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Neural Network Prediction of Surface Roughness with Bearing Clearance Effect

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ABSTRACT: *In manufacturing industry, the quality of manufactured machine components, is determined by how well they follow a defined product's criteria for dimensional accuracy, tool wear, and surface finish quality. For this reason, manufacturers must be able to regulate machining processes to ensure improved performance and service life of engineering components. This research work presents a study on the optimization of machining parameters for mild steel using artificial neural networks (ANNs). The focus is on developing an effective and efficient machining technique for mild steel by leveraging the capabilities of ANNs to predict optimal machining parameters. To bridge the gap between laboratory figures, model-simulated values, and real-world application, experiments were conducted to obtain data used in the research analysis. Levenberg-Marquardt method were utilized to train the ANNs, with input factors like depth of cut, bearing clearance, cutting speed, and feed rate considered, while the surface roughness of the cut, normalized within 0 to 1 range. A statistical measure of the surface roughness predicted using indicated MAPE value of 0.002% while the correlation coefficient (R) was 0.99995. The results showed that ANNs are a viable machining parameter optimization method and can improve product quality, while providing significant economic and production benefits.*

KEYWORDS: Artificial neural networks (ANN), optimization, turning parameters, surface roughness, modelling, machining processes, predictive modelling.

INTRODUCTION

In the manufacturing industry, manufacturers on the cutting edge of engineering face the problems of increased productivity, higher quality, and meeting economical standards. To address this challenge, machining processes is usually considered. Regularly, when machine components are manufactured, the quality of the components is determined by how well they follow a defined product's criteria for length, width, diameter, surface finish, and reflective qualities. In machine designs, dimensional accuracy, tool wear, and surface finish quality are three elements that manufacturers must be able to regulate during machining processes to ensure improved performance and service life of engineering components (Gaitonde et al., 2011). This is crucial because of the increasing demand for high-quality materials with increased durability on a global scale. Hence, the machining process and the optimization of machining parameters more than ever before must be given proper attention and be carefully carried out. Optimizing machining parameters will aid in manufacturing more efficient machine components, which can facilitate considerable improvements in the quality of final products. To ensure this, the turning operation which is one of the most typical machining procedures performed on materials like mild steel in the manufacturing industry is used. The turning operation basically involves feeding a high-precision single-point cutting tool rigidly held in a tool post past a spinning work piece on a lathe machine. This feeding exercise is done at a steady rate in a direction parallel to the work piece's axis of rotation (Grzesik, 2008). Turning operations can be performed manually under human supervision or automatically with the aid of a computer program, with the latter (automated supervision) reducing the need for human monitoring. When the turning process is in motion, the power necessary for an operation is typically transmitted to the spindle pulley or the gears of a lathe. It is vital to have a high degree of stiffness and a high load-carrying capability on the tool end of the spindle, where there is a heavy combined load. This operating criterion is required because unexpected spindle failure during operation might result in severe part damage and significant machine downtime. Such a challenge would have a negative impact on overall production, logistics, and productivity achieved (Girsang & Dhupia, 2015). Despite this, crucial to note is that, identifying the ideal machining parameters for a given work piece and cutting tool can be difficult due to the complicated and nonlinear interactions between the machining parameters and the resulting surface quality, tool wear, and cutting forces. To solve this difficulty, researchers have created a variety of optimization methods, including Response Surface Methodology (RSM) and Artificial Neural Network (ANN) modelling. RSM has been widely employed in the optimization of machining parameters due to its simplicity and effectiveness in modelling the process's operation to perfection (Montgomery, 2017). However, RSM has limits when dealing with complicated and nonlinear interactions between input and output variables. ANN, on the other hand, is a sophisticated modelling tool that can handle complicated and nonlinear interactions between input and output variables. ANN models are made up of a network of interconnected nodes that are capable of learning patterns and relationships in data (Maind et al., 2014). As a result, ANN may be used to model the relationship between the machining parameters and the response variables, and the model can be used to forecast the best machining parameters for a given set of input variables. In recent years, there has been a great deal of research into the application of ANN for optimizing machining settings.

Several researchers have reported effective uses of ANN in predicting optimal machining parameters for various materials and machining techniques (Nayak & Mahapatra, 2014). But, more research is required to investigate the potential of ANN in the optimization of machining parameters for mild steel turning processes. The purpose of this research is to look at the efficiency of ANN in the optimization of machining parameters for mild steel turning operations. Based on experimental data, create an ANN model that will be used to predict the best machining parameters for a given set of input variables. The research will also help to build a more efficient and effective machining technique for mild steel, which will lead to improvements in the completed product's quality and the manufacturing industry's overall productivity.

LITERATURE

Due to its low cost, high strength, and excellent machinability, mild steel is a frequently used material in the manufacturing industry. But for mild steel to be productive and effectively used in manufacturing processes, the cutting speed, feed rate, depth of cut, and tool geometry are key machining parameters that have significant impact which careful attention must be given to. Similarly, the inherent characteristics of mild steel, like include low thermal conductivity, high ductility, and toughness makes the optimization of machining parameters for mild steel turning operations a difficult task to resolve. However, the optimization of machining parameters is crucial because it helps to achieve high rates of material removal while preserving the desired surface finish and reducing tool wear in taking mild steel during turning operation. Artificial neural networks (ANNs) in recent times, have grown in popularity as an alternative to more established optimization methods like response surface methodology (RSM).

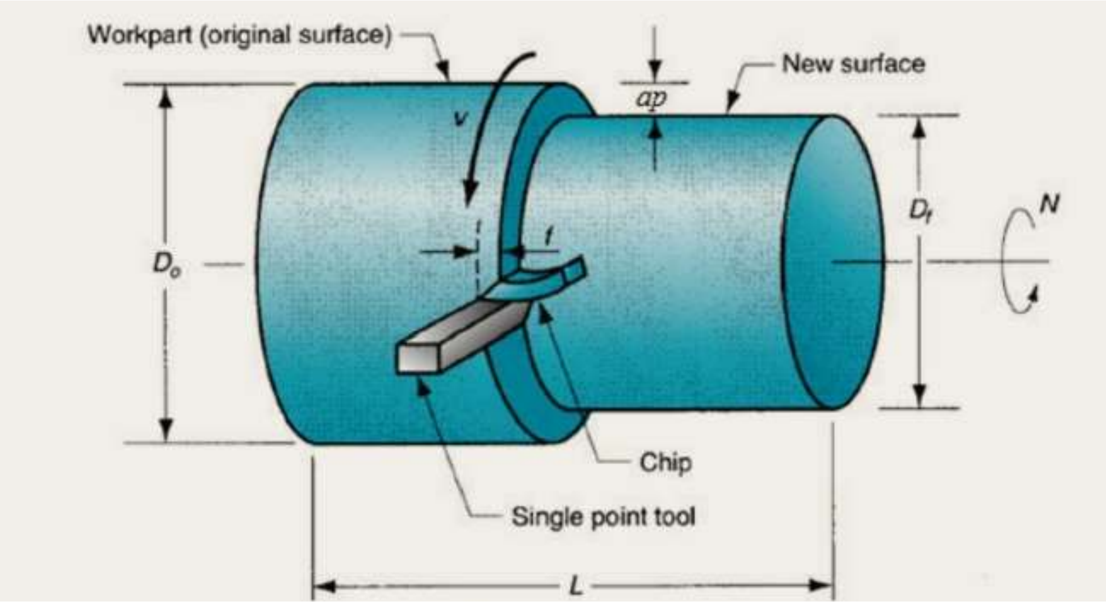

Figure 1. **Isometric representation of turning operation.**

This literature review investigates the use of ANNs in the optimization of machining parameters in mild steel turning operation. ANNs are a type of machine learning algorithm that learns from data to make predictions. They manage intricate, nonlinear relationships between input and output variables, making them a more potent tool for machining parameter optimization in mild steel turning operations (Sada, 2021). They operate differently when compared with RSM which assumes a quadratic relationship between the input and output variables, which might not adequately represent the complex nonlinear relationships that exist in machining processes. The various studies that investigated the use of ANNs in the optimization of machining parameters in mild steel turning operations are discussed in this paper. In 2015, researchers used ANNs to improve the cutting parameters during mild steel turning operations. The research work showed that, ANNs was combined with the imperialist competitive algorithm (ICA) to optimize cutting speed, feed rate, and depth of cut. The final outcomes demonstrated that the suggested method could successfully optimize machining parameters, resulting in enhancements to productivity and surface quality (Manohar et al., 2015). In a different investigation done in 2005, ANNs was used to model the behaviour of machining parameters during high-speed turning of Inconel 718 using a coated carbide tool. This research also showed that ANNs were employed to forecast cutting force, tool wear, and surface roughness, concluding that the ANN model could correctly forecast the ideal machining parameters, resulting in increases in output and quality (Ezugwu et al., 2005). In addition, further studies in 2013 revealed that, the machining parameters for turning operations on AISI 1045 steel were optimized using ANNs. For this research work, ANNs was combined with particle swarm optimization (PSO) algorithm to optimize feed rate, cutting speed, and cut depth. The outcomes also demonstrated the effectiveness of optimizing machining parameters with ANNs, resulting in gains in productivity and surface quality (Madić & Radovanović, 2013).

OPTIMIZATION OF MACHINING PARAMETERS IN MILD STEEL

Optimizing machining parameters in turning operation is critical for producing high-quality machined components at a low cost. The optimization method helps to determine the best combination of cutting parameters like depth of cut, cutting speed, feed rate, and tool geometry, to achieve maximum productivity and quality. This is significant because the inbuilt properties of mild steel, such as high ductility, hardness, and low heat conductivity, makes the process of obtaining a high material removal rate (MRR) while reducing tool wear and keeping the appropriate surface quality difficult (Dong et al., 2016). Optimization of machining parameters can be obtained by different machining models like Response Surface Methodology (RSM) or Artificial Neural Network (ANN). Using ANN for the processes has been discovered to increase the final machining products achieved as well as shown promising outcomes when used for different machining operations like turning, milling, and drilling. ANNs unlike RSM (which operates on the quadratic function of the input variables), do not work with assumptions on the relationship between the input and output variables.

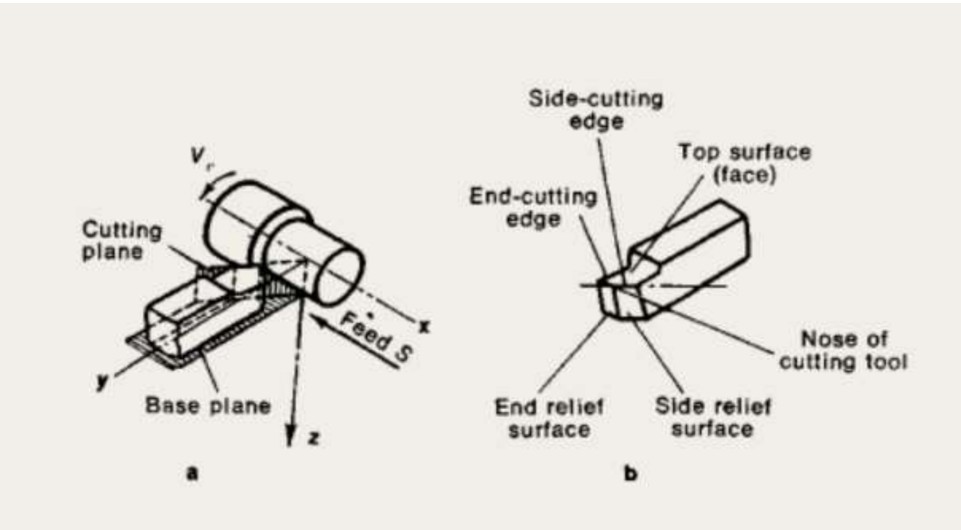

Figure 2. **Wire frame Isometric diagram of the machining processes.**

OVERVIEW OF THE ARTIFICIAL NEURAL NETWORK (ANN) SYSTEM

Artificial Neural Network (ANN) system has emerged as a viable and effective option in industrial engineering to solve the pressing need for accurate predictions in machining processes while overcoming the existing limitations in simulation technologies. ANN is a computer modelling artificial intelligence system that has the ability to handle complex and nonlinear relationships, much like the neural architecture of the human brain, making it highly applicable for simulating manufacturing operations (Venkatesan et al., 2009). Today, ANNs has garnered popularity and has become significant

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in solving real-world issues across several sectors. It is relatively grouped among other common nonlinear mapping systems in artificial intelligence. Based on its working principle, ANNs essentially provides two functions. The first is for classifications, and second for accurate predictions. Also, Artificial neural networks, with proper training, can develop patterns between input and output data, by exploiting their multi-layered and parallel structure. Behind the ANN system are input layer, an output layer, and hidden layers which forms the basic foundation of the network. Looking through the hidden and output layers reveals linkages that are represented by an output weight matrix. These prevalent foundational characteristics throughout the core of ANNs explains its capacity to handle difficult simulation problems. Previous research has claimed and showed excellent performance and exceptional effectiveness in employing ANN algorithms to capture the implicit association between process parameters and output variables in manufacturing processes.

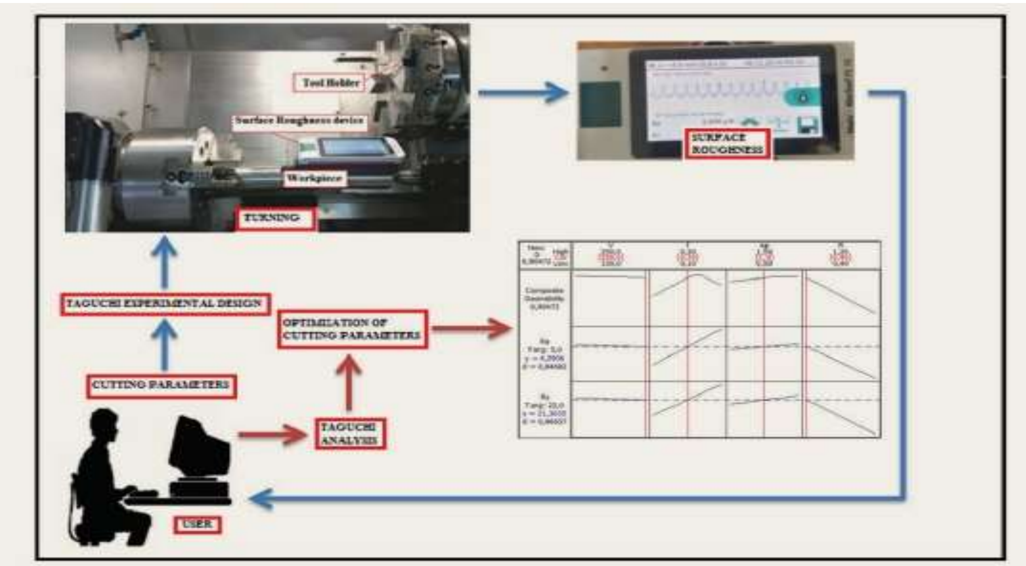

Figure 3. **The flow chart of optimization of cutting parameters.**

In recent years, research has revealed the emphatic call to utilize Artificial Neural Network system modelling approach for manufacturing processes and for explaining the link between process parameters and output variables. Typically, industrial processes are intrinsically complicated, posing obstacles for meaningful mathematical representation. In other industrial processes, output parameters like surface roughness and cutting forces, as well as input parameters depth of cut, feed, and spindle speed, are important in determining product quality and lifespan. To ensure a perfect equation that works, ANN has proven to be helpful and effective in forecasting even the most complex processes by leveraging previous data and demonstrating accurate predictions. Artificial neural systems, which represent the next generation of information processing networks, is often widely employed in forecasting surface roughness in a variety of cutting processes. Research by Feng and Wang, developed an empirical model for surface roughness prediction in turning finishing, and compared the predicted surface roughness values with existing models (developed using computational neural networks, data mining techniques, and nonlinear regression analysis). In this research, parameters such as work piece hardness, feed, depth of cut, cutter nose radius, and spindle speed were taking into account. Following the comparison and assessment of the metal cutting trials and hypothesis calculations, ANNs was shown to have acceptable excellence in fitting (Feng & Wang, 2003). In addition, Ozel and Karpat in

2005 used neural network modelling in their study to successfully estimate surface roughness and tool flank wear throughout the machining process for varied cutting circumstances in finish hard turning. They also created regression models to capture process-specific factors. This was done by acquiring a restricted collection of experimental data on finish turning of hardened AISI 52100 steel from literature sources (Özel & Karpat, 2005). In addition, they conducted their own studies on hardened AISI H-13 steel finish turning to gain further experimental data. These data sets, which included measurements of surface roughness and tool flank wear, were used to train the neural network models. After that, the trained neural network models were used to forecast tool flank wear and surface roughness under various cutting situations. Further research has revealed other network approach which has caught interest from industrial experts. One of these networks is the Back propagation networks. This form of neural network system, showed a great degree of accuracy when modelling various industrial processes. One of the primary reasons for the attention and widespread use of Back Propagation Neural Network (BPNN) is its capacity to generate good results even when presented with inputs not seen during training (Kuang et al., 2022).

BACK PROPAGATION NETWORK LEARNING ALGORITHM IN ANNS

Back propagation network learning is a popular approach in ANNs with several layers. It entails calculating the network's overall error rate and repeatedly modifying the weights and biases. This optimization approach is centred on reducing the error between the network's output and the desired output. The error reduction process is repeated until a convergence criterion is attained, hence indicating that an acceptable degree of accuracy is reached. Study showed the implementation of the Levenberg-Marquardt method in MATLAB using the "trainlm" syntax (Al Shamisi et al., 2011). This algorithm acts as a network training function, updating weight and bias values via Levenberg-Marquardt optimization. It is the default training function for many networks building methods, including feed-forward networks (newff). The "trainlm" technique is well-known for its speed in the MATLAB neural network toolbox and is frequently suggested as the preferred choice for supervised learning jobs. It does, however, function best when more memory is available compared to other methods, which doesn't require so much memory. The back propagation learning algorithm ANNs in artificial intelligence, is growing to become a dominant simulation approach widely used in engineering applications for prediction, optimization, pattern recognition, and others. The model when running its prediction takes input factors like depth of cut, bearing clearance, cutting speed, feed rate, etc, into account of cut, with its surface roughness being normalized within the range of 0 to 1.

BEARING INTERNAL CLEARANCE IN MACHINING COMPONENTS

Internal clearance in bearings across all rolling element is unique, and relates to the amount of gap present in the bearing. It is a crucial consideration in bearing selection since it directly impacts the lifespan of the bearing. The internal clearance in bearings is precisely defined as the overall clearance between the bearing rings and the rolling components, providing smooth rotation for the rolling parts, accommodating heat effects, and guaranteeing appropriate load distribution. Internal clearance is usually classified into two parts: radial clearance and axial clearance. Radial clearance is the gap between the ball and the raceway, perpendicular to the bearing axis, whereas axial clearance is the play parallel to the bearing axis and is often significantly bigger than radial clearance. Interference fit in bearings, reduces internal radial clearance by 80% on average (Fang et al., 2019). The importance of bearings across machine components makes it critical to maintain an optimum degree of internal

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clearance as they have substantial influence on vital parameters like noise, fatigue life, heat production, and vibration. Under unpleasant working conditions like high or low temperatures, it is even more critical to consider internal clearance in the overall bearing design, because it accounts for thermal expansion and contraction of housings and shafts. The right internal clearance for bearings is critical because it directly impacts the operation of a mechanism by guaranteeing the precise alignment of rotating elements under varying operating circumstances. The internal clearance, which relates to the interaction between the inner ring, outer ring, and ball, is crucial in bearing selection and has a major influence on aspects such as noise, vibration, heat production, and fatigue life. Neglecting the importance of internal clearance can be disastrous and should be avoided at all costs. It should be observed that the internal clearance is not constant and fluctuates when bearing rings expand or compress. In ball bearings, an increase in radial clearance (the space between the balls and the rings) results in an increase in axial clearance. Greater radial clearance allows the pieces to move relative to each other. As a result, internal clearance designations for bearings range from C1 (tightest) to C5 (loosest or biggest) (Warda & Chudzik, 2016).

BEARINGS EFFECTS ON VIBRATION IN MACHINED COMPONENTS

The bearing system is critical to spindle performance, delivering an appropriate rotational speed and load capacity while assuring a fair service life. Bearings for high-speed spindles are available in a variety of configurations, including taper roller bearings, angular-contact ball bearings, and cylindrical roller bearings, as shown in Figure 4.

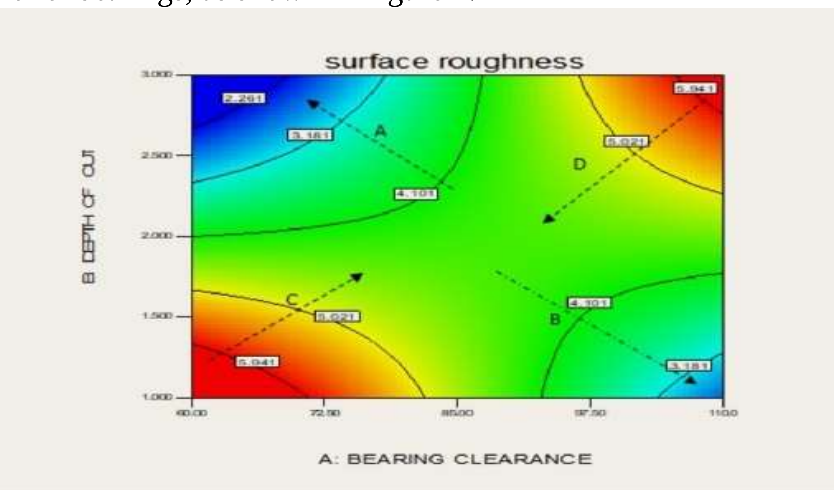

Figure 4. **Bearing clearance and Depth of cut representation in terms of contour plot of surface roughness.**

Ball and roller bearings are well-known machine components used widely in mechanical devices with rotating parts. Every bearing type has its own advantages. Roller bearings for instance, especially cylindrical roller bearings and taper roller bearings, are commonly used in applications needing high load carrying ability. These bearings excel in carrying heavy loads that cannot be achieved with ball bearings alone (Gao et al., 2021). Rolling element bearings are critical mechanical components that allow exact shaft rotation with little friction, provided they are free of flaws. When a bearing develops a flaw on one or more of its raceways, it can have a substantial influence on the shaft's stability and lead to increasing vibration levels. If these flaws are not detected early on, they might worsen and even damage other machine components. It is also crucial to understand that a broken bearing is a safety issue in the workplace and can go on to cause catastrophic failures or a chain of subsequent problems. Such incidents not only waste finance, time, and productivity, but also endanger the lives of those involved. Neglecting bearing difficulties and the dangers connected with them can have adverse effects, both in terms of monetary loss and possibly legal issues for the organizations or persons concerned. For this reason, it is critical to detect bearing faults in their early stage, as it will to save downtime and losses in industries. In addition, early detection of faulty bearing is crucial in averting accidents and maintaining the functionality of ongoing industrial systems. It ensures safe and effective operation of rotating mechanical systems, and great care should be taken to prevent them from

METHODOLOGY

The approach used in this study is both quantitative and experimental. To ensure universal application of the results and deductions in this study, tests were run to obtain the data used in the research and analysis leading to the optimization process. The Neural Network was generated in matrix laboratory (MATLAB) and used to optimize the data provided. In this section, we present details of the methods and materials used in the experiment as well as the procedural intricacies followed.

Specific techniques such as the statistical design of experiments helped mitigate economic excesses. Known as a means of predicting optimal experimental repetitions necessary for process modelling, it served as a bridge from the experimental stage to engineering application of this study. The cost and availability of electricity in Africa makes it problematic to conduct experiments of this nature at luxurious amounts. The statistical design approach is therefore a solution that can be embraced as it reduces the time and cost required to obtain experimental results sufficient to make real-life, universal conclusions. Applied to the turning process, this approach determines efficient data for creating a model that simulates real-world execution to near perfection.

The purpose for the experimental aspect of this study is to adequately bridge the gap between laboratory figures, model simulated values and real-world application. Surface roughness forecasting may result in commendable economic and production benefits if performed accurately. For this reason, we will adopt a Nonlinear Autoregressive with External (Exogenous) Input (NARX) solutions obtained in MATLAB. As shown in Fig 5, this NN algorithm takes the input of a series x(t) and previous values of $y(t)$ such as $y(t-1)$ to predict a value $y(t)$. Where $y(t)$ is a series that can represent say the surface roughness, $x(t)$ represents bearing clearance (μm), depth of cut (mm), feed rate (mm/rev), spindle speed (rpm).

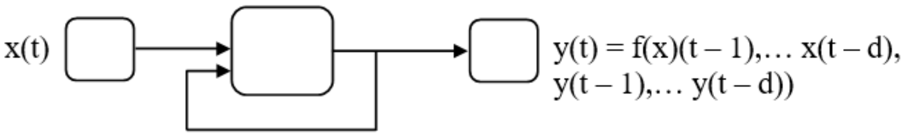

Figure 5. **Nonlinear Autoregressive with External (Exogenous) Input (NARX) Architecture.**

As discussed in section 2.2, substantial theoretical and practical advantages abound in the use of ANN for research, design and production. In the quest for efficient systems and better surface finish of mild steel, we will first look at the tools and techniques available and how we can adopt the ANN in the execution of better design and production strategies.

NETWORK CREATION AND TRAINING

In this section we will discuss the procedures for the creation and training of the ANN. It is however noteworthy that a substantial level of expertise in programming is required for the execution of the creation and training of the ANN to ensure practically useful solutions.

CREATION OF THE ANN WITH THE MULTI – LAYER PERCEPTRON (MLP) ALGORITHM

The Multi – Layer Perceptron (MLP) algorithm is used in this study. It has three layers: an input layer, a hidden layer and an output layer. The number of neurons used in the input layer depended on the number of input variables being considered in this case, the predictor generators that is bearing clearance (μm), depth of cut (mm), feed rate (mm/rev), spindle speed (rpm) and surface roughness (μm). The validation input data were also formed to the format for thirty (30) machine runs.

The number of neurons in the output layer depended on the number of variables to be predicted with this specific model (that is surface roughness). The number of neurons in the hidden layer was done (obtained) by trial-and-error procedure to determine a workable number of hidden neurons to use by selecting a few alternative numbers (adjusting network size) and then running simulations to find out the one that gave the best fitting (or predictive) performance in terms of the Mean Squared Error (MSE) and Regression Coefficient (R). The Mean Squared Error is the average squared difference between outputs and targets. Lower values are better, zero means no error. The correlation between outputs and targets was measured by the Regression Coefficient (R) value. An R value of one (1) means a close relationship, whereas zero (0) means a random relationship.

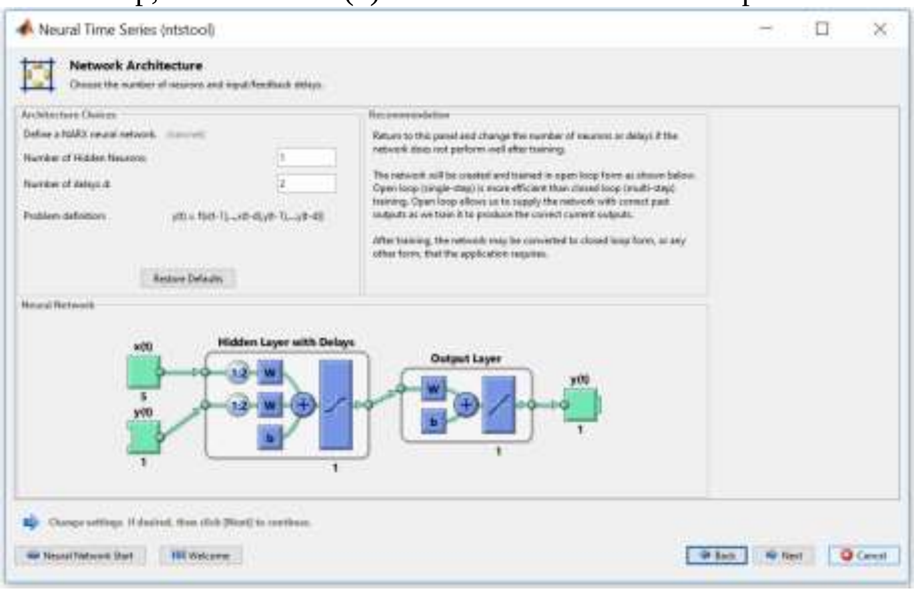

Figure 6. Number of Hidden Neurons.

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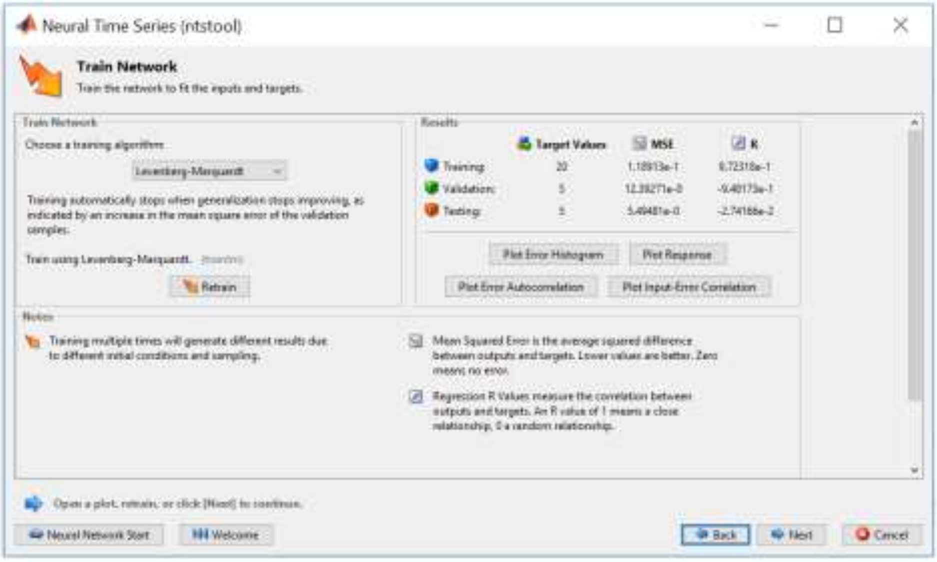

Figure 7. **Neural Network Training.**

LEVENBERG – MARQUARDT TRAINING ALGORITHM

In this study the Levenberg – Marquardt algorithm was used to train the Neural Network (NN) due to its faster convergence time. This process begun with a network which had 3 neurons in its hidden layer, and repeated, increasing the number of neurons up to 30, until the Levenberg Marquardt algorithm with 24 neurons in the hidden layer for network produced the best results, and it was used for generating the outputs.

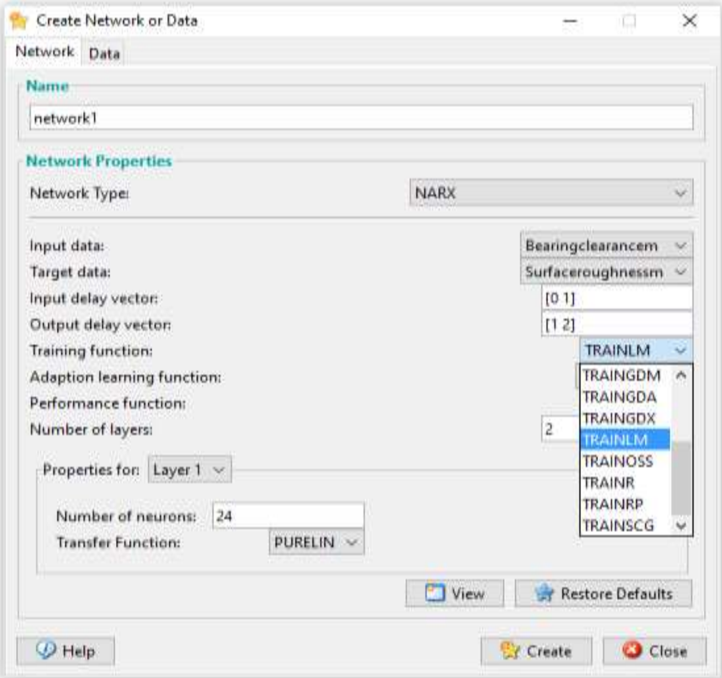

Figure 8. **Levenberg – Marquardt Training Function (TRAINLM).**

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The network performance adopted in this study was the mean absolute percentage error (MAPE) function which is a network performance function that measures network performance as the mean of absolute errors. The neural network was trained using the network with the model formed, the input to the network and the experimental surface roughness (µm) data.

NEURAL NETWORK SURFACE ROUGHNESS (µM) PREDICTION

The surface roughness (µm) prediction of the neural network is given by the relation below:

$$Neural\ Network\ Predicted\ (NNpredicted) = Simulate\left(\frac{Neural\ Network}{Validation\ Input}\right) \quad (1)$$

where simulate (*sim*) is a MATLAB syntax to simulate neural network. Network is the neural network trained and validation input (vin) are the inputs for the network validation (bearing clearance (μm), depth of cut (mm), feed (mm/rev), spindle speed (rpm) and surface roughness (μm).

The Error, Error Percentage and Mean Absolute Percentage Error (MAPE) of the network after training is computed as:

$$Error(err) \quad = Actual\ Surface\ Rroughness - NN\ Predicted \quad (2)$$

$$Error\ Percentage\ (errpct) = \frac{abs(Error)}{actual\ Surface\ Roughness} x\ 100 \quad (3)$$

$$MAPE \quad = mean(errpct(\sim isinf(errpct))) \quad (4)$$

where '*isinf*' is a MATLAB syntax for array element that are infinite, *abs* represent absolute value and complex magnitude. If the minimum error is less than or equal to the desired error, then the training converges (stops) and the network is saved.

EVALUATION OF OPTIMAL NUMBER OF NEURON IN HIDDEN LAYER

The selection of number of neurons in the hidden layer was done from the value of one (1) to thirty (30) and the plots of the first three neurons in terms of their performance curve and regression plots are depicted below:

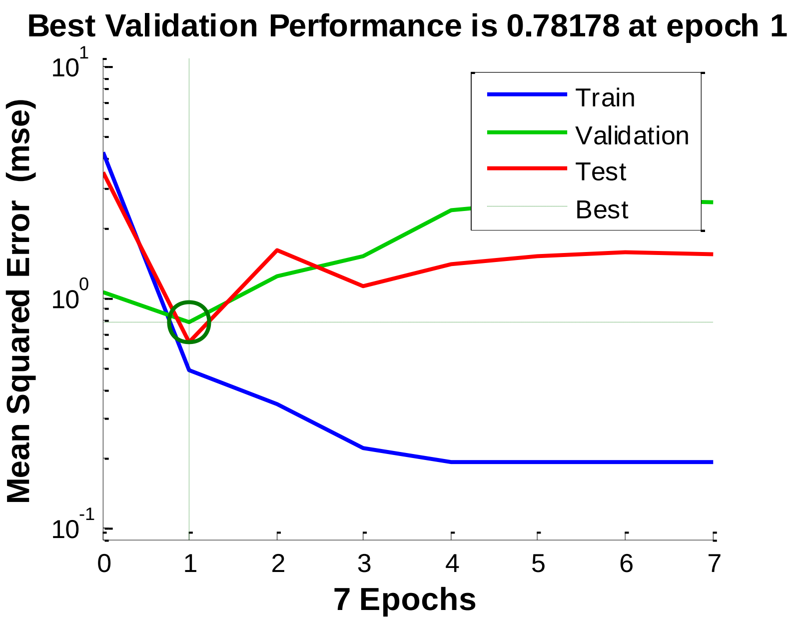

Figure 9. Mean Squared Error (MSE) Plot for One (1) Neuron in the Hidden Layer.

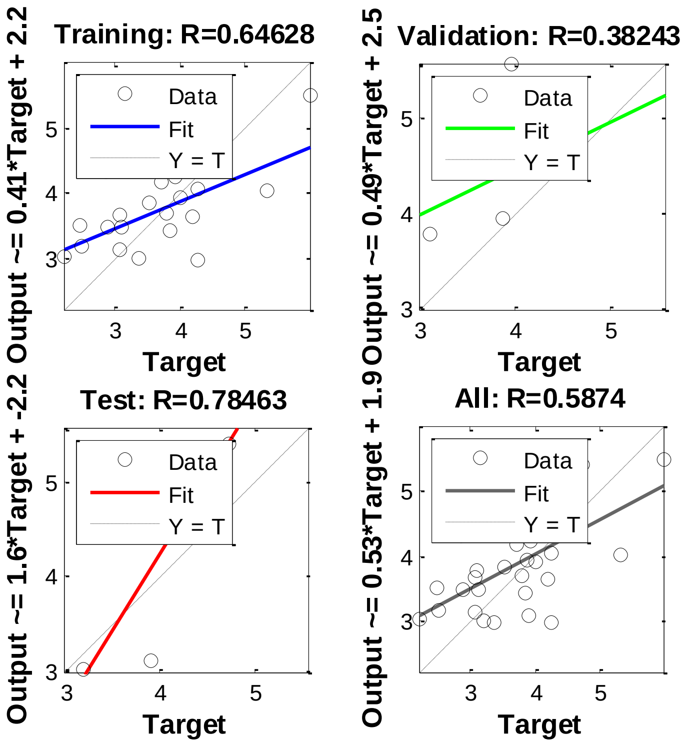

Figure 10. **Regression Plot for One (1) Neuron) in the Hidden Layer.**

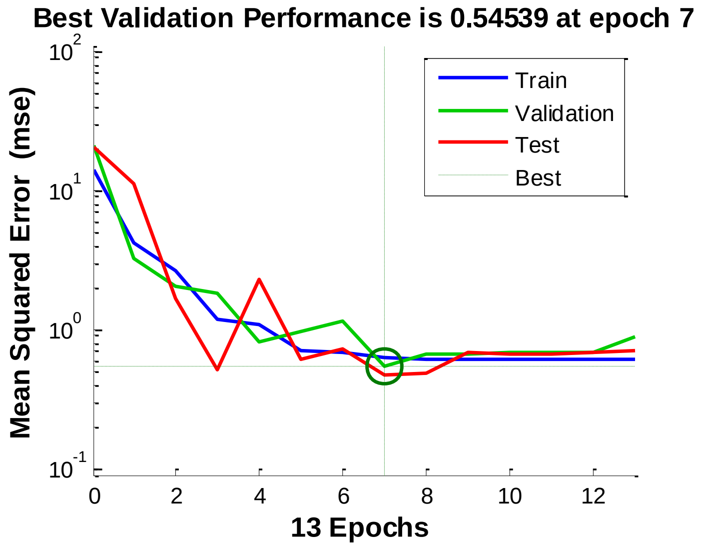

Figure 11. **Mean Squared Error (MSE) Plot for Two (2) Neurons in the Hidden Layer.**

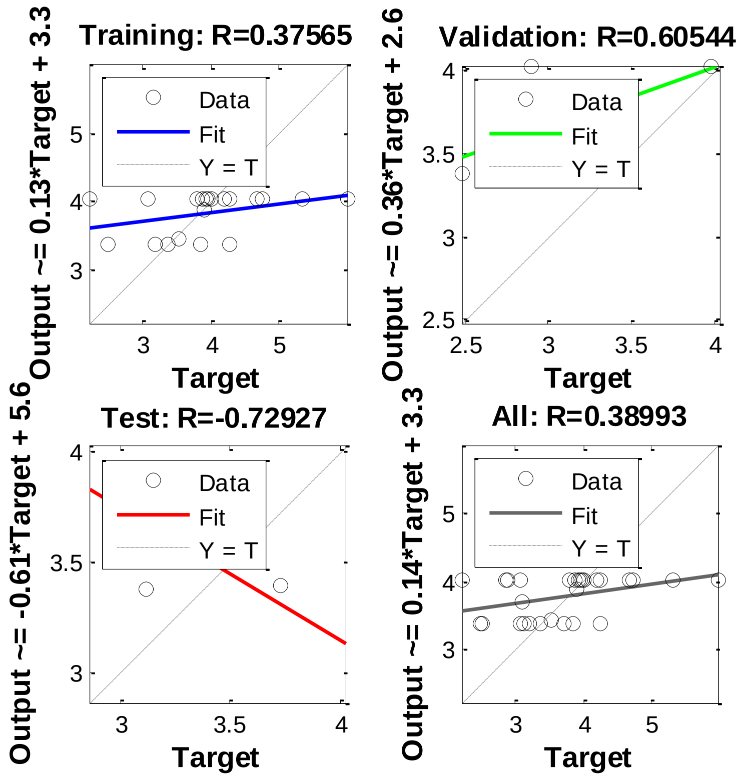

Figure 12. **Regression Plot for Two (2) Neurons in the Hidden Layer.**

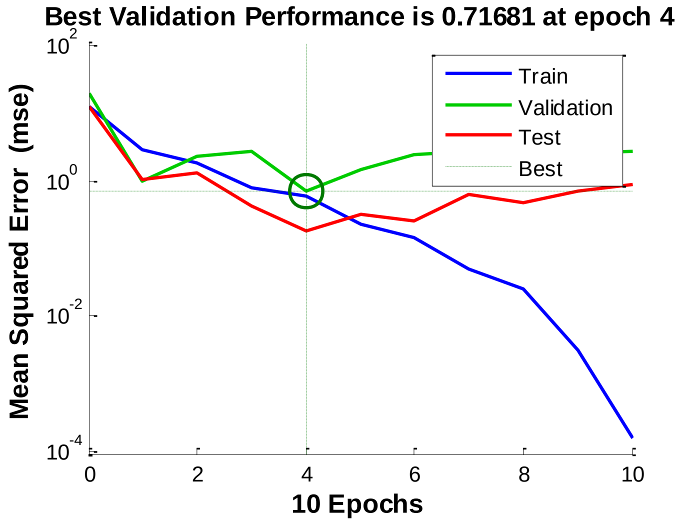

Figure 13. **Mean Squared Error (MSE) Plot for Three (3) Neurons in the Hidden Layer.**

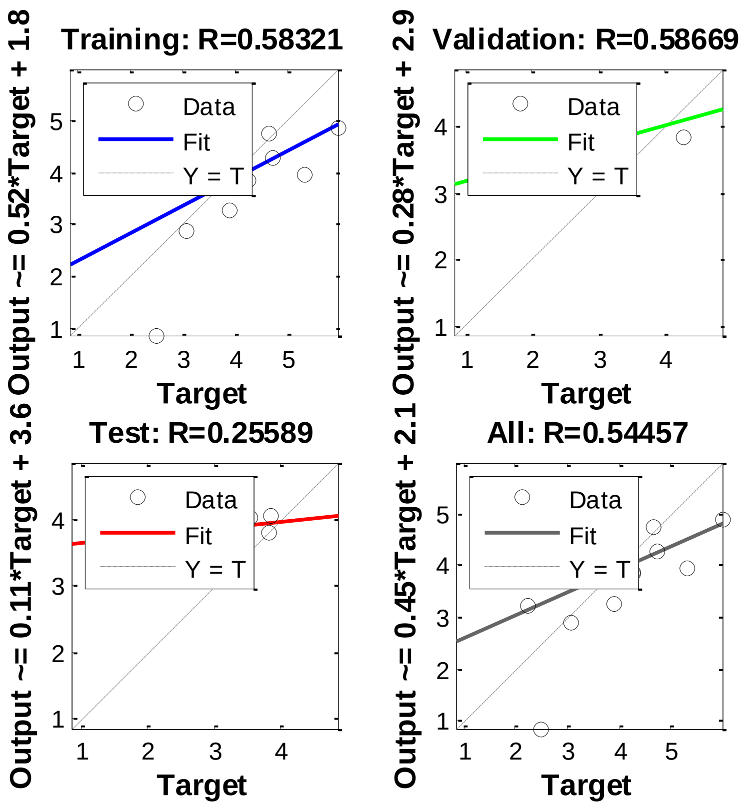

Figure 14. Regression Plot for Three (3) Neurons in the Hidden Layer.

SAMPLE AND SAMPLING TECHNIQUES

Interestingly, there are a variety of techniques used in the turning operation and other machining processes. There is therefore a need for a categorization of the processes. Categorizations such as process improvement control, play critical role in the determination of control factors. Other factors such as noise and system reaction time are critical to the determination of efficient and scalable machining processes. Although the tools and processes use in the experimental stage are important, more attention has been based on the ANN algorithm used and how it conforms to needed application and use to this study.

For the experiment, a design known as the rotatable central composite was used. Known as an efficient design for modelling a second – order response surface, it is a very common design used in various processes. The same magnitude of prediction error is associated with all points at the same radial distance (r) from the centre point in a rotatable design. k_2 fractional factorial points are some of the key components of rotatable CCD. They are usually coded as ± 1, increased by 2k axial points $[(\pm\alpha, 0, \ldots, 0), (0, \pm\alpha, \ldots, 0), (0, 0, \ldots, \pm\alpha)]$ and nC centre points $(0, 0, 0, 0 \ldots, 0)$. While the centre points for the rotatable design can vary from three to six, when a number of variables in a sample space are considered, the α rotatability is computed as $\alpha = (nf)1/4$. By definition of the terms used, rotatability refers to the uniformity of prediction error, α refers to the number of axial points required to achieve rotatability. Also, nf is the number of points in the k_2 factorial design. Lastly, k is the number of factors.

In this experimentation, sixteen (42) factorial points, eight axial points (2×4) and six centre runs, a total of 30 experimental runs are to be considered. A randomized experimental run has been carried out to minimize the error due to machining set-up. With an appropriate value of nC ,an orthogonal CCD can be made. A uniform precision design can also be adopted where necessary. We will proceed to discuss specific tools and techniques used in this study as follows:

INSTRUMENT FOR DATA COLLECTION AND VALIDITY OF THE INSTRUMENT

AISI 1018, a mild steel typically known for its excellent weldability, toughness and machinability is used as the work piece in this experiment. 30 round bars with a diameter of 30mm and a length of 100mm are used in the test and turning process. To ascertain the chemical composition of the steel in accordance with American Society for Testing of Materials (ASTM) standard, spectrometric analysis was performed on the steel rod at Metallurgical and Materials Testing Laboratory, University of Lagos, Akoko, Lagos State, as shown in Table 1 and Table 2.

Table 1. Chemical Composition of AISI 1018 Mild Steel Specimen.

Alloying Elements	Carbon	Silicon	Manganese	Sulphur	Phosphorous	Chromium	Molybdenum
Handbook of Percentage composition	0.14	0.26	0.96	0.019	0.023	0.11	0.007
Experimental Percentage composition	0.14	0.26	0.95	0.018	0.023	0.10	0.007

Table 2. Mechanical Properties/ Physical Properties.

Property	Density	Yield Strength	Ultimate Strength	Hardness	Shear Strength	Fatigue Strength	Poisson's Ratio
Handbook Values	7.858g/cc	370MPa	440MPa	126BHN	80GPa	140GPa	0.29
Experimental Values	7.788g/cc	367MPa	439MPa	127BHN	81GPa	142GPa	0.28

A Brinell Hardness test was performed using a Brinell Hardness test machine at the Engineering Materials Development Institute (EMDI), Akure, Ondo State, and a value of 127BHN was obtained, as shown in Table 1.

Instron tensile testing machine series 3369 was used for the tensile test at Obafemi Awolowo University in Ife, Osun State. The density of the samples of AISI 1018 mild steel material was assessed at the Physics Laboratory at the Faculty of Physical Sciences, Ambrose Alli University, Ekpoma. The values of the yield strength, ultimate tensile strength, shear strength, fatigue strength, and Poisson ratios were experimentally obtained as depicted in Table 2. According to test results shown in Table 2, the density was 7.788 g/cc.

Using the results from the experiment, ANN was trained on about seventy percent (70%) of the data. In the training of the neural network, the Mean Absolute Error (MAE) was used to determine error rate of the ANN model and it was seen that the error rate reached 0.0012472 minimum error rate with 10 iterations as shown in Figure 15. This gives the best validation performance of 0.0012472 at epoch 10 in. Fifteen percent (15%) of input data was used for testing and the remaining fifteen percent (15%) of input data was used for validation of the ANN prediction model.

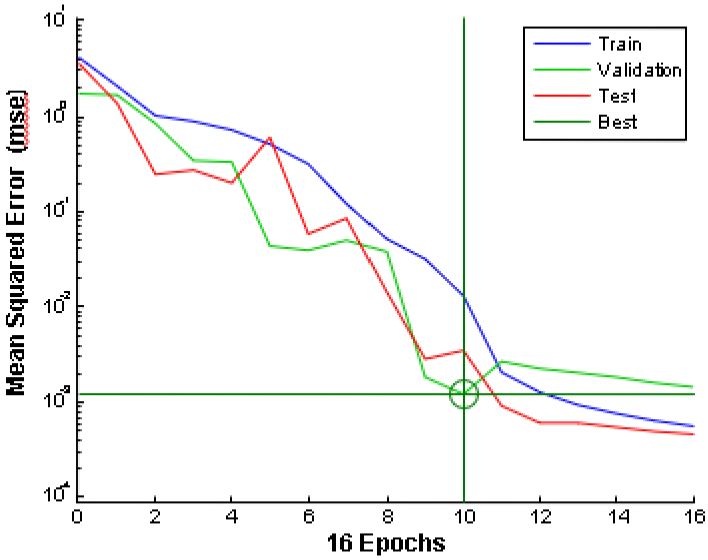

Figure 15. **Mean Absolute Error (MAE) Curve.**

RELIABILITY OF THE INSTRUMENT

To ensure the reliability of the study, a fitting line which is converging along the line $y = T$ is plotted during the learning process of the ANN model depending on the output data. The line convergence reveals the prediction effort of the model.

The regression rate between training and output data, the regression rate between validation and output data, the regression rate between testing and output data and the regression rate of whole data set used for learning process are shown in Figure 16.

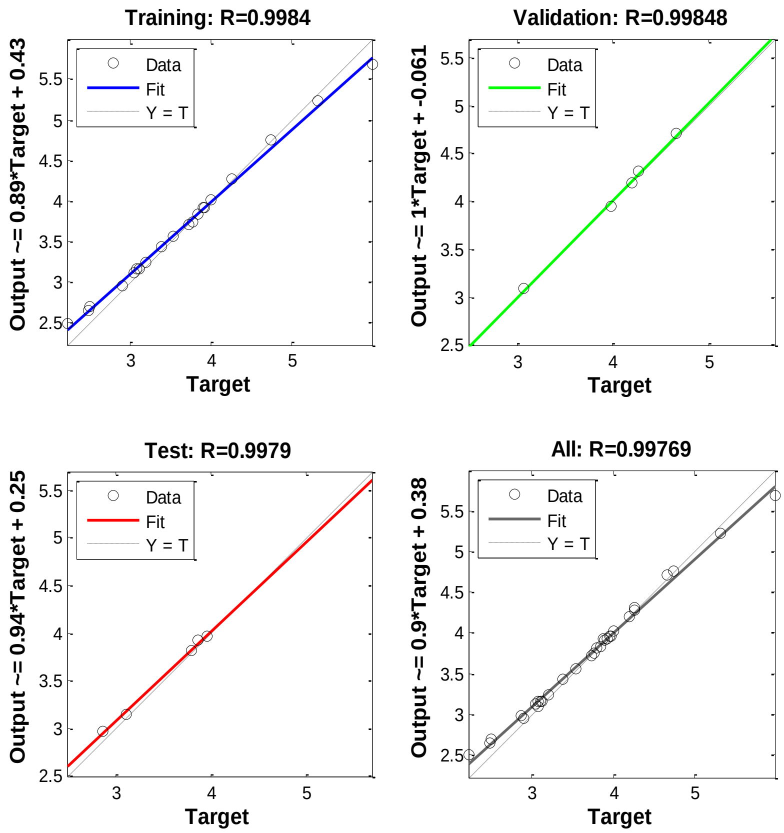

Figure 16. Regression Plot of Training Data, Validation Data, Test Data, All Data.

RESULTS

NEURAL NETWORK TRAINING AND LEARNING PERFORMANCE

An analysis of generated data based on statistical functions and artificial neural network was executed. To ensure that the results were valid, the mean absolute percent error (MAPE) of the data was computed with the use of MATLAB to check for their consistency with national and international specifications. In this analysis, care is taken to ensure that the data is used as obtained to avoid wide disparity between the original results and possible alterations made during the analytical process of introducing approximated block values into the entire process.

MEAN ABSOLUTE PERCENT ERROR (MAPE)

The desired error from the training entail considering the mean absolute percentage error (MAPE) of the best result. The behaviour of the surface roughness(µm) prediction model was estimated with a desire error of hundred (100) and the model converges quickly (stops training) at successive iterations until it reached a desired error of ten epoch (61.4) and going further, the network started overfitting. The various training procedure at achieving this desired error of 61.4 is enumerated in subsequent sections.

SURFACE ROUGHNESS PREDICTION FOR A DESIRED ERROR OF 100

The neural network training with a desired error of 100 gave a mean absolute percentage error (MAPE) of 1.982% for the predicted surface roughness (µm). The actual surface roughness(µm) was plotted against the predicted surface roughness(µm) as seen in the Figure 17.

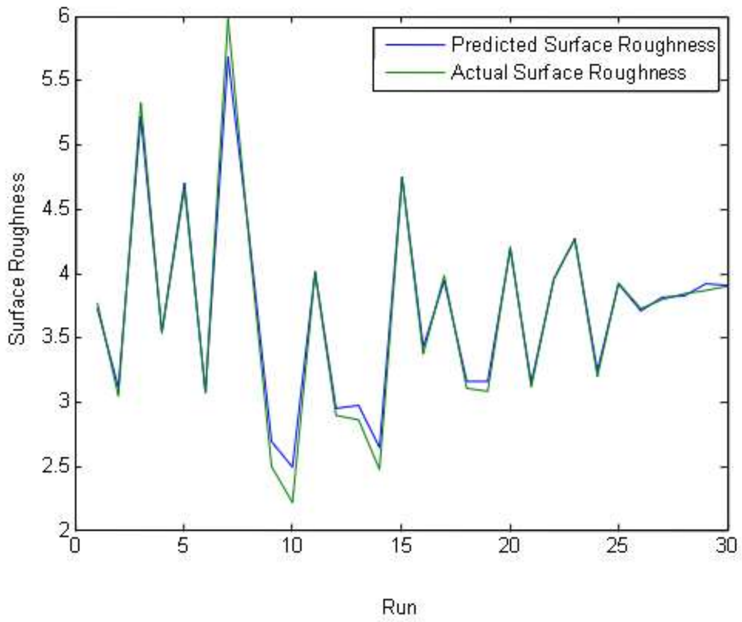

Figure 17. Plot of Actual Surface Roughness against the Predicted Surface Roughness.

Table 3. Prediction for Mean Absolute Percentage Error (MAPE) of 1.982%.

Run	Experimental Surface roughness (µm)	NN Surface Roughness	Error	Error Percent
1.	3.768	3.742	0.0256	0.6792
2.	3.042	3.118	-0.0757	2.4895
3.	5.322	5.227	0.0949	1.7833
4.	3.534	3.555	-0.0210	0.5928
5.	4.662	4.709	-0.0474	1.0171
6.	3.072	3.088	-0.0156	0.5065
7.	5.982	5.687	0.2954	4.9384
8.	4.260	4.314	-0.0541	1.2691
9.	2.502	2.695	-0.1929	7.7118
10.	2.220	2.492	-0.2724	12.2685
11.	4.002	4.017	-0.0151	0.3768
12.	2.898	2.951	-0.0532	1.8344
13.	2.862	2.974	-0.1116	3.8980
14.	2.478	2.650	-0.1723	6.9527
15.	4.740	4.758	-0.0180	0.3788
16.	3.378	3.430	-0.0524	1.5504
17.	3.978	3.951	0.0268	0.6737

18.	3.108	3.162	-0.0539	1.7345
19.	3.078	3.162	-0.0838	2.7228
20.	4.200	4.190	0.0102	0.2432
21.	3.120	3.149	-0.0290	0.9309
22.	3.960	3.960	0.0001	0.0019
23.	4.260	4.274	-0.0144	0.3383
24.	3.198	3.242	-0.0437	1.3658
25.	3.924	3.922	0.0019	0.0483
26.	3.726	3.714	0.0116	0.3117
27.	3.792	3.820	-0.0277	0.7317
28.	3.840	3.831	0.0094	0.2458
29.	3.870	3.925	-0.0554	1.4317
30.	3.900	3.917	-0.0167	0.4277

SURFACE ROUGHNESS (µM) PREDICTION FOR A DESIRED ERROR OF 100 AFTER RETRAINING

The network was retrained with the desired error still 100 and it was seen that the Mean Absolute Percent Error (MAPE) for predicted surface roughness (µm) was 0.849%. The error rate reached 0.00013464 minimum error rate with 9 iterations as seen in the Validation performance plot generated in Figure 18. Hence is the Best Validation Performance is 0.00013464 at epoch 9 as depicted in Figure 18.

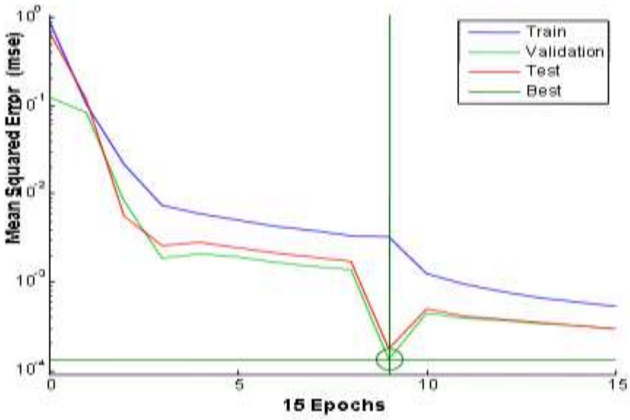

Figure 18. **Mean Absolute Error (MAE) Curve.**

After retraining the neural network, the regression plot generated is depicted in Figure 19.

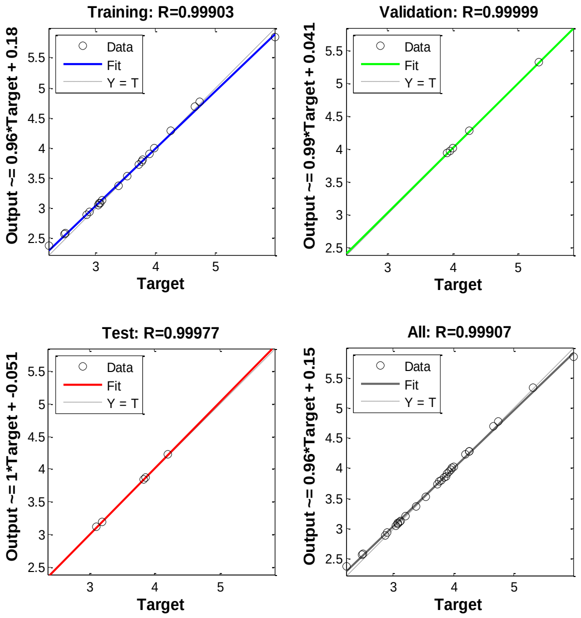

Figure 19. **Regression Plot of Training Data, Validation Data, Test Data, All Data.**

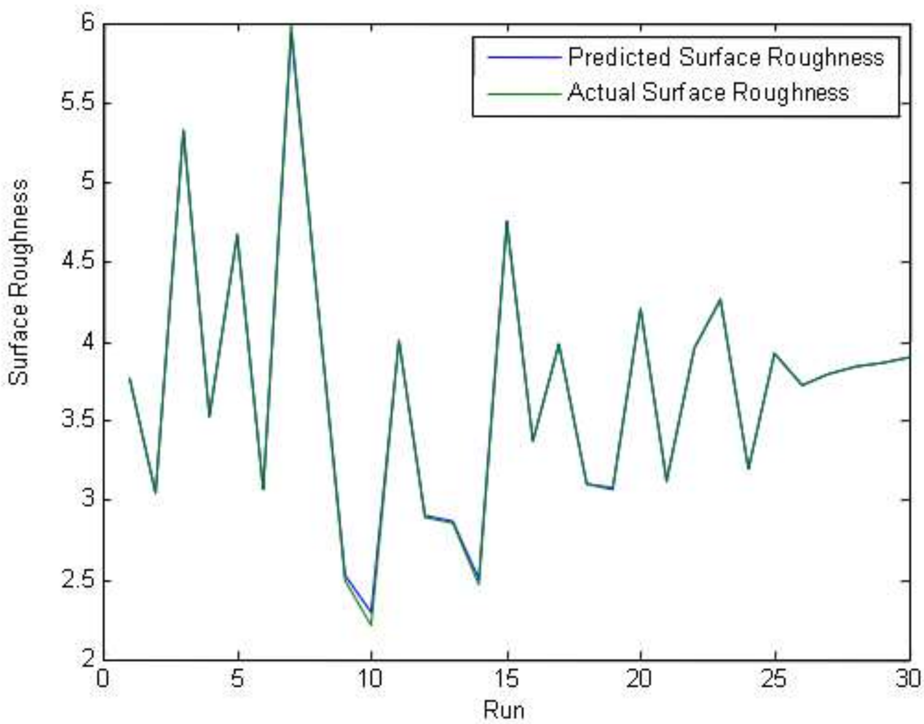

Figure 20. **Plot of Actual Surface Roughness against the Predicted Surface Roughness.**

Table 4. **Prediction for Mean Absolute Percent Error (MAPE) of 0.849%.**

Run	Experimental Surface roughness (µm)	NN Surface Roughness	Error	Error Percent
1.	3.768	3.779	-0.0114	0.3028
2.	3.042	3.049	-0.0072	0.2367
3.	5.322	5.326	-0.0038	0.0707
4.	3.534	3.529	0.0053	0.1508
5.	4.662	4.691	-0.0287	0.6160
6.	3.072	3.086	-0.0142	0.4617
7.	5.982	5.840	0.1422	2.3764
8.	4.260	4.271	-0.0110	0.2582
9.	2.502	2.582	-0.0796	3.1813
10.	2.220	2.378	-0.1580	7.1167
11.	4.002	4.013	-0.0114	0.2848
12.	2.898	2.928	-0.0300	1.0348
13.	2.862	2.889	-0.0267	0.9344
14.	2.478	2.570	-0.0916	3.6954
15.	4.740	4.776	-0.0360	0.7593
16.	3.378	3.366	0.0123	0.3647
17.	3.978	3.999	-0.0209	0.5250
18.	3.108	3.112	-0.0042	0.1338
19.	3.078	3.081	-0.0025	0.0818
20.	4.200	4.229	-0.0286	0.6809
21.	3.120	3.131	-0.0114	0.3645
22.	3.960	3.971	-0.0111	0.2809
23.	4.260	4.284	-0.0243	0.5701
24.	3.198	3.197	0.0007	0.0204
25.	3.924	3.941	-0.0169	0.4298
26.	3.726	3.728	-0.0017	0.0459
27.	3.792	3.797	-0.0049	0.1285
28.	3.840	3.845	-0.0051	0.1340
29.	3.870	3.866	0.0039	0.1004
30.	3.900	3.905	-0.0048	0.1230

SURFACE ROUGHNESS PREDICTION FOR A DESIRED ERROR OF 62.0

The desired error was reduced from 100 to 62 and the network was retrained with this new desired error. The Mean Absolute Percentage Error (MAPE) obtained for the predicted Surface Roughness was 0.299%. Best Validation Performance is 1.705e-05 at Epoch 20 as depicted in Figure 21.

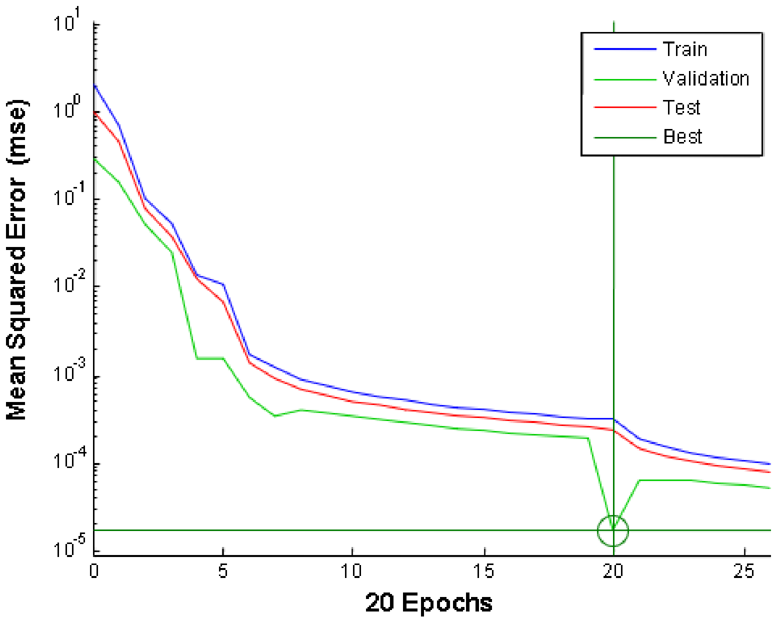

Figure 21. Mean Absolute Error (MAE) Curve.

The regression plot after training the network with the desired error of 62 is shown in Figure 22.

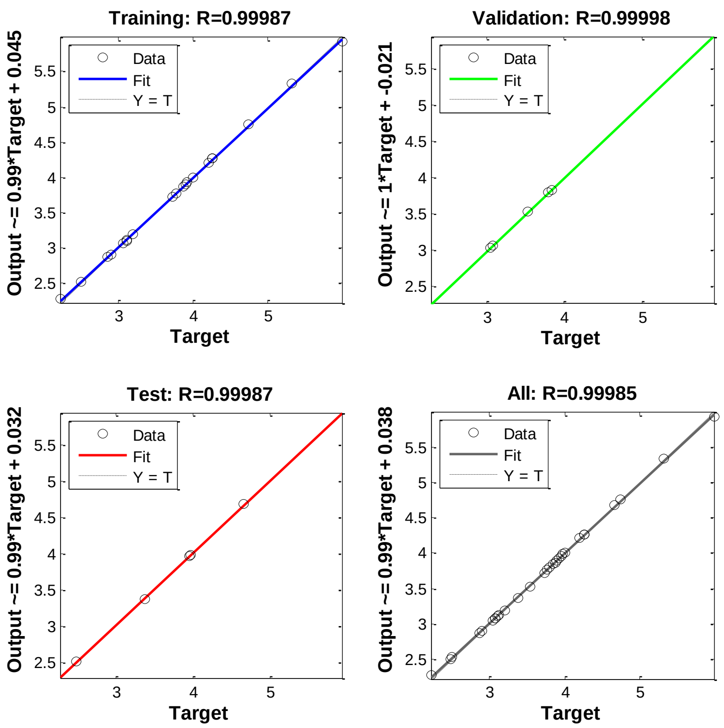

Figure 22. Regression Plot of Training Data, Validation Data, Test Data, All Data.

The plot of the actual surface roughness against the predicted surface roughness is shown in Figure 23. The corresponding data values of actual surface roughness and predicted surface roughness at Mean Absolute Percentage Error (MAPE) value of 0.299% is shown in Table 4.15.

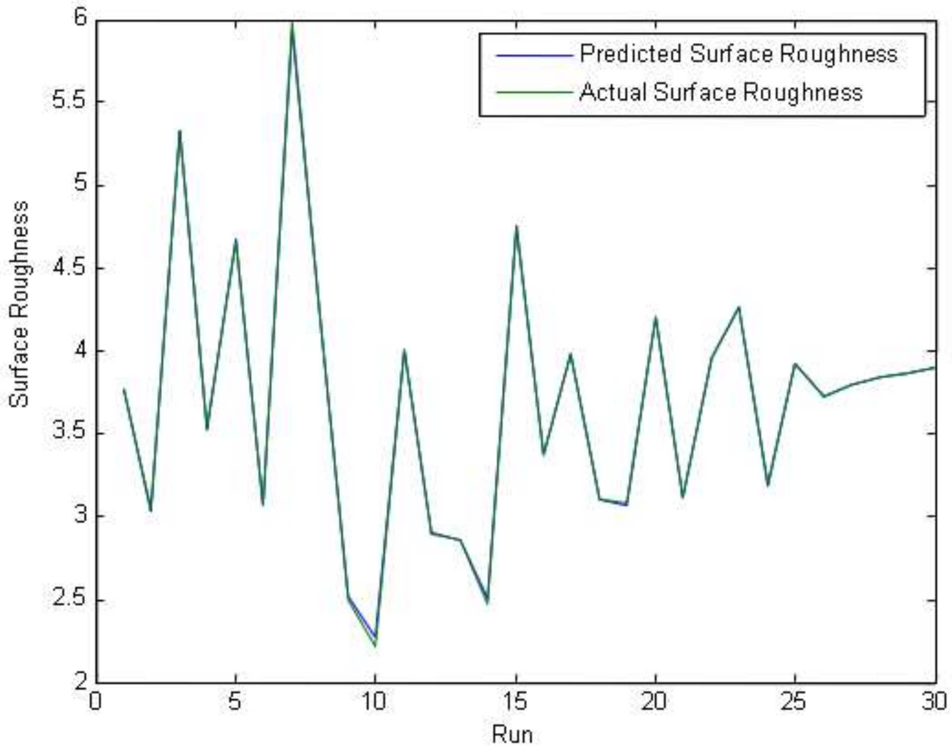

Figure 23. Actual Surface Roughness against the Predicted Surface Roughness.

Table 5. Forecast for Mean Absolute Percent Error (MAPE) of 0.299%.

Run	Experimental Surface roughness (µm)	NN Surface Roughness	Error	Error Percent
1.	3.768	3.770	-0.0020	0.0527
2.	3.042	3.037	0.0055	0.1798
3.	5.322	5.330	-0.0076	0.1426
4.	3.534	3.528	0.0063	0.1773
5.	4.662	4.675	-0.0129	0.2774
6.	3.072	3.071	0.0010	0.0334
7.	5.982	5.934	0.0484	0.8087
8.	4.260	4.265	-0.0052	0.1212
9.	2.502	2.525	-0.0225	0.8999
10.	2.220	2.274	-0.0539	2.4297
11.	4.002	4.004	-0.0021	0.0534
12.	2.898	2.905	-0.0069	0.2392
13.	2.862	2.865	-0.0031	0.1067
14.	2.478	2.507	-0.0293	1.1818
15.	4.740	4.756	-0.0160	0.3366

16.	3.378	3.369	0.0093	0.2763
17.	3.978	3.984	-0.0065	0.1634
18.	3.108	3.104	0.0043	0.1392
19.	3.078	3.074	0.0037	0.1194
20.	4.200	4.209	-0.0093	0.2211
21.	3.120	3.117	0.0026	0.0822
22.	3.960	3.964	-0.0040	0.1007
23.	4.260	4.268	-0.0083	0.1948
24.	3.198	3.192	0.0058	0.1826
25.	3.924	3.929	-0.0050	0.1282
26.	3.726	3.723	0.0034	0.0904
27.	3.792	3.793	-0.0010	0.0260
28.	3.840	3.839	0.0013	0.0330
29.	3.870	3.864	0.0061	0.1571
30.	3.900	3.900	-0.0001	0.0027

SURFACE ROUGHNESS PREDICTION FOR A DESIRED ERROR OF 61.4

In training the network, the desired error was reduced from 62.0 to 61.4 (as neural network generates a different result when initialized) the Mean Absolute Percent Error (MAPE) for predicted Surface roughness was 0.002%. The best Validation Performance is 8.0717e-08 at epoch 1000 as depicted in Figure 24.

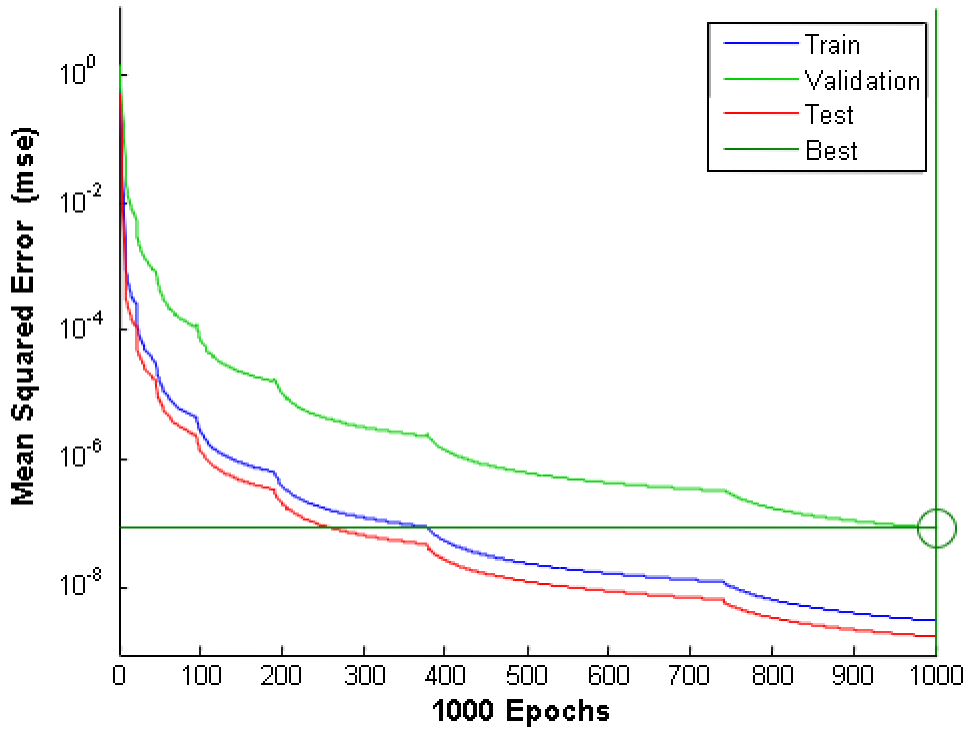

Figure 24. **Mean Absolute Error (MAE) Curve.**

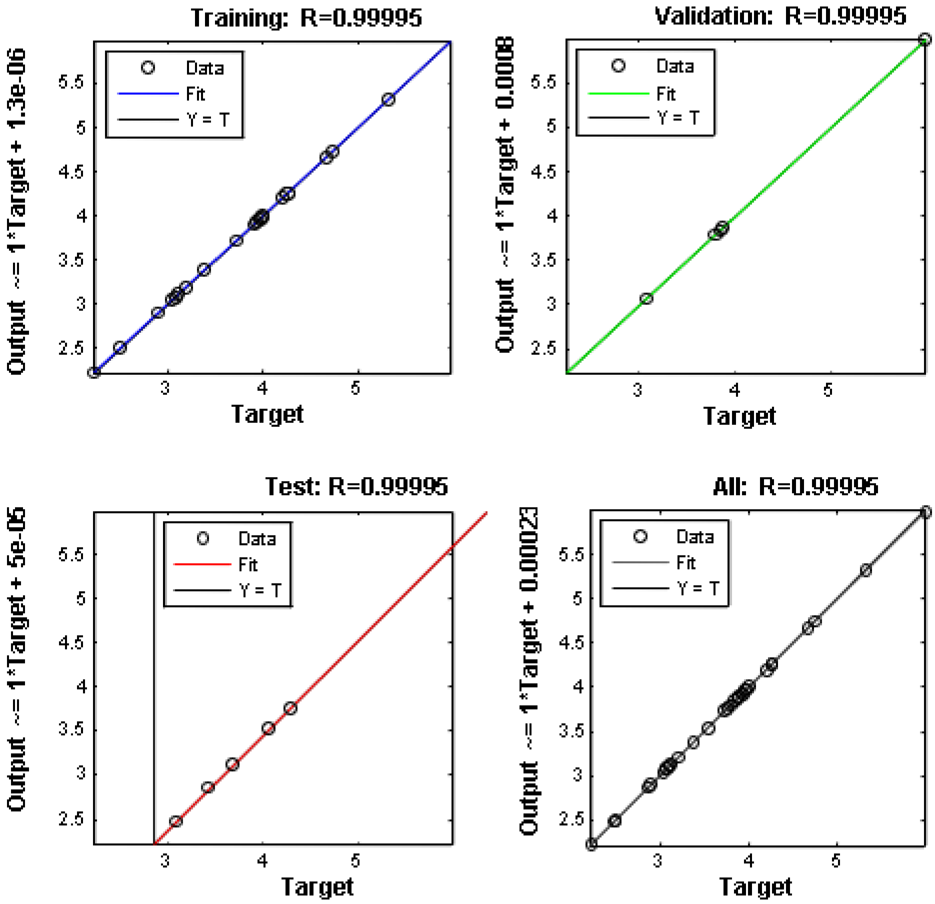

Figure 25. **Regression Plot of Training Data, Validation Data, Test Data, All Data.**

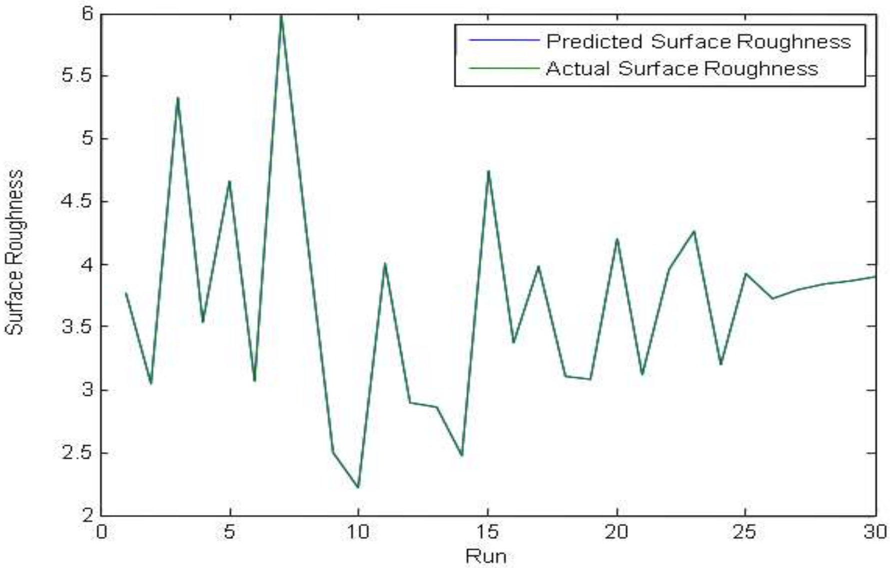

Figure 26. **Actual Surface Roughness against the Predicted Surface Roughness.**
Table 6. **Prediction for Mean Absolute Percentage Error (MAPE) of 0.002%.**

Run	Experimental Surface roughness (µm)	NN Surface Roughness	Error	Error Percent
1.	3.768	3.768	0.0000	0.0000
2.	3.042	3.042	0.0001	0.0025
3.	5.322	5.322	0.0001	0.0022
4.	3.534	3.534	0.0000	0.0011
5.	4.662	4.662	-0.0001	0.0011
6.	3.072	3.072	0.0001	0.0023
7.	5.982	5.981	0.0006	0.0105
8.	4.260	4.260	0.0000	0.0011
9.	2.502	2.502	0.0000	0.0002
10.	2.220	2.220	-0.0001	0.0055
11.	4.002	4.002	0.0000	0.0004
12.	2.898	2.898	0.0000	0.0010
13.	2.862	2.862	0.0000	0.0014
14.	2.478	2.478	0.0000	0.0014
15.	4.740	4.740	-0.0001	0.0011
16.	3.378	3.378	0.0001	0.0016
17.	3.978	3.978	0.0000	0.0006
18.	3.108	3.108	0.0001	0.0019
19.	3.078	3.078	0.0000	0.0013
20	4.200	4.200	0.0000	0.0009
21.	3.120	3.120	0.0001	0.0021
22.	3.960	3.960	0.0000	0.0007
23.	4.260	4.260	0.0000	0.0009
24.	3.198	3.198	0.0001	0.0019
25.	3.924	3.924	0.0000	0.0008
26.	3.726	3.726	0.0000	0.0008
27.	3.792	3.792	0.0000	0.0006
28.	3.840	3.840	0.0000	0.0005
29.	3.870	3.870	0.0000	0.0005
30.	3.900	3.900	0.0000	0.0003

DISCUSSION

The ANN predicted outcomes and properties were evaluated by considering the mean absolute percentage error and the regression analysis. Figures 17 - 26 shows the performance, training statistics and convergence plot for training and testing networks of the input and output variables. The performance plot mean square error (MAE) of all data sets is shown on a logarithmic scale. The training means square error showed a decreasing trend. Here, the training plot reveals a perfect training. Training was stopped when validation error increased to 10 epochs, 9 epochs, 20 epochs and 1000 epochs as depicted in Figures 9, 11, 13 and 15 respectively. The various best validation performance was obtained at 0.0125 at 10th epoch for Figure 15, 1.347 x10-4 at 9th epoch for Figure 17, 1.705 x10-5 at 20th epoch and 8.072 x10-8 at 1000th epoch respectively.

Figures 16, 19, 22 and 25 show coefficient of regression. The R plots explain the importance between the target (desired output) and ANN output (actual output). The dashed line in each plot represents the targeted values (the difference between the perfect result and output). The best fit linear regression line between the outputs and targets is represented by a solid line. The correlation coefficient (R) gives the relationship between the outputs and targets. Maximum value of the correlation coefficients (R) and minimum mean absolute percentage error (MAPE) defines a good ANN model. For exact linear relationship, R must be closer or equal to one. Given this fact, from Figure 25, it was observed that the targeted output R for training is 0.99995, validation is 0.99995 and testing is 0.99995. The corresponding total response is 0.9995, which verifies that the ANN output is in extremely close agreement with the target or actual output. The overall response reveals that the training has produced the optimal results.

A comparison of the experimental obtain surface roughness values with the ANN predicted values is presented in Tables 3, 4, 5 and 6 respectively. Corresponding to this tables are plots of experimental surface roughness value against ANN predicted values as depicted in Figures 18, 21, 23 and 26 respectively. The performance of the ANN model was determined by the value of the MAPE obtained. Arising from these, the best ANN model with least MAPE value of 0.002% was chosen. This shows that the ANN model developed can be used effectively for predicting the quality of surface finished.

IMPLICATION TO RESEARCH AND PRACTICE

The following are the implications of the findings and discuss from our study towards research and practice:

i. Embrace Advanced Modelling Techniques: Researchers and practitioners can explore and develop advanced modelling techniques for machining processes. Investigate nonlinear dynamic models, artificial neural networks (ANN), regression analysis, and genetic algorithm-based models to enhance accuracy and efficiency in machining operations. By utilizing these modelling techniques, researchers can uncover new insights and approaches to optimize various aspects of machining.
ii. Optimize Machining Processes: Practitioners can also focus on optimizing machining processes by utilizing techniques such as genetic algorithms and ANN models. They can also investigate the optimization of cutting parameters, tool selection, and other variables to improve productivity, reduce costs, and enhance quality in machining operations. By applying optimization methods, researchers can identify the most efficient combinations of parameters and improve overall process performance.
iii. Predict and Control Surface Roughness and Tool Wear: Develop predictive models to accurately forecast surface roughness and tool wear in machining processes. Utilize regression analysis, ANN, or other appropriate techniques to predict these critical factors. By understanding and controlling surface roughness and tool wear, researchers can enhance process control, improve product quality, and reduce the need for costly tool replacements.
iv. Leverage Machine Learning in Machining: Explore the application of machine learning techniques in machining operations. Implement ANN models or other machine learning algorithms to analyse

historical data, recognize patterns, and optimize machining parameters. By leveraging machine learning, researchers can make informed decisions, streamline processes, and reduce trial and error in machining operations.

v. Strive for Enhanced Productivity and Cost Savings: Aim to improve productivity and reduce costs in machining processes. Investigate the optimization techniques, modelling approaches, and predictive models available in the field. Identify opportunities to enhance efficiency, minimize waste, and optimize resource utilization. By implementing strategies to increase productivity and reduce costs, researchers can contribute to more sustainable and economically viable manufacturing practices.

CONCLUSION

While it is important to find values for production processes such as surface roughness through empirical methods, it is also crucial to weigh the economic and environmental sustainability of such experimental procedures. A thorough evaluation of the time and economic cost of conducting industry standard experiments to determine the surface roughness of the AISI 1080 mild steel shows developing an Artificial Neural Network for the prediction of the surface roughness for steel for different applications is more efficient. The ANN developed considered relevant machining parameters such as the cutting speed, feed, depth of cut and bearing clearance. A significant aspect of the ANN design was in the adoption of the Levenberg-Marquardt (LM) algorithm known for its efficiency and speed in finding the optimal solution. A numerical indication of the efficiency of the ANN is a statistical measure called the MAPE. The value of the MAPE was 0.002% while the correlation coefficient (R) was 0.99995. From previously established surface-roughness values using experimental procedures, the prediction of the ANN shows a good level of conformity. The strong agreement of the values obtained is an indication that the ANN with the right machining parameters and calculation can be used to predict the surface roughness value to be used for industrial and academic applications. In conclusion, the efficacy of an ANN model in accurately predicting the surface roughness of a material such as the AISI 1080 is in its potentials to eradicate the challenges that characterize experimental procedures. The ANN therefore provides an effective, fast and simple alternative to the native experimental methods for the determination of surface roughness.

FUTURE RESEARCH

While significant progress has been made in the field of machining and modelling techniques, there are several avenues for future research that can further advance the understanding and application of these concepts. The following areas warrant attention for future investigations:

i. Integration of Multi-Objective Optimization: Future research should focus on integrating multi-objective optimization techniques into machining processes. Considering multiple objectives such as productivity, surface quality, energy consumption, and tool life simultaneously will enable researchers to develop more comprehensive and efficient optimization strategies. Exploring approaches like Pareto optimization and evolutionary algorithms can provide valuable insights into finding optimal trade-offs among conflicting objectives.

ii. Incorporation of Hybrid Modelling Approaches: Investigating hybrid modelling approaches by combining different techniques such as neural networks, fuzzy logic, and evolutionary algorithms can offer improved accuracy and reliability in modelling machining processes. By integrating the strengths of multiple modelling techniques, researchers can enhance the predictive capabilities and robustness of the models, leading to more effective decision-making and process control.

iii. Exploration of Non-Traditional Machining Processes: While conventional machining techniques have been extensively studied, future research should also focus on non-traditional machining processes such as electrical discharge machining (EDM), laser machining, and abrasive jet machining. Investigating the modelling, optimization, and control aspects of these processes will contribute to a deeper understanding and effective implementation of these emerging technologies.

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