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Modelling and Analysis of Gas Turbine Blade Behavior to Predict Turbine Blade Resonance Amplitude

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***Abstract*: Turbine Gas Blades are an essential part of any turbine machine. When the blades are run in a specific amplitude with respect to the other environmental factors, the durability of the machine seems to enhance giving us maximum efficiency. When we maintain these factors, the turbine blades used in various gas turbines in power plants and in aircraft last for a longer duration of time. This ultimately helps to reduce the mechanical waste from old machines which affect the environment. Our paper aims to provide a comparative analysis between several machine learning techniques which fits best for the dataset. Machine learning is a popular application of artificial intelligence (AI) in which a computer program learns based on data provided to it. In this paper, major focus will be implementing neural network algorithms and fuzzy logic based algorithms using python language. The intersection of machine learning methods and gas turbine sensor data has expanded rapidly in the last decade to include numerous applications of regression, clustering, and even neural network algorithms. It begins with a review of several computational methods which will be used to monitor the condition of gas turbines currently employed by industry. Since it's an interdisciplinary paper with blending of Computer Science concepts and Gas turbine engine, our main focus would be on visualizing the data set obtained by previous experiments conducted and explore beyond the normal analysis using machine learning techniques.**

***Index Terms*: Neural Network, Fuzzy logic, Gas Turbine, Comparative Analysis.**

I. INTRODUCTION

In a Gas Turbine engine the Turbine rotor blades operate at very high temperature and speed which is a requirement to produce high thrust to weight ratios. In addition, the rotor blade experiences bending loads due to axial and tangential change in velocities of air flow around and across the blade aerofoil. The combined action of bending moment and high speed, the blade experiences high stresses, which are predominantly radial in direction. At each operating point these stresses act as steady state stresses in combination with high temperature. This stress state at very high temperature and high speed make it susceptible for creep. Creep is a primary mode of failure for turbine blades. The start stop cycles of mission causes Low cycle fatigue also as an important mode of failure [1]. Apart from these, every component will have its natural frequency at which if it is excited it will undergo resonance leading to large amplitudes.

Deep learning is a booming topic in the preset context. The thing that sets it apart from other machine learning aspects is its basic structure of neural networks. We can consider neural networks as the workhorse of deep learning. Neural networks are multi layer networks of neurons that are used to classify things, make predictions and so on. A simple neural network consists of the input layers, hidden layers, and the output layers. The different neural networking models are namely convolutional neural network (CNN), Recurrent Neural Networks (RNN), Generative Adversarial Network (GNN) etc.[2] For the analysis of the turbine gas amplitude we are considering a linear neural network model with multiple hidden layers as we have the numerical data regarding the attributes of the turbine blade. We will input these features of the gas turbine as the input for the neural network model and pass it through multiple hidden layers and finally get the result regarding the required amplitude in which the turbine blade should rotate in order to get the maximum efficiency.

The theory of fuzzy logic is based upon the notion of relative graded membership, which has been inspired by the process of human perception and cognition. Lotfi A. Zadeh [3] published his first famous research paper on fuzzy sets in 1965. Fuzzy logic can deal with information arising from computational perception and cognition, that is, uncertain, imprecise, vague, partially true, or without sharp boundaries. Fuzzy logic allows for the inclusion of vague human assessments in computing problems. Also, it provides an effective means for conflict resolution of multiple criteria and better assessment of options. New computing methods based on fuzzy logic can be used in the development of intelligent systems for decision making, identification, pattern recognition, optimization, and control [4]. We have opted for the fuzzy logic model as the data obtained from the tribune gas are dynamic and continuously changing. Hence, these data are uncertain when taken into consideration in the real time application. As the fuzzy logic model tends to give appropriate results for the uncertain dataset, we will be implementing a fuzzy logic model for the prediction of the turbine gas amplitude as well.

A comparative analysis of both the predictive models are performed by changing the various parameters in the model. We will see how each parameter affects the change in the training loss of the model and finally come to the conclusion of which model gives the prediction of the Turbine gas amplitude better and which one of them is more efficient.

Organization of the paper: Section II discusses the literature survey regarding various standard techniques as well as different approaches that have been taken for the prediction of the resonance gas amplitude. In section III, we discuss the preliminary concepts behind this work and purpose of our techniques. In section IV, we show experimental results and compare them with both our models as well as the previous works, and in Section V, we conclude our work and give light to the future work.

II. LITERATURE SURVEY

A lot of studies has been done in the field of Gas Turbine in order to come up with a better understanding of its behaviour and the ways to run the turbine blades efficiently and effectively. Research has shown that changing the amplitude of the turbine gas with respect to the various features/attributes like temperature of the blades, pressure as the blades and so on will result in proper functioning of the turbine blades. We have referred to the various predictive modelling techniques present so as to come with the best predictive model for our amplitude prediction of the turbine gas.

Mevissen[5] proposes an approach where Condition monitoring strategies are examined for gas turbine engines using vibration data. The focus is on data-driven approaches, for this reason a novelty detection framework is considered for the development of reliable data-driven models that can describe the underlying relationships of the processes taking place during an engine's operation.From a data analysis perspective, the high dimensionality of features extracted and the data complexity are two problems that need to be dealt with throughout analyses of this type. The latter refers to the fact that the healthy engine state data can be non-stationary.

Hanafi proposes [6] predictive models that describe the relationship between the independent machining variables: cutting speed, feed rate and depth of cut, and the criteria of machine ability: cutting force, cutting power and specific cutting pressure were derived. This was achieved by using either classical response surface regression technique or by implementing fuzzy logic models which are based on the compositional rule of inference that establish a parametric relation between a given response and the independent input variables.

Effectiveness of these models has been proved by analysing their coefficients of correlation and by comparing predictions they give with experimental results [7]. Predictive fuzzy logic models based on the compositional rule of inference that describe the relationship between the independent machining variables and the criteria of machine ability were derived.[8]

III. METHODOLOGY

We propose a method whose workflow is depicted in figure 1. It gives us complete knowledge of the various phases present in our approach. The process begins with the data collection phase in which we take the NSMS gas turbine dataset. We normalize the data obtained in order to increase the accuracy of our model as normalization decreases the deviation of the data. Analysis of the various data attributes is done referring to how the features are correlated with the resonance amplitude of the gas turbine. The training data is passed to the Neural Network function with back propagation to train the model. The parameter and the hidden layers are changed in each iteration to come up with the best parameters and the number of hidden layers. Then resonance amplitude for the required data is obtained. Similarly, for the fuzzy logic model, the neural network model is used to create the fuzzy rule base. At first, the crisp data is converted into the fuzzy set using the fuzzifier. Once, we fuzzify the data, the rule base is applied to the learning algorithm. For The test data, we defuzzify the value in order to get the resonance amplitude. The comparative analysis of the neural network model and the fuzzy model is done.

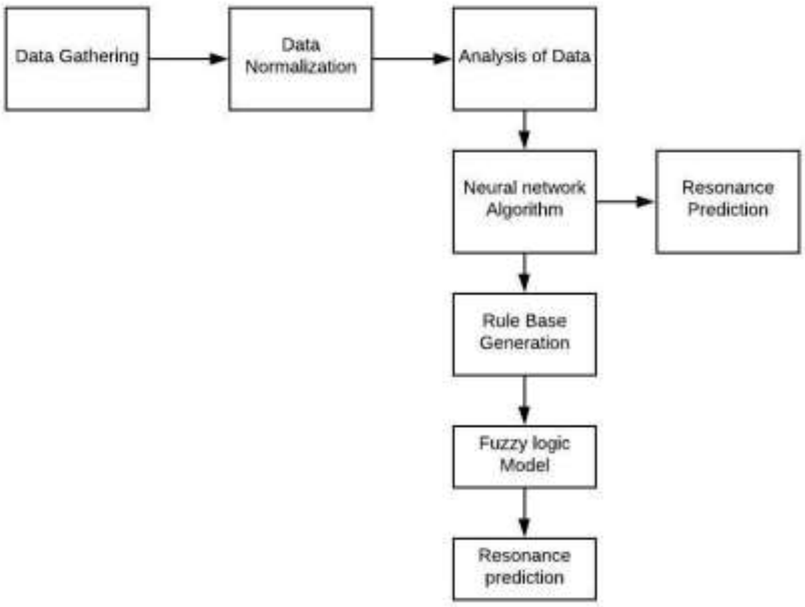

Figure 1. Workflow of the proposed method

1. Dataset:

The paper includes the NSMS dataset which has been derived by several experiments done in our institute for different engines. The corresponding engine operating data depicts measured parameters such are pressure temperature, mass, speeds etc. It consists of 7 input parameters and one output parameter which is the target variable. The variable names are N, M, P1, T1, P3, T3, TJC, and the target variable name is Amplitude. Here N and M are n1 and n2 speeds of turbine, P1 is inlet pressure, T1 is inlet temperature, P3 is outlet pressure, T3 is outlet temperature, TJC is Tandem Junction Cells.

The data provided is divided into three categories: training, testing and validation.
a) Training Dataset: The training dataset consists of 143 instances whose Amplitude value is also provided. Using this knowledge, we train our model.
b) Test Dataset: The test dataset consists of 24 instances and the amplitude values obtained from the statistical modeling is given. We test our model using this dataset.
c) Validation Data: The validation dataset consists of 43 instances whose Amplitude value is also provided. Using this knowledge, we validate our model.
As the pre-processing step we analyzed the data and found out that the range of the values of each attribute is very huge. This creates ambiguity in the construction of the model and does not give good results. To overcome this drawback, we normalized the data to reduce the variation in the values. Correlation between Training instances is given in figure 2. The computation of the neural a network model is efficient if the data are in the range zero to one. Hence, we have performed the same.

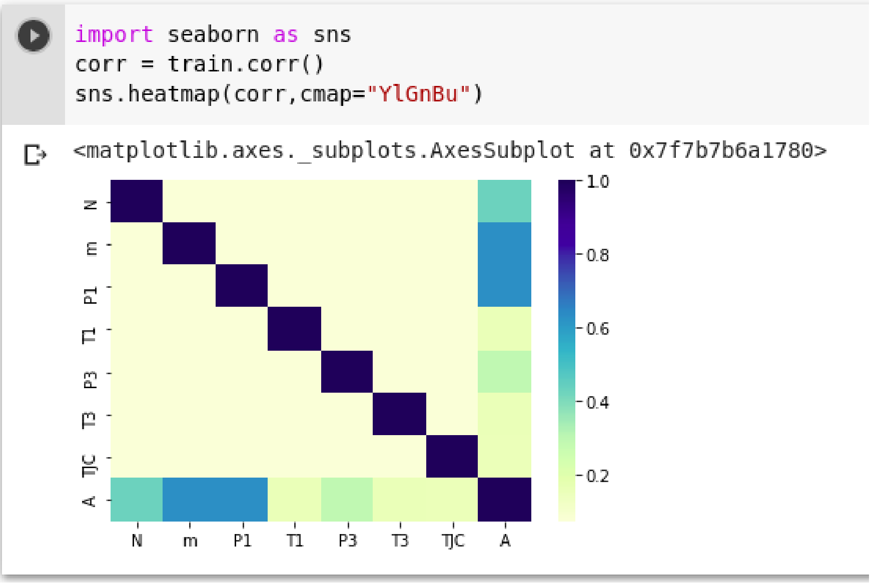

Figure 2. Correlation Matrix of Training data

2. Neural Network Model:

Here in this paper, we have used Keras and Tensorflow libraries to make our neural network model. Once we perform Neural network model on our data, and tune it using hyper parameters like number of hidden layers in neural network, number of epochs, number of neurons in one hidden layer, choosing the best loss function, thus obtaining the optimal results. We can see in the figure 3 below that the validation loss is less compared to train loss during one of the training of neural network model. [9]

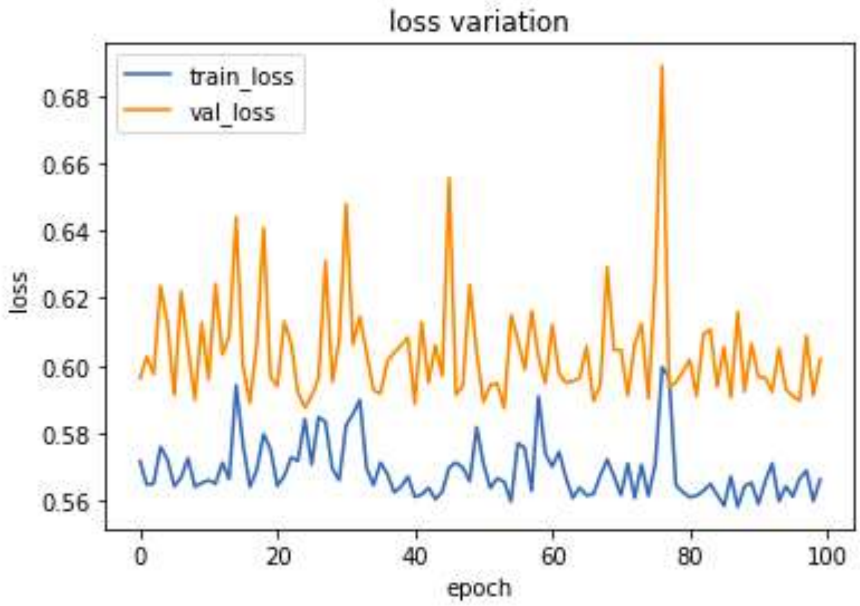

Figure 3. Comparison of train and validation loss while training of model

Now we can predict the resonance whereas we generate a rulebase for a fuzzy model using the neural network algorithm to make 2187 rules. The below figure 4 gives a view of the rule with low, medium and high values for all 7 attributes.

```
[20] rule = pd.read_csv("CNN_Rulebase3layer.csv")
```

```
[21] rule.head()
```

	R.No	sp	mf	IP	IT	CEP	CET	TCJ	AMP
0	1	L	M	M	M	L	M	H	M
1	2	H	L	L	L	H	M	L	L
2	3	M	H	M	M	L	L	H	M
3	4	H	L	H	L	L	M	L	L
4	5	H	L	M	M	H	H	M	L

Figure 4. Rulebase generation using Neural network model

3. Fuzzy Model:

The rules generated by neural networks are the basis for fuzzy based models. Now we change the input for fuzzy models into linguistic data such that it can define resonance according to the rules in the rulebase. The attributes are represented in a triangular membership function as represented in figure 5 and according to this we defuzzify the test set using the rulebase and finally predict the output value.

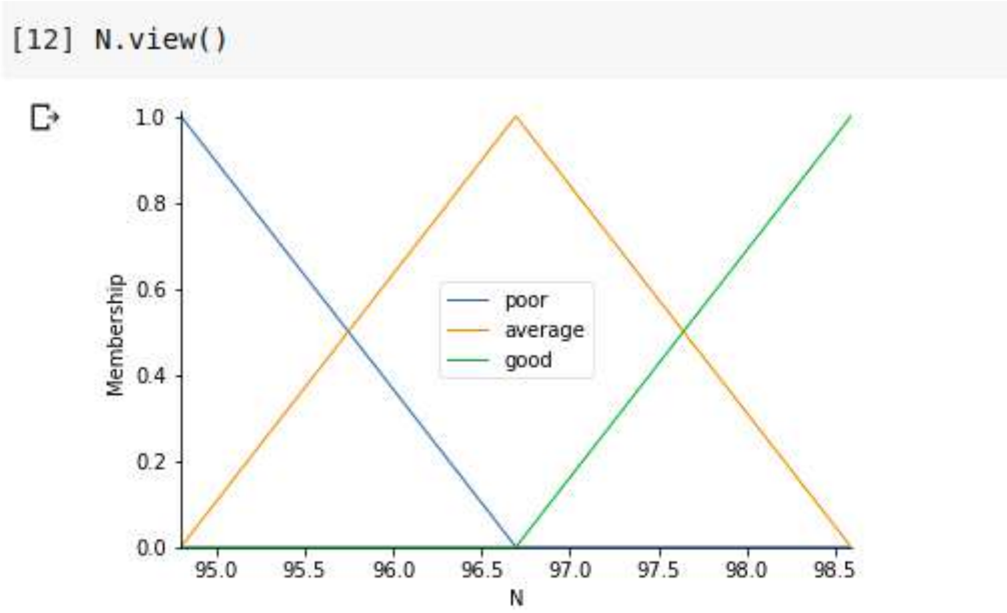

Figure 5. First attribute represented in form of Triangular membership function

IV. Results and Discussion

The results in this paper can be discussed in two parts mainly:

1. Neural Network Model : Neural network model has mainly been built with 2 hidden layers as well as 3 hidden layers such that for both hyper parameter tuning is done and the best optimized models have been created to make the RMSE value as least as possible . The below figure 6 gives a brief observation about it.

Sl No.	Layer 1 (neurons)	Layer 2 (neurons)	Layer 3 (neurons)	Loss Function	Best Epoch	Best RMSE
1	128	32	8	Mean_sqaured_error	310	8.2370
2	128	32	8	Binary_crossentropy	280	8.0912
3	128	128	128	Binary_crossentropy	120	8.3669
4	128	64	32	Binary_crossentropy	70	8.8667
5	128	32	-	Binary_crossentropy	330	7.9033
6	64	64	-	Binary_crossentropy	230	7.8979
7	64	16	-	Binary_crossentropy	550	7.7887
8	64	8	-	Binary_crossentropy	320	7.8070
9	16	8	-	Binary_crossentropy	1220	7.7408
10	8	4	-	Binary_crossentropy	1610	7.7285

Figure 6. Execution results from Neural Network

Thus we can observe that the most accurate 3 layer neural network with 128,32,8 neurons in respective layers gives the lowest RMSE value as **8.0912.** Whereas the most accurate 2 layer neural network with 8,4 neurons in each layer gives the lowest RMSE value as **7.7285.**

2. Fuzzy Logic Model: Fuzzy logic model is based on the rulebase made through the most optimized neural network model [8], so here two rulebase have been made one from best 3 layer neural network and one from best 2 layer neural network.But, the RMSE value after the test set is passed to the fuzzy model gives a value of **9.0677** for 3 layer based rulebase and **12.2779** for 2 layer based rulebase.

Hence the comparative analysis of both the models suggest that since the dataset does not have uncertainty so the neural network model performs better than the fuzzy logic model in predicting the resonance blade amplitude.

V. Conclusion And Future Work

There has been huge research going regarding the use of the gas turbine in the recent past. And to ensure the turbine blades of gas turbines work with maximum efficiency.. The rotational amplitude of the blades of the gas turbine needs to be set based on the various attributes such that it works good giving us the best performance. Our aim was to come up with a neural network model and a fuzzy logic model that would perform predictive analysis such that to obtain the resonance amplitude of the gas turbine. We wanted to achieve the lowest RMSE value for both the neural network model and the fuzzy logic model. To obtain this value we had to perform hyper parameter tuning so that we obtain the maximum accuracy for each model. A comparative analysis of the above two mentioned models is to be performed. We trained the model changing all the parameters like the number of hidden layers in NN, number of epochs in NN, number of nodes and so on to obtain the best neural network model. We can see that the model with three hidden layers performed better than the model with two hidden layers. Similarly, for the fuzzy logic model, we fuzzified the data given using triangular membership function and then obtained the rulebase by training it against a linear neural network model. Finally, we defuzzified the result. We can see from the RMSE value that the neural network model performed much better than the fuzzy logic model in the prediction of the turbine gas resonance amplitude.

Hence we were successful in predicting Turbine Blade Resonance Amplitudes by coming up with the best model for the analysis of gas turbine blade behavior such that we achieve the required knowledge for setting up the aero-gas turbines and marine gas turbines in the military aircraft and the submarines.

The future work of our project can be that we can have more instances of data in-order to train the models in order to increase the accuracy of the model. The data given to us is based on the knowledge of old turbine gas blades. We can find other multiple features of new gas turbine blades that are currently present which correlates with the resonance amplitude that enhances the analysis of the turbine gas.

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