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Methodology for short-term performance prognostic of gas turbine using recurrent neural network

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***Abstract*— The issue of performance prognosis has been a topic of considerable interest in industrial condition monitoring applications. An innovative data driven prognostic methodology has been introduced in the current study by utilizing artificial recurrent neural network (RNN) approach which intends to improve the capability of equipment performance prediction within a specified short time bound even with limited available data. The ability of the approach is demonstrated using condition monitoring parameters collected from a 20 MW industrial gas turbine. An appropriate selection and fusion of measured variables has been employed to feed RNN with the most influential performance information. The analysis demonstrated that the developed prognostic approach has a great potential to provide an accurate short term forecast of equipment performance which can be invaluable for maintenance strategy and planning.**

Keywords—condition-based maintenance, condition monitoring, performance prognostic, gas turbine, recurrent neural network, Elman network

I. INTRODUCTION

With growing application of gas turbine engines, maintenance play a crucial role in increasing overall profit as well as the safety of plant personnel and the environment. Recently, to sustain industrial gas turbine reliability and availability, the costly maintenance strategies such as corrective maintenance and time based preventive maintenance have been replaced by condition-based maintenance (CBM). Given the size, scope and complexity of gas turbines, it is becoming difficult for users to anticipate, diagnose and control serious abnormal events in a timely manner. In this circumstance, the main idea of CBM is strategized a predictive maintenance of equipment using the information obtained from condition monitoring (CM). Therefore, development of robust monitoring systems, which includes health assessments, prognostic and diagnostic is one of the key focuses for gas turbine users. This condition monitoring system would assist maintenance engineers in making appropriate decision to support maintenance action.

Today, the ability to first detect impending faults and then predict their future progression based on its current state and available operating data is a big challenge for machinery engineers. This unfold the importance of prognostics which in fact is the ability to predict future health of system for a specified time horizon, or in other words to predict the time to failure. In an integrated condition monitoring system, this module is critical for a smart maintenance scheduling and mission planning in order to reduce machine down time and therefore the maintenance cost. Prognostic is the core of condition-based maintenance, which can be implemented using different methods and techniques. An extensive review of progress in rotating machinery prognostics has been presented by Heng et al. [1]. Also Vachtsevanos et al. [2] investigated several intelligent fault prognostic techniques for various industrial applications. Moreover, Jardine et al. [3] summarised research and developments in prognostics of mechanical systems with emphasis on models, algorithms and technologies for data processing and maintenance decision-making.

Achieving the best possible prediction on a complex system such as gas turbines is often implemented using wide range of historical information, data fusion concepts, and algorithmic techniques. There are several important papers, mostly published in the last decade that treat prognosis of gas turbine defects based on performance health monitoring and/or mechanical condition monitoring, including works by Roemer et al. [4]; Lazzaretto and Toffolo [5]; Barad et al. [6]; and Li and Nilkitsaranont [7].

Due to its nonlinearity and adaptability properties, artificial neural network (ANN) is known as one of the most effective forecasting approaches. ANN models are fundamentally non-linear methods with adjustable weights. A collection of input/target data may be utilized to adjust the weights and train the ANN model. In order to perform a time series prediction, neural network can be trained as a generic non-linear mapping tool between a collection of machine history data and the forthcoming time-based values. Some published works for multi-step ahead condition prediction of industrial equipment using ANN could be found in [8-10]. Various neural network models have been used by researcher for this purpose, however as discussed by Tian and Zuo [11], recurrent neural networks which mainly comprised of Jordan network and Elman network, have achieved great interest among researchers. This approach firstly introduced by Elman [12] is a two-layer back propagation network with the addition of a feedback connection from the output of the hidden layer to its input. This feedback path allows Elman network to learn recognizing and generating temporal patterns, as well as spatial patterns. In order to investigate a framework for short-term performance prediction

of gas turbine, this paper attempts to develop an intelligent prognostic model based on Elman recurrent neural network (ERNN).

II. Prognostic Assessment

The performance of a gas turbine engine deteriorates during operation due to component degradation or malfunctioning of flow path entities. Monitoring these deteriorations could assist in finding an optimized maintenance schedule in order to reduce gas turbine downtime, increase availability and reliability, optimize the life cycle cost, decrease annual fuel consumption, and finally lessen the harmful environmental impacts. As discussed by Brotherton et al. [13], life monitors are usually based on statistics gathered over a large population of components. Sometimes physical models are included, however, even these models are a measure of an average component's health and do not account for the history of the specific component being monitored.

Component life monitors are coarse and all are essentially based on measuring "time" in some fashion (for example "cycles"). Fig. 1 demonstrates the principles of prognostic analysis which is necessary to be addressed. The figure shows the trajectory of a machine component's health as a function of time. When the component is new, its health is considered 100 percent. As time goes on and the component begins to wear out, its health, defined here somewhat arbitrarily, drops. There are two variations of the prediction problem. The first prediction type may have just a short horizon time—is the component able to operate in short future, say 7 to 10 next days. The second type is to predict how much time remain before a particular fault occurs and, by extension, how much time before necessary system stoppage for repair [14].

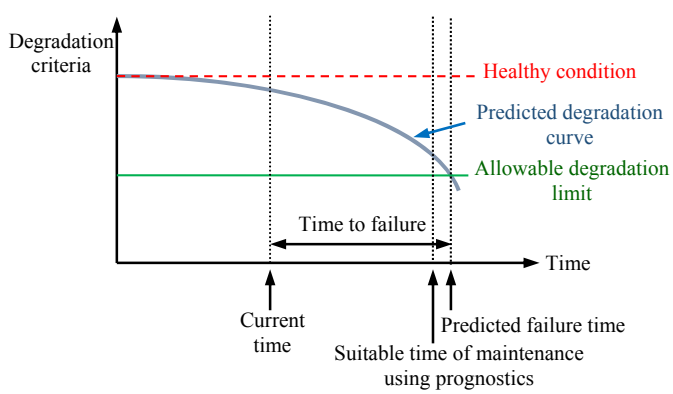

Fig. 1. Principles of degradation and equipment prognosis

This paper discusses the development of a prognostic algorithmic approach that has been demonstrated within gas turbine engines with the ability to predict the short term future performance. This model could provide many benefits including:

- Improved safety associated with operating and maintaining of gas turbine engines.
- Reduced overall engine life cycle costs from installation to retirement.
- Ability to prioritize necessary tasks for the impending maintenance event.
- Increased up-time of all machine within a fleet.
- Provides engineering justification for scheduling maintenance actions
- Reduction of failure frequency

III. Features of a Prognostic System

Prognosis is usually based on information measurements and historical information collected from of gas turbine operation. Fig. 2 shows the generic methodology to develop a prognostic system for gas turbine engine.

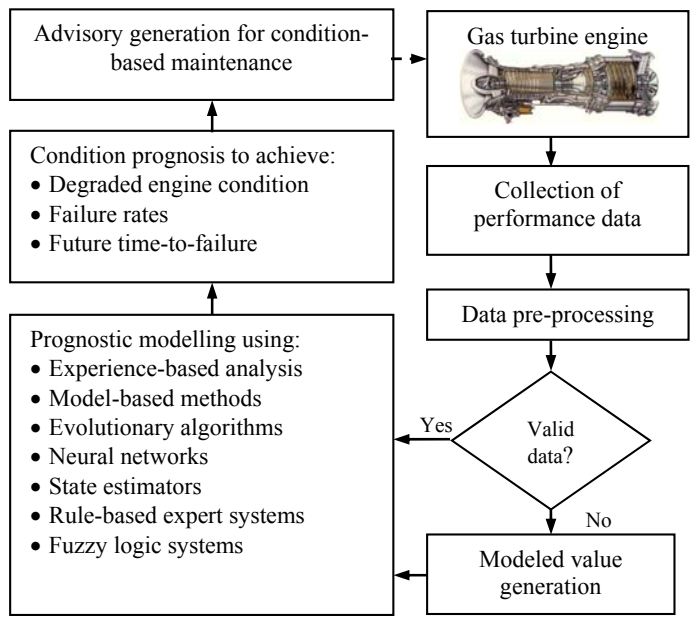

Fig. 2. Generic methodology to develop a prognostic system for gas turbine

This intelligent prognostic model consists of several key steps described in following.

Data collection: The various parameters that have been considered for prognosis are classified as direct measured parameters and derived parameters. The selection of these parameters is critical and can be further refined if one is looking for a particular phenomena. The situation differs to a great extent in case of a developmental engine program wherein the data is limited, engine configuration is not frozen, manufacturing deviations are accepted due to various constraints, and finally test schedules differ significantly.

Data pre-processing: Uuncertainties associated to noise and bias are great challenges in the forecasting of turbine degradation and gas pass analysis. In order to reach more reliable monitoring results, it is crucial to clean the measured information prior to analysis. Recently, to filter measurement noise and advance the input data quality, neural network [15] and genetic fuzzy system [16] based methods have been introduced as alternatives to the moving average and exponential average methods.

Data-Validation: Then, the measurements should be analyzed to determine if they are valid, i.e., they are within expected operating ranges. If any sensor is determined to be faulty, the observed value will be substituted by modeled value.

Prognostic modelling: Following the data validation, the data are processed by prognostic modules. Different prognostic techniques such as experience-based analysis, model-based methods, evolutionary algorithms [17], neural networks [8], state estimator, rule-based expert systems, fuzzy logic system and neuro-fuzzy [18] were investigated by many researchers.

Condition prediction analysis: Once prognostic modeling completed, results could be analyzed to determine engine deterioration condition, failure rate and future time-to-failure. Final output of this approach assists maintenance engineers for decision making in an integrated condition-based maintenance procedure.

IV. Features of Proposed Prognostic System Using RNN

This section demonstrates how RNN can be implemented to forecast gas turbine faults. The principle concept is to use the nonlinearity, adaptability and ability of arbitrary function approximation to predict a sequence of values in time series basis. The neural network model that was used for prediction in this study is an Elman network based model with the additional capability to find best network automatically and use early stopping method to solve over-fitting problem.

A. Recurrent Neural Network

While RNN has the ability to learn dynamics nonlinearity of equipment without the need to derive complicated mathematical models, recently, this technique also has been extended to machinery prognostics. The principle of this approach for time series prediction has been investigated by Connor, Martin et al. [19]. The architecture of RNN is like a feed-forward neural network, and also some additional feedback links has been added. Researches demonstrate that this closed loop structure would help the RNN to take the temporal manner of dynamic system. The model is a two-layer network with feedback from the first-layer output to the first layer input. This recurrent connection allows the Elman network to both detect and generate time-varying patterns. This network comprises three layers, namely input, hidden and output layers respectively. The input signals transmit through the nodes in the input layer, and then combine the feedback signals from the output layer to the hidden layer, where the combined signals are processed by the nodes using sigmoid activation functions. Next, the node in the output layer is activated via a linear function, where receiving the signals from the hidden layer and the output signal are obtained.

B. RNN Training Procedure

When the RNN is used for predicting a certain output/forecasting parameter, it should be trained with x_t, x_{t-q}, x_{t-2q},..., $x_{t-(R^1-1)q}$ as input and x_{t+q}as the desired output. In other words for these predictors, the input variables $p = \{x_{t-(R^1-1)q}, \dots, x_{t-2q}, x_{t-q}, x_t\}$, and output variable $y = a^2(k) = x_{t+q}$ are the performance assessment criteria that monitor the equipment health condition. Here, q denotes the forecasting step and R^1 represents the number of previous time steps; e.g. when q=4 and R^1=3, the purpose of network is to forecast four-step-ahead by using three value of past historical data, i.e. x_{t-8}, x_{t-4}, x_t. Collected historical machine measurements are utilized to train the RNN predictors. This network utilizes the gradient descent approach to tune its parameters. The training process terminates when proper training error has been attained or the number of training iterations reached a specified value. The proposed ERNN model is shown in Fig. 3.

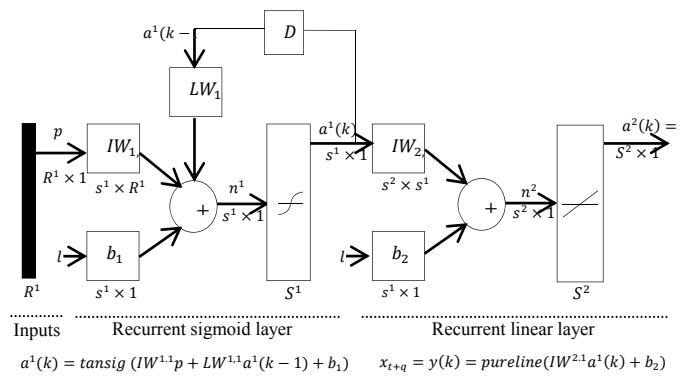

Fig. 3. Two-layer Elman Recurrenet Neural Network proposed in this study

C. Optimal Number of Nodes

To construct the network, the corresponding number of node in each layer should be determined in advance. The increase of nodes in input and hidden layer may improve the forecasting accuracy, but the computational complexity is increased as well [20]. In order to solve this problem, an innovative method has been used to find the best network automatically. To do this, firstly, the maximum number of nodes in input and hidden layer is considered equal to n and m, respectively. In consequence, $m \times n$ different networks can be created. Then, by using training and validation data sets, each of these networks is evaluated. The root mean square error (RMSE) was used to compare the performance of different models. When training finish, the network with best performance is chosen as the most suitable network and the corresponding number of nodes in its input and hidden layers will be number of hidden units and input lags.

V. Performance Simulation and Gas Turbine Prognostics

Nowadays, Industrial Gas Turbine (IGT) is one of the most versatile items of turbo-machinery. It can be used in several different modes in critical industries such as power generation, oil and gas, process plants, transport, and domestic applications. Consequently, present research investigates performance degradation and prognostics of gas turbines. Degradation can be recognized as the deviation in performance from that when the engine was new. There are always some projects where a pronouncement is made that efficiency is not of importance because fuel is free. This is a mistaken notation since firstly

there is always an opportunity cost associated with excessive fuel usage. In addition, performance deterioration results in higher turbine temperature for a given power and this leads to increased hot end degradation. If the turbine is temperature limited, then there will be a loss of power. Further, there is a close linkage between mechanical reliability and performance deterioration. An example would be the damaging effects of fouling on balding integrity. Generally, some most important possible faults of gas turbine can be classified into four categories as illustrated in Fig. 4.

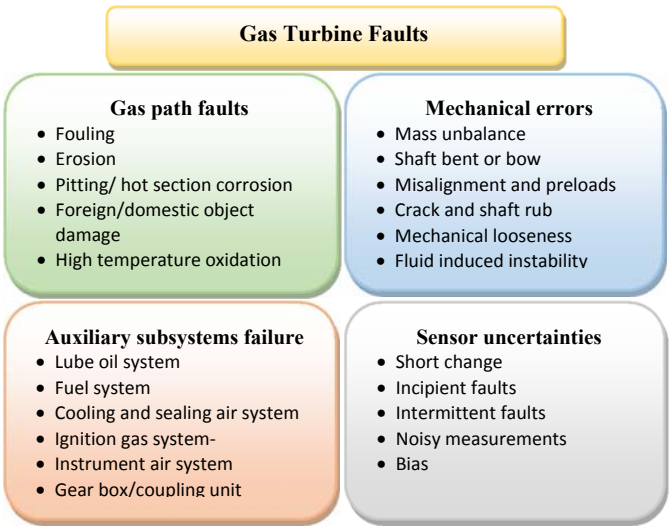

Fig. 4. Possible faults in gas turbine

When the emphasis of current research is to predict gas turbine engine performance deterioration, and since several problems which manifest themselves as mechanical errors may in fact have underlying causes that are performance related in nature [21], investigating a prognostic algorithm related to gas path faults will be of a great importance. Therefore, to make the prognostic approach described in this study applicable, it is assumed that only performance related defects which develop gradually over time and has a strong impact on turbine efficiency are discussed.

VI. Brief Description of Industrial Case-Study

The case study machine investigated in this study is a two-shaft GE LM2500 engine which has both industrial and marine applications. This gas turbine which is produced by General Electric Aviation and installed in an oil and gas offshore plant is shown in Fig. 5. Since the LM2500 had an initial design rating of 25,000 bhp, the engine family designation is determined by taking the nominal brake horsepower rating and dividing it by 10. In the industries, LM2500 gas turbine is used for power generation and combined heat & power as well as driver of other machinery such as compressors. The compressor part of this gas turbine is axial flow type and includes sixteen stages with an overall pressure ratio of 18:1.

Annular type combustion chamber utilizes a lean premix combustion system and is designed for operation on natural gas fuel. High pressure turbine (HPT) which extracts energy from the gas stream to drive the compressor has two stages of blades with a nominal speed of 9000 rpm. Power turbine (PT) consists of 6 stage blades with a nominal speed of 3000 rpm and is aerodynamically coupled to the gas generator and is driven by the HPT exhaust gas.

VII. Collected Data and Performance Simulation

Table 1 indicates the available performance measurements that were acquired from a gas turbine. A daily average of four-month operational data (1/10/2013 – 31/1/2014) was obtained which was assumed to represent the steady state operation of the plant. Obtained information was screened to remove any transient data during startup or shutdown of turbine operation which would otherwise reduce the accuracy of prediction of the final model. Furthermore, all corrupt data, e.g. obvious erroneous sensor signals, were removed before training the model. In total, data for 2880 hours remained and were hence used in the training and validation process.

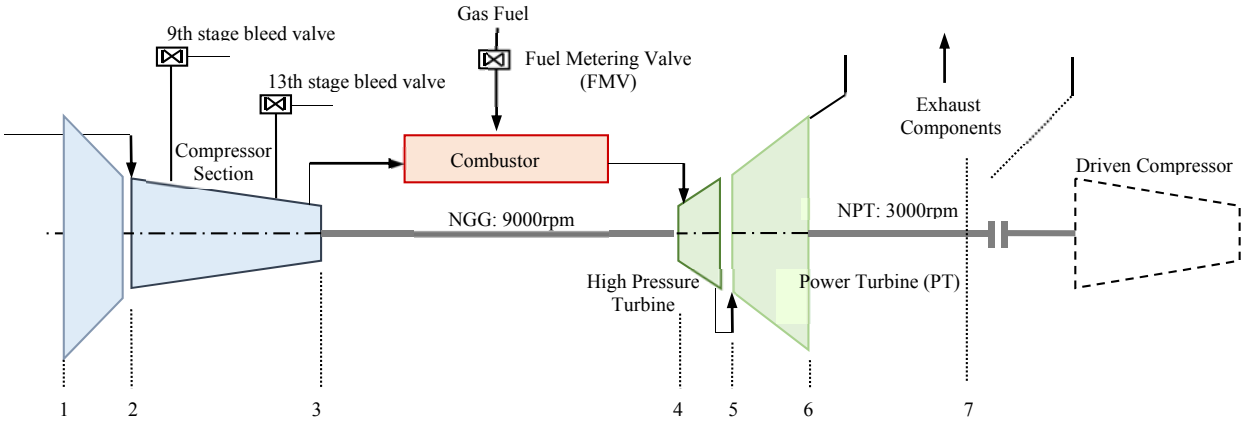

Fig. 5. Configuration of GE LM2500 gas turbine

TABLE I. AVAILABLE PERFORMANCE MEASUREMENTS

Measurement	Meaning	Unit
NGG	Gas Generator Speed	RPM
NPT	Power Turbine Speed	RPM
T_2	Compressor inlet temperature	°C
P_3	Compressor outlet pressure	Bar
T_5	Power Turbine inlet temperature	°C
P_5	Power Turbine inlet pressure	Bar
W_{out}	Output Power	Kw
FMV%	Fuel metering valve opening percentage	%

Various gas turbine performance criteria such as compressor efficiency, expander efficiency and gas turbine overall thermal efficiency can be chosen for gas turbine prognostic problem. Followings are the suitable equations to calculate the derived parameters.

A. *Thermal Efficiency Overal*

The equation for thermal efficiency of gas turbine cycle is [22, 23]:

$$\eta_T = \left[\frac{\eta_t T_3 - \frac{T_1 r^{\left(\frac{k-1}{k}\right)}}{\eta_c}}{T_3 - T_1 - \frac{T_1\left(r^{\left(\frac{k-1}{k}\right)} - 1\right)}{\eta_c}}\right] \cdot \left[1 - \frac{1}{r^{\left(\frac{k-1}{k}\right)}}\right] \quad (1)$$

Where η_T , η_c *and* η_t represent thermal efficiency overall, compressor component efficiency and expander component efficiency, respectively; r indicates pressure ratio of compressor, T_1 and T_3 represent compressor inlet and turbine inlet temperatures respectively; and finally isentropic exponent of the gas is presented by k which can be considered for the mean value through gas turbine.

B. *Compressor Efficiency*

Equation (2) defines compressor isentropic efficiency [22, 23].

$$\eta_c = \frac{R_c^{\left(\frac{k-1}{k}\right)} - 1}{\frac{T_o}{T_i} - 1} \quad (2)$$

Where R_c indicates the compressor pressure ratio, T_o and T_i represent the total temperature at the outlet and inlet of compressor respectively; and isentropic exponent of the air is presented by k which can be considered for the mean value between the inlet and outlet of compressor.

C. *Expander component Efficiency*

Expander isentropic efficiency can be calculated by equation (3) [22, 23].

$$\eta_t = \frac{1 - \frac{T_{EXH}}{TIT}}{1 - (R_t)^{\left(\frac{k}{k-1}\right)}} \quad (3)$$

Where R_t indicates the ratio of turbine total inlet pressure to turbine total exhaust pressure; TIT and T_{EXH} represent the total temperature at the inlet and exit of turbine, respectively; and isentropic exponent of the gas is presented by k which can be considered for the mean value between the inlet and outlet of the turbine.

In the current case study, due to insufficient available measurements, calculation of above parameters is impossible. Consequently, data fusion method was used in order to present a new Efficiency Indicator (EI) parameter as a criterion for prognostic analysis. To do this, the gas turbine overall efficiency could be calculated from equation (4) [22, 23].

$$\text{GT overall efficiency} = 860 \times \frac{W_{out}}{Q_{in}} \quad (4)$$

Where w_{out} indicates the turbine output power in kw; and transferred heat to the gas in combustion chamber is presented by Q_{in} in kcal/h which is directly proportional to product of heating value, density and flow rate of fuel. In this case study, turbine outlet power is available, as shown in Fig. 6; however, the only available measurement about fuel consumption is the exact value of fuel metering valve opening percentage (FMV %) as depicted in Fig. 7. We could assume, with good approximation, this value is proportional to fuel flow rate. Therefore, the normalized output power and normalized inverse of FMV% were used as an innovative efficiency indicator (EI) for the determining criteria in performance prediction. Hence, a self-organizing map based neural network is employed to fuse these two input sets into a single efficiency indicator as shown in Fig. 8.

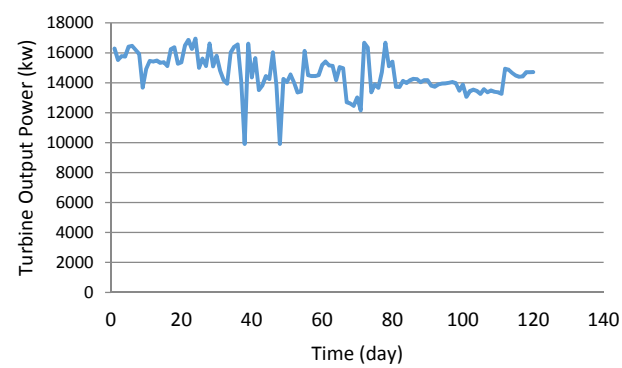

Fig. 6. Gas turbine output power

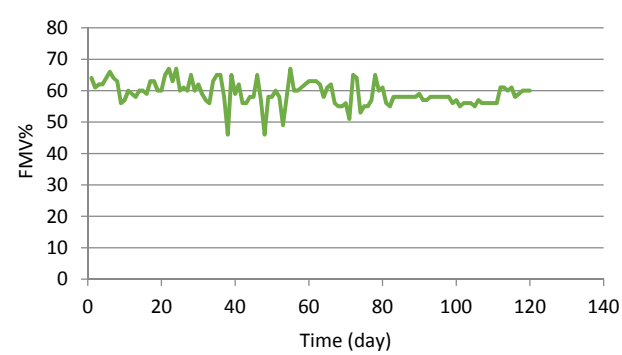

Fig. 7. Fuel metering valve opening percentage (FMV%)

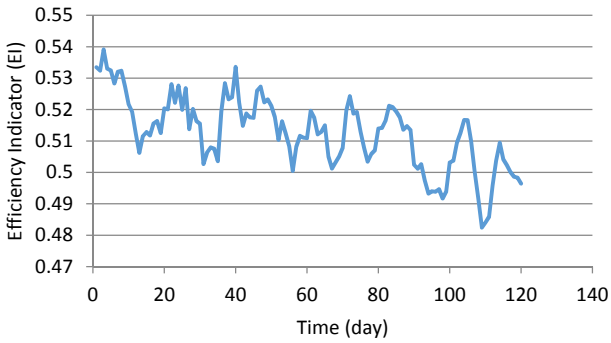

Fig. 8. Efficiency indicator achieved by data fusion

VIII. Performance Deterioration Prediction and Prognostic Analysis

Using the training data set with measurement of 110 days, the ERNN model was trained as shown in Fig. 9.

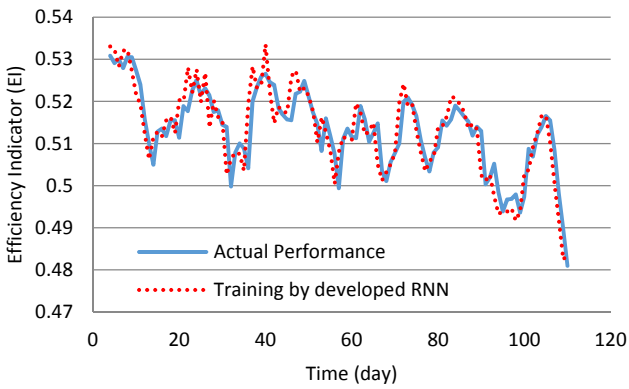

Fig. 9. Actual performance and training by RNN

Using the model which is capable to find best network automatically, 4 input neurons and 3 hidden neurons have been selected. In addition, since only one output is desired, the ERNN model includes only one output neuron. After running the model, the value of root mean square error (RMSE) for optimal network equals to 0.0421. Since the purpose of this study is to predict 10 future steps, firstly, one-step ahead prediction was done. This means, initially an ERNN model was trained using data set from first day up to day 110; then the trained model was used to predict the efficiency indicator value for data next incoming day, i.e. day 111. After that, real data sets from second day up to day 110 plus the predicted value for step 111 in last stage were used in order to train a new ERNN model for prediction of EI value in next incoming day, i.e. 112. Similarly, prediction for days 113 to 120 was done step by step. Fig. 10 shows the comparison of actual and predicted values by using developed RNN for next incoming 10 days.

Average normalized error (ANE), as given in equation (5), was used to measure performance prediction accuracy.

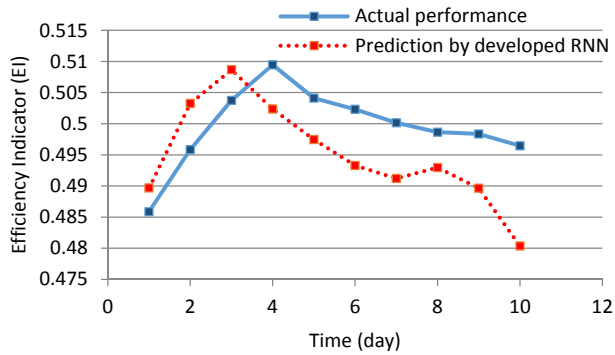

Fig. 10. Comparison of actual and predicted values

$$ANE=\frac{1}{n}\sum_{k=1}^{n}\frac{|EIa_k-EIp_k|}{EIa_k} \quad (5)$$

Where n is the number of data prediction points, which equals to 10 in current case study. EIa_k indicates the actual efficiency indicator value at time k, and EIp_k is the corresponding predicted value. Here, the average value of ANE for gas turbine performance prognostic is 0.0324, or 3.24%. In other words, in the gas turbine application using this proposed model, to predict 10 days ahead the performance of a gas turbine unit, the average ANE error is 3.24% which is deemed acceptable. Moreover, as is apparent in Fig. 11, when prediction interval increases, the accuracy of model decreases. This fact declares that this model is mostly proper for short-term prediction.

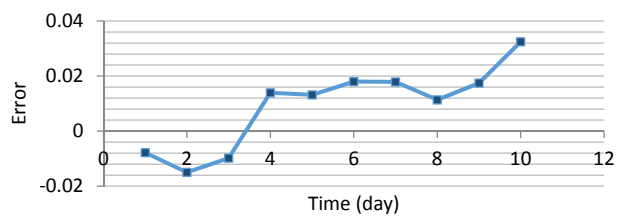

Fig. 11. Accuracy of prediction.

IX. Conclusion

In the current research, the prediction capability of an Elman recurrent neural network (RNN) model, for forecasting gas turbine efficiency degradation is intently examined. An RNN based model which is capable to find best network automatically and uses early stopping method to solve over fitting problem is presented for the health condition prediction using efficiency indicator obtained from data fusion. The model has been applied to a GE LM2500 industrial gas turbine operating at approximately constant ambient and operating condition. The outcomes have proved the effectiveness of the ERNN based approach for multi-step ahead prediction of gas turbine performance condition in a limited time period. The case study shows that the suggested prognostic method could bring several advantages. First and foremost, it assists identification of equipment deterioration and supports adopting an adaptive and dynamic maintenance strategy to increase reliability and availability of system. In addition, the proposed

prognostic approach is introduced and tested for short-term prediction of gas turbine based on limited measurements using standard data fusion strategy. Therefore, this approach can be easily designed and implemented for critical industrial equipment. In future, multi criteria techniques will be developed to promote the accuracy and validity of prediction. Moreover, the application of artificial intelligence approaches for both short-term and long-term prognostics will be investigated.

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Biography

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