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FAULT DIAGNOSTIC MODEL FOR ROTATING MACHINERY BASED ON PRINCIPAL COMPONENT ANALYSIS AND NEURAL NETWORK

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ABSTRACT

In the current economic challenge, methods to accurately predict system failure has become a holy grail in maintenance with the goal to reduce the cost of unavailability due to unscheduled shutdown. This has led to the current research with the aim to achieve a more accurate fault diagnosis for rotating machinery using a neural network (NN) with principal component analysis (PCA) as a pre-processing step to fuse multiple sensor data. The multisensor data fusion has been proven to improve the fault detection ability for machinery compared to single source condition monitoring. In this paper, an NN-based methodology is presented, where PCA is applied as preprocessing step to detect the rotating machinery faults during operation. The effectiveness of the proposed model is illustrated by a case study on two shaft industrial gas turbine where the real-time performance monitoring data collected from the plant and used to train and test the proposed algorithm. The analysis results show that the PCA-based fusion process has significantly enhanced the performance of NN-based model when compared against NN algorithm without PCA.

Keywords: fault diagnosis, principal component analysis, artificial neural network, rotating machinery.

INTRODUCTION

In the industrial sector, it is imperative to maintain a high level of machine reliability and performance through rigorous maintenance programs to reduce or eliminate unexpected breakdowns, minimize unscheduled downtimes, and ultimately to reduce maintenance costs. The main rotating machinery maintenance methods are breakdown maintenance, time-based maintenance and condition based maintenance (CBM) [1]. CBM, at the moment, has been widely applied only to the machines. It is reported that 99% of mechanical failures are preceded by noticeable indicators of machine conditions [2].

In order to reduce rotating machinery downtime, increase availability and reliability, optimize the life cycle costs as well as increase the personnel and environment safety, several fault diagnosis approaches have been proposed. These techniques can be chiefly categorized into three groups: model-based, knowledge-based and data driven-based fault diagnosis [3, 4]. Model-based approaches are based on mathematical models and Kalman filters techniques are quite popular among them [5]. On the other hand, knowledge-based techniques are a rule based computer program that uses expert knowledge or causal analysis to solve complex problems. Finally, data-driven methods are based on real time data or provided historical measurements and information [6]. These techniques do not need a complicated mathematical model but able to provide worthwhile tools for solving nonlinear problems with high flexibility [7].

This paper proposes the fault diagnosis model using neural network (NN) approach based on multiple condition monitoring (CM) data. The diagnostic object can be described more comprehensively [8, 9]. The fusion of these multisensor data is the process of merging or integrating with data or information from various sensors or sources to produce a set of more specific, comprehensive and unified global model about an entity or event of interest that has been examined.

Based on the different fusion process, principal component analysis (PCA) is better for the machine monitoring, fault diagnosis and prognostics due its learning capabilities and flexibility [10, 11]. Li *et al.* [12] have presented the data fusion model for condition monitoring and fault diagnosis (CMFD) system of a diesel engine using PCA with the fuzzy neural network (FNN). Xiong *et al.* [13] have also utilized NN and PCA for the fusion of multiple data of real time ship's sensors to diagnose its faults. Li and Yan [14] have proposed fault diagnosis method based on the data fusion of oil analysis data, microscopic debris data, and vibration data using PCA.

Artificial neural network

An artificial neural network (ANN) is a computational paradigm to sort out patterns and learn from analysis and mistakes, perceptive and deriving the connections that underlie the data. The structure of a neural network (NN) consists of several processing units or neurons; each unit is linked to the others in different ways.

In this study, the multilayer feedforward neural network has been used. It can consist of an input layer, one or more hidden layer(s) and an output layer as shown in the Figure-1. The inputs will be multiplied by their adjustable weights w_i, summed and passed through a transfer function f to get the outputs, as mathematically expressed in Equation. (1). The data used as inputs is transmitted through the network, layer by layer, and a set of outputs is obtained.

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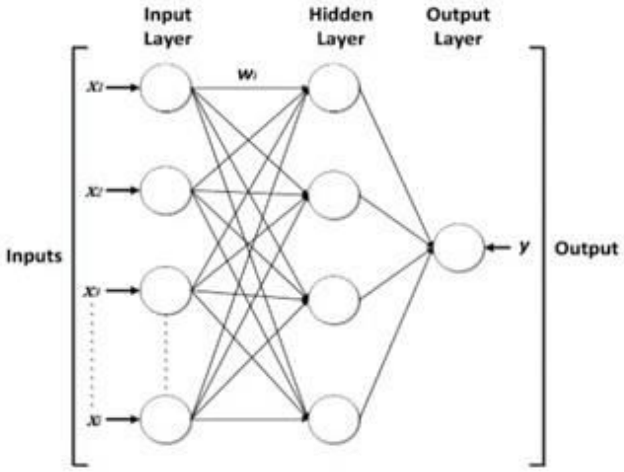

Figure-1. A multilayer feedforward neural network.

The output of neuron is mathematically calculated as;

$$y = f(\sum_{i=0}^{N} w_i x_i + b) \tag{1}$$

Where, x and y are the inputs and outputs of the network respectively. While i = 1,2,3,...N where, N is the number of neurons. In addition to this, a bias term b, is generally added to the input.

Principal component analysis

Principal components analysis (PCA) is a statistical analytical tool to explore, sort and group the data in which a large number of correlated (interrelated) variables is gathered and transformed into a number of uncorrelated variables known as principal components. Principal component (PC) is a linear combination of the original variables (1st principal component explains most of the variation in the data, 2nd PC explains most of the rest of the variance and so on).

In the present work, the PCA is used to fuse the multiple CM data parameters into one distinctive characteristic. Mathematically, consider for the data parameters X, make their parameters as the feature matrix D_{n*p} (p is the data variables and n is the total measurement samples). Then calculate the covariance matrix C_{ab} of D_{n*p}, as expressed in Equation. (2).

$$C_{ab} = \frac{1}{n-1}\sum_{i=1}^{n}(X_{ai} - \bar{X}_a)(X_{bi} - \bar{X}_b) \tag{2}$$

Where C_{ab} is the covariance matrix, while X_a and X_b are two different data variables of X. Respectively, $\bar{X}_a$ and $\bar{X}_b$ are the mean of the X_a and X_b data variables. Later compute the Eigenvalues λ_p of C_{ab} where $\lambda_1 > \lambda_2 > \lambda_p$ from the relation below;

$$|C_{ab} - \lambda_p \boldsymbol{I}| = 0 \tag{3}$$

Where $\boldsymbol{I}$ is an identity matrix. Now calculate the Eigenvectors U_p for each Eigenvalue;

$$|C_{ab} - \lambda \boldsymbol{I}| U_p = 0 \tag{4}$$

U is known as the loadings or the transformation matrix. In every principal component, the loadings are the weights of the original variables. Once these Eigenvectors are observed from the covariance matrix, the following process is to organize them by Eigenvalue, highest to lowest. This provides the PCs in order of significance.

Proposed fault detection methodology

In this section, a neural network based fault diagnosis approach has been developed using PCA as a preprocessor. PCA is employed to obtain the optimal features for training neural network. The methodology of fault diagnostic model is shown in Figure-2.

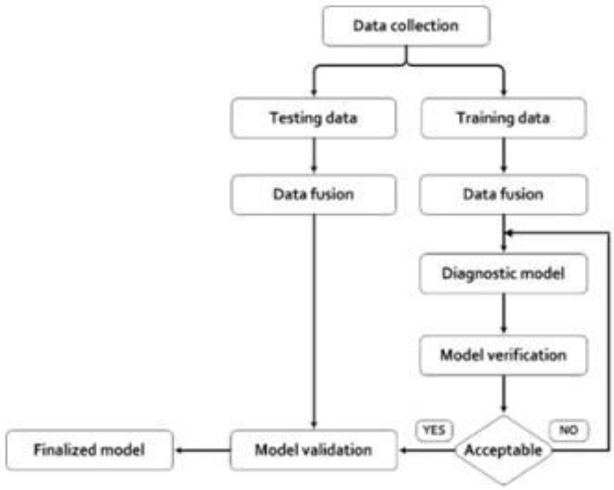

Figure-2. The flowchart of fault diagnosis model.

The training process for the proposed model is carried out by using the backpropagation algorithm. The function of the data normalization was performed before connecting the data from individual sensors to one larger data in order to limit them to the same value range i.e. [0, 1], and mathematically expressed as in Equation. (5).

$$Nx = \frac{(x - x_{min})}{(x_{max} - x_{min})} \tag{5}$$

Where x is the input data and Nx is the normalized input data. While x_{min} and x_{max} are the minimum and maximum values of the input data x.

In this study, three different training functions of the network functions as Levenberg-Marquardt (LM), Bayesian regulation (BR), and Scaled conjugate gradient (SCG) algorithm are selected due to good learning and fast processing capabilities [15]. The diagram of neural network based model is depicted in Figure-3.

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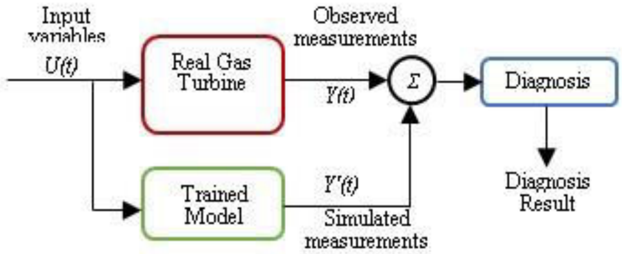

Figure-3. Neural network architecture proposed for fault diagnostic.

Where in Figure-3, $x(t)$ is the CM data as the input to network with the time t. While $y(t)$ is the actual obtained output of the machine and $y'(t)$ is the calculated output of the trained network based on the collected machine CM data. On the other hand, $r(t)$ is the generated residual signal.

Case study

In this paper, an industrial case study using industrial gas turbine (IGT) is carried out to assess the effectiveness of the proposed technique. The detailed information of the turbine is summarized in Table-1.

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	

A total of 4200 data samples after pre-processing are used to train and test the network.

RESULTS AND DISCUSSION

The main objective of this paper is to detect the faults of the IGT using the proposed model. The proposed model was evaluated with two case studies of two different network outputs. For the presented case studies, we have selected the power output (PO) and fuel metering (MF) data parameters individually as the outputs of the network from the nine obtained data measurements. Both of these parameters have a key role in evaluating the performance of the gas turbine. Apart from these two quantities, other quantities can also be chosen as the network output parameter.

Case-1

In this section, PO data parameter is selected as the network output of the proposed model. The remaining eight data measurements were used as inputs to the network, layer by layer, and subsequently, a set of output data were acquired. The eight collected CM data parameters are used to fuse into one single output using PCA. Figure-4 depicts one example of the fused output of testing dataset.

The result shows that the degradation process started at time 227min, as illustrated in Figure-5. While at time point 1189min, engine bell-mouth was totally broken and the turbine was shut down. The proposed model has diagnosed the engine bell-mouth fault of IGT at very early stage, as the generated residual signal is swiftly raised with the fault detection.

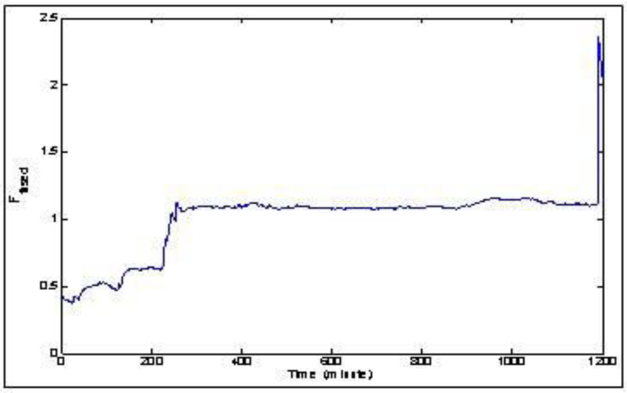

Figure-4. Data fusion of testing data set with PO as target.

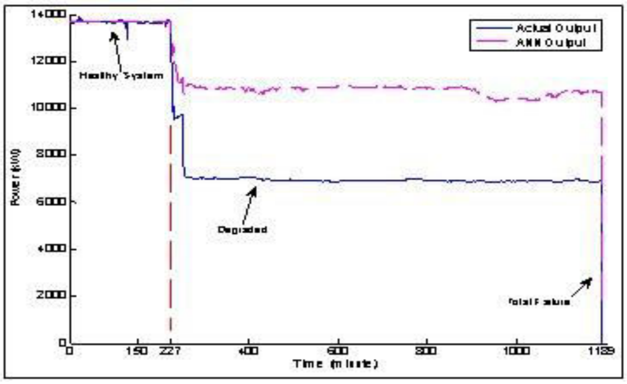

Figure-5. Comparison between actual and network output data using LM training function with PO as a target.

Based on the residual signal theory, one can easily detect the fault in the turbine when error graph crosses the defined threshold limit, as shown in Figure-6. In this study, the failure threshold is defined as 6.0% for IGT data measurements. The residual error is suddenly increased up to 40% as the fault was diagnosed in the engine bell-mouth of the turbine. The performances of the model are measured using mean squared error (MSE) and mathematically expressed in Equation. (6). The mean squared error is arguably the most important criterion used to evaluate the performance of a predictor or an estimator.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y(t) - y'(t))^2 \tag{6}$$

Where $y(t)$ is the actual IGT output data, $y'(t)$ is the network output data and N is the number of

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observations in the dataset for which the model is made. The MSE is calculated on the normalized data parameters.

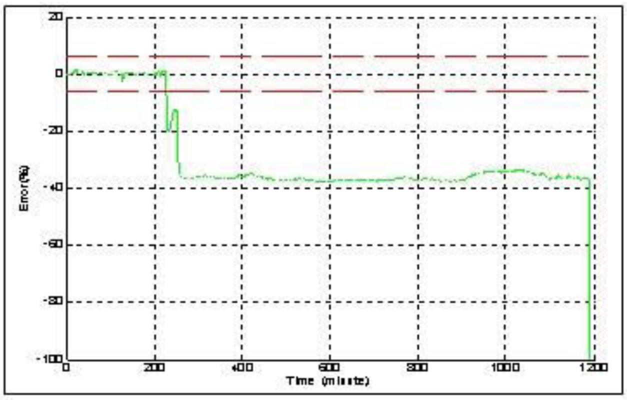

Figure-6. Calculated residual error using LM training function with PO as a target.

The maximum MSE of training and testing datasets for each training functions of the proposed model were calculated as shown in Table-2. The result shows that LM is the good training function for the power output parameter rather than two other training functions with the minimum MSE error.

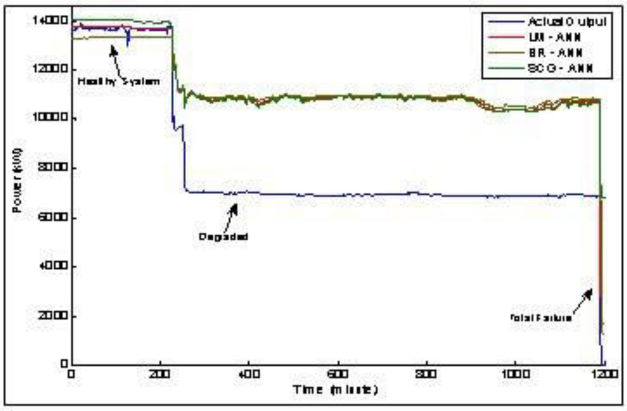

Figure-7. Comparison between actual and network power output data using LM, BR, and SCG training functions with PO as a target.

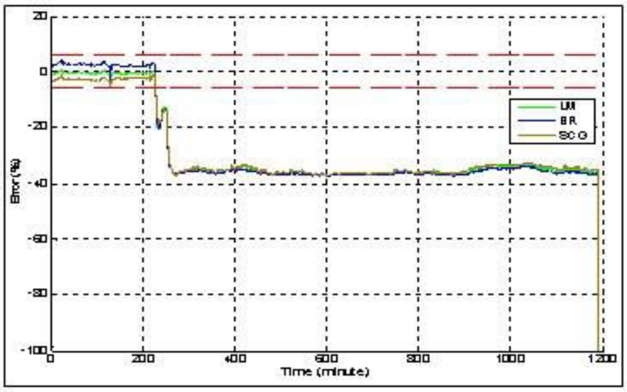

Figure-8. Calculated residual error using LM, BR, and SCG training functions with PO as a target.

Case-2

In this section, for further validation of the proposed model fuel metering (MF) data parameter is this time selected as the network output. The three collected sensor variables (temperature, pressure and flow rate) associated with fuel (methane) were analyzed to form one variable. This was done by utilizing the perfect gas equations [16]. To do so, the density of fuel has been calculated by applying the general gas law at the given temperature and pressure using molar mass of flow and gas constant, as declared in Equation. (7). In the result, the volumetric fuel flow rate has been converted into the respective mass fuel flow rate values.

$$PV = nRT \tag{7}$$

$$\frac{m}{M}/V = P/RT \tag{8}$$

The Equation. (8) is further simplified to the final Equation. (9);

$$M_f = d * Q_f \tag{9}$$

Where, T, P and d are the fuel temperature, pressure, and density. R is general gas constant respectively. Moreover, M_f is fuel molar mass and Q_f is volumetric fuel flow rate.

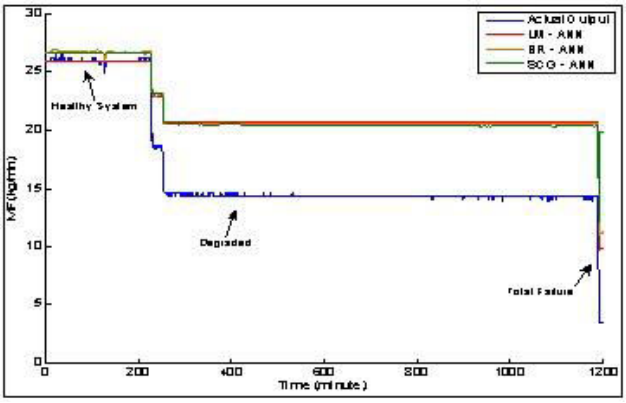

Figure-9. Comparison between actual and network output data using LM, BR, and SCG training functions with MF as a target.

Table-2. MSE performance of different network training functions.

Network Output		Training Function					
		PCA			No PCA		
		LM	BR	SCG	LM	BR	SCG
PO	Training	0.00173	0.00178	0.00193	0.0071	0.0089	0.0088
	Testing	0.0563	0.0630	0.0632	0.144	0.154	0.224
MF	Training	0.0050	0.0051	0.0054	0.044	0.051	0.053
	Testing	0.0597	0.0621	0.060	0.217	0.230	0.216

It can be seen from Table-2 that data fusion of the input data using PCA is beneficial for both the network outputs of proposed model.

CONCLUSIONS

Due to the complex nature of rotating machinery, data from a single sensor is not capable of providing enough information enough for accurate condition monitoring and fault diagnosis activity. This paper presented the new method to improve fault diagnosis for based on PCA and ANN techniques utilizing multi-sensor data. The performance of the proposed scheme is finally demonstrated by the results obtained from the simulation of a two-shaft industrial gas turbine real data.

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