Performance improvement of power generation in gas turbines by using random forest and recurrent neural networks

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***Abstract* - In order to improve the power generating performance of gas turbines, machine learning based models are developed. In this paper, random forest and recurrent neural network algorithms are combined to improve the power generation. Average errors based on the operating characteristics are captured by this model. Furthermore, these models are established for capturing the gas turbine part-load performance and full-load performance. Simulation performance is computed by embedding the air compressor and air turbine and individual dataset are used for the validation of these models. The correction curves of gas turbine performance are constructed by predicting the full load performance of RNN model and it possesses reduced complexity and increased accuracy. The obtained curves of the RNN model to predict the part-load performance produces extreme results for continuous turbine monitoring and diagnosis of fault. This proposed method is suitable to any gas turbines and it will be aided to all the power plants for studying the quantitative performance degradation with respect to time.**

***keywords* - RNN, air turbine, random forest, recurrent neural networks, gas turbine, complexity.**

I INTRODUCTION

In order to generate power, Gas Turbines (GTs) are used widely with higher thermal efficiency and lower emissions of CO2. Installations of GT are rising steadily for meeting the demands of soaring electricity. The demands of electricity are caused due to the increasing populations and economies [1]. The working behavior of GT follows load-following approach because of the improving renewable energy's penetration. Frequent ramp up and down of GT is required by this operation mode and therefore the performance of GT is predicted precisely and it is vital to maintain effective operation. Finally, the modeling of GT is reliable and accurate and it is necessary.Tree classifiers are combined by every tree called random forests based on the independent sampling of random vector values having same distribution for each and every trees in the forest. The classifiers in the random forest have generalization is based on the individual tree's strength inside the forest and its inter correlation. The features are selected randomly for splitting every node producing the rate of output error and it is compared by adaboost, but they are highly strong in terms of noise. Whereas the conventional tree algorithms used enormous time to choose the node splitting, lower computational effort is accompanied by the random forests [2].The structure of network based on RNN is required to be established first for number of responding neurons and its topology of network. In the conventional manner, number of neurons was established majorly by the first experience. Then the network training and adjusting the number of neurons in step by step manner as per the network characteristics till it touches the satisfactory solution [3].In this paper, Random Forest (RF) and Recurrent Neural Network (RNN) algorithms are combined to improve the power generation of GT and the performance of the proposed system is compared with the existing methods like Decision tree (DT), Convolutional Neural Networks (CNN), K-Nearest Neighbor (KNN).

II RELATED WORKS

Most of the research in the power field [4,5] and neural network (NN) has proved to perfect technique for diagnosis of fault, identification of process and nonlinear system's modeling in this field. Nowadays, Computation of power, big data and efficient algorithms were affected, the technology of deep learning is merged with brain like cognitive networks to process the data has created huge progress with conventional neural networks are compared in practical applications [6]. Deep neural network (DNN) are used widely as per the learning tool in the techniques of computer vision and the Natural Language Processing (NLP) and obtained huge success. Various deep architectures in dep learning incorporates deep feed-forward neural network (DFNN), restricted Boltzmann machine, deep trust network, auto encoder, convolutional neural network (CNN), Recurrent Neural Network (RNN), and Generative Adversarial Network [7]. Most of the deep learning architectures have nodal connections. Typically, as Multilayer Neural Network comprises multiple hidden layers in Deep Neural Network [8]. Some number of computing units are modeled by complex functions as contrasted with the shallow network because of the nonlinear hierarchical learning ability of multilayer [9]. Because of the simple architecture and model's training, most prevalent architecture between the practioners and researchers in all fields of engineering. In fault diagnosis and simulation field, efficiency is increased by RNN through the sequential processing of data and it is highly prevalent than CNN [10], which is a form of feedforward network that spans adjacent time steps. Different from DFNN, RNN can establish the connection between the units in the directional loop, and realize the memory of time and the mapping of the entire historical sequence of original data to the target vector through the chain rule of the data cycle on the hidden layer [11,12].

III METHODOLOGY

To predict the performance of GT is established and developed by heavy duty GT in a power plant. GT's performance is established by the random forest and recurrent neural network. Multi-stage axial flow air compressor is comprised by GT, the combustion chamber comprised with dry low-NOx and a multi-stage expansion turbine. The compressor with air filter is passed with an ambient air. The combustion chamber occupied with the compressor by the pressurized air, while fuel with natural gas is seared with the air. Power produced by the turbine is expanded by the resulting hot gas. The compressor's proper stages extracts air and it is precooled to cool the turbine blade. Unavailable cooling parameters are explained in detail with the approximation of turbine blade cooling from the discharge of compressor and it is precooled by the ambient air for cooling the turbine rotor blades are shown in figure 1.

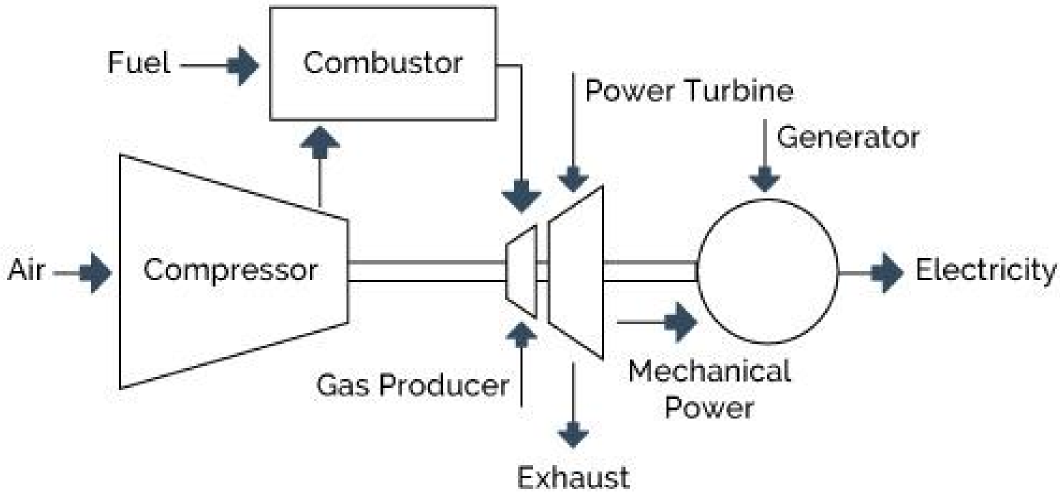

Figure 1: Gas turbines

The structure of network is required to be established first and it corresponds to the number of neurons responded and its topology of the network. In the conventional manner, the number of neurons was mostly established by the first experience. Network training and number of neurons are adjusted in the stepwise manner as per the network characteristics, till reaching the most satisfactory solution. Two input nodes are set as per the flow of input fuel and air flow in 1D continuous variables with the requirement of two input nodes. The requirements of hidden layers are analyzed and these experiments are compared. One is considered as the output layer node number as the output's exhaust temperature is 1D variable. After the network structure determination and the parameter characteristics are determined for training the neural network. The training process is shown in Figure.2

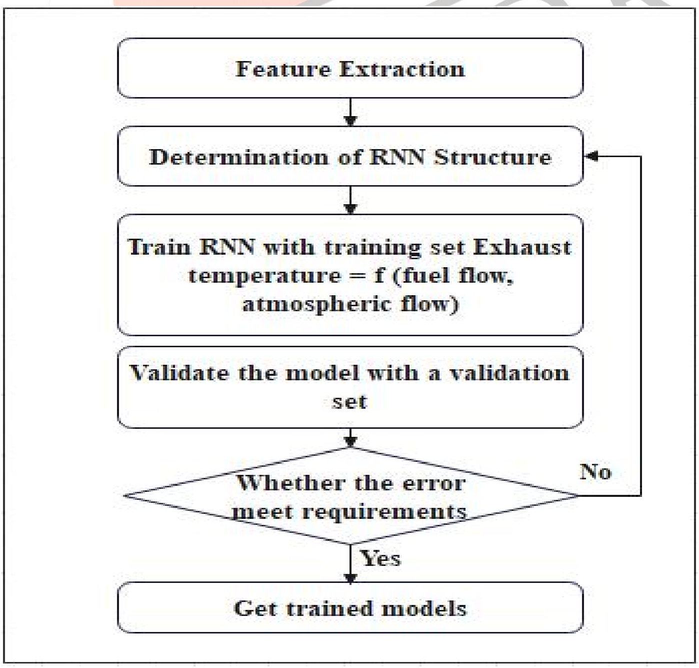

Figure 2: Flow Chart of training process

Depending on the fuel flow measured and air flow, the exhaust temperature predicted for the subsequent and current periods was computed by RNN. The exhaust temperature predicted requires to be contrasted with the value of threshold for normal exhaust temperature for predicting the gas turbine's working state in certain time period. If exhaust temperature's predicted value is inside the range of threshold, and it proves that the gas turbine proceeds in the normal state. The generation of power is established by RNN through RNN by the succeeding steps, the operating characteristics of turbine and compressor are described by the requirements of GT.

Furthermore, the performance of GT part-load and full-load is predicted by the development of random forests. The operation of GT is determined fully for any ambient temperature, because the adjustment of DCS based on the individual strategy of operation. Henceforth, the performance of GT part-load was predicted and random forest is used and d1 and T4 are considered as input parameter and output parameters respectively. The GT performance of full-load happens once IV is opened fully (i.e.) and inlet temperature of turbine (T1) is preserved at 100% and maximum value is acquired by the adjustments.

Briefly, four RNN models are established in this work with the succeeding input and output parameters.

RNN-1a: Predict the compressor input and output temperature

RNN -1b: Predict the turbine input and output power

RNN -2: Used for reverse prediction

RNN -3: Used for Forward prediction

Moreover, their average errors are lower than 1.0%. This designates that the RNN models can denote the compressor, turbine, and GT's operating characteristics.

IV RESULTS AND DISCUSSION

Performance improvement of power generation in gas turbines by using random forest and recurrent neural networks are obtained by the parameters like accuracy, precision, recall and precision. Figure 3a, 3b,3c and 3d indicates the analysis of accuracy, precision, recall and F1-score. In this figure 3a to 3d, X-axis indicates GT power in (KW) and Y-axis indicates the parameters in percentage. Yellow color indicates decision tree, red color represents KNN, Violet color represents CNN. Green color represents Random forest and RNN.

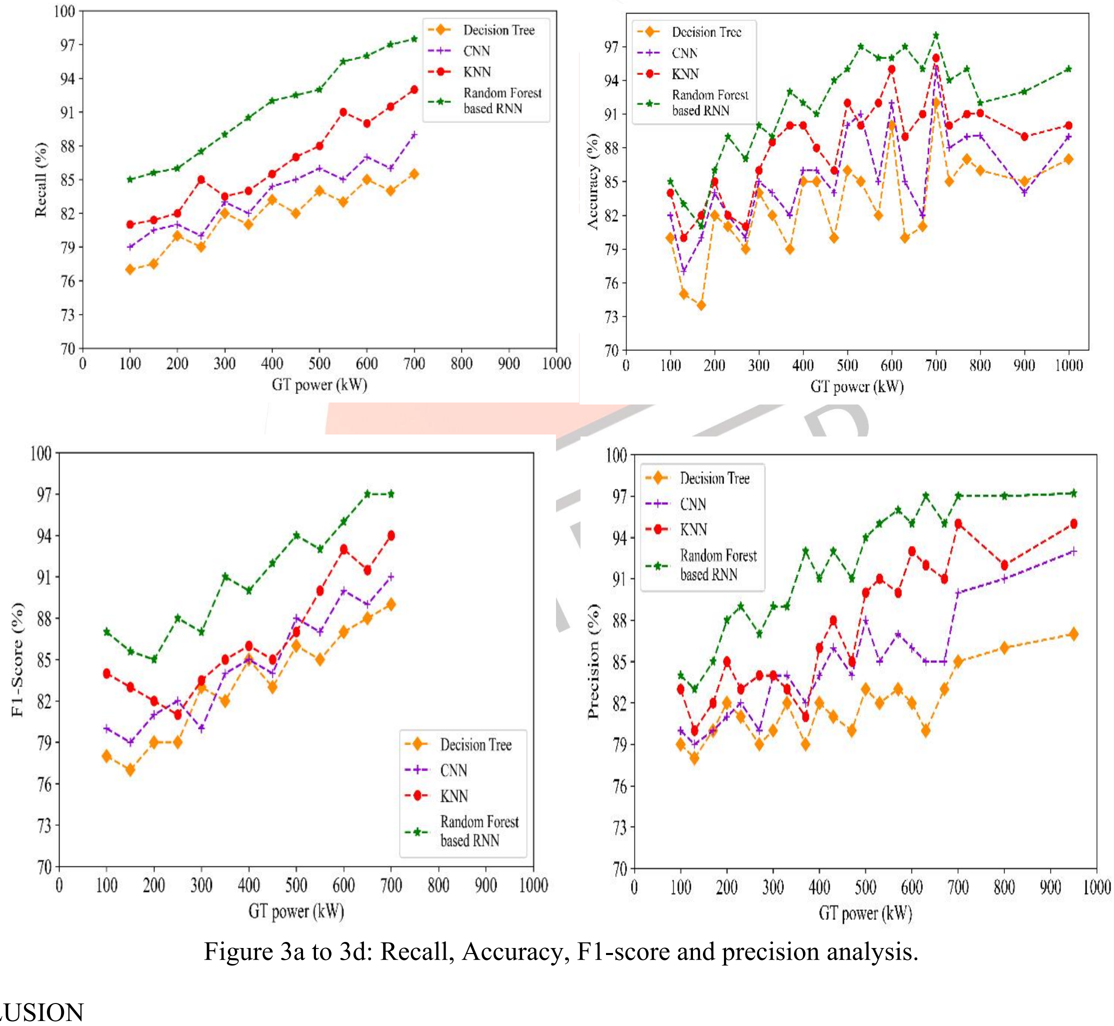

Figure 3a to 3d: Recall, Accuracy, F1-score and precision analysis.

V.CONCLUSION

Random forest and recurrent neural network algorithms are combined to improve the power generation in this paper. Simulation performance is computed by embedding the air compressor and air turbine and individual dataset are used for the validation of these models. The correction curves of gas turbine performance are constructed by predicting the full load performance of RNN model and it possesses reduced complexity and increased accuracy. The obtained curves of the RNN model to predict the part-load performance produces extreme results for continuous turbine monitoring and diagnosis of fault.

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