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ORIGINAL PAPER

An Intelligent Approach to Predict Vibration Rate in a Real Gas Turbine

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Abstract Bearings vibration in gas turbines is considered as an injurious event, which results in incidents such as emergency shutdown or damages in turbine blades and imposes expensive costs to the system. Thus, measuring and analyzing of vibration rate in gas turbines is very important and knowing about its operational conditions and prediction of this phenomenon can help a lot in reducing vibration, avoiding damage to the blades and eventually financial savings. In this paper, we are modelling the vibration rate of a real double shaft 25 MW gas turbine, located in Iran, by making use of a hybrid intelligent model based on multi-layer perceptron neural network and cuckoo optimization algorithm; so, the model in this paper is abbreviated as MLP-COA. It should be noted that this work is an absolutely novel work and the idea is implemented in a real turbine for first time. We have used a real dataset with 161 samples which are collected during a year from a gas turbine in a gas pressure booster station. Furthermore, to obtain the effect of each input parameter on the vibration rate, we have applied sensitivity analysis using the cosine amplitude technique. Evaluation of predicted vibration rates was performed and prove satisfactory efficiency of this model than other predictive models such as radial basis function and multi-layer perceptron. The model can also be used for prediction of online vibration rate without any constraint in selection of data points in training phase.

Keywords Industrial intelligence · Gas turbine · Neural networks · Cuckoo optimization algorithm · Intelligent system · Prediction · Vibration rate

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1 Introduction

Nowadays, it is very often to use gas and steam turbines in different branches of industry and jet motors to generate electricity or load booster. One of the most important threats to such an equipment is vibration which results huge financial loses. Damage of turbine blades and emergency shutdown (ESD) of the unit are another of the most serious results of such a phenomenon. In general, turbines are designed to work in a static and risk-free place. Many researchers believe turbine vibrations should be continuously monitored to make sure they are working correctly; consequently, a proper method should be chosen based on different damages. Basically, there are four levels of observing and monitoring turbine vibration. At the first level, measuring is done manually in the case it is needed (old turbines). At the second level, vibration is continuously observed using the installed sensors on the related places. At this level, when the control room operators observe emergency state, they should trip the unit if it is needed. The third level is similar to the second level, while a module is automatically trips the unit. Finally, in the fourth level by collecting various data, predicting and analyzing turbine vibration spectrum, the unit will trip whenever it is needed. Gas turbines are considered as sensitive and spare-less equipment. This important equipment should be equipped with at least the second level monitoring system. Recently, some accelerometers are proposed by producers of vibration transducers with 4–20mA current as output which is useful for control system. These transducers could be installed on bearings with their output connected to the distributed control system (DCS) so that the vibration could be shown permanently. Among these methods, employing vibration analysis is known as a reliable method, in which the vibration sensors output are received by experts in the control room at a far place from powerhouse. Experts analyze these data to measure turbine blades damage and estimate their lifetime.

Generally, the main factors of vibration in turbines are consists of mass unbalancing, non-coaxially, over-looseness of bearing, unstable operation environment and variable inside turbine. To recognize the reason of a turbine vibration, forth level of vibration analysis is needed. Powerhouses and stations personnel could prevent inopportune failure of turbine by monitoring turbine vibration continuously. In addition, vibration prediction could be a good guidance and appropriate troubleshooter to recognize, control or remove vibration reason, before serious problems happen.

Usually, the vibration is caused by very fast spiral movement of rotor which continue from several seconds to several minutes, resulting severe damages such as shaft fracture and turbine blades cracking [1]. Based on researches that are done, 42 % of gas turbine damages is caused by the damage of turbine blades, which among all vibration-induced damage modes has the maximum damage rate [2]. Since turbine blades work in an unstable operating conditions within the enclosure of the turbine such as heterogeneous distribution of pressure, different conditions of bearings oil level and their vibrations, knowing about operational conditions and predicting unseen conditions can help a lot in reducing vibration, avoiding damage to the blades and eventually financial savings. In general, lifetime of a turbine and its equipment depends on forces applied to it such as centrifugal and dynamic forces [3]. It should be noted that the results of vibration analysis are used to make Campbell diagram, which depicts natural frequency of turbine blades that are derived from rotor speed (RPM) [4]. Analysis of vibration and natural frequency of blades along with analyzing their derived stress is done in a laboratory mode using a finite element software called analysis system (ANSYS) [5–8]. Researchers in recent researches on modelling gas and steam turbines blades lifetime use statistical and analytical methods [9–16]. As stated in [17] practical parameters such as vibration rate of gas turbine, bearings temperature, oil level, etc. are used to predict gas turbine damages, and using data mining techniques such as preprocessing data, sampling, feature selection and dimension reduction is very common to predict power and speed of wind and optimizing wind turbines efficiency [18,19]. As a double shaft turbine is equipped with four bearings and vibration of each bearing results vibration in a specific part of turbine, we have to use the most important bearings for analysis. The bearings are of tilting pad design with a directed lubrication system. During operation, oil is continuously supplied to the bearing. Each bearing is equipped with temperature and vibration sensors which are continuously monitoring the temperature and vibration rates. As analyzed in [20] and a double shaft turbine that has been depicted in Fig. 1, considering vertical and horizontal load amount that a bearing has to bear, the bearing #2 is the most important one; also damage has been known to be resulted from the vibration of this bearing by observing the cracked shaft and analyzing all bearings vibration. Furthermore, it has been emphasized on the effect of some factors on vibration such as tank oil level. The work described in [21] is able to predict six different type of common damage in steam turbines, by making use of 8 frequency domain of signals that are resulted from vibration and applying support vector machine technique. Similarly, in [22] one type of damage is recognized using vibration signals and optimized support vector regression technique. In a data-driven model [23] which made use of combination of particle swarm optimization algorithm and prediction techniques such as artificial neural network and support vector regression, is able to predict the amount of wind turbine vibration; it is aim at controlling wind turbine, emphasizing on maximizing power of electricity generation and reducing vibration. In the most recent research described in [24], a damage detector filter which is based on multi-layer perceptron neural network is used to discover damage in gas turbine motors (JET motor).

To overcome the problems of empirical methods such as high computations and their complexity on calculation of growth rate of turbines vibration, artificial neural network technique is recommended. Using this technique, it is possible to solve problems in which there is a very large number of parameters and related values that correlating between them is not feasible. The topology of an artificial neural network is determined by number of layers, nodes in each layer and the nature of activation functions. Taking into account that optimizing an artificial neural network is a very important step in making a predictor model with high accuracy [25], we have used cuckoo optimization algorithm to optimize our network. The rest of this paper is organized as follows. "Theoretical routines" section describe the multi-layer perceptron neural network structure in detail, as well as cuckoo optimization algorithm. "The proposed method" section examines the hybrid model proposed in this paper. Then, "Results and discussion" section compares the obtained results from previous section with other predictive methods. Finally, "Conclusion" section summarizes and concludes the present and future works.

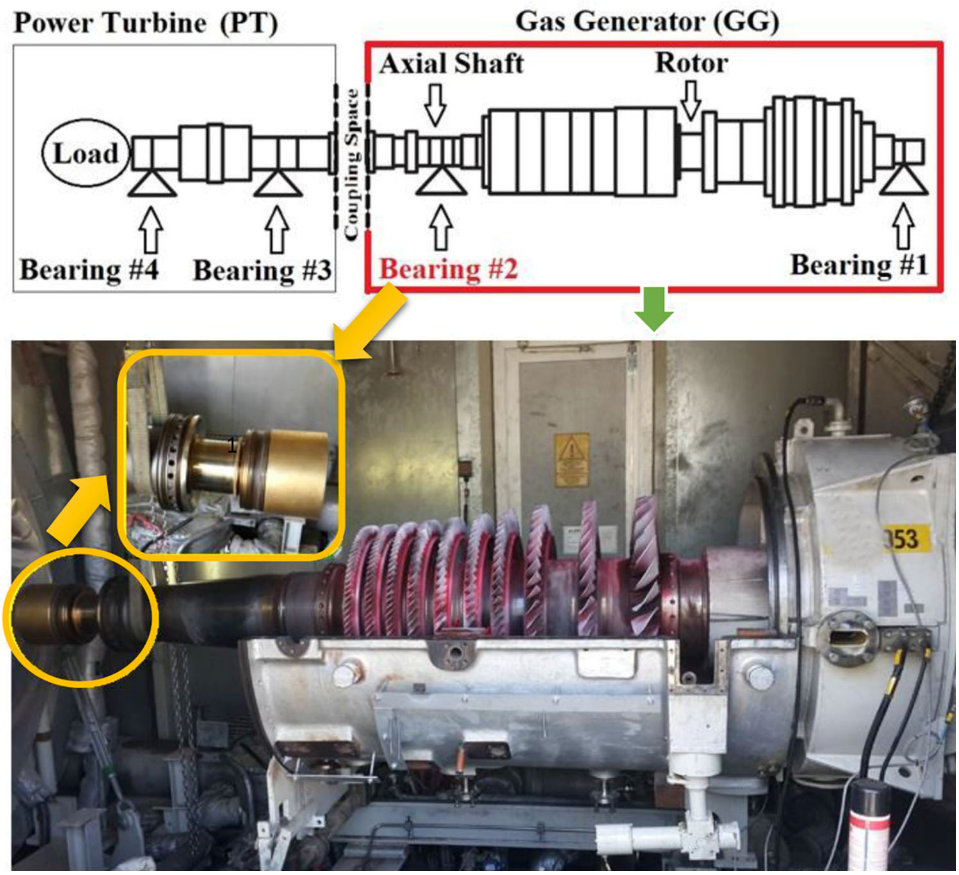


Fig. 1 A real double shaft 25 MW gas turbine along with its equipments (Iran—Gas booster station)

2 Theoretical Routines

2.1 Artificial Neural Networks

ANN is used as an efficient tool to simulate the human's brain. Nowadays, it has a wide range of applications in science, engineering [26,27]. Also, it has been used widely in gas and oil industries [28,29].

Mathematically speaking, nervous systems of human could be assumed as a large number of layered elements. Multi-layer perceptron is one of the most common used feed forward ANNs. Hidden layers of a MLP are usually fully connected to each other. Figure 2 depicts a typical schematic of this architecture. This figure shows three layers of neurons, i.e. input layer, hidden layers and output layer. Also, Fig. 3 shows a simple neuron. In this figure, p stands for the number of inputs, w the weight, b the bias which employs the result as the argument for a singular valued function, f the transfer function and a the output neurons. Common transfer functions are the log-sigmoid, hyperbolic tangent sigmoid, Gauss–Hermite and the linear functions. Among this, the sigmoidal and Gauss–Hermite is the most widely considered for the non-linearity parameters.

The internal weights of the network are adjusted in the course of an iterative process termed training and the algorithm used for this purpose so-called training algorithm. The back-propagation algorithm is the most common form of learning, utilized in ANN. Indeed, to evaluate the performance of the ANN, MSE could be adopted. Standard back-propagation algorithm for adjusting weights and biases

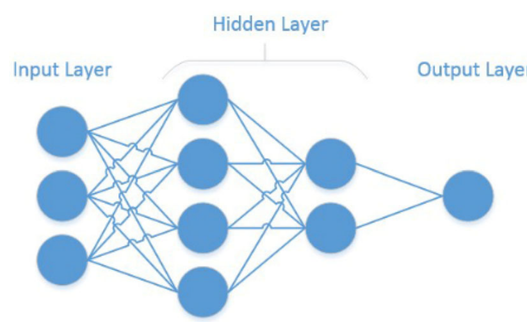


Fig. 2 Four layers MLP neural network example with input, hidden and output layers

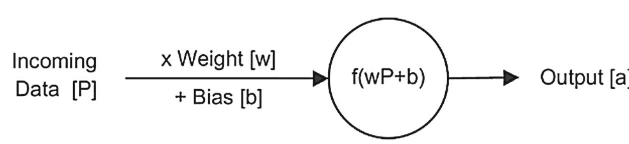


Fig. 3 Structure of a simple neuron

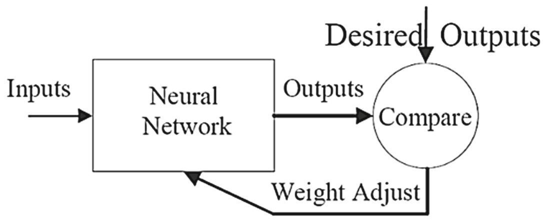


Fig. 4 Procedure of neural network learning

uses the following equations (Fig. 4):

$$w(k+1) = w(k) + 2\mu e(k)p^T(k) \tag{1}$$

$$b(k+1) = b(k) + 2\mu e(k) \tag{2}$$

Where w, b, e, p and μ represent weight matrix, bias matrix, error, input matrix and learning rate, respectively. The commonly employed error function is the MSE as defined by:

$$MSE = \frac{1}{2}\sum_{k=1}^{n}\sum_{j=1}^{m}\left[P_j(k) - T_j(k)\right]^2 \tag{3}$$

Where m is the number of outputs and n is the number of training samples. $P_{j(k)}$ and $T_{j(k)}$ are the predicted output, and the actual output, respectively. Generally, minimizing the MSE is the priority of training an ANN. BP is a gradient descent algorithm on the error space which most willingly gets deceive into a local optimum making it entirely dependent on initial settings (weights). To overcome this obstacle, different optimization algorithm such as genetic algorithm (GA), particle swarm optimization (PSO) and ant colony optimization (ACO) can be implemented due to global searching ability of them. Cuckoo optimization algorithm (COA) has been proposed as a new evolutionary algorithm by Rajabioun [30]. In his experiments, COA has shown effective results in comparison with some other evolutionary algorithms such as GA and PSO. Also, COA has been freshly used in many applications [31,32]. So, in this paper we preferred to use COA instead of other evolutionary algorithms to find the best weight vectors. Minimizing of the MSE is the main end of the COA which implemented in this study.

2.2 Cuckoo Optimization Algorithm

Rajabioun [30] inspired from behavior of a group of birds and proposed a new evolutionary algorithm as "Cuckoo Optimization Algorithm". Figure 5 shows a simplified flowchart of the COA algorithm.

In order to solve an optimization problem, it's necessary that the values of problem variables be formed as an array. In GA and PSO terminologies this array is called "Chromosome" and "Particle Position", respectively. But here in COA it is called "habitat". In an N-dimensional optimization problem, a habitat is an array of 1 × N, representing current living position of cuckoo. This array is defined as follows:

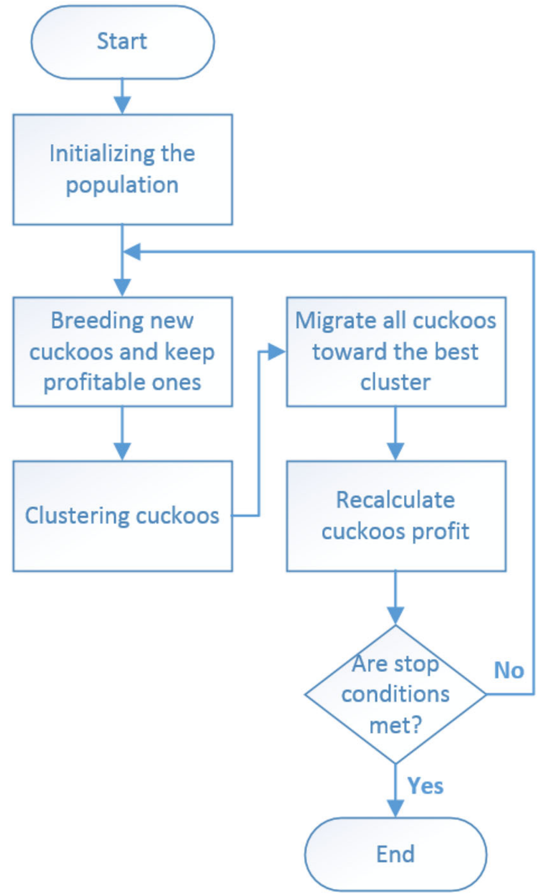


Fig. 5 The flowchart of COA

$$habitat = [x_1, x_2, x_3, \ldots, x_N] \tag{4}$$

Each of the variable values $(x_1, x_2, x_3, \ldots, x_N)$ is floating point number. The profit of a habitat is obtained by evaluation of profit function f_p at a habitat of $(x_1, x_2, x_3, \ldots, x_N)$. So

$$profit = f_p(habitat) = f_p(x_1, x_2, x_3, \ldots, x_N) \tag{5}$$

As it is seen COA is an algorithm that maximizes a profit function. To use COA in cost minimization problems, one can easily maximize the following profit function:

$$profit = -cost(habitat) = -f_c(x_1, x_2, x_3, \ldots, x_N) \tag{6}$$

To start the optimization algorithm, a candidate habitat matrix of size $N_{population} \times N_{varibales}$ is generated. Then some randomly produced number of eggs is supposed for each of these initial cuckoo habitats. In nature, each cuckoo lays from 5 to 20 eggs. These values are used as the upper

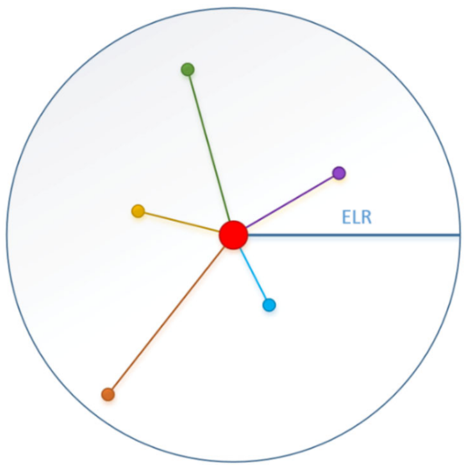


Fig. 6 Random egg laying in ELR, central *red circle* is the initial habitat of the cuckoo with five eggs; other *small circles* are the eggs' new nest

and lower limits of egg dedication to each cuckoo at different iterations. Another habit of real cuckoos is that they lay eggs within a maximum distance from their habitat. From now on, this maximum range will be called "Egg Laying Radius (ELR)". In an optimization problem with upper limit of var_{high} and lower limit of var_{low} for variables, each cuckoo has an egg laying radius (ELR) which is proportional to the total number of eggs, number of current cuckoo's eggs and also variable limits of var_{high} and var_{low}. So ELR is defined as:

$$ELR = \alpha \times \frac{number\ of\ current\ cuckoo's\ eggs}{total\ number\ of\ eggs} \times \left(var_{high} - var_{low}\right) \tag{7}$$

where α is an integer, supposed to handle the maximum value of ELR.

Each cuckoo starts laying eggs randomly in some other host birds' nests within her ELR. Figure 6 gives a clear view of this concept.

When moving toward goal point, the cuckoos do not fly all the way to the destination habitat. They only fly a part of the way and also have a deviation. This movement is clearly shown in Fig. 7. As it is seen in this figure, each cuckoo only flies λ% of all distance toward goal habitat and also has a deviation of φ radians. These two parameters, λ and φ, help cuckoos search much more positions in all environment. For each cuckoo, λ and φ are defined as follows:

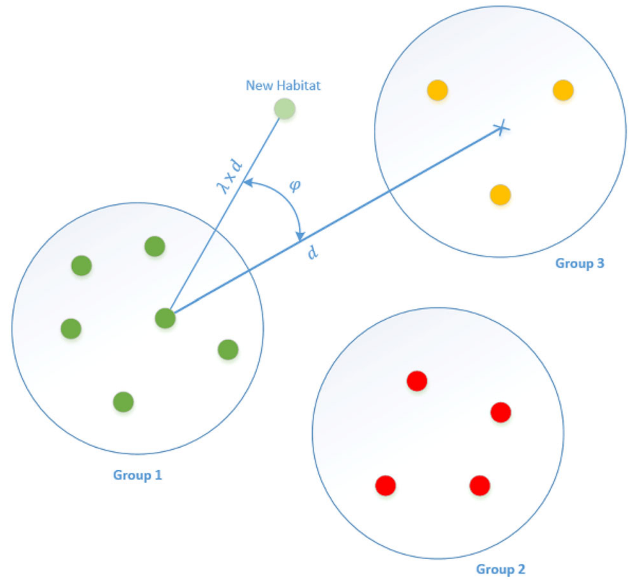


Fig. 7 Immigration of a sample cuckoo toward goal habitat

1. Initialize cuckoo habitats with random values
2. Define ELR for each cuckoo
3. Let cuckoos lay eggs inside their ELR area
4. Kill eggs that are not profitable
5. Keep top N_{max} most profitable cuckoos
6. Clustering cuckoos and determine the best cluster and its goal habitat
7. Immigrate population toward the goal habitat
8. If stop conditions are met then return the most profitable habitat, otherwise go to step 2

Fig. 8 Pseudo-code for Cuckoo optimization algorithm

$$\lambda \sim U(0, 1) \tag{8}$$

$$\varphi \sim U(-\omega, \omega) \tag{9}$$

where $\lambda \sim U(0, 1)$ means that λ is a random number (uniformly distributed) between 0 and 1. ω is a parameter that constrains the deviation from goal habitat. An ω of $\pi/6$ (rad) seems to be enough for good convergence of the cuckoo population to global maximum profit. When all cuckoos immigrated toward goal point and new habitats were specified, each mature cuckoo is given some eggs. Then considering the number of eggs dedicated to each bird, an ELR is calculated for each cuckoo. Afterward new egg laying process restarts.

The main steps of COA are presented in Fig. 8 as a pseudo-code.

3 The Proposed Method

In this research, a three layer MLP neural network was implemented to construct a predictive model to estimate the vibration rate in a 25 MW gas turbine. To optimize the connection weights of the neural network, COA was implemented. The connection weights of the neural network were chosen as variables of an optimization problem. As discussed earlier, in COA each individual is called "*habitat*". Each individual has a profitability value which is defined as '*profit*' in COA. As we want to make more accurate predictions, we have to find individuals which have less MSE when they are used as weights in the MLP. So, we have used inversed MSE for our profit function (i.e. the less MSE of our MLP means the more profit of that individual which is used as weights in the MLP).

Our profit function is as follows:

$$profit = MSE = \sum_{i=1}^{n} (p_i - r_i)^2 / n \tag{10}$$

Where n is the number of training samples, p_i represents our prediction of vibration rate with the i_{th} sample as input, and r_i stands for the actual vibration rate. Based on considered profit function, the best ANN architecture was: 5–10–1 (5 input parameters, 10 hidden neurons, 1 output neuron). As MLP is a fully connected network, we have 60 connections in our network ((layer1 × layer2) + (layer2 × layer3) = 5×10 + 10×1= 60). Each connection has a weight value, which multiplies the input and transfer it to the next neuron. A habitat is an array of floating point numbers. Thus, we can use weight vectors directly as our habitats. As we need to find 60 optimum weights for our MLP, the habitats look like the following:

$w_1 \in [-2, 2]$	$w_2 \in [-2, 2]$	...	$w_{59} \in [-2, 2]$	$w_{60} \in [-2, 2]$

It should be mentioned that in this network each weight was firstly set in the range of $[-2, 2]$ (initial population is made completely with random values from -2 to 2 for weights). Also, bias value in all stages was considered constant value 1. Furthermore, the transfer functions i.e. sigmoid and linear functions were assigned in hidden and output layers, respectively. These functions are shown below:

$$LogSig\,(x) = 1/\,(1 + EXP\,(-x)) \tag{11}$$

$$Lin\,(x) = x \tag{12}$$

Also, as orthogonal basis functions of the feed-forward neural network, Gauss–Hermite activation functions are considered. The function is shown below [33]:

$$\psi\,(x) = [2^k \Pi^{\frac{1}{2}} \mathrm{k}!] \mathrm{H}_k(x) e^{\frac{-x^2}{2}}, \mathrm{k} = 0, 1, 2, ... \tag{13}$$

where $\mathrm{H}_k(x)$ are the Hermite orthogonal functions.

As all evolutionary algorithms, COA has different parameters which needs to be tuned to work best with our situation. We have set all these parameters as follows.

- Initial Cuckoos count = 20

The population size in the beginning.

- Population size = 30

The population size during each generation.

- Cluster count = 1

Number of clusters that should be made using K-Means algorithm.

- Cuckoos minimum eggs = 7

Minimum eggs that each cuckoo could lay.

- Cuckoos maximum eggs = 15

Maximum eggs that each cuckoo could lay.

- Migration coefficient = 0.7

The coefficient which is used in migration formula.

- Egg laying radius = 0.8

Maximum distance that all eggs should be laid within.

These values are obtained by performing different experiments, even though COA is almost stable against slight variation in these parameters. In each generation, we have kept the top 30 suitable individuals as the population of the next generation. Additionally, the modeling and predicting were progressed by using the 161 samples. There are different parameters which influence vibration on the bearing #2. In this paper, we have chosen the most important ones under the supervision of experts, such as rotor speed, bearing #2 differential pressure, oil tank temperature, oil tank pressure, and fuel consumption inside the turbine enclosure. The flowchart of proposed method is depicted in Fig. 9.

3.1 Dataset and Data Normalization

In this paper, a total number of 161 data samples were accumulated during one year from a 25 MW double shaft gas turbine and obtained from supervisory control and data acquisition system located in a gas pressure booster station, Iran. Fig. 10 depicts position of all materials that are considered in this research and have obtained from Supervisory Control and Data Acquisition System (SCADA)-embedded Human-Machine Interface (HMI). Indeed, in order to maintain the statistical consistency, the dataset was divided into training and testing parts. It should be mentioned that to establish a

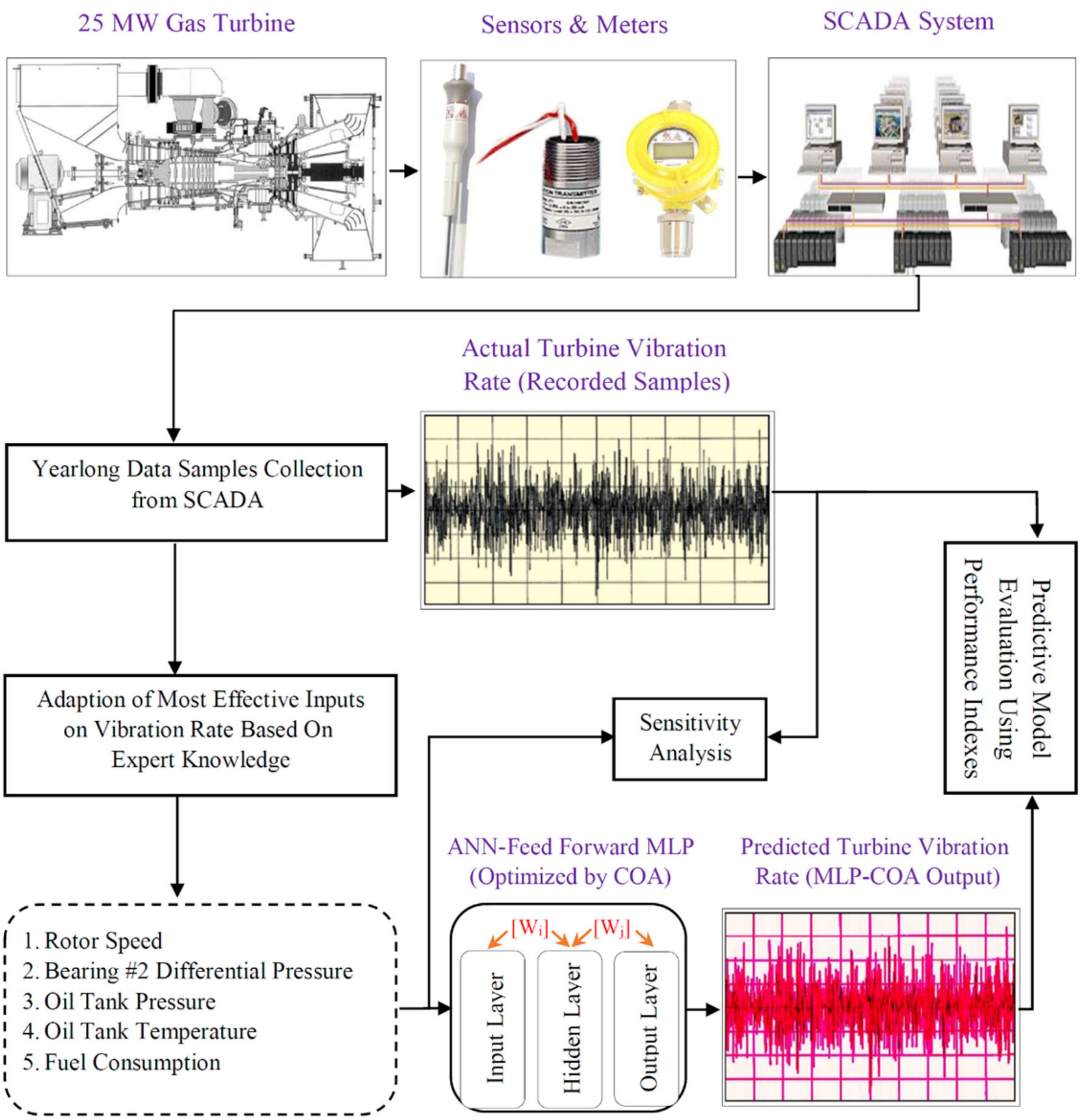


Fig. 9 The proposed method

comparable analysis the same datasets were used for the proposed model and other predictive models. Data samples for training and testing were adopted randomly. So, 129 and 32 data samples were used in training and testing phases, respectively. Table 1 shows 11 samples out of 161 samples from the dataset. The dataset contains all turbine related parameters with vibration rate in a real world turbine. Also, Table 2 shows the domain of variation for each input and output parameters.

In the process of MLP-COA, raw data may not be suitable to be utilized, when values of input and output parameters are extremely low or high. Thus, raw data need to be preprocessed and scaled. One approach to scale the data is by using the following formula (min–max method) which normalizes the data to values between 0 and 1 [34,35]:

$$X_i' = X_i - X_{min}/X_{max} - X_{min} \quad (14)$$

Where X_i is original value of parameter, X_i' is normalized value of X_i, X_{min} and X_{max} are minimum and maximum values of parameter that is related to X_i.

3.2 Evaluation Criteria

To assess performance of designed models to predict vibration rate, two most famous statistical indicators such root mean square error (RMSE), and X^2 (chi-squared distribution) were applied through this research. The description to evaluate the above parameters and also the relating explanation are as follows. The first performance index is the RMSE. As known in statistical analysis, the value indicating the per-

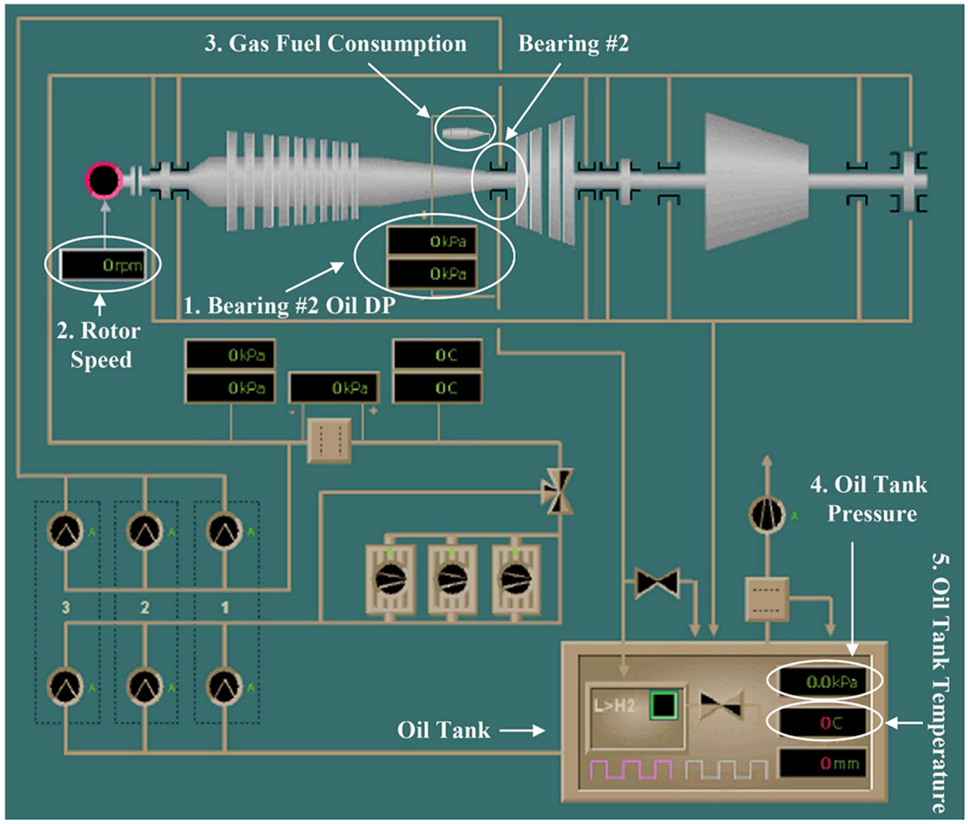


Fig. 10 Position of all equipments in a real double shaft 25 MW gas turbine (inputs and output) in HMI system

Table 1 11 data samples out of 161 accumulated during one year, consists of five inputs and an output

No.	Rotor speed	Fuel consumption	Bearing #2 Differential pressure (DP)	Oil tank temperature	Oil tank pressure	Vibration rate
1	8909	29.1	173	60	544	1.5
2	8770	26.8	175	59	544	1.6
3	8888	27.9	191	61	530	2.8
4	8750	28	194	59	531	2.9
5	8794	28	174	59	544	1.7
6	8882	27	175	59	544	1.8
7	8850	28	173	60	544	1.7
8	8922	28.2	204	59	529	3
9	8862	27.2	192	59	530	2.9
10	8836	28.6	191	60	531	2.9
11	8862	25.1	220	60	531	3.2

Table 2 Input and output parameters used for vibration prediction modeling and their ranges

No.	Parameters	Type	Unit	Range (min–max)
1	Rotor speed (S)	Input	Round per minute (˙RPM)	0–9770
2	Oil tank temperature (T)	Input	Centigrade (C)	0–150
3	Oil tank pressure (P)	Input	Kilo Pascal (kPa)	0–600
4	Bearing #2 differential pressure (D)	Input	Kilo Pascal (kPa)	0–300
5	Fuel consumption (F)	Input	Mega Joule per second (MJ/S)	0–70
6	Vibration rate (Rate)	Output	Millimeter per second (mm/s)	0–11

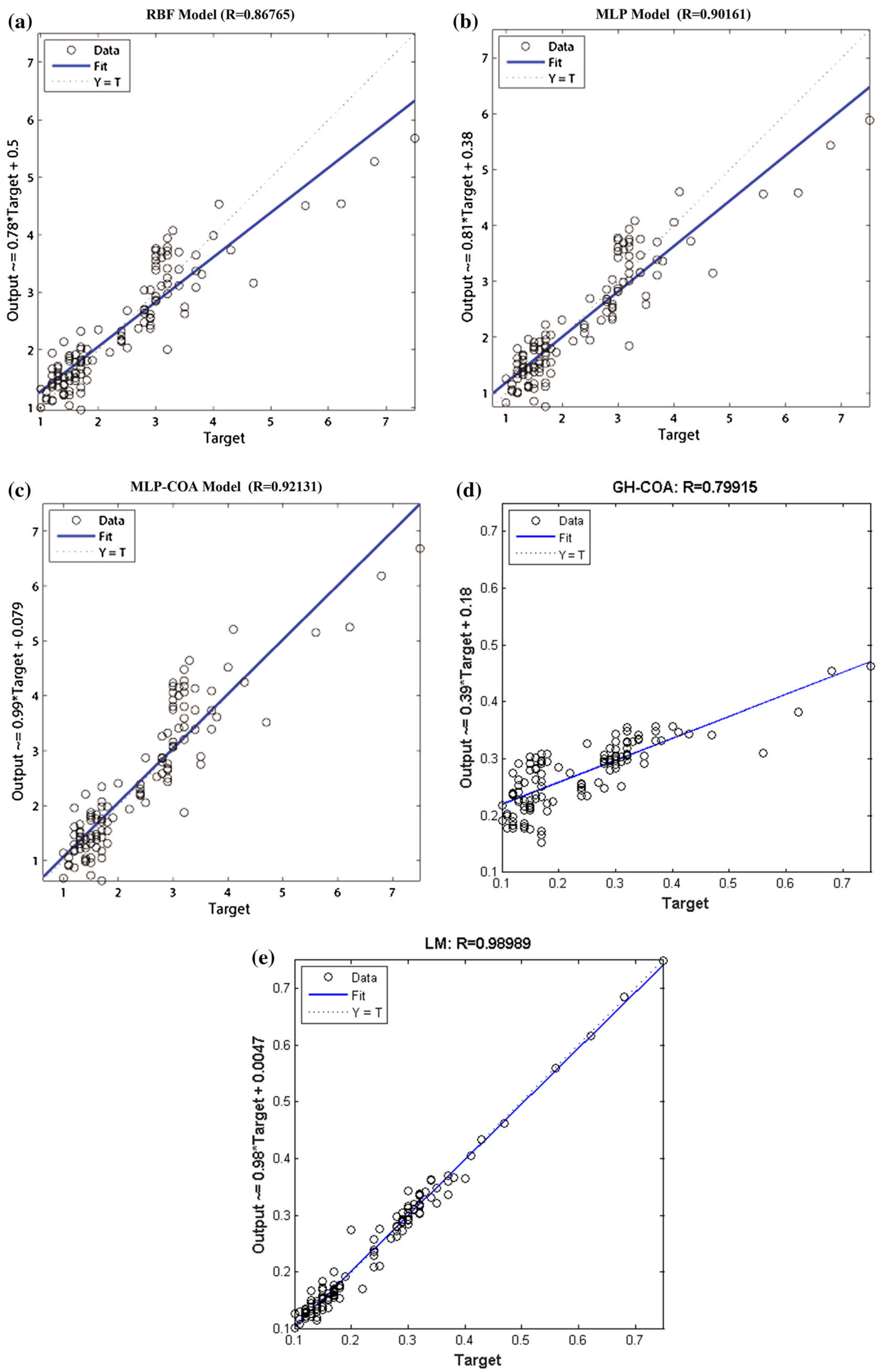


Fig. 11 Cross-correlation graphs between the predicted and target vibration rate for: **a** RBF model, **b** MLP model, **c** MLP-COA model, **d** GH-MLP model and **e** LM model (Training & Validating Phase)

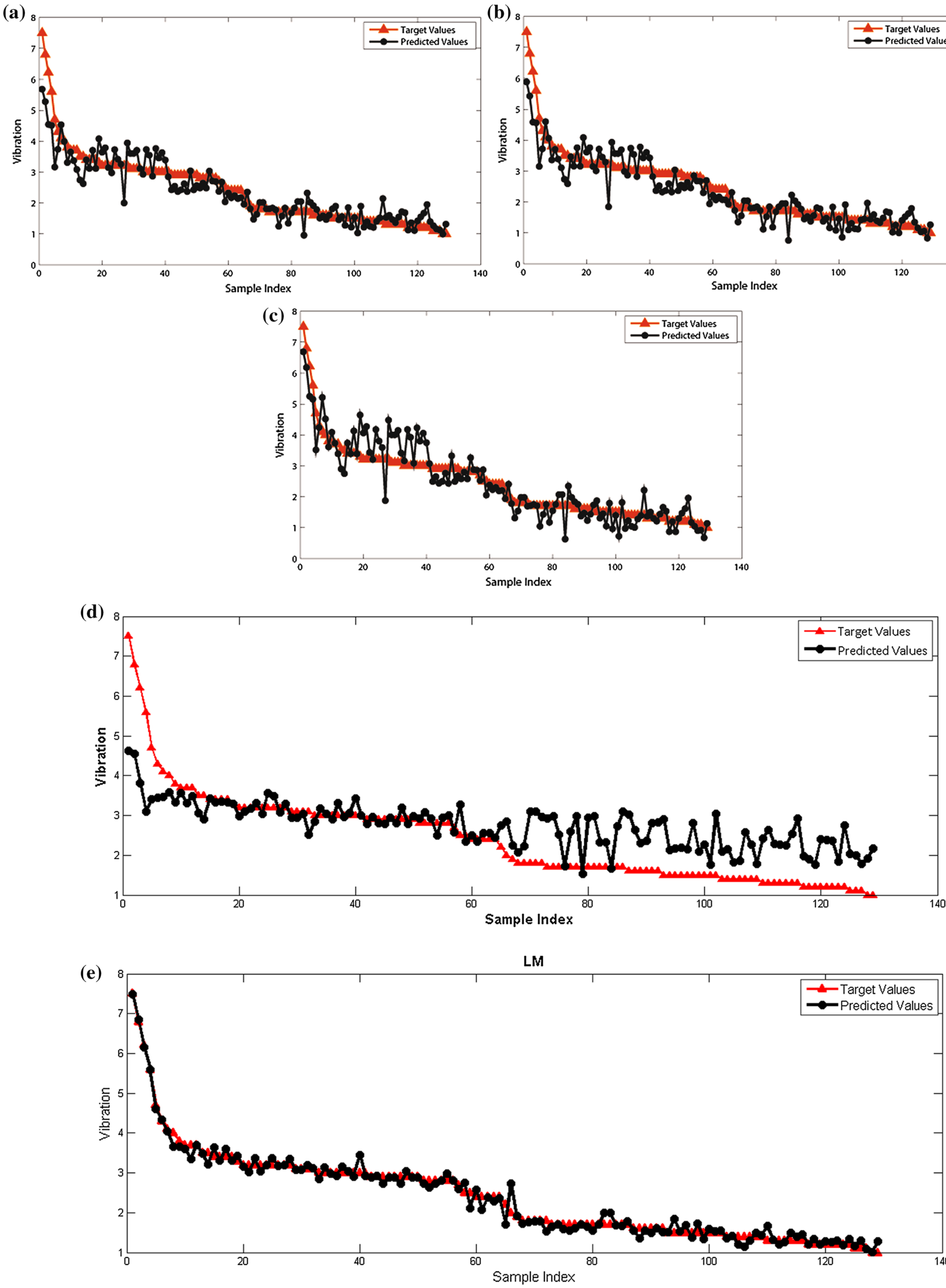


Fig. 12 Comparison of target vibration rate with predicted vibration rate for: **a** RBF model, **b** MLP model, **c**, MLP-COA model, **d** GH-MLP model and **e** LM model (training & validating phase)

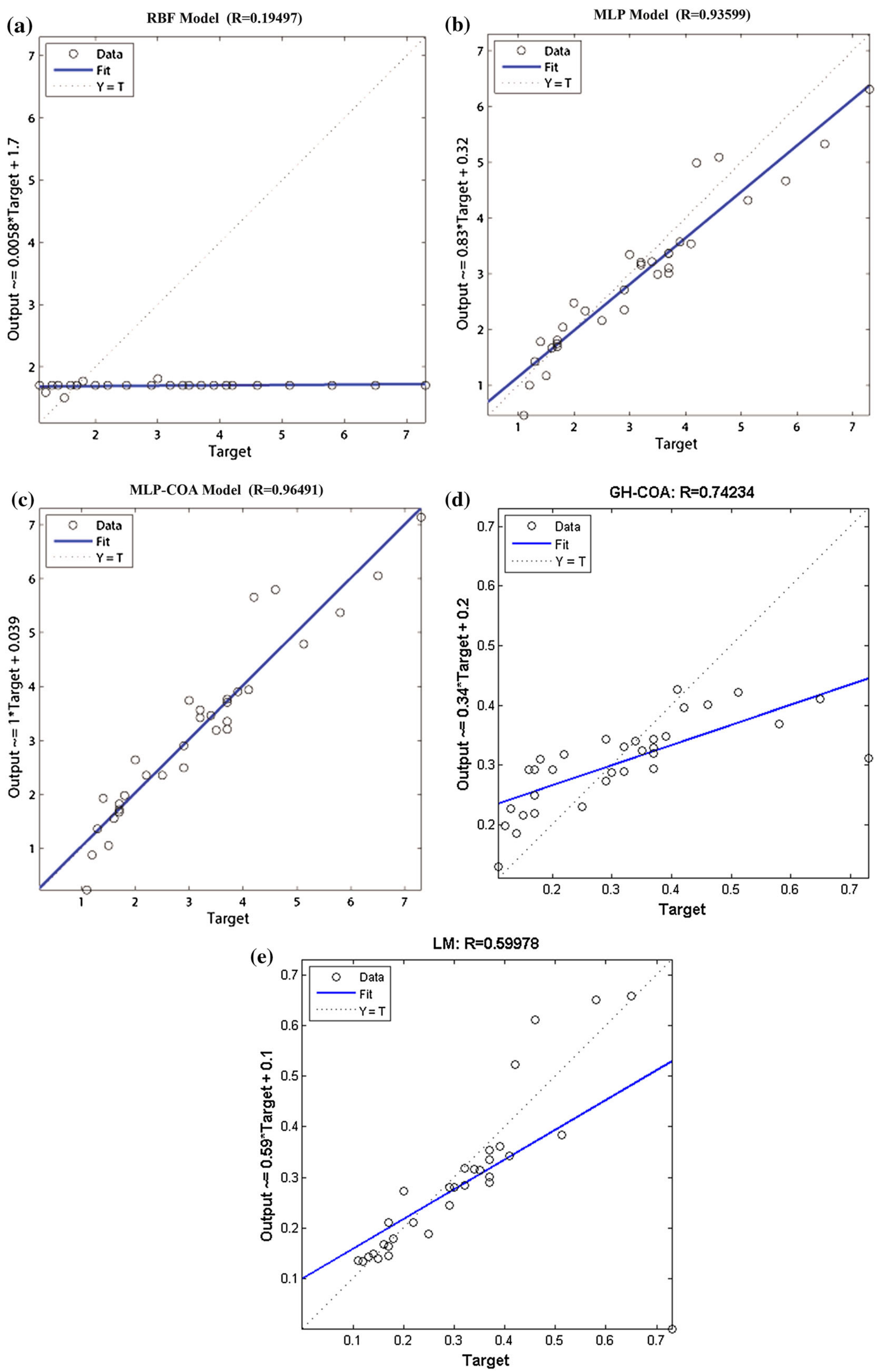


Fig. 13 Cross-correlation graphs between the predicted and actual vibration rate for: **a** RBF model, **b** MLP model, **c** MLP-COA model, **d** GH-MLP model and **e** LM model (testing phase)

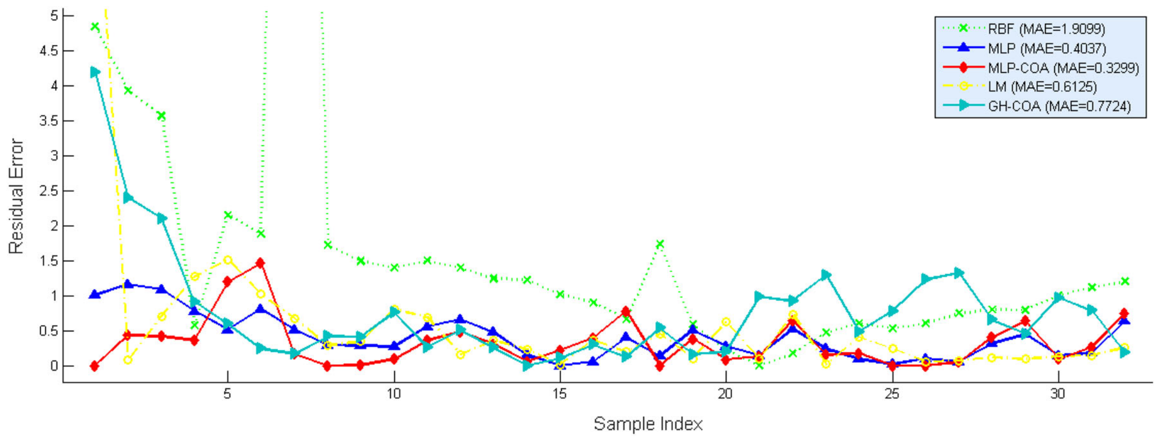


Fig. 14 Residual error along with MAE for all of the predictive models (testing phase)

fect prediction performance for RMSE is 0.0. In other words, model performance increases as RMSE decrease. RMSE is described by the following equations:

$$\boldsymbol{RMSE} = \sqrt{1/n\left(\sum_{i=1}^{n} \boldsymbol{vibration}_i^M - \boldsymbol{vibration}_i^p\right)^2} \quad (15)$$

In the above equations, n is the samples number. In the above equation, the lowest RMSE belongs to the most successful model among others.

Furthermore, a chi-square test (X^2) for independence compares two variables in a contingency table to see if they are related. In a more general sense, it test to see whether distributions of categorical variables differ from each another. A very small chi square test statistic means that your observed data fits your expected data extremely well. In other words, there is a relationship. The formula for the chi-square statistic used in the chi square test is as follow:

$$X^2 = E(Y_i, \hat{Y}_i)\mathrm{Cov}(Y_i, \hat{Y}_i)\left[E(Y_i, \hat{Y}_i)\right]^T, i = 1, 2, ..., n \quad (16)$$

In the above equation, E is the residual vector and Y_i, $\hat{Y}_i$ the actual and expected values, respectively.

4 Results and Discussion

Furthermore, the obtained results from hybrid predictive model based on MLP and COA along with other predictive models are investigated. To do this, first, the results of applying the training samples to the all models is individually examined in training and validating phase. Then, after determining best structure of each model, the testing samples are fed to them. Details are given in each section. At the end, the results of the proposed model will be compared with other presented methods.

Figures 11a to 11e show the plots of target values of turbine vibration rate versus predicted values in training and validating phase, calculated by RBF (Radial Basis Function), MLP and MLP-COA, GH-COA (Gauss–Hermite-COA), and LM (Levenberg–Marquardt) respectively. Also, for more comprehension the amount of overlap in all of the models Fig. 12a–e have been shown.

In addition, the coefficient of determination of testing phase are shown in Fig. 13a–e.

Figure 14 shows the residual errors for 32 testing samples applied for all of the models. It can be seen that the MLP-COA model yielded in less residual error than the other predictive models. In other words, the deviation from the predicted vibration rates by MLP-COA is less than the other predictive models. This low deviation obtained by MLP-COA model also proves that the prediction capability of MLP-COA model is better than the other.

Also, Fig. 15 depicts the convergence procedure (learning rate) for MLP-COA model. It can be seen that the model has been converged after 800th iteration. Furthermore, the calculated evaluation criteria i.e. RMSE and X^2 of the identified models for testing phase are presented in Table 3. As can be seen from Table 3, the high performance of the models for testing set can be considered as an indication of good generalization capabilities of the models. Irrespective of the data set the lowest RMSE and the highest, X^2, belong to MLP-COA model indicating that this model gives better prediction performance than the other models. Obviously, it can be seen that MLP-COA demonstrates superiority over widely used vibration rate predictors.

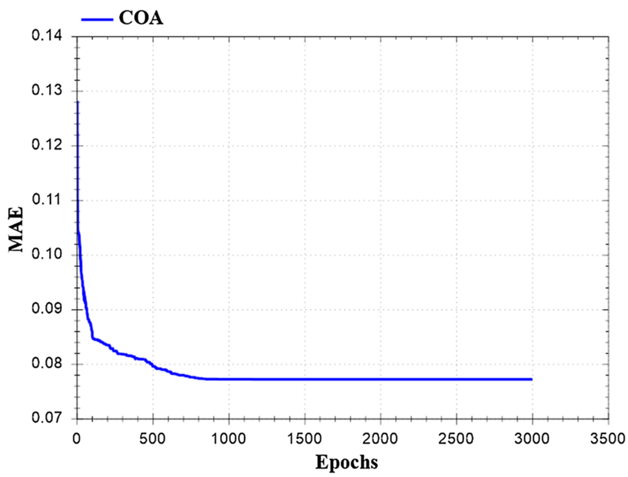


Fig. 15 The convergence diagram for the proposed intelligent model (COA-MLP)

Table 3 Comparison of the obtained values for evaluation criteria in testing phase for all predictive models

	Model name				
Index	RBF	MLP	MLP-COA	LM	GH-COA
RMSE	4.067506	0.508225	0.4763252	1.396914	1.126101
X^2	3.1893	0.3204	0.2568	0.5248	0.4797

4.1 Sensitivity Analysis Using Cosine Amplitude Method (CAM)

There are several methods in order to extract the strength of relationships between the vibration rate as single output and the five input parameters. Thus, we applied the CAM as a good technique for evaluating the relations. As can be seen in Fig. 16, sensitivity analysis was done for all the 5 input parameters to understand the relative significance of each parameter on vibration rate. To apply this method, by considering n data samples in the dataset, we specify an array namely X:

$$X = \{x_1, x_2, ..., x_i, ..., x_n\} \tag{17}$$

Which each data sample have m dimension as follows:

$$x_i = \{x_{i1}, x_{i2}, x_{i3}, ..., x_{im}\} \tag{18}$$

So that each dimension of x_{ij} have a strength of relationship with another dimension of x_{jk}. Consequently, the strength of the relation between the dimension of x_{ij} and dimension of x_{jk} is given by the following equation:

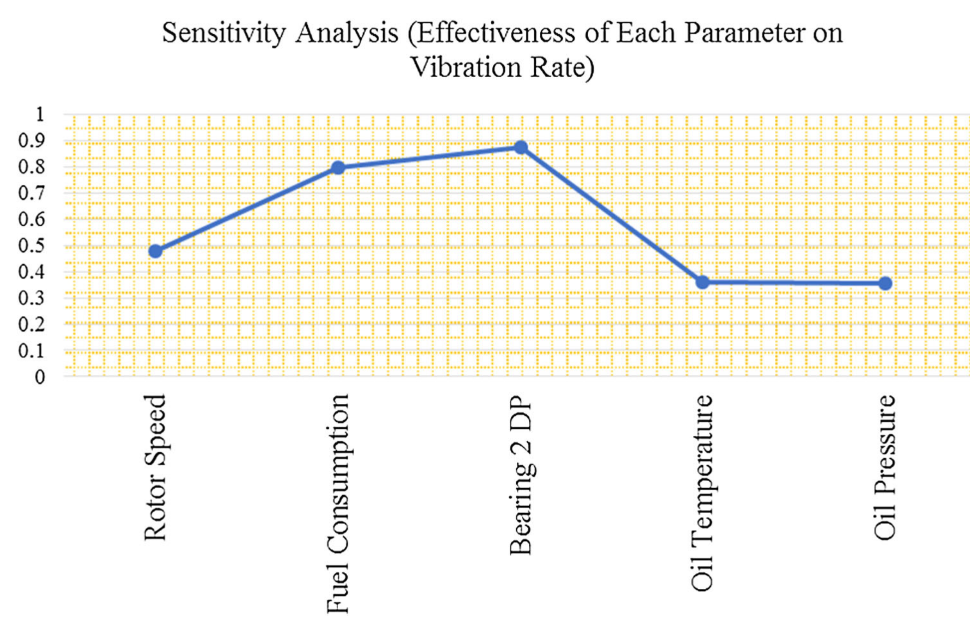
$$S_{ij} = \left[\sum_{k=1}^{n} x_{ij,n} \times x_{jk,n}\right] / \sqrt{\sum_{k=1}^{n} (x_{ij,n})^2 \times \sum_{k=1}^{n} (x_{jk,n})^2} \tag{19}$$

In this paper, n data samples and dimension numbers are 161 and 6 respectively. Figure 16 shows that vibration rate is mainly influenced by bearing #2 DP, fuel consumption, and rotor speed whereas, oil temperature and oil pressure are the least effective parameter in this regard.

5 Conclusion

It is obvious to use gas turbines in gas pressure booster stations in order to meet the requirements of compressors. In the

Fig. 16 Sensitivity analysis of vibration rate



meantime, as the cost of purchasing and maintaining such an equipment are very high, it is very important to keep them far from any damage. The most significant risks that threaten mentioned equipment and as a result the overall pressure booster system are incident of internal vibrations of gas turbines, because the failure of a turbine, results in disrupting the compressor and all its associated equipment and undergoing huge cost to the whole system. Vibrations up to a certain threshold could be ignored, but in the case of resonance vibrations we will face unpleasant and even irreparable events.

In this paper, the most important motivations to establish of a precise predictor model and a correct analysis of a gas turbine vibration consists of:

1. Online usage of prediction model to increase the system reliability (comparing with the output of installed vibration sensors or using as an alternative equipment in case of sensors failure.)
2. Informing the operator of control room about the effect of parameters on the vibration by varying their operation range (discovering the main factor of vibration among all effective factors and controlling it).
3. Calculating lifetime of blades in an unpredicted conditions by analyzing their vibration frequency (using the predictive model).
4. To prevent turbine blades from damage and erosion, so that their lifetime could be increased (increasing the working performance of the turbine).
5. To prevent from turbine emergency shutdown (ESD).
6. Economizing the time and cost of repairing damages resulted from vibration (such as blades cracking).
7. Using the proposed model to predict steam turbines vibration by considering proper operational parameters.

Also, we applied a hybrid intelligent and practical model with a low computational complexity and acceptable precision in order to predict gas turbine vibration using effective input parameters such rotor speed, bearing #2 oil differential pressure, oil tank pressure, oil tank temperature, and fuel consumption. Four criteria of X^2, RMSE, and were adopted to evaluate the proposed hybrid method and their values were obtained as much as 0.25 and 0.47, respectively. The obtained results were compared with predicted values from other predictive methods such RBF, MLP, GH-MLP and LM. Accordingly, the superiority of the proposed method was proved. Indeed, we applied cosine amplitude technique in order to determine the effect of each effective parameters on the vibration (sensitivity analysis). Based on this analysis importance of each parameter obtained and among all of the inputs was specified that the bearing #2 DP is influencing factor on vibration rate. It should be noted that to make this model, we have considered input parameters in an ideal environment and free of any excess solid material in the inner space of turbine (isolate environment). Also it is assumed that the turbine blades are free from any kind of damage.

Compliance with Ethical Standards

Funding This study is a completely autonomous research and has not been funded by any company.

Conflict of Interest Amin Zadeh Shirazi (Author A) declares that he has no conflict of interest. Majid Hatami (Author B) declares that he has no conflict of interest. Mehdi Yaghoobi (Author C) declares that he has no conflict of interest. Seyyed Javad Seyyed Mahdavi Chabok (Author D) declares that he has no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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