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VIBRATION-BASED DIAGNOSTIC OF STEAM TURBINE FAULTS USING EXTREME LEARNING MACHINE

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ABSTRACT

Automatic detection of faults and accurate diagnostic of them is very critical task in turbo machinery. Vibration signal is one rich source of information about turbo machinery conditions. Steam Turbine ST is one example of high-complicated tubro-machinery process where a mathematical modeling of its components is not easy. In this context, we propose an Artificial Neural Network ANN based model for condition monitoring of ST based on vibration signal. Four High Pressure HP vibration variables for rotor in ST are analysed. Fault trends are inserted in the same time interval. Time domain shapelet features are extracted, and used to train one hidden layer, feed-forward, ANN using Extreme Learning Machine ELM training method. The outcome is a condition-monitoring model based on artificial neural network ANN. Root Square Mean Error (RMSE) is reported as a validation measures for different neurons numbers, and activation functions. ELM based neural network showed a convergence toward less than 10% RMSE for more than 60 neurons in hidden layer.

Keywords*: Fault diagnostic; Vibration; Steam Turbine (ST); Artificial Neural Network (ANN); Extreme Learning Machine (ELM); Classification*

1. INTRODUCTION

A fault diagnostic system can be defined as the system that includes the capability of detecting, isolating, and identifying the fault [1], [2].Fault monitoring and diagnostic of rotary machinery is a quite important task. Typically, carrying this task is difficult and costly because it requires human being in the loop of production. Therefore, it is very essential for reducing the dependence of labors to have an automated fault detection and identification. In other words, the goal of any fault detection and identification system is to replace experts by a fully automated diagnostic system. Fault diagnostic can increase the efficiency of the system functionality, reduce the cost, and avoid the possible damage that might result from the system shutdown or any caused catastrophe.

Power plantsare very dependent on fault diagnostics systems. Because they are designed in a way that it should allow for working without any interrupt; any shutdown due to a sudden failure can cause serious economical damage. Moreover, this type of generator cannot be stopped temporary for any inspection. Therefore, an automated intelligent diagnostic system has to be developed and enabled to work simultaneously while machines are generating power [3].

In this context, we propose an Artificial Neural Network ANN based model for condition monitoring of ST based on vibration signal. Four High Pressure HP vibration variables for rotor in ST are analyzed. Fault trends are inserted in the same time interval. Time domain shapelet features are extracted, and used to train one hidden layer, feed-forward, ANN using Extreme Learning Machine ELM training method. The outcome is a condition-monitoring model based on artificial neural network ANN. Root Square Mean Error (RMSE) is reported as a validation measures for different neurons numbers, and activation functions. All result data are discussed with future work and recommendations.

The rest of the paper is organized as following: Section II introduces reviews of state-of-the-art literature of fault diagnostic using ANN methods. Our methodology is presentedin section III. Results are given and discussed in section IV. Section V contains conclusion and future work.

2. RELATED WORKS

The literature of turbo-machinery diagnostic systems is full with different techniques. Traditional diagnostic of faults is developed using the concept of signal processing in time, frequency, or both domains [4], [5]. Neural Network is very powerful technique to perform fault diagnostic of rotary machinery comparing with other approaches such statistical based techniques [6], signal processing based [7]. ANN attracts researchers for diagnostic application due to two factors. The first one is the learning ability. The second one is its capability to handle the non-linearity in the real world diagnostic problems. See [8].In [9]multi-layer feed-forward neural network for detecting of rotor propagating cracks in rotary machinery based on vibration data was presented. The neural network is trained by using vibration data with/without propagating cracks. In this approach it was proven that simple two-layer feed-forward neural network is capable of identifying propagating crack while three-layers feed-forward neural-network is capable of detecting both propagating and non-propagating cracks. It was found that increasing the number of neurons in hidden layers improves the accuracy of identification. In [9] a neuro-fuzzy diagnostic system for faults in water pumps set in oil plants has been proposed. The fuzzy neural network can memorizes patterns of faults and the associated fault type. It was compared with other distance based diagnostic systems and with back propagation neural network. The finding was the fuzzy neural network has a better recognition rate.

In [10] a seven type of faults are classified by using two models: an artificial neural network (ANN) and multi-support vector machine (M-SVM).

In [11] a neural network based system for condition monitoring of rotating mechanical machine have been introduced. A genetic algorithm was used to help to select the best features as inputs for the neural network and to optimize the structure of the neural network. This improved the speed of the identification process.

3. METHODOLOGY

Our methodology is combined of phases in processing, analyzing, and then training a neural network by using Extreme Learning Machine (ELM) to deliver a decision about the status of the steam turbine. Firstly, data is collected and vibration variables - which represent our concern-are extracted. Then, data cleaning is applied. Data size is relatively small. Therefore, an interpolation is applied on the data. Next, simulated trends of error are inserted. Then, data is normalized between negative one and positive one. Finally, ELM is used to train one hidden layer feed-forward neural network. Performance is evaluated by using RMSE evaluation measure.

3.1 Dataset

Data were collected from a ST station. More than 1000 variables are included in the data file. However, only vibration signal is under concern. Vibration variables are isolated from the data sheet. They consist of 34 variables. We tested onone phase of rotor vibration variables of fourphases: HP, IP, and LP, and in the generator.The number of variables in each phase is 4. See table -1-.

3.2 Data Cleaning or De-noising

Sensor data are likely to be interfered with noise that has a nature related to the sensing concept, the measured signal physical attributes, and to the environment nature. Research has shown that vibration data in turbines is likely to be affected with background noise. Therefore, it is important to select some proper method to de-noise vibration data. The method that is selected in this framework is a low pass filter of type of moving average window.Window of size 3 is applied on the data.

3.3 Interpolation

Interpolation was used for increasing the framerate of the data from one sample in one minute to two samples in one minute. More size of data adds more reliability to the result of training the ANN based system. Piecewise polynomial interpolation was chosen. It has the capability of optimizing the smoothness of the fitted curve while passing through all the data points. Also, using it has the advantage of reducing the order of degree polynomial function because in each subinterval different polynomial is selected.

3.4 Error trend Simulation

Two types of rotors faults were simulated through adding their frequency components to the rotor vertical and horizontal vibration. In order to indicate to the fault status, A Boolean variable was created. This variable gets the value one in the time interval when the fault trend exists and zero otherwise. The ANN diagnostic part is supposed to be trained on the two vertical and horizontal variables as inputs, and on the Boolean fault status variable as output.

3.5 Data normalization

It is important to point out that Data was subject to data normalization in order to limit the values of the data between 0-1. This step is needed because the neural network is trained on the relative change in the input not on the absolute values.

3.6 Feature extraction

Shapelets are subsequences of the time series that are represented by vibration signals in this research [12]. These features have many benefits; it provides ANN with memory. The reason is that the decision is relied on a collection of samples distributed on an interval of time. Subsequently, it increases the potential of capturing better knowledge about the dynamics behavior of the vibration signal collected from the turbine in both: healthy, and unhealthy conditions.

3.7 ELM based ANN

The data is combined of N arbitrary distinct samples (x_j, t_j) where $j = 1, \dots N$ where $x_j = (x_{j1}, x_{ij}, \dots, x_{jn})$. It is possible to model standard Single Hidden Layer Feed-forward Network (SLFN) with an activation function $g(x)$ and $\tilde{N}$hidden layer neurons as following:

$$\sum_{i=1}^{\tilde{N}} \beta_i \, g\big(w_i x_j + b_i\big) = t_i \qquad (1)$$

where

$j = 1, \dots N$, $w_i = (a_{i1}, a_{i2}, \dots, a_{in})^T$, b_i is the threshold of the ith hidden node, and β_i is the weight connecting the ith hidden node and the output.

Another more compact form of the equation is:

$$H\beta = T \qquad (2)$$

Where

$$H = H(a_1, a_2, \dots, a_{\tilde{N}}, x_1, x_2, \dots, x_N, b_1, b_2, \dots b_{\tilde{N}})$$

$$H = \begin{bmatrix} g(a_1 x_1 + b_1) & \dots & g(a_{\tilde{N}} x_1 + b_{\tilde{N}}) \\ \vdots & \ddots & \vdots \\ g(a_1 x_N + b_1) & \dots & g(a_{\tilde{N}} x_N + b_{\tilde{N}}) \end{bmatrix}$$

$$\beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_{\tilde{N}} \end{pmatrix}$$

Where H is called the hidden layer output matrix of the neural network. It has been proved by (Huang, Zhu and Siew, 2006) that if the activation function is differentiable then the required number of the hidden layer neurons is lower than the data size.

The training algorithm of the ANN described above is introduced in three steps as following:

1. Assign randomly random weights and biases as w_i, and b_i.
2. Calculate the hidden layer output matrix.
3. Calculate the output weights β by using the equation

$$\beta = H^{T}T$$

Where H^{T} is the Moore-Penrose generalized inverse of hidden layer output matrix.

4. RESULTS AND DISCUSSION

Data was partitioned into two groups: 50% training and 50% checking. The purpose of the testing data is to avoid over-fitting. The evaluation on testing data is needed to be confident that the estimation on training data is over-fitting free.

We selected four vibration variables from HP phase of ST. See table--.

Table-1: four variables selected from hp phase for diagnostic

Components	Variable description
V1	HP Front Rotor Vertical Vibration
V2	HP Front Rotor Horizontal Vibration
V3	HP Rear Rotor Vertical Vibration
V4	HP Rear Rotor Horizontal vibration

Data visualization was done to check about any data gap or corruption. Figure -1- shows the four variables. Then data is normalized between 0 and 1. See figure -2-

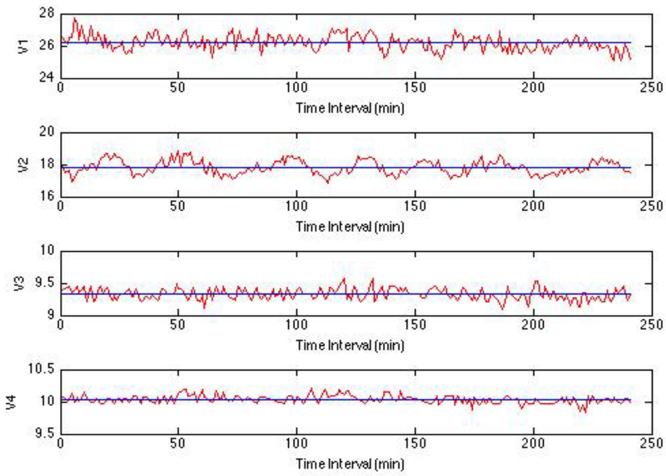

Figure 1: HP four rotor vibration variables

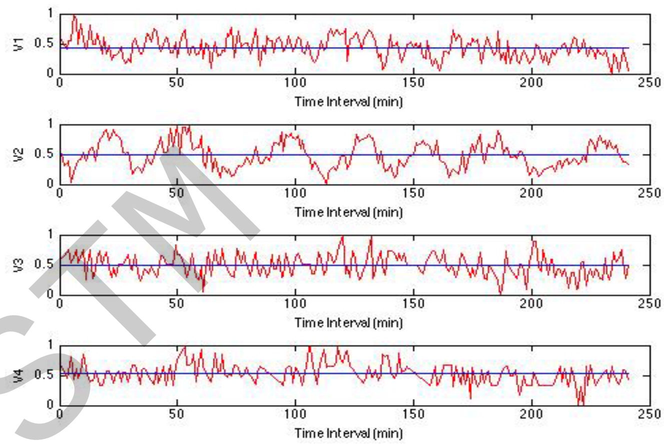

Figure 2: HP four rotor vibration variables after initial normalization.

Next, data is interpolated in order to have more data size for feeding the neural network. Then faulty trend is added to the four variables between sample 200 and sample 300. As shown in figure -3-

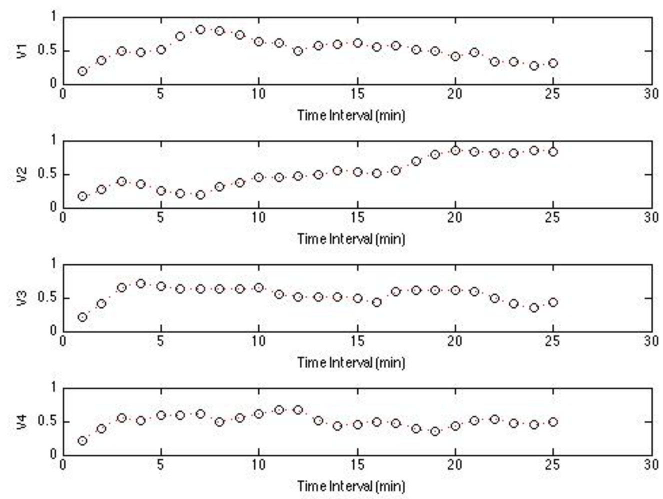

Figure 3: HP interpolation of vibration variables.

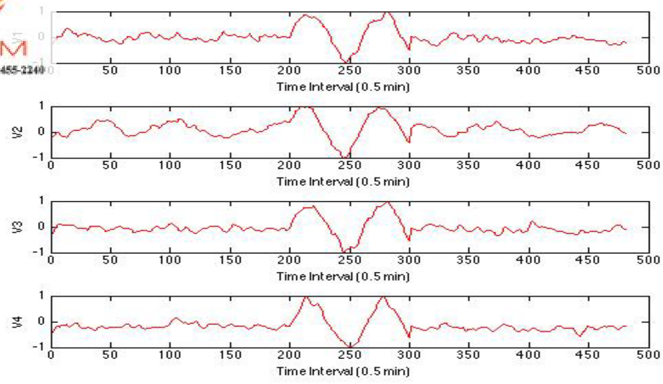

Figure 4: Inserting error trends between sample 200 and sample 300.

Shapelets or time series subsequences are used as features. Figure –5- shows shapelet features extracted from variable v1. Each shapelet can be considered as an input to ELM. As shown in the figure, the decision is based on the shapelet if it is a part of the error trend or not. When shapelet is a part of the error trend then the corresponding output is positive one. Otherwise, it is negative one.

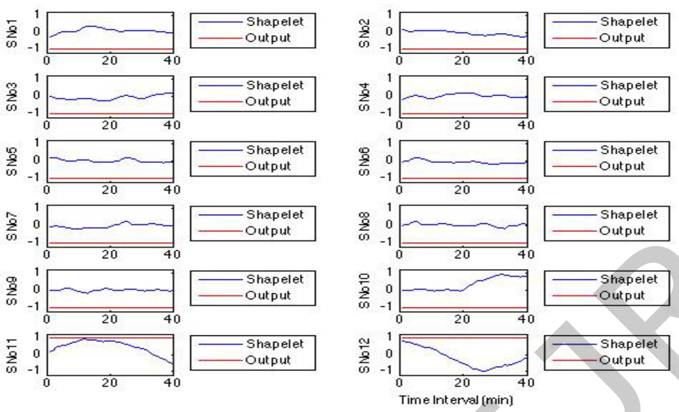

Figure 5: Shapelet features extracted from variable V1.

For evaluation of the method RMSE measure is plotted against number of neurons in hidden layer. Performance was outstanding. Four activation functions are tested: radial basis function (RBS), SIN, Hardlim, and Sigmoid. All of them have converged toward less than 10% error for more than 60 neurons in hidden layer. Sigmoid and RBF showed faster convergence. See figure.

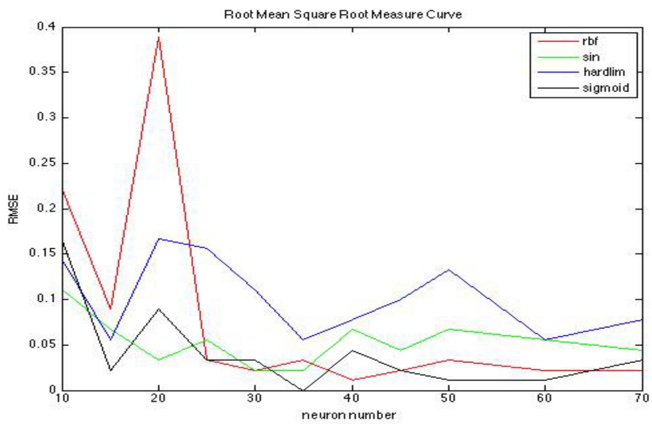

Figure 5: RMSE evaluation measure with four different activation functions

5. CONCLUSION

In this paper, four vibration variables are collected from steam turbine. Four error trends are inserted. Then shapelet features are extracted and used to train a neural network using ELM training method. Four activation functions are tested with different number of neurons in hidden layer. ELM based neural network showed a convergence toward less than 10% RMSE for more than 60 neurons in hidden layer. This performance proves the concept of using ELM for fault diagnostic based on vibration signal. Future work is to further verify this diagnostic system on faulty data with different type of faults.

REFERENCES

[1] Patton R, Uppal F, Lopez-Toribio C. Soft computing approaches to fault diagnosis for dynamic systems: a survey.*European Journal of Control.*7.248-286.2001.

[2] Haghani Abandan Sari A. Data-driven design of fault diagnosis systems. *Springer*. 1.128.2014.

[3] Hussey A, Hesler S, Bickford R. Automation of Troubleshooting and Diagnostics of Power Plant Equipment Faults. *Proceedings of 53rd ISA POWID Controls & Instrumentation Conference*. 6-11.2010.

[4] Yu J, Yip L, Makis V. Waveletanalysis with time-synchronous averaging of planetary gear box vibration data for fault detection, diagnostics, and condition based maintenance. *IEEEXplore*1:1-132. 2010.

[5] Chow T, Hai S. Induction machine fault diagnostic analysis with wavelet technique. *Industrial Electronics, IEEE Transactions on.51*(3):558-565.2004.

[6] Yufeng M, Yibing L, Hongwen A. Statistical analysis of steam turbine faults. *IEEEXplore*2413-2417.2011.

[7] Rongtao H. The Research and Application on Wavelet Energy Eigenvalues of a Faulty Generator Set. *IEEEXplore*530-534.2007.

[8] Shuting W, Heming L, Yonggang L. Adaptive radial basis function network and its application in turbine-generator vibration fault diagnosis. *IEEEXplore*3:1607-1610.2002.

[9] Zhang Y, Zhou Z, DongX. Design and Implementation of Real-Time Diagnostic Expert System in Nuclear Power Plant [J]. *Atomic Energy Science and Technology*. 4:009.2006

[10] S. Devi, L. Sivakumar. An Innovative Approach in Fault Diagnostic of Steam Turbine Performance Using ANN and M-SVM Algorithms. *IREME*,8(2),350-359.

[11] A Saxena, A Saad. Classifier for condition monitoring of rotating mechanical.systems. *Applied Soft Computing,7*(1),441-454. 2007.

[12] Arathi, M. (2014). An Efficient and Accurate Time Series Classification Using Shapelets. *IJIEE*, *4*(5).

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