Implementation of Adaptive Neuro Fuzzy Inference System in Determining the Influence of Bearing Clearance in Mild Steel Turning

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Abstract—The metal cutting industry constantly seeks to optimize machining techniques to guarantee highly accurate parts while minimizing costs. However, the complexity of the relationship between process parameters and performance measures such as metal removal rate (MRR), surface finish, chip flow pattern, specific energy consumption, and tool life presents a significant challenge for manufacturers. The paper introduces an innovative solution for determining the influence of bearing clearance on mild steel turning operations using the Adaptive Neuro Fuzzy Inference System (ANFIS) optimization model. By assimilating insights from training data onto a fuzzy inference system, ANFIS effectively maps solutions to complex problems. The proposed approach accurately predicts surface roughness, MRR, and tool wear for different sets of cutting parameters, offering a viable approach for improving product quality and profitability while reducing associated manufacturing costs. By applying substrative clustering with values of radius of parameter equal to 0.1, 0.2, and 0.3 respectively, the initial membership function of the independent variables and fuzzy rules were developed. Training was done by using an initial step size of 0.1, the value of MAPE obtained was 3.123% and correlation coefficient (R) of 0.9072. The results obtained indicate that the ANFIS model predicts surface roughness with high accuracy, with an average error of 0.17µm. The study also found that increasing bearing clearance results in a decrease in surface roughness, as seen with a reduction from 3.96µm to 2.22 µm. Furthermore, the model predicted MRR with an average error of 0.6%, and it revealed that increasing bearing clearance results in a significant increase in MRR, ranging from 2.22 m^3/min to 5.98 m^3/min at a clearance level of 0.010mm. The findings contribute to the body of knowledge in manufacturing engineering, offering valuable insights into the relationship between bearing clearance, machining parameters, and performance measures.

Indexed Terms—Accurate machining techniques, ANFIS model, Bearing clearance, Surface roughness in mild steel, Manufacturing engineering, Optimization modeling

I. INTRODUCTION

In recent times, advancements in engineering design have played a crucial role in driving technological developments across various fields of engineering. One area where these advancements have been witnessed is in the metal cutting industry, where manufacturers are constantly on the lookout for suitable machining techniques that can guarantee highly-accurate parts while minimizing costs. According to Struzikiewicz and Sioma, developing appropriate machining techniques is crucial to meet engineering design requirements such as shape and dimension accuracy, surface quality, and optimal cost and/or rate of production [1]. However, relating the process parameters such as the number of passes, depth of cut for each pass, bearing clearance, feed rate, and cutting speed to performance measures like metal removal rate (MRR), surface finish, chip flow pattern, specific energy consumption, and tool life [2] is often challenging and complex for manufacturers. This challenge prevents them from achieving acceptable process performance [3]. Manufacturers in the past relied heavily on large empirical databases compiled from previous machining operations to carry out designs. This approach is associated with limitations, and it is therefore a less preferred option in modern times. According to Koenigsburger and Melkote, in manufacturing, discrepancies can be classified into two main categories: random and assignable variations. Random fluctuations, such as those originating from machine cycles and vibrations, often occur unpredictably. In contrast, assignable variations surface due to inadequate control over the machining process. This differentiation holds immense significance [4], [5]. As pointed out by Groover, a lack of expertise when applying machining parameters in the production of batch components often leads to the creation of numerous substandard machined parts [6]. Alarmingly, it has been noted that roughly 50% of machining operations involve the improper use of cutting tools and process parameters [7]. To confront these challenges and elevate machining procedures, systematically developed methodologies like artificial intelligence (AI) tools have emerged as potent solutions. According to Rao and Mukherjee, artificial intelligence (Al)AI techniques encompass a broad spectrum of approaches, including adaptive neuro-fuzzy inference systems, neural-based fuzzy interference systems (ANFIS), artificial neural networks (ANNs), particle swarm optimization (PSO), genetic algorithms (GAs), and geometric programming (GP). These AI-driven strategies have demonstrated remarkable efficacy in simulating and optimizing input and output machining parameters in machining processes, rendering them not only more efficient but also more effective [8]. Numerous research endeavors have been dedicated to enhancing the machining process, encompassing the quest for optimal process parameters [9] and the determination of hyper-parameters in artificial neural network (ANN) applications for modeling machining processes [10]. However, it is imperative to assess the adequacy of these techniques by evaluating their performance in predicting both process parameters and responses. Notably, ANFIS stands out as an exceptionally potent modelling technique, capable of delivering remarkably accurate outputs, even in the presence of variations within machining process parameters [11], [12]. ANFIS, classified as a soft computing modeling technique, harnesses the strengths of both artificial neural networks (ANNs) and fuzzy logic theory techniques [13]. Through the assimilation of insights gleaned from training data, which may encompass complex mathematical models, ANFIS effectively maps out solutions onto a fuzzy inference system (FIS) [14]. The incorporation of an FIS into the ANFIS framework endows it with the capability to ascertain hidden layers and enhance its predictive prowess. This removes the need for the laborious process of manually determining hidden layers, often a requisite in other simulation and modelling techniques employed for input and output machining parameters [15].

The theme of this study is focuses on the implementation of adaptive neuro fuzzy inference system in determining the influence of bearing clearance in mild steel turning operations. 30 experimental runs will be the dataset used for surface roughness prediction in this work, while the data preparation will employ statistical preprocessing steps that are essential for sorting out "good" data from the "bad".

Justification of Study

The significance of this study in providing a solution to the challenges faced by manufacturers in constantly looking for suitable machining techniques that can guarantee highly accurate parts while minimizing costs the metal is justified by several reasons.

First, in today's manufacturing landscape, being excellent isn't just an option; it's a must to stay competitive. The quality of machine-made parts directly impacts how well products perform, how long they last, and whether they find acceptance in the market. This research unquestionably justifies itself through its notable achievements in improving surface quality. By introducing a smart and highly effective method for optimizing machining operations, this study offers a practical solution to a persistent real-world problem faced by the metal cutting industry. It delves deep into the details of fine-tuning machining parameters using a blend of advanced techniques, including a hybrid Taguchi-genetic learning algorithm, ANFIS, ANN, and RSM. The tangible result is a set of optimized parameters that consistently lead to better surface quality. This isn't just theory; it's a real advantage that manufacturers can use to outshine their competition [16], [17][18].

Also, this research holds immense importance for various industries reliant on mechanical components. The surface roughness of these parts, a crucial factor, affects how well they function and how long they last. By enabling manufacturers to enhance product quality through better machining processes, this study directly addresses a fundamental concern in industrial production. Furthermore, the impact goes beyond quality improvement as manufacturing processes often carry substantial expenses related to quality control, waste, and rework. Hence, the precision and predictability achieved using the ANFIS model can help reduce these costs by minimizing deviations from desired surface roughness standards [19].

Additionally, this research is firmly grounded in the forward march of mechanical engineering. Its use of cutting-edge computational techniques, including ANFIS optimization models, demonstrates a commitment to technological advancement. The engineering industry is embracing a digital transformation where advanced methods play an increasingly central role in process optimization. The use of ANFIS doesn't just deepen our understanding of the intricate relationships between machining parameters and surface roughness; it also translates this understanding into practical benefits. By making machining processes more precise and efficient, this study aligns itself with the current trend of integrating computational intelligence and automation into manufacturing [17], [19][16].

Lastly, beyond its immediate applications, this work enriches the body of knowledge in mechanical engineering. It contributes valuable insights into surface roughness prediction, serving as a reference for future researchers and practitioners. The predictive models developed here act as a solid starting point for further research endeavors. In essence, this research isn't just about providing solutions; it's also a guiding light for future exploration in the field.

II. LITERATURE REVIEW

A. Historical Background of the Previous Use of ANFIS in Machining Processes

ANFIS, or Adaptive Neuro Fuzzy Inference System, stands as a potent artificial intelligence model, drawing on the strengths of both artificial neural networks (ANNs) and the principles of fuzzy logic theory. This system of operation significantly enhances ANFIS's predictive capabilities, making it a formidable tool for various prediction and modeling tasks. Being first proposed by Jang in 1993, ANFIS closely mirrors the functional characteristics of the Takagi-Sugeno type inference model. It possesses the unique ability to learn from training data and dynamically adjust the parameters of the Takagi-Sugeno inference model based on this acquired knowledge. ANFIS's prowess in prediction is further accentuated by its representation of solutions in linguistic terms, accomplished through a Fuzzy Inference System (FIS) [20]. The architecture of the ANFIS model comprises five distinctive strata: fuzzification, rule base, normalization of membership functions (MFs), defuzzification, and summation. For a more detailed understanding on how these layers synergize to enhance its predictive potential, observe Figure 1.

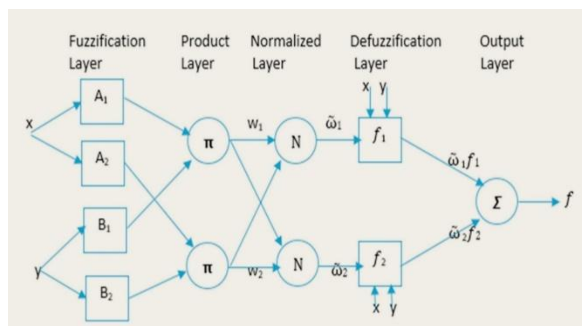

Figure 1. General Architecture of ANFIS model

In 2003, Lo conducted a study in which an ANFIS model was employed to predict the surface roughness subsequent to end milling. This investigation encompassed input variables such as spindle speed, feed rate, and depth of cut. These inputs underwent fuzzification employing triangular and trapezoidal functions. A set of 27 rules was formulated to showcase their association with surface roughness. The triangular membership function exhibited remarkable efficacy, yielding an average prediction error of merely 4%, resulting in a commendable accuracy rate of 96% [21]. Expanding upon Lo's groundwork, Ho and his collaborators in 2009 also harnessed ANFIS. They incorporated the Genetic Algorithm (GA) technique to govern workpiece surface roughness while drawing upon the same dataset. In this methodology, 48 samples were allocated for training purposes, with 24 samples earmarked for testing. This approach, which adopted the Gaussian membership function, yielded outcomes related to those observed in Lo's 2003 study, registering an average error rate of 4.06% [22]. In 2011, an investigation led by Sharkawy ventured into the region of surface roughness modeling during end milling procedures. This study harnessed three distinct artificial intelligence (AI) methodologies, specifically Radial Basis Function Neural Networks (RBFNs), the Adaptive Neuro Fuzzy Inference System (ANFIS), and the Genetic Fuzzy Inference System (G-FISs). It's important to underline that ANFIS represents a fusion of artificial neural networks and fuzzy logic theory. This order of operation enables ANFIS to acquire knowledge from training data and adapt the parameters of the Takagi-Sugeno inference model. The hallmark of ANFIS lies in its capacity to translate solutions into linguistic terms through a Fuzzy Inference System (FIS), thereby amplifying its predictive capabilities [23]. Dong et al. also utilized ANFIS with a leave-one-out cross-validation (LOO-CV) approach to predict workpiece surface roughness in 2011. Based on the same dataset as the previous study, the predictive results of their ANFIS model outperformed the models reported recently in the literature, with an average error of only 3.62%. This study highlights the superiority of ANFIS models in predicting surface roughness compared to other models using the same dataset [24]. In a distinct exploration undertaken by Paturi, Devarasetti, Fadare, &Narala in 2018, an artificial neural network (ANN) model and the response surface methodology (RSM) were enlisted for surface roughness modelling. Their findings underscored the potential of both statistical and AI modelling as credible substitutes for time-intensive experimental endeavours, thereby curtailing the need for expensive machining test trials [25]. However, it is noteworthy that the utilization of a neural network can be relatively labor-intensive due to the iterative process involved in configuring the network structure, especially concerning middle layer nodes. In contrast, ANFIS offers a precise methodology for ascertaining nodes and concealed strata through the employment of fuzzy inference techniques. Therefore, ANFIS emerges as a highly auspicious avenue for the future of surface roughness modelling and control within machining processes. The creation of an ANFIS model necessitates the partitioning of input-output data into rule patches, a task that can be accomplished through a myriad of techniques, including grid partitioning, the subtractive clustering method, and fuzzy c-means (FCM) [26].

B. *Fuzzy Logic*

Fuzzy sets were introduced by Zadeh[27], [28] as a means of representing and manipulating data that was not precise, but rather fuzzy. There is a strong relationship between Boolean logic and the concept of a subset, there is a similar strong relationship between fuzzy logic and fuzzy subset theory. It has been used to model complex systems that can be monitored, controlled and operated by humans based on if-then rules that were develop over years of knowledge and experience. It was used to predict the surface roughness in different cutting operations. Abd El-Raaouf, Osman, El-Axir and Elshanawani in 2001 studied the applicability of the fuzzy technique in the field of machined surface quality. The document includes the operation of the fuzzy technique in combination with the parametric analysis for generating the different combinations of machining conditions that lead to high surface quality [29]. A mathematical model was developed to relate the four cutting parameters namely; cutting speed, un-deformed chip thickness, tool rake angle and tool wear. The response considered were total force and power consumption in addition to the surface roughness during orthogonal cutting. The membership function was utilized to generate the fuzzy model. The nonlinear program is used throughout de-fuzzification process. The comparison of the results with respect to the reference crisp model proves the efficiency of the fuzzy technique in a wide class of engineering applications.

C. *Overview of Neuro-Fuzzy System*

Fuzzy logic can model nonlinear functions of arbitrary complexity. It involves creating fuzzy systems to match any set of input-output data. This process is made particularly easy by adaptive techniques like Adaptive Neuro-Fuzzy Inference Systems (ANFIS), which are available in Fuzzy Logic Toolbox software in Matlab. In most fuzzy systems, fuzzy rules were obtained from the human expert. However, every expert does not want to share his knowledge and there is no standard method that exists to utilize expert knowledge. As a result, ANNs were incorporated into fuzzy systems to be able toacquire knowledge automatically by learning algorithms. The learning capability of the NNs was used for automatic fuzzy if then rules generation [30]. The connection of fuzzy systems with an ANN is called neuro-fuzzy (NF) systems.

D. Membership Function and Rules Selection for ANFIS

In a conventional fuzzy inference system, the number of rules is decided by an expert who is familiar with the target system to be modeled. While in ANFIS simulation, the services of an expert are not needed. The number of membership functions (MFs) assigned to each input variable is chosen empirically, that is, by plotting the data sets and examining them visually, or simply by trial and error. For data sets with more than three inputs, visualization techniques are not very effective so the practice relied on trial and error. This situation is similar to that of neural networks where, there is just no simple way to determine in advance the minimal number of hidden units needed to achieve a desired performance level. There are several other techniques for determining the numbers of MFs and rules, such as CART and clustering methods. In a fuzzy inference system, there are basically two types of input space partitioning and these are the Grid partitioning method and the Scatter partitioning method. The term Fuzzy-C refers to the clustering method and the subtractive clustering method.

E. Subtractive Clustering

When there is no clear idea of how many clusters there should be for a given set of data, subtractive clustering provides the solution in a fast, one-pass algorithm for estimating the number of clusters and cluster centers in a set of data. Subtractive clustering operates by finding the optimal data point to be defined as a cluster center, based on the density of surrounding data points. All data points within the radius distance of these points are then removed, in order to determine the next data cluster and its center. This process is repeated until all of the data is within the radius distance of a cluster center. This method is used for rules generation when number of inputs is larger.

III. METHODOLOGY

A. Data Collection and Assessment ANFIS Surface Roughness Prediction

The dataset used for surface roughness prediction in this work consists of 30 experimental runs. The first four (4) columns in every set represent the input variables while the last column represents the output. The set of input variables are bearing clearance (µm), depth of cut (mm), feed (mm/rev), spindle speed (rpm) while surface roughness is the output.

B. Data Preparation, Preprocessing and Removal of Outliers

Data preparation includes statistical preprocessing steps that are essential for sorting out "good" data from the "bad". Experimental and personal error are often incurred when measurements were taken and recorded. The raw dataset was preprocessed in other to eliminate offset and remove outliers which are unusual points in the dataset. The presence of outliers in datasets is mostly due to error in measurement and recording. They were removed by running short program written using MATLAB.

C. Exhaustive Search

To use ANFIS for system identification, the first step is to select the inputs. The sequential forward search method selects the input sequentially in such a way that the Root Mean Square Error (RMSE) is minimized. Exhaustive search method reveals the best "inputs" combination that yields the least RMSE. Two choice criteria was investigated in selecting the "best input combination". These criteria are; the minimum training RMSE and minimum checking RMSE as depicted in Figure 2.

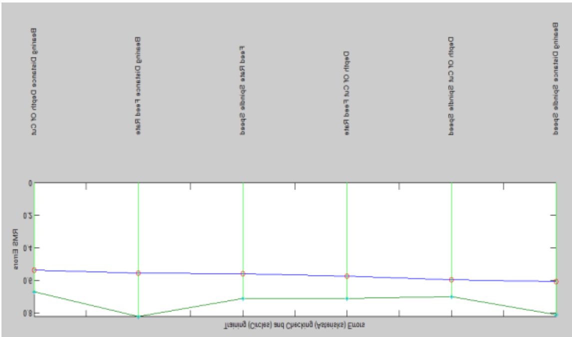

Figure 2. Exhaustive search graph showing best two inputs combination that affects the surface roughness

D. ANFIS Based Subtractive Clustering Method

Fuzzy subtractive clustering (FSC) method is implemented by dividing the data space into fuzzy clusters, in which each part represents a specific part of the system behaviour. the fuzzy rules are generated from each cluster. Cluster centres are generated based on the following procedure; selection of data points with highest potential to be the first cluster centre, the removal of all data points in the vicinity of the first cluster (as predetermined by radii) in order to determine the next data cluster and its centre location and lastly perform again the process until all data are within the radius of a cluster centre. After clustering the data space, the number of fuzzy rules is determined and that of the premise fuzzy membership function (MF). Then the linear squares estimation is used to determine the consequence in the output MFs, resulting in a valid FIS.

The MATLAB fuzzy logic toolbox was used for ANFIS model development. Subtractive clustering has four significant parameters; accept ratio $\bar{\varepsilon}$, reject ratio $\underline{\varepsilon}$, cluster radius r_a, and squash factor η. These parameters have influence on the number of rules and the error performance measures. For example, a large value of cluster radius generally results in fewerclusters that lead to a coarse model. However, a small value of cluster radius can produce excessive number of rules that may result in an over-defined system. The optimal parameters suggested by Chiu are $1.25 \leq \eta \leq 1.25$and $0.15 \leq r_a \leq 0.3$.The membership functions of all data points in each input space are assigned with respect to all cluster centers as follows:

$$u_{ij} = exp(-\frac{\gamma||x_i-c_k||^2}{r_a^2}) \quad (1)$$

where$||x_i - c_k||$is the distance measure between the ith data point and kth cluster center.

To understand the ANFIS architecture, consider the following fuzzy system which has two rules and is a first order Sugeno model:

Rule 1: $if\ (x\ is\ A_1)\ and\ (y\ is\ B_1), then\ (f_1 = p_1x + q_1y + r_1)$ (2)

Rule 2: $if\ (x\ is\ A_2)\ and\ (y\ is\ B_2), then\ (f_2 = p_2x + q_2y + r_2)$ (3)

The output of each rule is a linear combination of input variables plus a constant term, and the final output is the weighted average of each rule's output. A possible ANFIS architecture to implement these two rules is shown in Figure 3. Note that a circle indicates a fixed node whereas a square indicates an adaptive.

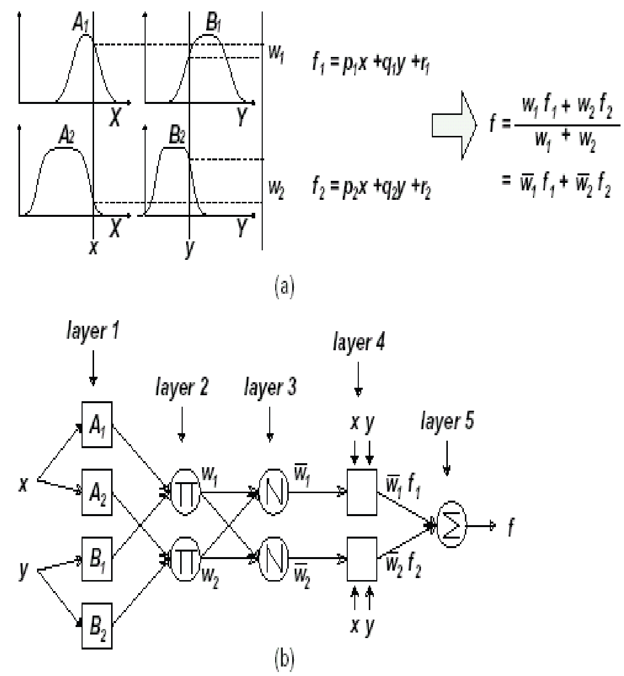

Figure 3. ANFIS Architecture The explanation of the layers of ANFIS is as follows:

Layer 1: All the nodes in this layer are adaptive nodes. The output of each node is the degree of membership of the input of the fuzzy membership functions represented by the node:

$$O_{1.i} = \mu_{A_i}(x) \quad i = 1, 2 \quad (4)$$

$$O_{1.i} = \mu_{B_i}(x) \quad i = 3, 4 \quad (5)$$

where, A_i and B_i are any appropriate fuzzy sets in parametric form, and $O_{1,i}$ is the output of the node in the i^{th} layer. The most common membership functions encompass Gaussian, generalized bell shaped, triangular, and trapezoidal shaped functions with maximum value of 1 and minimum value of 0. This study used the Gaussian membership function. A Gaussian membership function can be shown as follows:

$$Gaussian\ \mu(I) = e^{-\frac{(1-c)^2}{2\sigma^2}} \quad (6)$$

Layer 2: The nodes in this layer are fixed (not adaptive). They are labelled by *M* to indicate that they play the role of a simple multiplier. The outputs of these nodes are given by:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{Bi}(y)\ i = 1,2 \quad (7)$$

The output of each node in this layer represents the firing strength of the rule.

Layer 3: Nodes in this layer are also fixed nodes. They are labelled by N to indicate that they perform a normalization of the firing strength from the previous layer. The Output of each node in this layer is given by:

$$O_{3,i} = \varpi_i = \frac{W_i}{W_1+W_2}\ \ i = 1,2 \quad (8)$$

Layer 4: All the nodes in this layer are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for first order Sugeno model):

$$O_{4,i} = \varpi_i f_i = \varpi_i(p_1 x + q_1 y + r_1)\ \ i = 1,2 \quad (9)$$

where p_i , q_i and r_i are design parameters (referred to as consequent parameters since they deal with the then-part of the fuzzy rule).

Layer 5: This layer has only one node labelled by S to indicate that it performs the function of a simple summation. The output of this single node is given by:

$$O_{5,i} = overall\ output = \sum_i \varpi_i f_i = \frac{\sum_i W_i f_i}{\sum_i W_i}\ \ i = 1,2$$

(10)

E. Adaptive Neuro Fuzzy Systems Modeling

Below is the basic flow diagram of computations in ANFIS

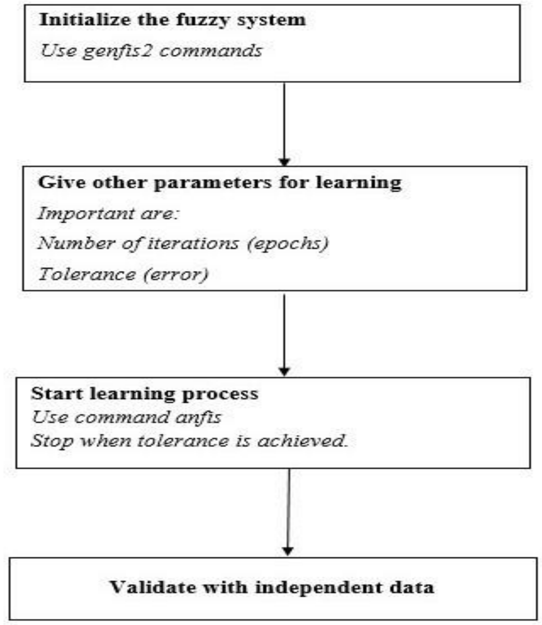

Figure 4. Flow diagram of ANFIS Computation

F. Loading of Training and Checking Data

Matlab files *ssdata and ssdata1* which contain the training dataset and checking dataset respectively where loaded from the Matlab workspace. The training data appears in the plot in the center of the graphical user interface (GUI) as a set of *circles* while the checking or test data *pluses* as depicted in Figure 5.

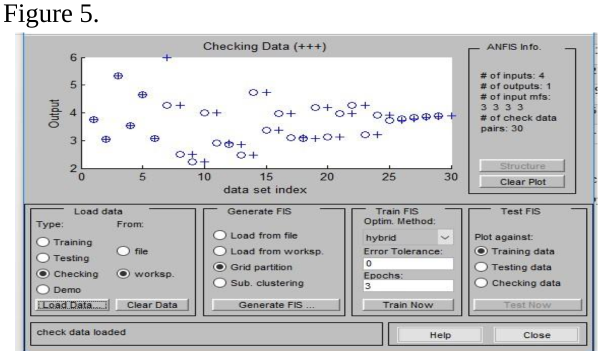

Figure 5. Training and Checking Data Loaded into ANFIS GUI

G. Generating Fuzzy Inference System using Subtractive Clustering

The *genfis2* function generates a model from data using clustering and required specifying a cluster radius as depicted in Figure 6. The cluster radius indicates the range of influence of a cluster when the data space is considered as a unit hypercube. Specifying a small cluster radius usually yield many small clusters in the data, (resulting in many rules). Specifying a large cluster radius will usually yield a few large clusters in the data, (resulting in fewer rules). Three cluster radii of 0.1, 0.2, and 0.3 was used when the *genfis2* function was called.

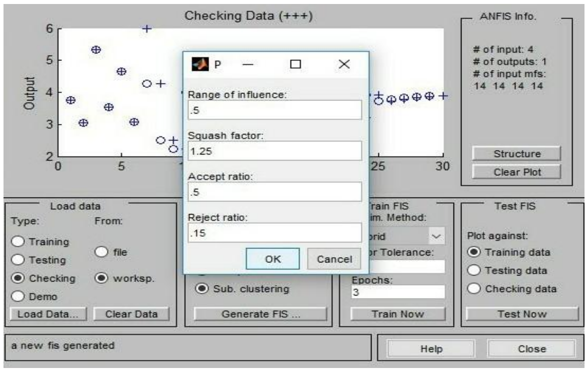

Figure 6. FIS Generated from Subtractive Clustering

H. Training of Fuzzy Inference System to Generate ANFIS Model

In other to generate the ANFIS model, a hybrid optimization method (least-squares estimation and back propagation algorithm) was employed. Error tolerance and epoch number were set to 0 and 500 respectively. In Figure 7, the ANFIS model is shown as generated by training the Fuzzy inference system (FIS). Inputs and membership functions appear to the left of the ANFIS model, while the output on the right. All membership functions used in the chosen ANFIS model were Gaussians ones. There four input nodes, while 14 nodes representing the total number fuzzy rules are connected to input membership nodes. It is vital to examine the reliability of the ANFIS-based model using statistical measures. The statistical measure that was employed for this analysis is the Mean Absolute Percentage Error (MAPE).

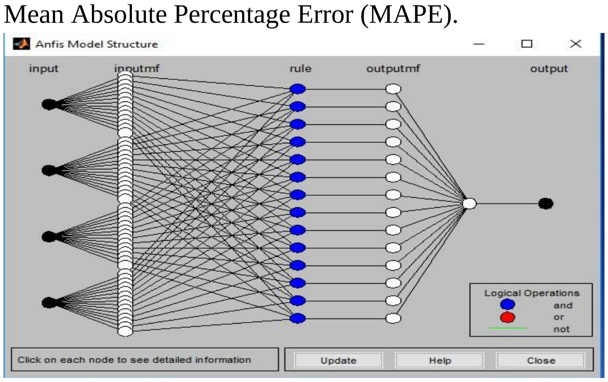

Figure 7. ANFIS Model Structure with input-output membership functions generated by FIS training

I. Membership and Rules Generation

The Gaussian membership function (mf) was selected for the input (mf) variables and linear for the output (mf) surface roughness as depicted in the membership function plots of Figure 8 to Figure 12 respectively. Membership plots of training data evaluated to establish the fuzzy model. Three – dimensional (surface) views was generated using the ANFIS rule viewer in Figure 13. Figure 14 reveals that surface roughness is minimized at low values bearing clearance and depth of cut. Figure 15 shows that surface roughness is reduce at high feed and at moderate high bearing clearance. Figure 16 reveals that a combination of spindle speed and feed has no significant effect on the quality of surface roughness obtained. Figure 17 reveals that moderately high combination of feed and depth of cut minimizes surface roughness. Figure 18 depicts a combination of low spindle speed and a high depth of cut reduces surface roughness while Figure 19 reveals that moderately high bearing clearance minimizes surface roughness, while a varying spindle speed has a marginal effect on the surface quality obtained. The rule editor of ANFIS was used to generate the ANFIS rules (14) in as shown overleaf.

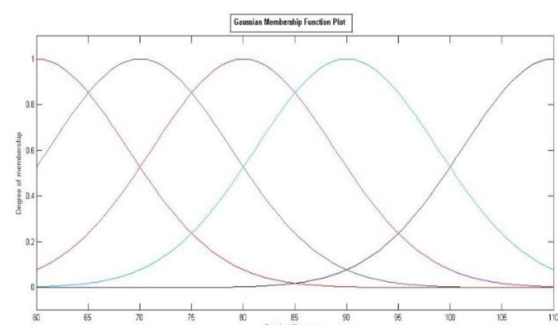

Figure 8. Membership functions plot for bearing clearance

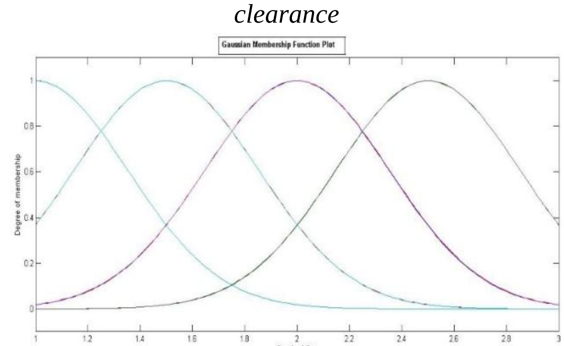

Figure 9. Membership functions plot for depth of Cut

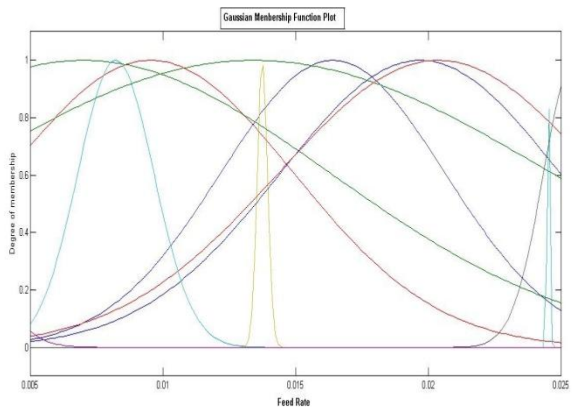

Figure 10. Membership functions plot for feed

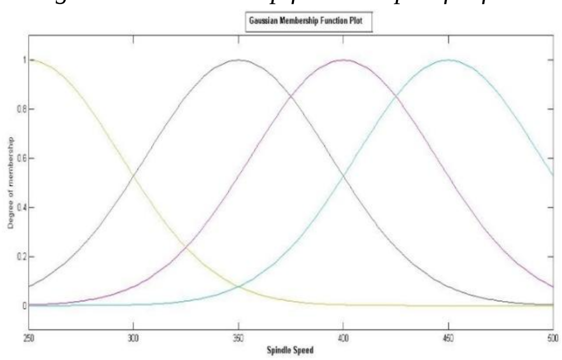

Figure 11. Membership functions plot for spindle speed

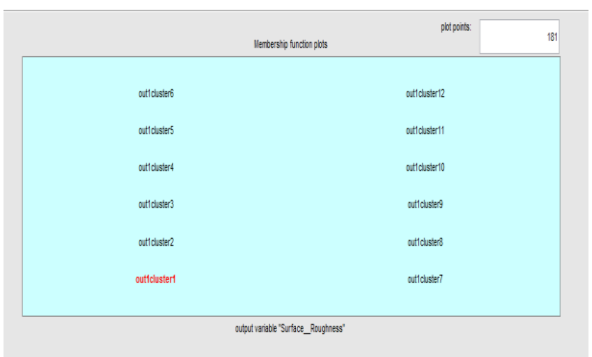

Figure 12. Membership function plot for surface roughness

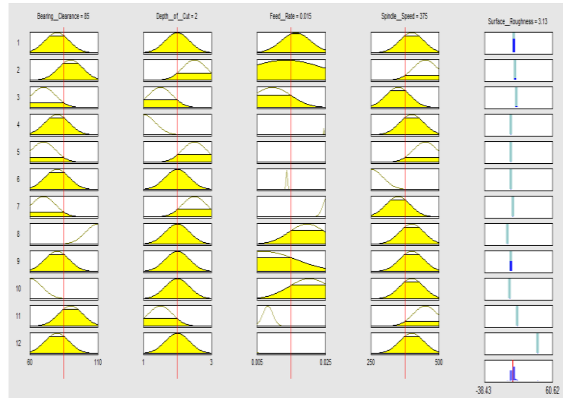

Figure 13. Sensitivity rule viewer

(Figure 13 displays the rule viewer showing input values framed as rules in ANFIS. Input values were experimented in the left-bottom box and the result shown in the output column. The Rule Viewer shows one calculation at a time and in great detail. In this sense, it presents a sort of micro view of the fuzzy inference system).

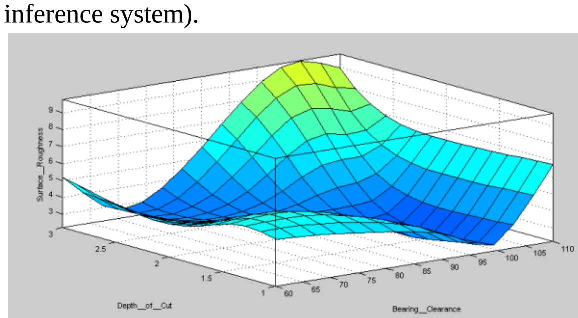

Figure 14. Effect of depth of cut and bearing clearance on surface roughness

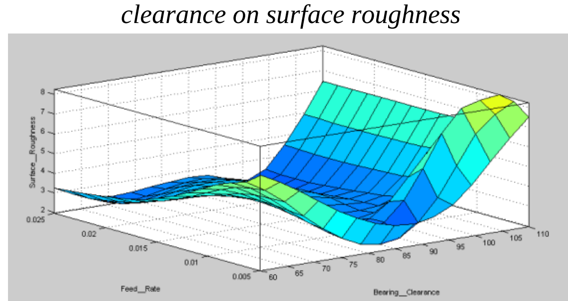

Figure 15. Effect of feed and bearing clearance on surface roughness

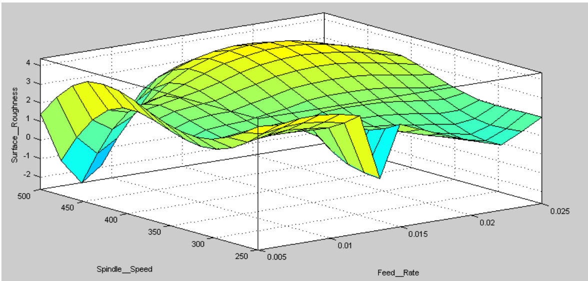

Figure 16. Effect of spindle speed and feed on surface roughness

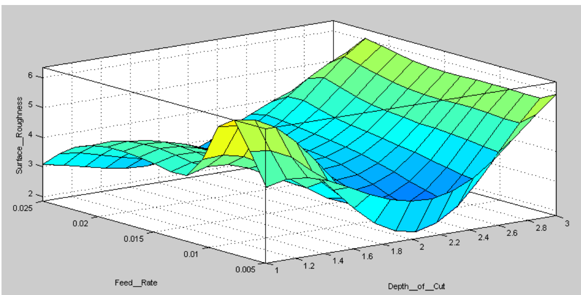

Figure 17. Effect of feed and depth of cut on surface roughness

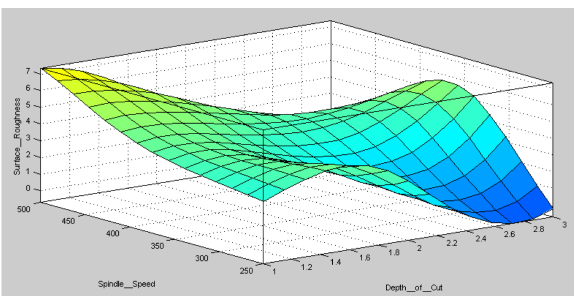

Figure 18. Effect of depth of cut and spindle speed on surface roughness

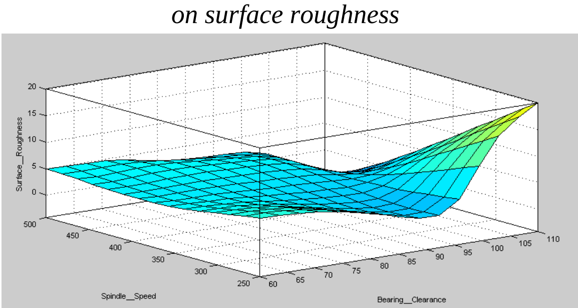

Figure 19. Effect of bearing clearance and spindle speed on surface roughness

J. Model Evaluation and Validation

The analysis was carried out with Matlab 7.0. ANFIS toolbox was for training and checking or testing data. Subtractive clustering algorithm was applying to the training set. The membership functions and the fuzzy if then rules which were estimated by substractive clustering algorithm were employed as initial membership functions and if –then fuzzy rules in the neuro-fuzzy system as depicted in Fig. 3.20. Using cluster radius parameter of step size 0.1, each training process was done at the designated cluster radius. After the completion of each training process, the final mean absolute percentage error (MAPE), Root mean Square (RMS) of training data and correlation coefficient (R) of test data were recorded respectively based on various cluster radius.

IV. RESULTS

A. Examination of The ANFIS-Based Model Reliability and Validation

The performance of the ANFIS-based model in its ability to predict surface roughness was tested by comparing the actual surface roughness output and the ANFIS-based model output using Fig. 4.42- 4.53. The results of using various cluster radii in developing ANFIS-based models and their corresponding MAPEs values are shown below.

B. Predicted Surface Roughness when cluster radius = 0.1

As depicted in Table 1 and Figure 20 and Figure 21 the values of MAPE, RMSE and R-value obtained when cluster radius was set to 0.1 are given below. MAPE = 6.7018%; RMSE = 1.143; R-value = 0.1249 respectively

Table 1. Comparison Between Actual and Forecasted Surface Roughness Radius = 0.1

Actual Surface Roughness	ANFIS Surface Roughness
3.768	3.87297424744423
3.042	3.04197863621449
5.322	3.90400039930464
3.534	3.90400039930464
4.662	4.66200015570525
3.072	3.07203726174231
5.982	3.30359032731013
4.26	4.26001025664795
2.502	2.50201514777220
2.22	2.21998868576469
4.002	3.90400039930464
2.898	2.89801600163166
2.862	2.86195359221552
2.478	2.47797377231471

4.74	4.73998704383266
3.378	3.37797548898793
3.978	3.87297424744423
3.108	3.90400039930464
3.078	3.07799780957485
4.2	4.20005900288492
3.12	3.12009063189457
3.96	3.96004034012049
4.26	3.90400039930464
3.198	3.90400039930464
3.924	3.92392472914219
3.726	3.72597996703528
3.792	3.79194754877787
3.84	3.84006996253995
3.87	3.87004865680532
3.9	3.90003668208677

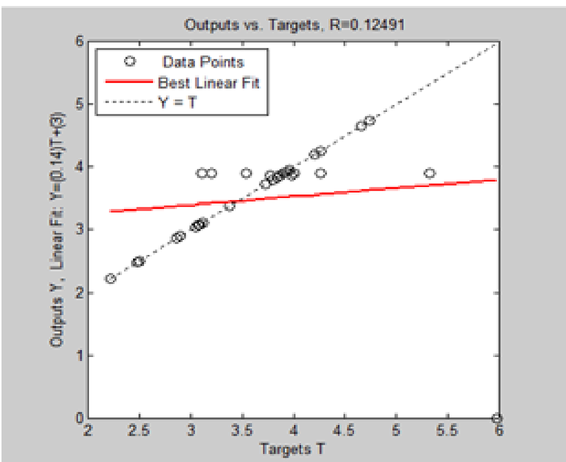

Figure 20. R-value = 0.1249 when cluster radius =0.1

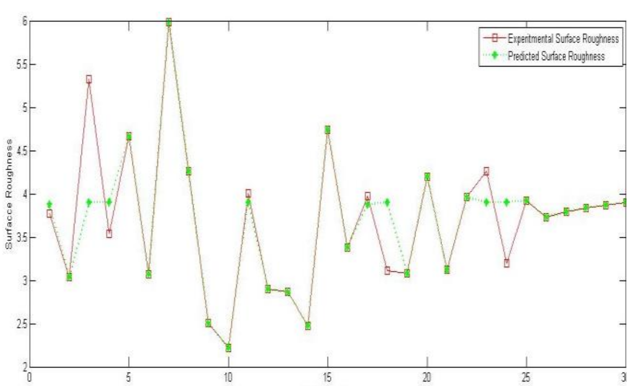

Figure 21. Actual Surface Roughness against the Predicted Surface Roughness.

C. Predicted Surface Roughness when cluster radius = 0.2

As given in Table 2 and Figure 22 and Figure 23 the values of MAPE, RMSE and R-value obtained when cluster radius was set to 0.2 are MAPE = 3.6545%, RMSE = 0.3440 and R-value = 0.9072 respectively.

Table 2. Comparison Between Actual and Forecasted Surface Roughness Radius = 0.2

Actual Surface Roughness	ANFIS Surface Roughness
3.768	3.87295852785345
3.042	3.04198134852021
5.322	3.90399120337429
3.534	3.90399120337429
4.662	4.60337461375213
3.072	3.07202293850242
5.982	6.30573977497569
4.26	4.26003983734925
2.502	2.50197260188469
2.22	2.21995945339053
4.002	3.90399120337429
2.898	2.89791301811571
2.862	2.86204767051341
2.478	2.47798498580938
4.74	4.73993426619983
3.378	3.37797020985640
3.978	3.87295852785345
3.108	3.90399120337429
3.078	3.13666417364239
4.2	4.19990983954815
3.12	3.12000139793288
3.96	3.95997624849304
4.26	3.90399120337429
3.198	3.90399120337429
3.924	3.92404546633559
3.726	3.72599845974517
3.792	3.79194786553262
3.84	3.83998136972471
3.87	3.87009225115465
3.9	3.90022011489956

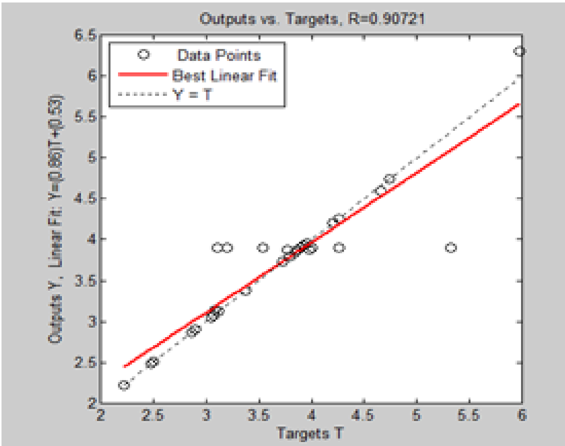

Figure 22. R-value = 0.9072 when cluster radius =0.2

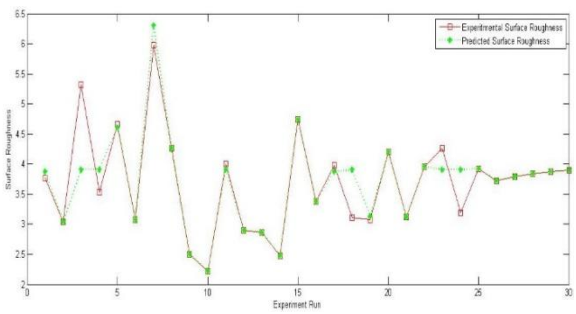

Figure 23. Experimental Surface Roughness against Predicted Surface Roughness

D. Predicted Surface Roughness when cluster radius = 0.3

As depicted in Table 3 and Figure 24 and Figure 25, the values of MAPE, RMSE and R-value obtained when cluster radius was set to 0.3 are MAPE = 4.6744%, RMSE = 0.5453 and R-value = 0.8582 respectively.

Table 3. Comparison between Actual and Forecasted Surface Roughness Radius = 0.3

Actual Surface Roughness	ANFIS Surface Roughness
3.768	3.87288683557864
3.042	3.04203644349054
5.322	3.90397323633056
3.534	3.90397323633056
4.662	4.66202224032497
3.072	3.07226291849535
5.982	8.32318328977092
4.26	4.26002485136123
2.502	2.50192584178921
2.22	2.21986942992832
4.002	3.90397323633056
2.898	2.89837851265937
2.862	2.86180662446920
2.478	2.47813690450970
4.74	4.74015174416318
3.378	3.37798500897465
3.978	3.87288683557864
3.108	3.90397323633056
3.078	3.07799195584409
4.2	4.19994915717955
3.12	3.12007713541054
3.96	3.96005791156725
4.26	3.90397323633056
3.198	3.90397323633056
3.924	3.92403218072368
3.726	3.72589427180518
3.792	3.79203106154122
3.84	3.83997955301256
3.87	3.86985160147591
3.9	3.89998094061090

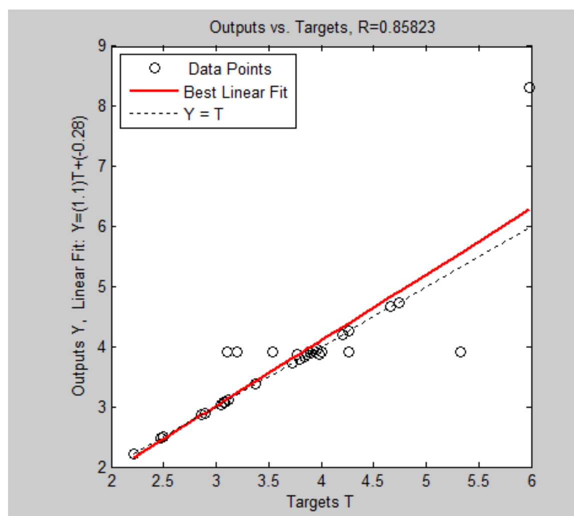

Figure 24. R-value = 0.8582 when cluster radius = 0.3

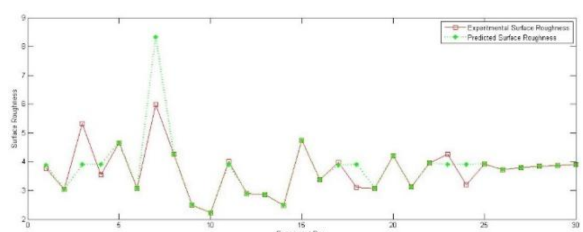

Figure 25. Experimental Surface Roughness against Predicted Surface Roughness

The best model is one with the least MAPE of 3.6545%. Table 4 depicts the values of experimental and predicted values of surface roughness obtained when cluster radius was set to 0.2. An *R-value* of 0.9072 obtained in Figure 25 shows good correlation between predicted and experimental surface roughness. The reliability of the model was therefore validated.

From the *R-value* and MAPE obtained, it is conspicuously evident that given all the assumption on the data, the ANFIS-based model was appropriate for predicting surface roughness, which is considered as the performance parameter for monitoring surface texture in metals.

Table 4. Best Model Developed using Adaptive Neuro Fuzzy Inference Systems

Run	Bearing Clearance (µm)	Depth of cut (mm)	Feed rate (mm/rev)	Spindle speed(rpm)	Actual Surface roughness (µm)	ANFIS Surface Roughness (µm)
1.	90	2.500	0.020	450	3.768	3.8729585278
2.	70	1.500	0.010	450	3.042	3.0419813485
3.	80	2.000	0.015	400	5.322	3.9039912033
4.	80	2.000	0.015	400	3.534	3.9039912033
5.	90	1.500	0.010	350	4.662	4.6033746137
6.	70	2.500	0.020	450	3.072	3.0720229385
7.	70	1.500	0.010	350	5.982	6.3057397749
8.	80	2.000	0.015	250	4.260	4.2600398373
9.	70	2.500	0.010	350	2.502	2.5019726018
10.	70	2.500	0.010	450	2.220	2.2199594533
11.	80	2.000	0.015	400	4.002	3.9039912033
12.	80	2.000	0.025	400	2.898	2.8979130181
13.	90	1.500	0.010	450	2.862	2.8620476705
14.	70	2.500	0.020	350	2.478	2.4779849858
15.	80	1.000	0.015	400	4.740	4.7399342661
16.	90	2.500	0.010	350	3.378	3.3779702098
17.	90	2.500	0.020	450	3.978	3.8729585278
18.	80	2.000	0.015	400	3.108	3.9039912033
19.	90	1.500	0.015	350	3.078	3.1366641736
20.	70	1.500	0.020	450	4.200	4.1999098395
21.	80	2.000	0.015	500	3.120	3.1200013979
22.	90	2.500	0.020	350	3.960	3.9599762484
23.	80	2.000	0.015	400	4.260	3.9039912033
24	80	2.000	0.015	400	3.198	3.903991203

.						3
25.	90	1.500	0.020	450	3.924	3.9240454663
26.	60	2.000	0.020	400	3.726	3.7259984597
27.	110	2.000	0.015	400	3.792	3.7919478655
28.	80	3.000	0.015	400	3.840	3.8399813697
29.	80	2.000	0.005	400	3.870	3.8700922511
30.	70	1.500	0.020	350	3.900	3.9002201148

V. CONCLUSION AND RECOMMENDATION

A Neuro-fuzzy inference system was implemented in order to predict surface roughness in turning. By applying substrative clustering with values of radius of parameter equal to 0.1, 0.2, and 0.3 respectively, the initial membership function of the independent variables and fuzzy rules were developed. Training was done by using an initial step size of 0.1, the value of MAPE obtained was 3.123% and correlation coefficient (R) of 0.9072. Considering to values of MAPE and correlation coefficient obtained, the ANN model has better predictive capability compared with the ANFIS model.

Recommendations

Predictive modelling and optimization is a complex and re-emerging field of research. The scope of the research work is endless due to large number of variables involved in machining of materials. The effect of machining parameters like tool geometry, tool coatings, coolants, considering the bearing clearance effect on the surface roughness and power consumption has not been studied. Further, the effect of machining parameters on material removal rate can be analyzed. This work can be extended to include the advanced materials like titanium alloys and composites materials. However, in practice surface roughness is not taken as a variable of the machining process but a fixed parameter (predefined range by designers). Therefore, future research can be directed at mapping of optimum machining parameters for minimum energy consumption for a range of expected surface finish. The results can also be analyzed using other optimization techniques such as particle swarm optimization, simulated annealing, artificial bee colony, etc., and the effectiveness of various optimization techniques can be compared.

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