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Adaptive Neuro-Fuzzy Inference System for Performance Health Monitoring of Industrial Gas Turbines

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***Abstract*—Figuring whether or not a gas turbine is inclined to faults provides useful help for determining the required preventive action before failure happening. System identification is a discipline that learns the behavior of the healthy engine and employs it to predict the fault proneness. This study aims to discuss the performance of the Adaptive Neuro-Fuzzy Inference System (ANFIS) compared to the Artificial Neural Networks (ANNs) for the purpose of gas turbine performance identification. Toward this end, three system identification Bank of Networks (B-Ns), each corresponding to seven variables that are commonly measurable on most twin-shaft industrial gas turbine engines, are developed. The accuracy of the trained B-Ns are analyzed using the healthy performance data of an industrial 18.8 MW open-cycle offshore gas turbine. Making a comparison between the gained results from ANFIS and two various ANNs models revealed that ANFIS model is able to forecast various performance parameters with higher correlation coefficient and smaller MAPE values.**

Keywords—industrial gas turbine, performance monitoring, diagnostics, computational intelligence, ANFIS.

I. INTRODUCTION

Industrial Gas Turbine (IGT), as one of the most versatile machinery, is widely being used in power generation, oil, gas and petrochemical companies. The operation and maintenance cost of an IGT contribute a major portion of companies' annual ownership budget. Condition Monitoring (CM) is known as an effective tool to decrease maintenance costs and, additionally, improve safety and environmental issues [1]. Gas turbine CM generally consists of two main categories including mechanical condition monitoring and Performance Health Monitoring (PHM). It is well known that PHM has a prominent ability in all three steps of gas turbines Condition-Based Maintenance (CBM) including system identification, diagnostics, and prognostics.

Over the last two decades, significant research efforts are directed at the development of gas turbine PHM. The main idea behind PHM and subsequently engine identification and fault detection is to simulate the healthy engine in various operating conditions and then through the passage of time monitor its deviation from these accepted reference performances. However, the selected key performance parameters and the analyzing methods characterize various PHM and diagnostic methodologies which can generally be classified in three categories. The first category which mainly relies on the mathematical modeling of the engine operation includes conventionally investigated methods such as gas-path analysis with ICM inversion [2], kalman filter [3] and weighted Least Squares [4]. 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 decreases. The next category, known as a data-driven method, mostly relies on real-time and 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 and diagnosis of gas turbines, as for example the application of Artificial Neural Networks (ANNs) [5] and Genetic Algorithms (GA) [6]. Research results prove that these methods provide a flexible tool to deal with complexity and non-linearity characteristics of dynamical systems. The last group includes rule-based methods that employ domain expert knowledge in a computer program in order to perform reasoning for problem solving using an automated inference engine. Examples of these systems are rule-based Expert Systems (ES) [7] and Fuzzy Logic (FL) methods [8]. Although these methods are capable of providing the explanations about the way of reaching to a particular solution, it is very complex to find a proper set of rules, functions, and tuning to obtain a satisfactory solution, especially when system complexity increases.

It is broadly acknowledged that a practical and efficient implementation of gas turbine performance monitoring gadget shall be upon an appropriate coupling of some approaches. To date, some examples have been introduced in the literature, including works are done by Dewallef, Romessis et al. [9], Kobayashi, Simon et al. [10] and Verma, Roy et al. [11]. ANFIS is an integration of FL and ANNs algorithms which utilizes the learning abilities of ANNs with human knowledge representation abilities of FL. Therefore, the result offers a powerful grey-box mean to handle complicated non-linear problems with sensible numerical accuracy and affordable interpretability. Recently, this method is also employed as an enhanced tool for CM in industrial applications.This study aims to compare the capabilities of ANFIS with two different ANNs methods for the purpose of system identification in an industrial gas turbine engine. Toward this end, these data-driven methods are applied to the data acquired from a gas turbine performance simulator model which is developed for an 18.8MW twin-shaft open-cycle offshore turbine.

II. CASE STUDY OFFSHORE GAS TURBINE

A schematic diagram of the studied gas turbine which is twin-shaft open loop type is shown in Fig. 1.

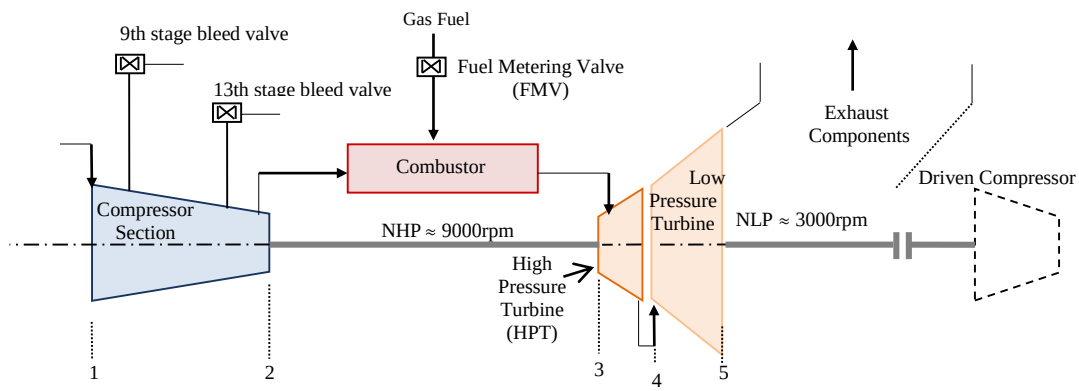

Fig. 1 Schematic layout of the case study gas turbine.

The compressor part is of axial-flow type and includes sixteen stages with an overall pressure ratio of 17.05:1. Its annular type combustion chamber utilizes a lean premix combustion system and is designed for operation on natural gas fuel. High-Pressure (HP) turbine, which extracts energy from the gas stream to drive the compressor, includes two stages of blades with a nominal speed of 9000 RPM. Power turbine or Low-Pressure (LP) turbine, which includes 6 stage blades with a nominal speed of 3000 RPM is aerodynamically coupled to the gas generator and is driven by the HP turbine exhaust gas. The basic performance parameters of this IGT are summarized in TABLE I.

TABLE I. ISO PERFORMANCE OF THE STUDIED GAS TURBINE ON NATURAL GAS.

Parameter	Value	Unit
Compressor pressure ratio	17.05	Bar
Compressor outlet temperature	470.82	°C
Gas generator speed	9160	RPM
Output shaft speed	3023	RPM
Air flow	60.51	kg/s
Output power	18669	kW
Fuel type	Natural gas	-

III. IGT MODEL AND NETWORK TRAINING DATA

System identification is one of the most important steps in the condition monitoring process. Using data-driven methods, in order to learn and represent the dynamic characteristic of the equipment, one or several networks should be trained for this purpose. The accomplished Bank of Networks (B-Ns) can then be used to evaluate the real-time performance and behavior of the equipment. To implement this idea for IGT, a complete set of engine performance data at healthy condition is required. Toward this goal, the gas turbine part-load simulation model which is developed by the authors in previous works is employed. The ambient condition and operation load are the input requirements for this model and the pressure and temperature values through the gas path as well as 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. Through the data collected from main gas turbine during two months, it was found out that the most common operating range of engine is from 26.5 to 33.5 °C and 1bar as ambient condition, 10 to 17 MW output power and 2600 to 3100RPM output rotational speed, as olso discussed in [12]. Therefore, the model has been run in the aforementioned condition and the output is considered as the data for the training and testing of the networks. Due to the highly complex and nonlinear dynamics of the gas turbine engine behavior, 3200 sample points are collected to be applied to the networks for learning its dynamics. In addition, to improve the learning capability of the networks, sample data shuffling is also applied. Moreover, normalization which is the scaling of data in the same range of values for each input feature is employed. This practice yields to faster training and lower bias during the network training. The Min-Max normalization method, as in (1) [13], is used for this purpose.

$$x_n = \frac{x - min(x)}{max(x) - min(x)}(ubl - lbl) + lbl \qquad (1)$$

Where x represents the original data matrix, x_n is the normalized data matrix, ubl stand for upper normalization boundary limit and lbl is the lower normalization boundary limit.

IV. ARCHITECTURE OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

ANFIS combines the fuzzy qualitative layered structure, with the gradient descent training algorithms, known from the area of neural networks, in order to eliminate the knowledge requirement which is usually required for the design of the standard fuzzy logic systems. This technique provides a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership functions and coefficients of the consequent polynomials for training the associated fuzzy inference system tracking the given input/output data. Fig. 2 demonstrates ANFIS general architecture and the work stages of modeling is explained in the following.

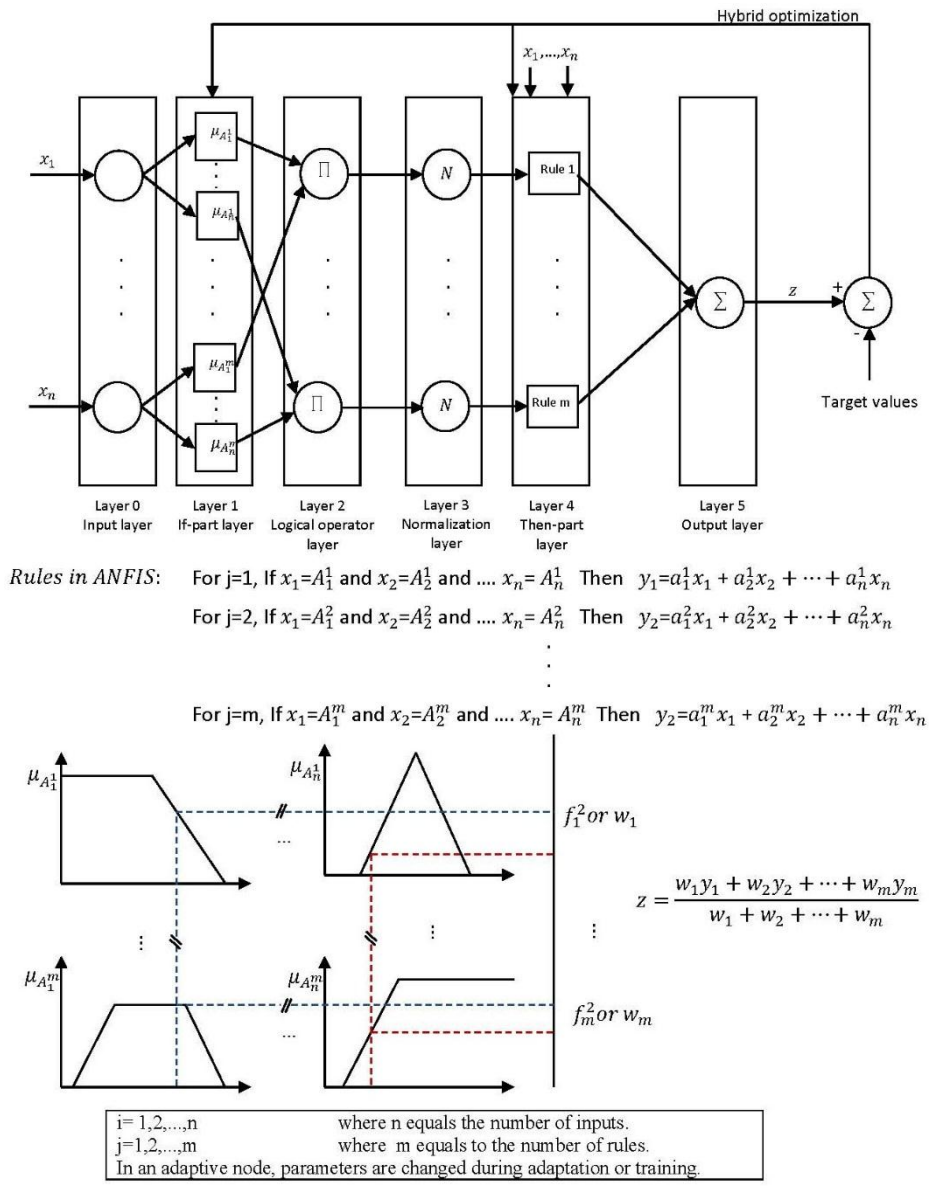

Fig. 2 General architecture of Adaptive Neuro-Fuzzy Inference System

A. *Data loading*

Data loading is about assigning the data set for training, testing, and checking. To train an ANFIS network, the work begins by loading a training data set that contains the desired input/output data of the system to be modeled. The testing data set lets checking the generalization capability of the resulting ANFIS network. The idea behind using a checking for model validation is that after a certain point in the training, the model begins overfitting the training. Overfitting occurs when a statistical model describes random error or noise instead of the underlying relationship and generally happens when a model is excessively complex.

B. Data partitioning

Partitioning or clustering stage is the initial step of 'Fuzzification' in the ANFIS. The propagation of each input is broken into the different clusters of Fuzzy to see the behavior of input variables on the output. Clustering includes a selection of membership function and definition of Linguistic value. In a Fuzzy interface system, basically, there are two main types of input space partitioning: Grid Partitioning, and Scattering (Subtractive) Clustering. Grid Partitioning generates rules by enumerating all possible combinations of membership functions of all inputs; this leads to an exponential explosion even when the number of inputs is moderately large. For instance, for a fuzzy inference system with 10 inputs, each with two membership functions, the Grid Partitioning leads to 1024 (=2^10) rules, which is inhibitive large for any practical learning methods. The "curse of dimensionality" refers to such situation where the number of fuzzy rules, when the grid partitioning is used, increases exponentially with the number of input variables. On the other hand, using Subtractive Clustering yields to notably a fewer number of rules. This method selects the optimal number of rules applying the lower training error, ydiscussed by Chiu [14].

C. Selection of membership functions

To select the best type of membership functions, different nonlinear types can be examined in the Sugeno Fuzzy inference system. Three of the most popular ones widely used are triangular, trapezoidal, and Gaussian.

D. Training algorithm

Back propagation gradient descent and the least square of errors are two main optimization methods for training the generated ANFIS. The hybrid optimization method is the combination of these two methods, can be employed to adjust the Fuzzy sets coefficients and the parameters of the consequent polynomial function, simultaneously. The number of iteration selected to do the training process through the hybrid learning algorithm can be determined to do different simulations in order to achieve the lower training error. Training can be started by 50 simulations then increased to 100, 150, and 200 to see if there was any possibility to more error reduction, and make sure the error is not increasing and no overfitting.

E. Training process

The theory of training can be explained by using the five-layered feed-forward ANFIS architecture, shown in Fig. 2, as follows.

Layer 0: Input layer

- The input data transferred directly to the second layer without any process.
- All nodes are non-adaptive and the function of each node can be expressed by (2).

$$f_i^0 = x_i \qquad \textit{for } i=1,2,\ldots, q_1 \tag{2}$$

Where f_i^0 is the output of node i in the zero level.

Layer 1: If-part layer

- Every node in this layer is an adaptive node and corresponds to a linguistic label.
- Function of each node can be expressed by (3).

$$f_{ij}^1 = \mu_{A_i^j}(f_i^0) \qquad \textit{for } i=1,2,\ldots, n \textit{ and } j=1,2,\ldots,m \tag{3}$$

Where f_{ij}^1 is respective to the ith input variable in the jth fuzzy rule, A_i^j is is the fuzzy set associated with the i-th input variable in the j-th fuzzy rule, and $\mu_{A_i^j}$ is the output of each node respective to the ith input variable in the j-th fuzzy rule.

Layer 2: Logical operator layer

- Every node in this layer is an adaptive node and estimates the firing strength of a rule (w_j).
- A suitable operator can be chosen as a fuzzy T-norm in this layer. The function of each node can be expressed by the multiplication of the incoming signals, as (4).

$$f_j^2 = f_{1j}^1 \times f_{2j}^1 \times \ldots \times f_{nj}^1 \qquad \textit{for } j=1,2,\ldots,m \tag{4}$$

Layer 3: Normalization layer

- Every node in this layer is a non-adaptive and estimates the ratio of the j-th rule's firing strength to the sum of all firing strengths.
- The function of each node which is finding normalized firing strength of the i-th rule can be expressed by (5).

$$f_j^3 = \frac{f_j^2}{\sum_{j=1}^{m} f_j^2} \tag{5}$$

Layer 4: Then-part layer

- Every node in this layer is an adaptive node.
- The output of each node is the product of the previously found normalized firing strength of the j-th rule to j-th rule function and can be expressed by (6).

$$f_j^4 = f_j^3 \times (y^j) \qquad for\ j=1,2,...,m \tag{6}$$

where $y^j = a_1^j x_1 + a_2^j x_2 + \cdots + a_n^j x_n + r^j$, and a_i^j, r^j are design parameters to be determind during the training process.

Layer 5: Output layer

- The fifth layer includes only one node which its output corresponds with network output.
- Through a linear combination of the input signals, the output of the ANFIS, z, can be calculated by (7).

$$z = f_j^5 = \sum_{j=1}^{m} f_j^4 \tag{7}$$

V. DEVELOPING BANK OF NETWORKS (B-NS) FOR IGT DIAGNOSTICS

To develop a system identification model, a B-Ns corresponding to seven (7) variables which are commonly measurable on most twin-shaft industrial IGTs are developed. These variables includes P_2, P_4, T_4, N_1, N_2, PKW and $\dot{m}_f$ where they represent compressor outlet pressure, gas generator turbine outlet pressure, gas generator turbine outlet temperature, gas generator shaft speed, power turbine rotational speed, fuel mass flow rate and power output. The associated seven networks are denoted by Net_{P2}, Net_{P4}, $Net_{T4}, Net_{N1}, Net_{N2}, Net_{PKW}$ and $Net_{\dot{m}f}$. Once the training of all networks is finalized, they can then be used as a reference model to represent the principle operational variables of the gas turbine, corresponding to the healthy condition. Fig. 3 shows the procedure of training these neural networks for the purpose of performance monitoring.

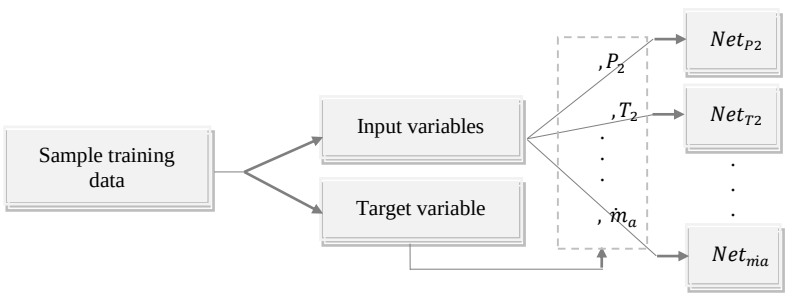

Fig 3. Training of B-Ns for the purpose of gas turbine performance monitoring.

The main properties of the developed bank of seven networks are indicated in TABLE II.

TABLE II. PROPERTIES OF THE BANK OF SEVEN NETWORKS.

	Net title	To predict	Unit	Range
1	Net_{P2}	P_2	Bar	12.3-14.6
2	Net_{P4}	P_4	Bar	2.9-3.4
3	Net_{T4}	T_4	°C	715-795.5
4	Net_{N1}	NN1	RPM	2500-3200
5	Net_{N2}	NN2	RPM	8500-9400
6	Net_{PKW}	PKW	kW	11799.5-16439.7
7	$Net_{\dot{o}f}$	$\dot{m}_f$	Kg/s	0.8-1.2

In this study, there are six sets of data as input and one set of data as output. The seven (7) networks are trained by using 3200 normalized data points, which are divided into three subsets for training (70%), testing (20%) and checking (10%) for ANFIS training. The other settings of ANFIS model are presented in TABLE III. Since the number of input variables is six, in order to decrease the number of rules, Subtractive Clustering method is employed for data partitioning. The subtractive clustering parameters in ANFIS are the squash factor, accept ratio, reject ratio, and range of influence. Squash factor is used to multiply the radii values that determine the neighborhood of a cluster center. The purpose is to squash the potential for outlying points to be considered as part of that cluster. The accepted ratio is a fraction of the potential of the first cluster center. The reject ratio is a fraction of the potential of the first cluster center.

TABLE III. PROPERTIES OF THE ANFIS FOR NETWORK TRAINING.

Network parameter	Specification
Data partitioning method	Subtractive clustering
Squash factor	1.5
Range of influence	0.5
Accept ratio	0.5
Reject ratio	0.15
Membership function	Gaussian
Learning algorithm	Hybrid
Maximum iteration	100

In most network training, the most suitable and efficient membership functions were found Gaussian membership function, with the lowest training error. All the ANFIS models were structured by four to five rules. The trend of training error showed no over-fitting during the training process and the error rate was reducing. This showed that the combination of the least squares method and back propagation gradient descent method used for training membership function parameters generated lower training error.

To present a comparison of ANFIS learning quality, two of most common neural network training algorithms namely Levenberg-Marquardt (LM) and Bayesian Regularization (BR) are also employed to develop two other B-Ns. In using LM, in order to prevent overfitting, the early stopping technique is employed. Therefore, the training dataset is divided into two subsets for training (80%) and validation (20%). Note that this set of validation data is employed to monitor the network error during training. On the other hand, due to the great ability of the BR algorithm in controlling network complexity, there is no need to separate training and validation data sets. Therefore, all sample data points are employed for training purpose. 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 and BR training functions. In order to determine the most optimum structure of the neural networks, k-fold cross-validation method introduced by Kohavi [15] is used.

VI. A COMPARISON BETWEEN DEVELOPED B-NS USING VARIOUS MODELS

The forecasting accuracy of various developed networks is calculated using Mean Absolute Percentage Error (MAPE) and Pearson Correlation methods using (8) and (9).

$$MAPE = \frac{1}{n}\left(\sum_{i=1}^{n} \frac{F_a - F_f}{F_a}\right) \times 100 \tag{8}$$

$$R_{F_a,F_f} = \frac{cov\ (F_a,F_f)}{\sigma_a,\sigma_f} \tag{9}$$

Where F_a denotes the actual and F_f is the forecasted target values, cov is the covariance and σ_a is the standard deviation of F_a. The statistical results of the trained neural networks for all seven networks using various ANNs and ANFIS structure corresponding to an unseen data sets are given in TABLE IV.

TABLE IV. A COMPARISON BETWEEN THE ACCURACY ANFIS AND ANN'S METHODS

Net in B-Ns	ANFIS		ANNs-LM		ANNs-BR	
	R	MSE	R	MSE	R	MSE
$\mathbf{Net_{P2}}$	0.99485	0.13857	0.99485	0.13874	0.99172	0.15233
$\mathbf{Net_{P4}}$	0.99464	0.10383	0.99465	0.10257	0.99358	0.11848
$\mathbf{Net_{T4}}$	0.99723	0.05347	0.99646	0.06495	0.99646	0.06481
$\mathbf{Net_{N1}}$	0.99199	0.12532	0.98935	0.17238	0.98977	0.16762
$\mathbf{Net_{N2}}$	0.99053	0.28805	0.99016	0.30957	0.98672	0.49690
$\mathbf{Net_{PKW}}$	0.99498	0.05347	0.91365	0.06495	0.91372	0.06481
$\mathbf{Net_{of}}$	0.99464	0.06278	0.90432	0.08704	0.98837	0.09158

Throughout the testing stages, it can be found that the ANFIS network predicted the performance parameters with higher accuracy compared to the ANNs models. The result of the ANFIS network produced more than 0.99 of Pearson correlation and less than 0.3 MAPE for all seven networks.
In addition, nineteens trials are carried out to examine the accuracy of B-Ns developed by various models. The corresponding plots are given in Fig.4.

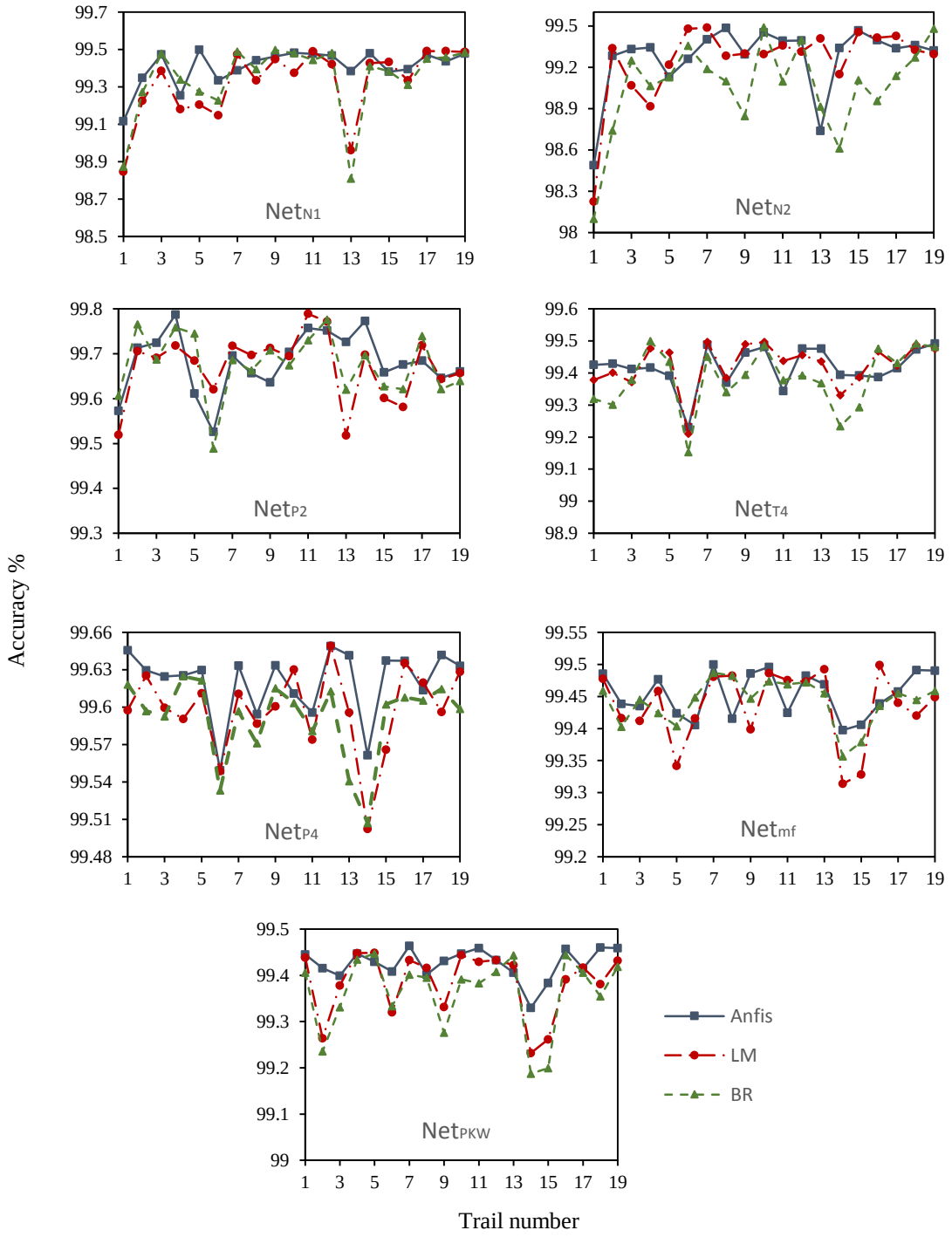

Fig 4. The accuracy of the 19 trials of various developed B-Ns.

It is noticed that the training accuracy is close to 1 in the trials using all ANFIS, ANNs-LM and ANNs-BR methods. However, it can be seen that the ANFIS indeed have a better capability to recognize nonlinear characteristics of the gas turbine engine so as to facilitate the diagnosis.

I. CONCLUSION

This paper presented in detail a study on the application of ANFIS approach for developing a Bank of Networks to monitor the performance parameters of an industrial gas turbine engine. The accuracy of the trained B-Ns are analyzed using the healthy performance data of an industrial 18.8 MW open-cycle offshore gas turbine. To develop a system identification model, a bank of networks corresponding to seven (7) variables which are commonly measurable on most industrial IGTs are developed. The model was then optimized, and the best membership function and the number of membership functions were found to be Gaussian and 4 to 5, respectively. This optimized model was finally used for predicting the output parameters in response to the input parameters not introduced to the model during the training and validation processes. It was found that the predicted parameters were found to be mostly in excellent agreement with the target values for all seven networks. R and MAPE were calculated as higher than 0.99 and lower than 0.3 for all developed ANFIS networks. This demonstrates the high accuracy, effectiveness and reliability of the ANFIS method for predicting the performance parameters of an IGT. Additionally, the ANFIS prediction results were compared against the ANN prediction results and it is shown that the ANFIS model performed slightly better than the ANN model. However, the ANN method provided more flexibility in terms of model implementation, computing speed and user-friendly capabilities compared to the ANFIS method.

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BIOGRAPHY

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