Life Estimation and Prediction for Rotating Machines using Minitab and ANN Methods

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Abstract

Nowadays industrial maintenance is focused only on alarm indications and expertise reviews. The hazards of motor rotating at higher rpm leads to failure of machines if properly not maintained regularly also leading to major economic losses. Data-driven fault diagnostic techniques depend solely on historical data. Signal-based methods use signal processing techniques to make diagnostic judgments. The constant and proper operation of manufacturing machinery is a critical goal in this competitiveness. This may be accomplished by achieving higher equipment and developing an effective maintenance regime. The research paper investigates the optimization and prediction of life for industrial equipment by suitable optimization and prediction tools and techniques to enhance the life of the machine using Taguchi and neural networks using pattern recognition methods. Results show the maximum sustainability of machine and accuracy to be greater than 95% under validation from regression plot. The main strategy to stay away from disastrous disappointment and save upkeep costs for turning machines is to utilize condition checking.

Keywords: Maintenance, Regression, Taguchi, Neural network, Histogram

1. Introduction

The recent public economic condition is marked by severe competition among various firms. The constant and proper operation of manufacturing machinery is a critical goal in this competitiveness. This may be accomplished by achieving higher equipment and developing an effective maintenance regime. Fault diagnosis is critical to the safe operation of rotating machinery. Data-driven fault diagnostic techniques depend solely on historical data. Signal-based methods use signal processing techniques to make diagnostic judgments. Machine learning-based methods rely on machine learning techniques to make decisions. Fault diagnosis consists of three major tasks: defect detection, malfunction isolation and fault identification.

2. Machine Fault Detection and Diagnosis

Fault detection may be categorized based on both detections by way of a sign model-based totally method and model-primarily based approach. Version-based totally strategies of fault detection use the relationship between numerous measured variables to extract data on possible adjustments resulting from faults. The signal fashions which permit the principle frequencies and their amplitudes to be immediately estimated and which are particularly sensitive to small frequency modifications can also be used. Any form of fault that happens in a system that ends in mechanically to sudden protection risks, decreased efficiency, energy availability, systems reliability and protection. An average fault detection method includes the following levels: information acquisition, parameter extraction, fault analysis, and choice making. Fault detection techniques have a rich history in the control community.

The model-primarily based technique is extensively used due to the fact it's far the most reasonably-priced. Statistics-pushed methods produce accurate results than a version based totally on fault detection because the analysis is a method of determination of nation failing additives and figuring out the cause of the failure. Diagnosis is the process of predicting imminent issue screw ups or peculiar machine states earlier than they surely occur and estimates their remaining useful life. The critical machine is identified and data collected for three dimensional positions and subjected to various parameters for optimization to predict the machine failure using neural network

3. Optimization technique – Taguchi

The Taguchi design selected for this work is L9 orthogonal array having 3*3 matrix and 3 factors in order to factor estimation that influence of performance criteria. Smaller the better is chosen to minimize the responses. The surface plots as shown below Figure 1(a,b,c) represents the frequency peaks achieved at different speeds(A), feed rate(B) and depth of cut(C).

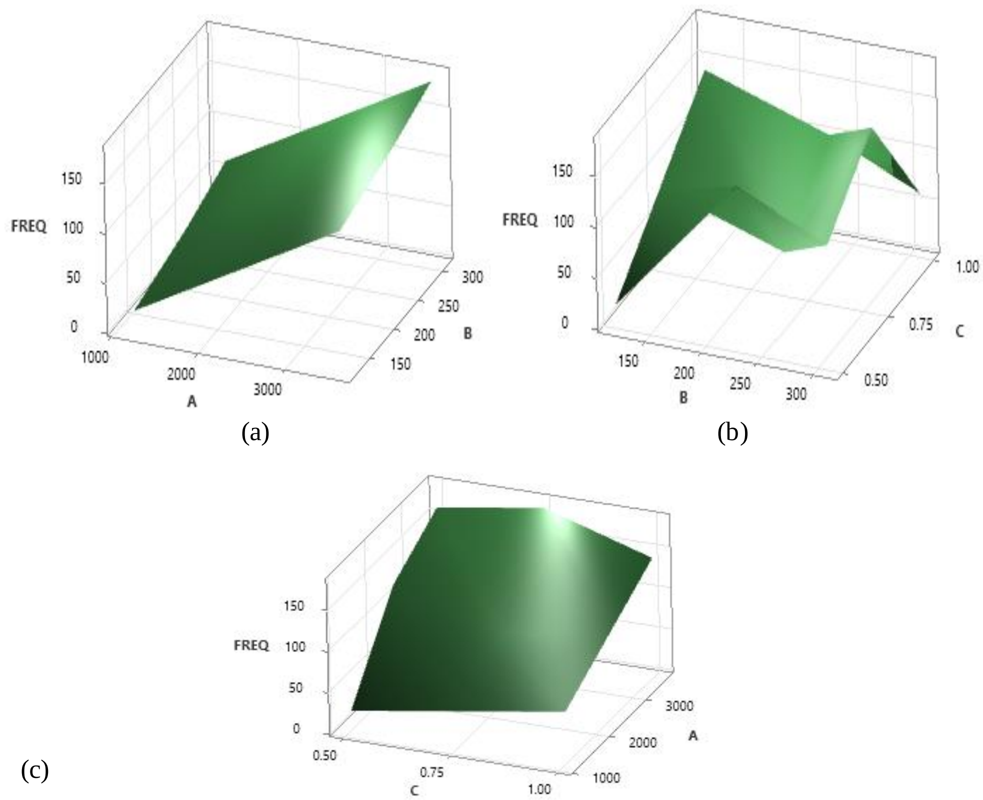


Figure 1: Surface Plots of Frequency versus (a) Speed & Feed Rate (b) Feed Rate & Depth of Cut (c) Depth of Cut & Speed

The input parameters for machining operations are speed, feed rate and depth of cut to verify the parameter contribution, ANOVA reveals the influence of cutting parameters. Three-dimensional surface plots are drawn using Minitab to analyse the full vision of interaction between the parameters. The relative models are drawn for three variables and analysis has done pair wise such as AB, BC, CA simultaneously for Horizontal, vertical, axial and frequency parameters. From the surface plots we observe that all the input parameters have higher influence on three dimensional positions respectively.

4. Response Table for SN Ratio

The response table for SN ratios shown in below Table 1 represents the major contribution for the failure of machine and need to be diagnosed by considering smaller the better.

Table 1: Ranking response method to different parameters

Level	Speed(A)	Feed Rate(B)	Depth of Cut(C)
1	-28.20	-32.66	-34.22
2	-36.87	-35.70	-35.39
3	-41.03	-37.74	-36.48
Delta	12.83	5.08	2.27
Rank	1	2	3

From the above table it is observed that Spindle speed contributing higher for machine failure and also it is observed from the main effect plots from the below Figure 2.

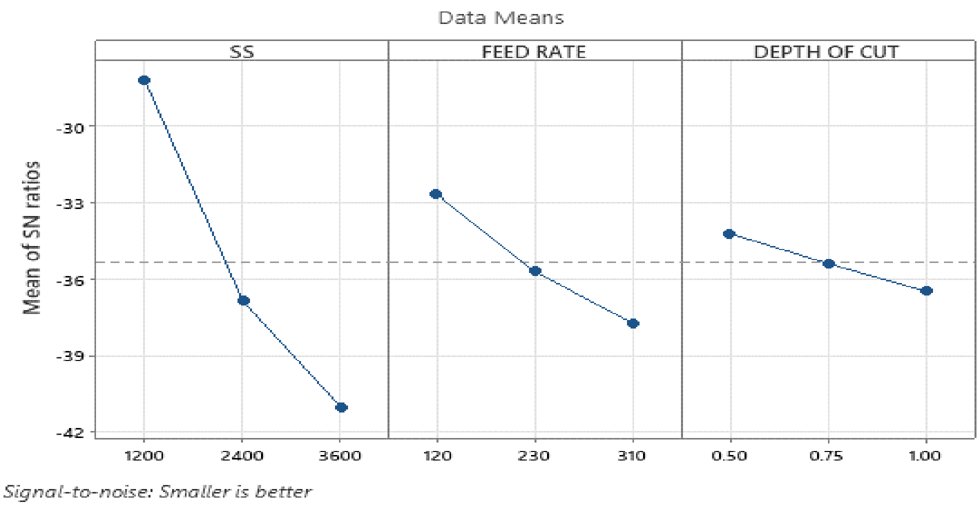


Figure 2: Main effect plots for SN ratios

Hence, validation of fault diagnosis by Neural network is must in order to run the machine in stable condition from the prevention of failure also enhances life.

5. Neural Network approach for validating fault diagnosis

A neural network generally consists of 3 different types of layers namely input, hidden, output which has a data driven diagnosis of fault such that input data needs to be standardized before processing to the desired output. The information from the input data is effectively transferred to hidden layer by selecting the number of neurons for the achievement of higher accuracy levels. Flow diagram network as shown below in figure 3, Levenberg algorithm is selected for data training.

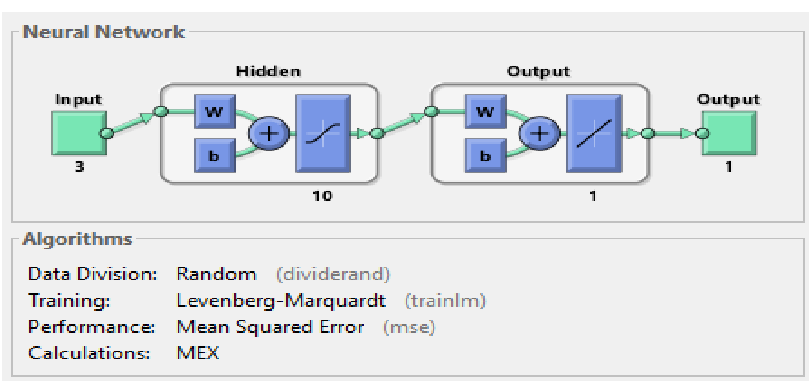


Figure 3: Neural network model

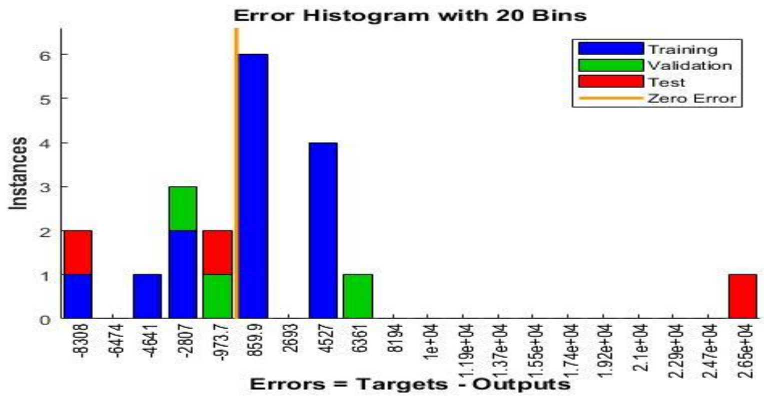
The algorithm applied in the present work is Levenberg Marquardt which has less time with more memory. The training data stops automatically as and when improvement in generalization stops in turn shows an increase relative to mean square error and R value.

Results

	Samples	MSE	R
Training:	14	12565540.84720e-0	6.10440e-1
Validation:	3	16902456.19940e-0	9.03716e-1
Testing:	3	280467727.80337e-0	-5.99786e-2

Figure 4: Results of train, validation and test data

Here 70% of data is selected for training and remaining 30% is distributed equally for validation and testing purposes and results of “R” value are drawn as shown in above figure 4 respectively.



Graph 1: Error Histogram based on targets and outputs

Performance evaluation is done using mean square error and peak SN ratio which are computationally fast in histogram. Effectiveness of data is analyzed and drawn as shown in the above graph 1. The graph is computed by instances and error having 20bins but zero error can be found at 859.9instance.

6. Plot Training state and Regression

The epoch number indicates with forward and backward gradient pass and validation checks at value 9.

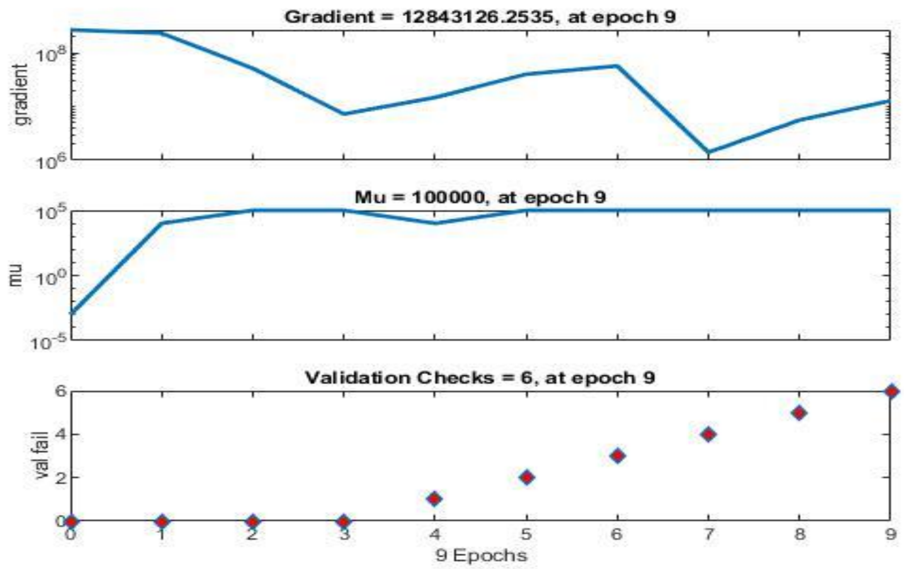


Figure 5: Plot of Gradient, mu and Valuation fail checks

The above figure 5 shows the plot of gradient value 12843126.2535 at epoch 9 and mu value 100000 at epoch 9 having 6 validation checks at epoch 9 is obtained for the machine. The results represent that minimum number of epochs is be obtained from the training data. Gradient plot is a first order optimization in algorithm that takes into account while performing many parameters.

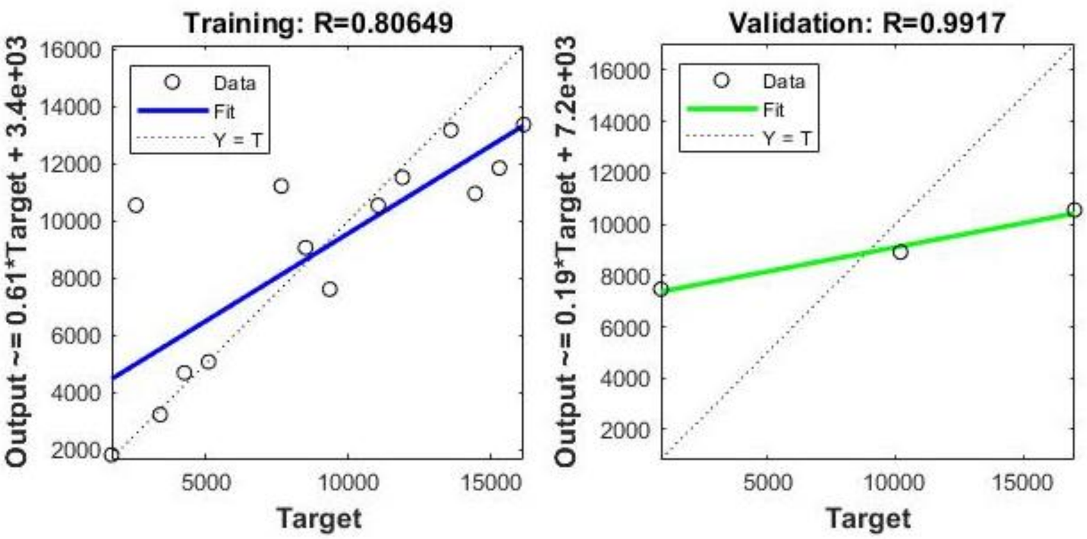


Figure 6: Validation output from R value

The above figure 6 shows the validation output 15% is considered and obtained from training data is 99.17% accurate.

7. Conclusion

It is valuable to diminish stoppages and lift the effectiveness of the hardware by taking on dynamic strides during activity and support to forestall impromptu breakdowns, lessen recurrence of upkeep, and for proactive condition-based upkeep. The main strategy to stay away from disastrous disappointment and save upkeep costs for turning machines is to utilize condition checking. The results and validation in this paper shows the usage of neural network importance for evaluating the fault in the machine. Paper concludes with accuracy of 99.17% upon network performance.

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