg-Marquardt (LM) training function are updated using (3) [13].

$$w_{i+1} = w_i - (J_i^T J_i + \mu_i I)^{-1} J_i^T e_i \tag{3}$$

Where w is the weight matrix, J is output errors Jacobian matrix, I is identity matrix and μ represents a learning component.

Development of multi-nets system

To develop the Multi-Nets model for the purpose of system identification, four networks corresponding to key performance variables of the gas turbine engine are developed. Compressor outlet pressure, gas generator turbine outlet pressure, gas generator turbine outlet temperature, gas generator rotational speed, power turbine rotational speed, fuel mass flow rate, and output power, respectively represented by P_1, T_1, P_2, P_4, T_4, N_1, N_2, Pkw and $\dot{m}_f$, are commonly measurable on the most twin-shaft IGTs. Here, in order to develop the Multi-Nets models, the associated four networks are trained individually using four (4) input parameters including ambient condition (P_1 and T_1), rotational speed (N_2), and fuel flow rate ($\dot{m}_f$). In addition, one of the four (4) measurable engine performance parameters including P_2, P_4, T_4 and N_1 are selected as the network output. The corresponding networks are denoted by Net_{P2}, Net_{P4}, Net_{T4} and Net_{N1}. Once the training of all networks is finalized, they can be used as a reference model to represent the principle operational variables of the engine, corresponding to the healthy condition. Figure-3 shows the procedure of training these neural networks for the purpose of performance monitoring. The main properties of each network in the multi-nets model are indicated in Table-2.

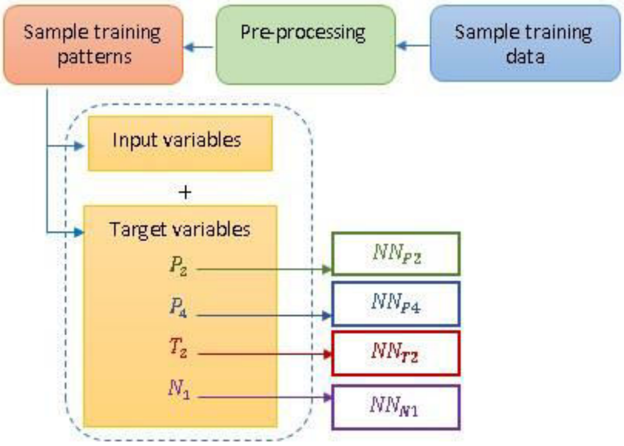

Figure-3. Training a multi-nets model for the purpose of gas turbine performance monitoring.

Table-2. Properties of the developed networks.

	ANN title	To predict	Unit	Range
1	NN_{P2}	P_2	Bar	12.3-14.6
2	NN_{P4}	P_4	Bar	2.9-3.4
3	NN_{T4}	T_4	°C	715-795.5
4	NN_{N1}	NN1	RPM	2500-3200

To use k-fold cross-validation method, the 1200 collected sample data points are split into four smaller subsets, i.e. k=4. Models are training using three of these folds, i.e. 900 sample points, as training data. The resulting model is then validated on the remaining 300 sample points. All four MAPE corresponding to these folds are averaged to calculate the network accuracy.

Using LM algorithm for training purpose, the early stopping technique is used to prevent overfitting. Therefore, the 1200 observations of training dataset are divided into two subsets: 80% for training and 20% validation. It should be noted that this set of validation data is employed to monitor the network training error, in order to determine the optimal number of training iteration or epochs. Following settings are considered as training performance parameters: maximum number of epochs 300, maximum validation failures 10, performance goal 0.0, and minimum performance gradient 1e-5. All other training parameters were left intact to their default values in Matlab R2015a. Various structures with different numbers of hidden layers and neurons are examined during the training phase using both LM algorithms.

In order to explain the method of finding proper network structure, detail procedure of NN_{t4} training is described here. A k-fold cross-validation process is employed to train the network using LM algorithm with a diverse set of hidden neurons and the outputs of cross-validation are recorded. Figure-4 shows the MAPE of NN_{P2} repetitively trained with one (1) hidden layer and different numbers of hidden neurons. The optimum number of hidden neurons is determined by finding the lowest average evaluation error.

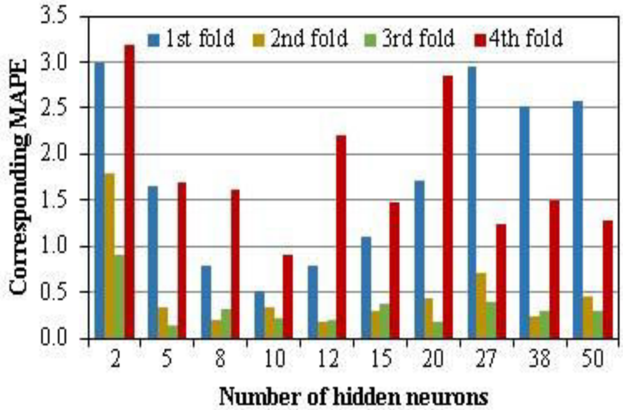

Figure-4. Illustration of k-fold (k=4) cross-validation errors corresponding to NN_{P2} with single-hidden layer as a function of the number of hidden neurons.

The results indicate that the most optimized NN_{N1} network is achieved using BRTF training function and 10 neurons in single hidden layer structure which yields to 0.4915 average MAPE. This implies that an ANN with one hidden layer and 10 neurons is the most robust network for prediction of P_2. To develop Multi-Nets model, the four ANNs are trained by the similar procedure. The ANN tools providing the most accurate forecasts and exhibiting the best performance indices are summarized in Table-3.

Table-3. Number of hidden layers and MAPE of final ANNs in multi-nets model.

ANN title	No. of hidden neurons	MAPE
NN_{P2}	10	0.4915
NN_{P4}	12	0.4187
NN_{T4}	13	0.6812
NN_{N1}	9	0.1616

Starting with a relatively small structure, the Multi-Nets are developed by incrementally increasing the number of neurons in the hidden layers until the desired performance specification is satisfied. Prediction accuracy is still high enough to validate the inclusion of this output parameter in fault detection model. Considering Table-3, one can conclude that for the IGT monitoring purposes, the proposed Multi-Nets model can predict all performance parameters with MAPE of less than 0.7.

The performance of a neural network in a practical application depends on the degree to which it can generalize when confronted with data that was not seen during training. Hence, a test set is performed to assess how well the learning algorithm works. Fifty unseen data sets are used to examine the accuracy of developed networks in Multi-Nets model. The corresponding plots for NN_{N1} network is given in Figure-5.

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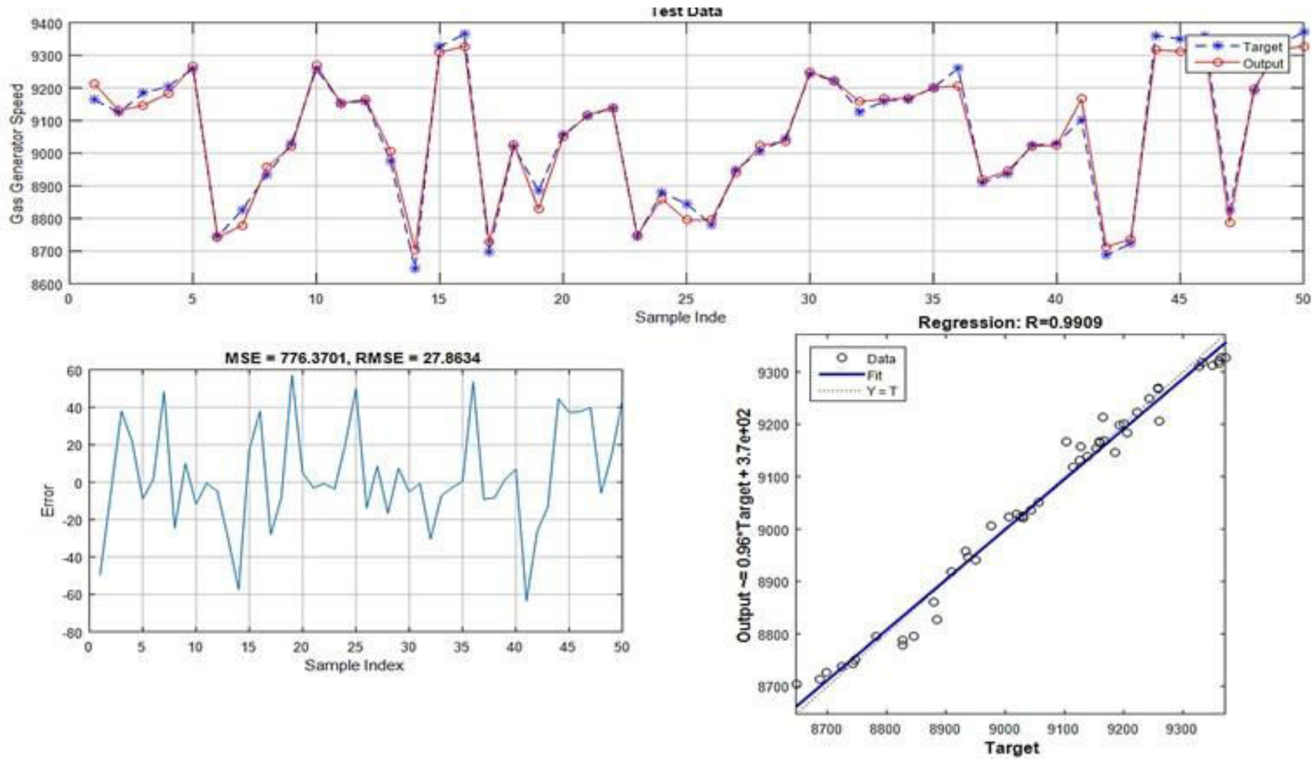

Figure-5. The performance of NN_{N1} for 50 unseen testing trials.

Interpretation of the weights

Sensitivity analysis can be employed to evaluate the effect of input neurons on outputs and demonstrate how a trained network reacts to the change of each input. This method can be implemented by changing various input slightly and calculating the corresponding output variation. In order to assess the importance of each input neurons, the connection weight matrix of the neural network can be used, as presented in (4) [14].

$$I_j = \frac{\sum_{i=1}^{h}((|W_{ji}|/\sum_{k=1}^{n}|W_{ki}|).|WO_i|)}{\sum_{k=1}^{n}(\sum_{i=1}^{h}((|W_{ki}|/\sum_{k=1}^{n}|W_{ki}|).|WO_i|))} \quad (4)$$

Where n and h are the values of input factors and hidden neurons, respectively, $W$and WO are the synaptic weight matrix between input-hidden layers and hidden-output layers, respectively, and I_j is the relative importance of the input factors j for the output. Table-4 shows the relative importance of four input neurons on the output neuron for the trained ANNs.

Table-4. The relative importance of input neurons for LMNN and BRNN models.

No.	Input neuron	Relative importance of input neurons (%)			
		NN_{P2}	NN_{P4}	NN_{T4}	NN_{N1}
1	T_1	0.1963	0.1631	0.2071	0.1657
2	P_1	0.2402	0.1741	0.1796	0.1839
3	N_2	0.2540	0.3540	0.2887	0.1101
4	m_f	0.3096	0.3028	0.3246	0.5402

The result shows that the relative importance of fuel mass flow rate is almost the highest for training of all networks except NN_{T4} which in it the rotational speed of load is more important. However, one should note that due to the non-linear nature of the activate functions, the relative importance can only be a coarse measure of the effect.

CONCLUSIONS

This paper studied the problem of Modeling and sensitivity analysis of a Multi-Nets ANNs Model for real-time performance-based condition monitoring of an industrial gas turbine engine. The Multi-Nets employs standalone ANNs as multiple learners, each of which represents a performance parameter of the gas turbine engine. Toward this goal, four variables which are commonly measurable on most gas turbine engines are monitored and their corresponding four neural networks to simulate the healthy condition are trained. The networks are of feed-forward type with one hidden layer structure which are trained using Levenberg-Marquardt function. To select the optimum network constructions, the cross section validation method is used. The result shows that for the IGT monitoring purposes, the proposed Multi-Nets model can predict all performance parameters with MAPE of less than 0.7. In addition, the relative importance of each input variable was assessed using the achieved synaptic weights of neural networks. The results prove that in most trained networks, the importance of fuel mass flow rate is relatively higher than the other input variables.

ACKNOWLEDGEMENTS

The authors are grateful for the funding and facilities support by Universiti Teknologi Petronas.

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