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Optimizing Dimensional Accuracy in Machining Thick Materials: A Comparative Analysis of RSM and ANN for Rigidity Index Enhancement

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Abstract: Enhancing the dimensional accuracy of thick materials is crucial in manufacturing processes, directly impacting the quality and performance of the final products. This study investigates the optimization of machining parameters to maximize the rigidity index, a key factor in maintaining dimensional stability. Utilizing Response Surface Methodology (RSM) and Artificial Neural Networks (ANN), this research aims to predict and optimize the rigidity index, thereby improving precision in machining thick materials. The methodology involves designing experiments using a central composite design matrix. Statistical tools were employed to analyze the data, and the quadratic model was identified as the best fit for predicting rigidity index. Results indicate that optimizing parameters such as depth of cut, cutting speed, and feed rate significantly enhances the rigidity index, leading to improved dimensional accuracy. Experimental validation and predictive modeling demonstrate that both RSM and ANN are effective in optimizing machining parameters. The study provides a robust framework for manufacturers to achieve higher precision and efficiency in processing thick materials, contributing valuable insights into the optimization of rigidity index for enhanced manufacturing outcomes.

Keywords: Dimensional Accuracy, RSM, ANN, Rigidity Index Enhancement
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1. INTRODUCTION

Dimensional accuracy in manufacturing processes involving thick materials is significantly influenced by the rigidity index. A higher rigidity index typically correlates with improved dimensional stability and accuracy. Dimensional accuracy is a cornerstone of manufacturing quality, ensuring that components fit together seamlessly and function as intended. Achieving precise dimensions is especially challenging when working with thick materials, as these often undergo significant deformation during processing. One key factor that can influence dimensional accuracy is the rigidity of the material being processed. Dimensional accuracy is critical for ensuring the functionality and reliability of manufactured components. According to Chatterjee et al. (2019), inaccuracies in dimensions can lead to issues such as poor fit, increased wear, and potential failure of components. In the context of thick materials, maintaining dimensional accuracy is particularly challenging due to the inherent material properties and the significant forces involved in their processing (Smith et al., 2021). Rigidity, defined as the material's resistance to deformation under applied forces, plays a crucial role in maintaining dimensional stability. The rigidity index of a material is a quantifiable measure that can be optimized to enhance the precision of manufacturing processes. By accurately predicting and optimizing the rigidity index, manufacturers can minimize deviations from desired dimensions, thus improving the overall quality and performance of the final product. This is particularly important in industries such as aerospace, automotive, and heavy machinery, where stringent dimensional tolerances are required. Rigidity, or stiffness, of a material is a crucial factor that affects its deformation under applied forces. A higher rigidity index indicates a material's greater resistance to deformation, which is beneficial for maintaining dimensional stability during manufacturing processes. Lee and Sahu (2018) highlighted the importance of material rigidity in achieving precise dimensions, especially when dealing with thick materials that are prone to warping and deformation during machining or forming. Predictive modeling techniques have been extensively used to estimate the rigidity index and its impact on dimensional accuracy. Machine learning algorithms, such as neural networks and support vector machines, have shown promise in accurately predicting material behavior based on various input parameters (Zhang et al., 2019). These models consider factors such as material properties, processing conditions, and geometric configurations to provide reliable predictions. Optimization methods, including genetic algorithms and particle swarm optimization, have been employed to determine the optimal rigidity index that minimizes dimensional deviations. Yadav et al. (2022) demonstrated the effectiveness of these techniques in optimizing material properties to enhance manufacturing precision. In the context of thick materials, optimizing the rigidity index can help in balancing the material's resistance to deformation with the need for efficient processing. Numerous studies have explored the application of rigidity optimization in various manufacturing contexts. For example, Kim et al. (2021) investigated the optimization of rigidity in the machining of titanium alloys for aerospace components, finding significant improvements in dimensional accuracy. Similarly, Gupta et al. (2023) examined the benefits of optimizing material rigidity in the precision forging of automotive parts, demonstrating enhanced dimensional stability and reduced defect rates. Meiabadi, Moradi, and Karamimoghadam (2021) explored the use of artificial neural networks in predicting the producibility of 3D printed parts made from polylactic acid. Their study demonstrated that an accurate model could predict toughness and dimensional accuracy, suggesting optimized settings for enhanced producibility (Meiabadi, Moradi, & Karamimoghadam, 2021). Their research underscores the potential of machine learning in fine-tuning manufacturing parameters to improve material rigidity and accuracy. Glaesener et al. (2023) investigated the impact of geometric imperfections on the mechanical response of 2D and 3D trusses. Their findings indicate that addressing imperfections can significantly enhance rigidity and dimensional accuracy (Glaesener et al., 2023). Vidakis et al. (2022) focused on the effects of nozzle temperature, layer thickness, and infill density on surface roughness and dimensional accuracy in 3D printing. Their prediction models and optimization techniques demonstrated substantial improvements in accuracy (Vidakis et al., 2022). The research highlights the intricate relationship between processing parameters and material properties. Also, Forés-Garriga, Gómez-Gras, and Pérez (2023) conducted an experimental and numerical analysis on additively manufactured cellular solids. They found that optimized microarchitectures enhance rigidity and dimensional accuracy (Forés-Garriga, Gómez-Gras, & Pérez, 2023). Their study provides insights into the design considerations necessary for achieving high-performance materials. Sun and Lian (2018) analyzed the stiffness and mass optimization of parallel kinematic machines, focusing on improving accuracy and rigidity through dimensional adjustments (Sun & Lian, 2018). Their findings contribute to the broader understanding of mechanical optimization in precision machinery.

The reviewed studies collectively underscore the importance of optimizing the rigidity index to achieve high dimensional accuracy in thick materials. The methodologies employed range from artificial intelligence to experimental validation, each offering unique advantages in specific contexts. Machine learning models, such as artificial neural networks, have shown significant promise in predicting and optimizing material properties. Meanwhile, numerical and experimental approaches provide robust validation and insights into the underlying mechanics of material behavior. Optimizing the rigidity index is crucial for enhancing the dimensional accuracy of thick materials. Advances in artificial intelligence, numerical analysis, and experimental methodologies have provided substantial progress in this field. Future research should continue to integrate these approaches, focusing on developing more precise and efficient optimization techniques.

2. METHODOLOGY

A central composite design matrix will be employed for the experiment and a design expert software wil be used considering a widely established machining parameters The response surface methodology will be employed to optimize this target response The RSM methodology was selected because of its robustness to handle multi response parameters.

2.1 Design of experiment

DOE refers to planning, designing and conducting an experiment. To achieve this an appropriate combination of the experimental parameters is required. One of the conventional common approaches utilized by many engineers in manufacturing companies is one-variable-at-a-time (OVAT), where the engineer varies one variable at a time keeping all other variables involved in the experiment fixed. This approach required large resources to obtain a limited amount of information about the process. OVAT experiments are often unreliable, time consuming, may not yield the optimal condition and do not address the interaction effect between the process variables. Methods that have statistical bases can replace OVAT experimental approach. The most popular Response Surface Methodology design is CCD. CCD has three groups of design points: (a) two-level factorial or fractional factorial design points, (b) axial points (sometimes called star points) and (c) centre points. CCD's are designed to estimate the coefficients of a quadratic model. All point descriptions will be in terms of coded values of the factors

2.2 Models employed

In the present study two expert systems were employed in the modeling, optimization and prediction which are RSM and ANN.

2.2.1 Response Surface Methodology

RSM are used to develop empirical models, commonly called response surface, for the response of a process in terms of the relevant controllable factors. RSM determines the operating conditions that produce the optimum response. Response Surface Methodology allows you to specify and fit a model up to the second order, RSM fits a model and provides the ANOVA and the 'Lack of Fit' test separately when there is more than one response. Contour and Surface plots of each response for pairs of factors are also produced.

2.2.2 Artificial Neural Networks

Neural network are data mining tool for finding unknown patterns in databases, a neural network is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects. Knowledge is acquired by the network through a learning process, Interneuron connection strengths known as synaptic weights are used to store the knowledge.An elementary neuron with *R* input is weighted with an appropriate *w*. The sum of the weighted inputs and the bias forms the input to the transfer function *f*. Neurons can use any differentiable transfer function *f* to generate their output. Multilayer networks often use the log-sigmoid transfer function logsig. The function logsig generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity. Alternatively, multilayer networks can use the tan-sigmoid transfer function tansig. Sigmoid output neurons are often used for pattern recognition problems, while linear output neurons are used for function fitting problems.

3. RESULTS AND DISCUSSION

3.1 Modeling and Optimization using RSM

Response Surface Model is a variation of the simple linear regression, with the incorporation of the second order effects of non-linear relationships. It is a popular optimization technique to determine the best possible combinations of variables to determine a specific response to a phenomenon

Table 1: Experimental Results

	Depth of	Cutting speed	Feed rate	Rigidity index
1	165.00	17.50	11.50	0.55
2	150.00	16.00	10.00	0.85
3	165.00	17.50	14.02	0.59
4	165.00	20.02	11.50	0.56
5	165.00	17.50	11.50	0.55
6	180.00	19.00	13.00	0.67
7	150.00	19.00	10.00	0.67
8	180.00	16.00	13.00	0.52
9	180.00	16.00	10.00	0.52
10	190.23	17.50	11.50	0.46
11	139.77	17.50	11.50	0.51
12	165.00	17.50	11.50	0.55
13	180.00	19.00	10.00	0.67
14	150.00	19.00	13.00	0.44
15	165.00	14.98	11.50	0.55
16	165.00	17.50	8.98	0.88
17	165.00	17.50	11.50	0.46
18	165.00	17.50	11.50	0.5
19	165.00	17.50	11.50	0.5
20	150.00	16.00	13.00	0.48

To validate the suitability of the quadratic model in analyzing the experimental data, the sequential model sum of squares was calculated for rigidity index response as presented in Table 2.

Table 2: Sequential Model Sum of Square for Rigidity Index

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Mean vs Total	6.59	1	6.59			
Linear vs Mean	0.089	3	0.030	2.56	0.0913	
2FI vs Linear	0.081	3	0.027	3.39	0.0507	
Quadratic vs 2FI	0.093	3	0.031	29.86	< 0.0001	Suggested
Cubic vs Quadratic	3.210E-003	4	8.026×10^{-4}	0.67	0.6376	Aliased
Residual	7.214E-003	6	1.20210^{-4}			

The sequential model sum of squares table shows the accumulating improvement in the model fit as terms are added. Based on the calculated sequential model sum of square, the highest order polynomial where the additional terms are significant and the model is not aliased was selected as the best fit. To test how well the quadratic model can explain the underlying variation associated with the experimental data, the lack of fit test was estimated for each of the responses. Model with significant lack of fit cannot be employed for prediction. The model statistics computed for rigidity index response based on the model sources is presented in Table 3.

Table 3: Model Summary Statistics for Rigidity Index

Source	Std. Dev.	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	
Linear	0.11	0.3244	0.1977	-0.1790	0.32	
2FI	0.089	0.6210	0.4461	0.1727	0.23	
Quadratic	0.032	0.9619	0.9277	0.8561	0.039	Suggested
Cubic	0.035	0.9737	0.9166	0.8580	0.039	Aliased

The summary statistics of model fit shows the standard deviation, the r-squared, adjusted r-squared, predicted r-squared and predicted error sum of square (PRESS) statistic for each complete model. Low standard deviation, R-Squared near one and relatively low PRESS is the optimum criteria for defining the best model source. Based on the results,the quadratic polynomial model was suggested while the cubic polynomial model was aliased hence, the quadratic polynomial model was selected for this analysis. To detect the presence of mega patterns or expanding variance a plot of residuals and the predicted was produced for rigidity index is shown in the Figure 1.

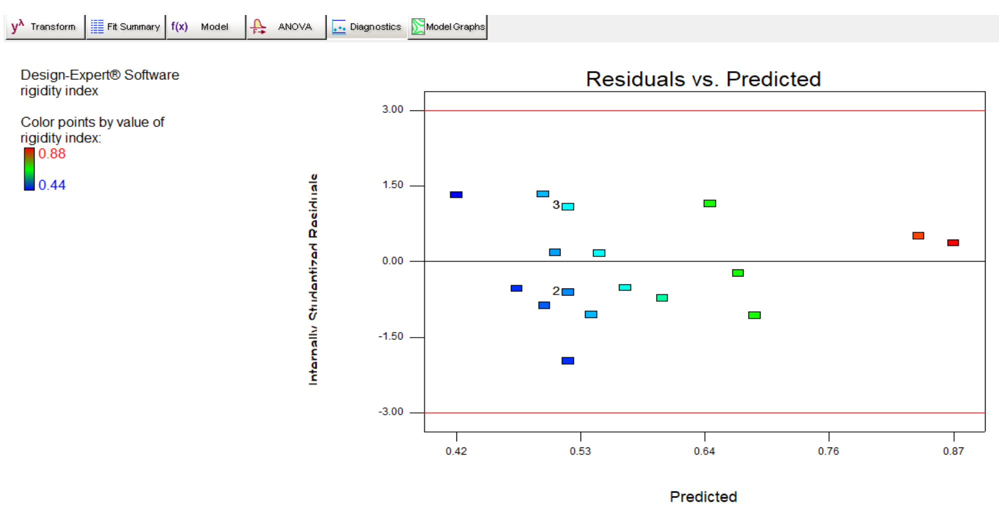

Figure 1: Plot of Residuals against Predicted for Rigidity Index

In order to detect a value or group of values that are not easily detected by the model, the predicted values are plotted against the actual values, for rigidity index which is shown in Figure 2.

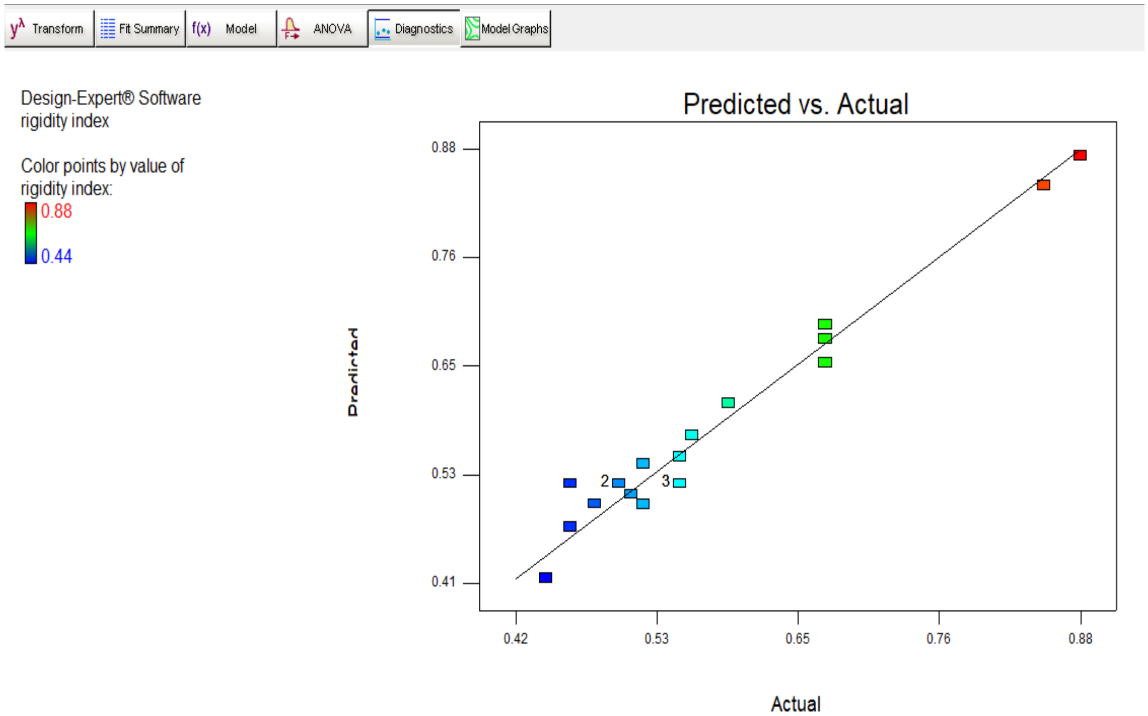

Figure 2: Plot of Predicted Vs Actual for Rigidity Index

To determine the presence of a possible outlier in the experimental data, the cook's distance plot was generated for the different responses. The cook's distance is a measure of how much the regression would change if the outlier is omitted from the analysis. A point that has a very high distance value relative to the other points may be an outlier and should be investigated.

3.2 Artificial Neural Network (ANN) Model

The same data used for the RSM analysis was used for theANN, the configuration interphase for neural network, where all parameters were set and the feed forward backpropagation was chosen amongst other network type to yield the best results depth of cut, cutting speed and feed rate information provided. It is recommended that a set of data be set aside for validation and testing, therefore, that data obtained form this research were divided into three parts with 70% of the experimental sample data, used for training 15% used for validation, while the remaining 15% was used to test the neural network model. This resulted in 20 samples of the entire date used for training while 5 samples each was employed for validation and testing. The ANN network architecture for the rigidity index has 3 input, 10 neurons in the hidden layer and 1 neuron in the output layer, the network architecture. The best prediction for the rigidity index responses was achieved at epoch 2, although, a total of 6 epochs were used in the iteration process.the performance curve for rigidity index is presented in Figure 3.

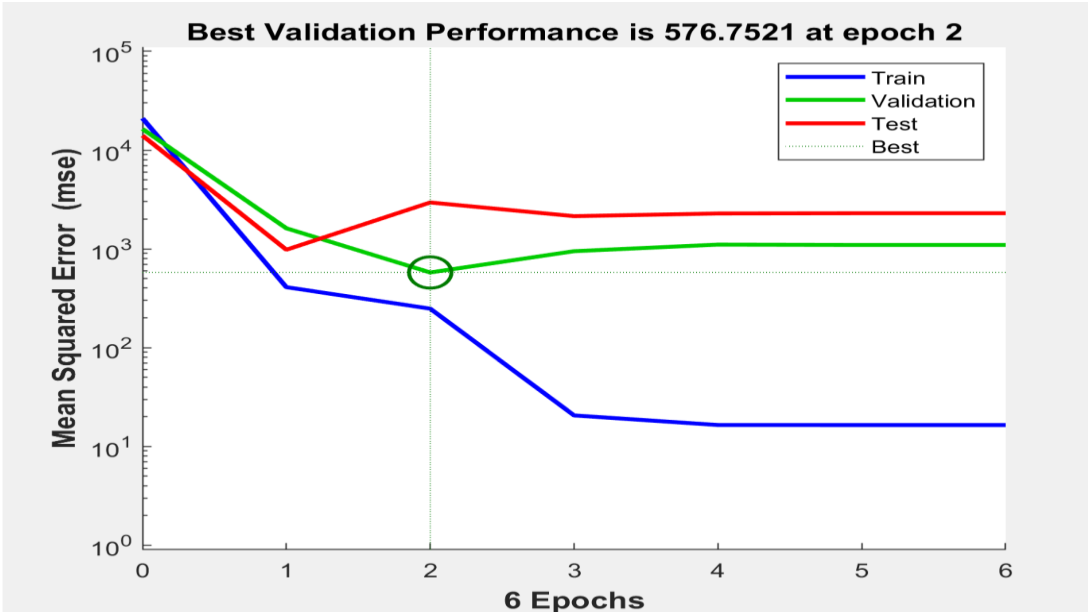

Figure 3: Performance Curve for Trained Network to Predicting Rigidity Index

A gradient function diagram which shows the momentum gain and optimal epoch value of the network epoch is produced. Figure 4 shows the gradient function plot.

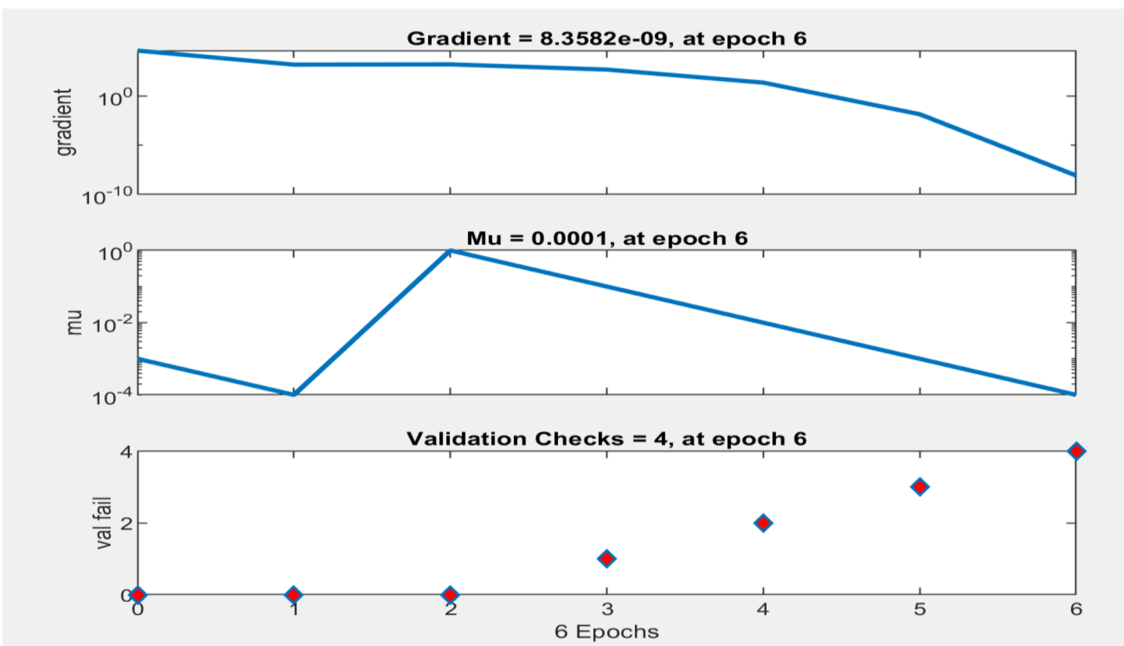

Figure 4: gradient plot for predicting rigidity index

A regression plot is produced to check for the correlation between the network output and the observed values. The dotted diagonal line on each plot indicates the line of best fit which indicate a perfect prediction and a correlation of 1. The regression plot is shown in Figure 5.

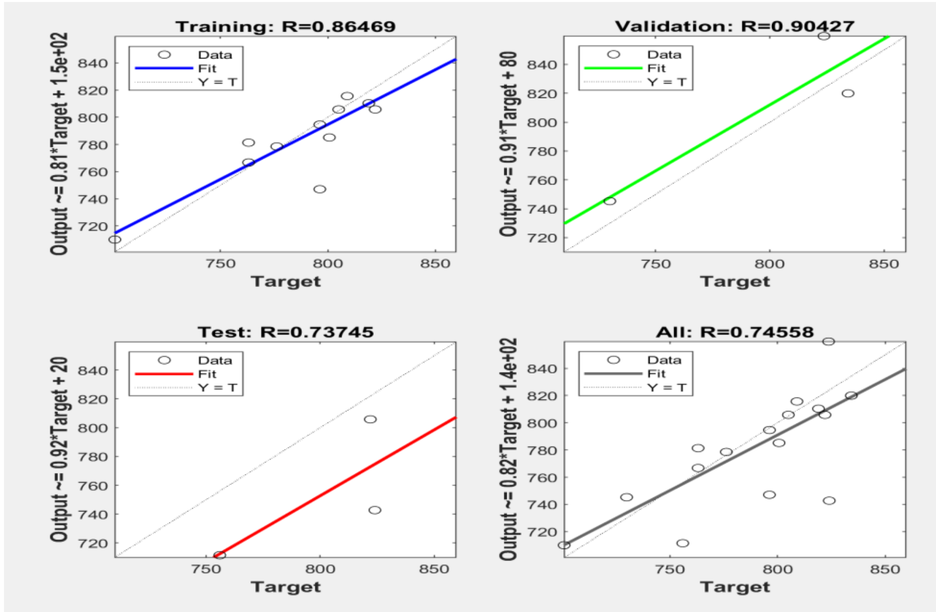

Figure 5: Regression plot for rigidity index

The network output has been able to produce predictions for the rigidity index which is shown in Table 4

Table 4: rigidity index prediction

	Input Parameters			Rigidity index		
	Depth of cut	**cutting speed**	**Feed rate**	**EXP**	**ANN**	**Error**
1	165.00	17.50	11.50	0.85	0.87	-0.02
2	150.00	16.00	10.00	0.52	0.64	-0.12
3	165.00	17.50	14.02	0.67	0.63	0.04
4	165.00	20.02	11.50	0.67	0.65	0.02
5	165.00	17.50	11.50	0.48	0.55	-0.07
6	180.00	19.00	13.00	0.52	0.5	0.02
7	150.00	19.00	10.00	0.44	0.52	-0.08
8	180.00	16.00	13.00	0.67	0.64	0.03
9	180.00	16.00	10.00	0.51	0.61	-0.1
10	190.23	17.50	11.50	0.46	0.43	0.03
11	139.77	17.50	11.50	0.55	0.65	-0.1
12	165.00	17.50	11.50	0.56	0.7	-0.14
13	180.00	19.00	10.00	0.88	0.84	0.04
14	150.00	19.00	13.00	0.59	0.6	-0.01
15	165.00	14.98	11.50	0.55	0.52	0.03
16	165.00	17.50	8.98	0.46	0.51	-0.05
17	165.00	17.50	11.50	0.5	0.55	-0.05
18	165.00	17.50	11.50	0.5	0.47	0.03
19	165.00	17.50	11.50	0.55	0.6	-0.05
20	150.00	16.00	13.00	0.55	0.62	-0.07

4. CONCLUSION

In this study a scientific approach was employed to understudy machining parameters required to enhance dimensional accuracy of thick materials using robust techniques such as response surface methodology (RSM) and artificial neural network (ANN). A cause and effect relationship between the process parameters has been established. The experimental procedure was well planned and optimal results was obtained with reasonable statistical significance.

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