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Modelling and Prediction of Gas Turbine Blade Failure Induced by Centrifugal Force using Expert Analytical System

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ABSTRACT

To provide accurate forecasts of a gas turbine blade failure and operational condition, the intricate relationship between centrifugal force and gas turbine blade failure has to be understood and established using advanced expert modeling approaches. The present research has explored the use of Artificial Neural Networks (ANN) to simulate and forecast a gas turbine blade failure induced by centrifugal forces. A multilayer feedforward neural network was trained using operational data such as speed of rotation, blade material properties and induced blade stress values. The results gotten from the blade modelling using the ANN showed that the ANN comparatively outperforms traditional approaches in terms of the blade failure and operational condition prediction accuracy, making it a valuable tool for enhancing turbine performance and operational sustainability. The ANN was a choice expert analytical modelling tool for the blade due to its ability to handle nonlinear interactions and big datasets. It was therefore concluded that it is a significant machine learning tool for predicting failures in mechanical systems such as the gas turbine blade.

1. **Introduction**

Gas turbines are vital components in modern power generating, aviation, and industrial applications, where operational efficiency and dependability are critical to overall system performance and safety. These turbines rely on blades that are subjected to intense mechanical stresses while in operation, particularly centrifugal forces that grow with rotational speed. Centrifugal force is a major factor to blade failure, causing material deformation, fatigue, and ultimately catastrophic failure. Predicting and preventing these breakdowns is critical to ensuring the turbine's integrity and lifetime.

The complicated nature of gas turbine blade behavior under such high-stress settings makes it difficult to effectively anticipate blade failure using existing approaches. While traditional engineering techniques like finite element analysis (FEA) and stress-strain calculations can provide useful insights into material behavior and stress distribution, they frequently fall short of addressing the dynamic, nonlinear, and multifactorial nature of blade failure. As a result, there is a rising interest in using advanced computational approaches, specifically Artificial Neural Networks (ANN), to model and predict gas turbine blade failures more accurately.

Artificial Neural Networks (ANN), a form of machine learning technique, have shown considerable promise for simulating complicated systems where standard methods may fail. ANNs can learn from big datasets, find hidden patterns, and make predictions based on historical data, which is especially valuable when the underlying causes of failure are unknown or too complex to describe analytically. In the context of gas turbine blades, ANN-based algorithms can be trained to recognize patterns associated with centrifugal force-induced failures, taking into account material qualities, rotational speed, temperature, and blade materials properties. The purpose of the present research was to create and implement an expert analytical system based on artificial neural networks for modeling and predicting gas turbine blade failure caused by centrifugal forces.

The suggested system will be able to forecast prospective blade failures using a dataset of historical failure incidences as well as operational factors, allowing for timely maintenance interventions and improving turbine reliability. The findings of this study are projected to make a substantial contribution to the field of turbine maintenance by providing an intelligent, data-driven approach for predicting blade failures, reducing downtime, and improving overall operational efficiency.
The following sections will go over the fundamentals of centrifugal force and its effect on gas turbine blades, evaluate existing predictive models, and present a thorough approach for developing and implementing the ANN-based expert system for forecasting turbine blade failure. The study will also compare the performance and accuracy of the ANN model to previous prediction methodologies, resulting in a comprehensive tool for engineers and maintenance personnel.

Chowdhury et al [1-5] carried out a critical review on gas turbine cooling performance and failure analysis of turbine blades. Highlights of the research included the followings;

i. Review of appropriate coating methods and blade-cooling systems for gas turbines.

ii. Identifying the gas turbine blade failures with possible causes and remedies.

iii. Selection of suitable blade materials for proper functioning of the gas turbines.

iv. Review of working fluids and fuels for economic and environmental requirements.

The authors highlighted the need for the research on one of the most important turbo-machineries (gas turbine) which they asserted can be a pathway for further improvement of the performance and efficiency of the gas turbine, and the prevention of gas turbine failures by identifying the root causes from previous failure case studies.

Swain et a l [2] Carried out a review on the failure analysis of gas turbine blades. To overcome those imminent failures, the development of materials was also discussed by the authors. The authors emphasized in their research the importance of coating in gas turbine blade. After the brief investigation of the failure analysis and materials developed, they asserted that it was observed that there are some properties to be developed to obtain an optimum gas turbine blade. A significant assertion from the work was that the pathway of the development of the gas turbine performance go through an increase in engine's efficiency, reliability, lifespan, capacity and a decrease in fuel consumption and expenses. Some beneficial inputs in an efficient gas turbine are the initial are high temperature inlet gas, high pressure turbine feeding, and the use of more resilient materials and method of manufacturing.

Rao et al [3] carried out research on failure analysis of a 100MW gas turbine blade in a gas turbine engine used for marine applications. The gas turbine blade that was under examination was operated at elevated temperatures in corrosive environmental where it was exposed to attack such as oxidation, hot corrosion and sulphidation etc. Scientific investigation carried out on the gas turbine blade included visual inspection, determination of material composition, microscopic examination and metallurgical analysis. The metallurgical examination revealed that there was no micro-structural damage due to blade operation at elevated temperatures within its designed temperature conditions. However; it was observed that the blade might have suffered both corrosion (including HTHC & LTHC) and erosion. LTHC was prominent at the root of the blade while the regions near the tip of the blade were affected by the HTHC. It was concluded by the authors that the turbine blade failure might be caused by multiple failure mechanisms such as hot corrosion, erosion and fatigue. Hot corrosion could have reduced the thickness of the blade material and thus weakened the blade. This reduction of the blade thickness decreased the fatigue strength which ultimately led to its failure.

Rani et al [4] performed a failure analysis on the first stage of a gas turbine using the blade tip cracking determination of a gas turbine, to localize and isolate further degradation of the blade coating blades, based on several tests and investigations to confirm the presence of a combined effect of degradation due to failure of the turbine blades

Zhang Zhixin et al [5] carried out research on the failure analysis of a first stage turbine blade made of directionally solidified GTD111 super alloy and repaired by welding process. The authors asserted that failure of a turbine blade made of DS GTD111 and repaired by welding process was investigated by fracture surface investigation and metallurgical observation. The methods employed to investigate the fracture surface and the metallurgical structure by them included optical microscope (OM), scanning electron microscopy (SEM) and energy dispersive X-ray spectrometry (EDS) analysis. They asserted that the spallation of the top coating of TBC near the fracture surface accelerated the formation of cracks. Based on the metallurgical observation, it was found that the bond coating of TBC did not play any positive role in promoting the initiation and propagation of the cracks. Findings of the research outcomes included the followings;

i. The fracture surface of the turbine had penetrated the welding zone and entered the directional solidification zone.

ii. The degradation of the grain boundary in the welding zone appeared to be the primary cause of numerous secondary cracks in the turbine blade.

iii. The bond coating of TBC did not play any positive role in promoting the initiation and propagation of the cracks.

Darcía-Martínez et al [6] carried out failure study of an aircraft engine high pressure turbine (HPT) first stage blade. The authors asserted that in machineries like jet engines, almost 50% of failures were located in the damage of turbine blades and discs. In respect of that, the authors research was to study and determine the root cause of the failure of a high-pressure temperature blade in a turbofan engine. Visual observation of the blades indicated that initially, one blade was fractured. Subsequently, detachment of the airfoil from the single fractured blade and its impact with the rest of the blades of the first turbine disc trigged a catastrophic damage to them and affected later stages blades. Turbine blades rotate at tens of thousands of revolutions per minute (RPM), which often exposes the blade to stresses from fluid and centrifugal forces that may cause yielding failure, creep, or fracture [7-10]. This work aims to predict gas turbine blade failure induced by centrifugal force using artificial neural network.

2. Methodology

The methodology consists of the following steps:

2.1 Data Collection and Preprocessing

Operational data, including rotational speed, material properties, and stress distributions, was collected from simulations or real-world operations. The dataset was normalized to ensure consistency and improve model training.

2.2 ANN Architecture and Model Development

A multilayer feedforward neural network was designed, consisting of an input layer (operational parameters), one or more hidden layers (to capture nonlinear interactions), and an output layer (failure probability). The network was trained using supervised learning techniques, employing backpropagation and an optimization algorithm like Adam to minimize error.

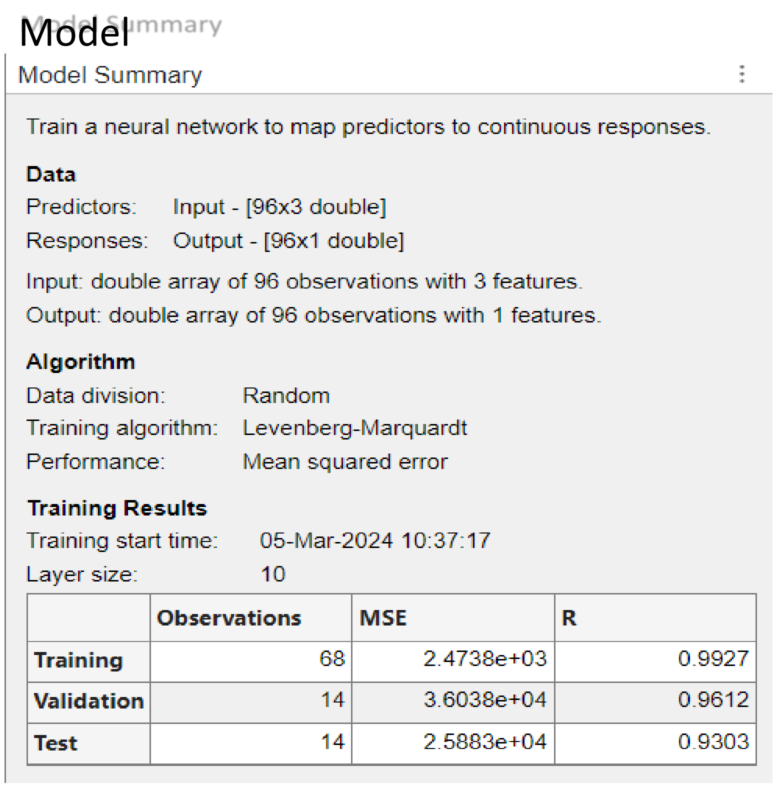
2.3 Model Training and Validation

The dataset was divided into training, validation, and testing subsets. The model was trained iteratively, with its performance evaluated using metrics such as mean squared error (MSE) and R^2. Hyperparameters such as the learning rate and number of hidden neurons were tuned to optimize performance.

2.4 Performance Evaluation

The trained ANN is tested on unseen data to assess its predictive accuracy. Sensitivity analysis was conducted to determine the contribution of individual parameters to failure prediction. The results were compared with traditional methods to demonstrate ANN's advantages.

The model summary is shown in Figure 1.



Model Summary

Model Summary

Train a neural network to map predictors to continuous responses.

Data

Predictors: Input - [96x3 double]

Responses: Output - [96x1 double]

Input: double array of 96 observations with 3 features.

Output: double array of 96 observations with 1 features.

Algorithm

Data division: Random

Training algorithm: Levenberg-Marquardt

Performance: Mean squared error

Training Results

Training start time: 05-Mar-2024 10:37:17

Layer size: 10

	Observations	MSE	R
Training	68	2.4738e+03	0.9927
Validation	14	3.6038e+04	0.9612
Test	14	2.5883e+04	0.9303

Figure 1. Model Summary

3. Results and Discussion

The improved second order method of gradient also known as Levenberg Marquardt Back Propagation training algorithm was selected as the best learning rule and was therefore adopted in designing the network architecture. To determine the exact numbers of hidden neuron, different numbers of hidden neurons were selected to create a trained network using Levenberg Marquardt Back Propagation training algorithm. From the Figure above, the Levenberg Marquardt Back

Propagation training algorithm having 10 hidden neurons was used to train a network of three (3) input processing elements (PEs) and one (1) output processing elements. The number of hidden neurons was set at 10 neurons per layer and the network performance was monitored using coefficient of determination (r^2) and MSE. The input layer of the network used the hyperbolic tangent (tan-sigmoid) transfer function to calculate the layer output from the network input while the output layer used the linear (purelin) transfer function. The network generation process divided the input data into training data sets, validation and testing. For this study, 70% of the data was employed to perform the network training, 15% for validating the network while the remaining 15% was used to test the performance of the network at a maximum training cycle of 1000 epochs was used. Using these parameters, an optimum neural network architecture was generated as presented in the Figure 2.

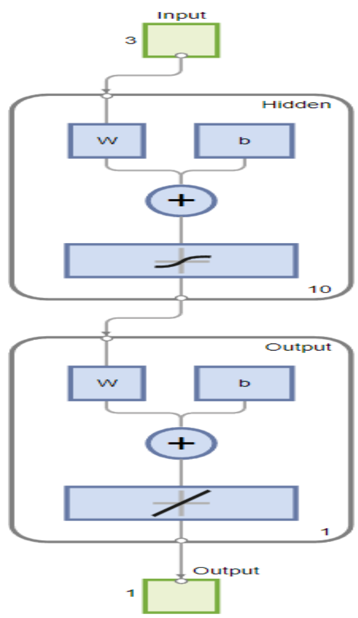


Figure 2. Artificial Neural Network Architecture

A performance evaluation plot which shows the progress of training, validation and testing is presented in the Figure 3.

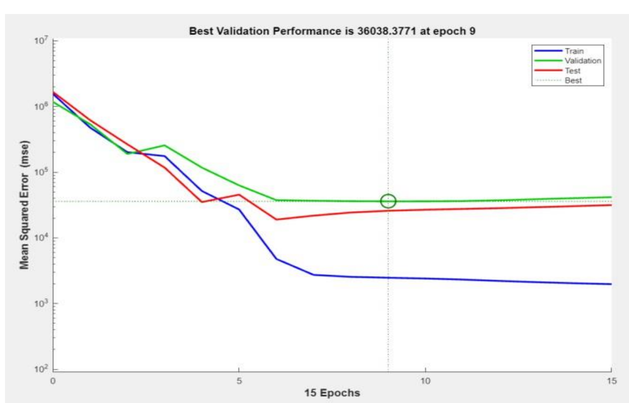


Figure 3. Performance curve of trained network for predicting centrifugal force

From the performance plot of the Figure 2, it was observed that there was no evidence of over fitting. In addition, similar trend was observed in the behaviour of the training, validation and testing curve which was expected since the raw data were normalized before use. Lower mean square error was a fundamental criterion used to determine the training accuracy of the network. The best validation performance of 36038.3771 at epoch 9 was evidence of a network with strong capacity to predict the centrifugal force. The training state, which showed the gradient function, the training gain (Mu) and the validation check, is presented in the Figure 4.

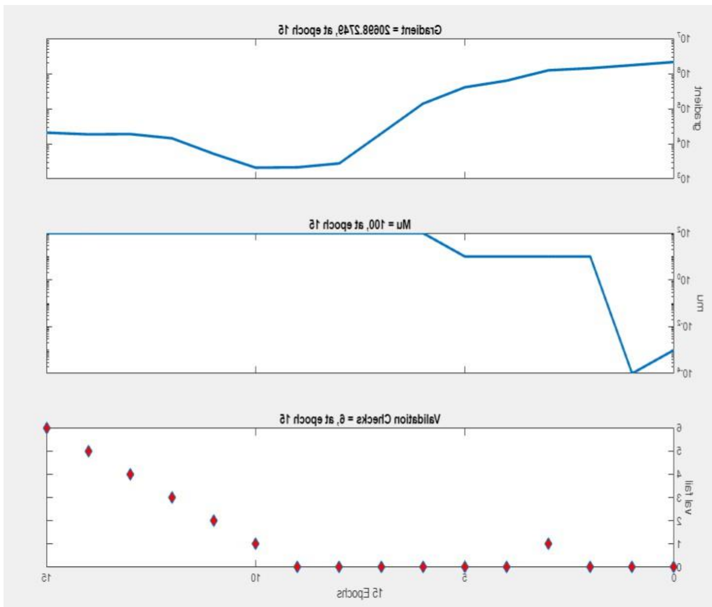


Figure 4. Neural network training state for predicting centrifugal force

Back propagation is a method used in artificial neural networks to calculate the error contribution of each neuron after a batch of data training. Technically, the neural network calculates the gradient of the loss function to explain the error contributions of each of the selected neurons. From Figure 4 the computed gradient value of 20698.2749 at epoch 15 indicated that the error contributions of each selected neuron were very minimal. Momentum gain (Mu) is the control parameter for the algorithm used to train the neural network. The training gains and its value must be less than unity. Momentum gains of 100 showed a network with high capacity to predict the centrifugal force. The regression plot which showed the correlation between the input variables (temperature, pressure and speed) and the target variable (centrifugal force) coupled with the progress of training, validation and testing were presented in the Figure 5.

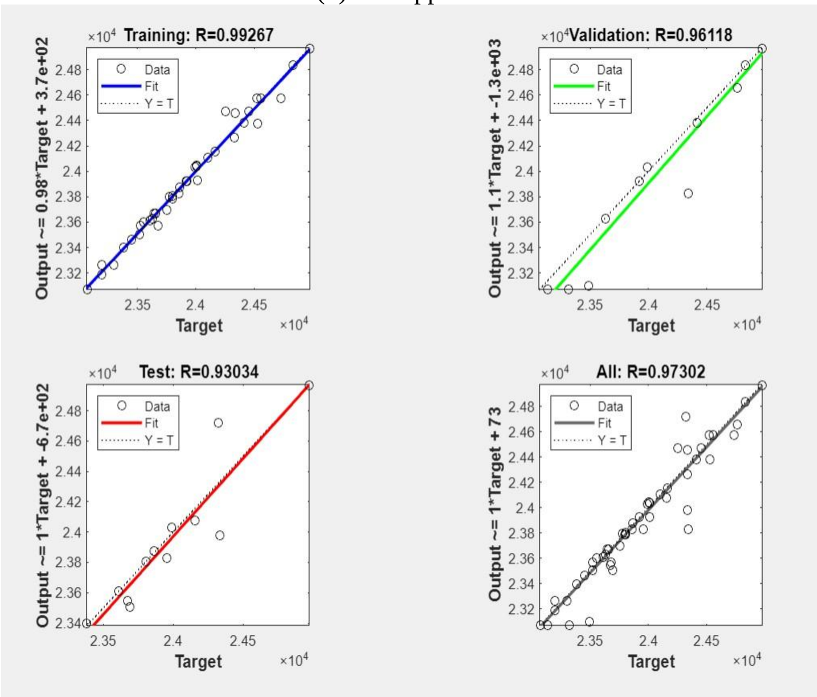


Figure 5. Regression plot showing progress of training validation and testing

Based on the computed values of the correlation coefficient (R) as observed in the above Figure, it was concluded that the network has been accurately trained to predict the centrifugal force as R has an overall value of 0.97302.

4. Conclusion

The findings of the Artificial Neural Networks (ANN) model revealed its suitability for forecasting turbine blade failure caused by centrifugal forces. The ANN successfully caught nonlinear correlations and complicated patterns between operational factors and failure probability, resulting in a high forecast accuracy. The sensitivity study made clear how important centrifugal force-related factors—specifically rotational speed—are in determining blade failure. The model is a priceless tool for real-world applications in turbine maintenance and design optimization because of its versatility with regard to big datasets and its ability to learn from intricate interactions. The study does, however, also recognizes the computational resources needed for ANN implementation as well as its requirement of extensive and high-quality data for efficient training. Notwithstanding these drawbacks, ANN is a strong and dependable method for failure prediction that greatly advances predictive failure and maintenance frameworks.

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