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Full Length Research Paper

Cutting parameters identification using multi adaptive network based Fuzzy inference system: An artificial intelligence approach

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The influences of the machine parameters on machined parts are not always precisely known and hence, it becomes difficult to recommend the optimum machinability data for machine process. This paper proposes a method for cutting parameters identification using Multi adaptive Network based Fuzzy Inference System (MANFIS). Three Adaptive Network based Fuzzy Inference System (ANFIS) models were used in the first step to identify the initial values for the cutting parameters (cutting speed, feed rate, and depth of cut) using surface roughness as a single input, in the next step these parameters were modified and verified using another set of ANFIS models. Then, workpiece surface temperature is used as input for another set of ANFIS models to amend the final values of the cutting parameters. In this way, multi-input-multi-output ANFIS structure presented, which can identify the cutting parameters accurately once the desired surface roughness and in-process measured surface temperature were entered to the system. The test results showed that the proposed MANFIS model can be used successfully for machinability data selection.

Key words: Multi ANFIS, surface roughness, workpiece surface temperature, machinability data selection.

INTRODUCTION

Cutting parameter identification in turning operations, which included cutting speed, feed rate and depth of cut plays a very important role in the efficient utilisation of machine tools and directly influences the product quality. Thus it significantly influences the overall manufacturing costs. In practice, the machinists select cutting parameters from their specified ranges in machining handbooks, mainly based on experience, in order to satisfy the required accuracy of the final product.

There are several Fuzzy based model that has been developed to determine machining parameters and responses. Surface roughness is one of the most important quality evaluation responses. Wong et al. (1997) developed a Fuzzy model for machining data selection. The model is based on the assumption that the relationship between the hardness of a given material and the recommended cutting speed is an imprecise relationship and can be described and evaluated by the theory of Fuzzy sets. The model has been applied to data extracted from the Machine data handbook, and good correlation was obtained between the handbook and that predicted using the Fuzzy logic model.

Lin et al. (2001) used a criterion for determining a network's architecture automatically. The aim was to develop a prediction model prior to the implementation of the actual machine process to determine certain cutting conditions (cutting speed, feed rate and depth of cut) in order to obtain a desired surface roughness value and cutting force value. Furthermore, using the obtained cutting force, the cutting power and optimal metal removal rate could be calculated next. The abductive networks that were created using the Predicted Square Error (PSE) criterion performed more accurately than the respective regression analysis models.

Suresh et al. (2002) were adopted a two stage approach

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towards optimizing for surface roughness. First, experimental results were used to build two mathematical models for surface roughness by a regression method according to Response Surface Methodology (RSM). Secondly, the second-order mathematical model was taken as an objective function and was optimized with a GA to obtain the machine conditions for a desired surface finish. The GA program gives minimum and maximum values of surface roughness and their respective optimal machining conditions.

Al Assadi et al. (2004) developed an artificial neural network to acquire the skilled of machinists on-line, while performing the turning process. The system results show its ability to predict the appropriate cutting parameters. The development of a Fuzzy Genetic optimization algorithm is presented and discussed by (Wong and Hamouda, 2002), for metal cutting data selection. An object-oriented to handle Fuzzy rules has been developed.

The Adaptive Network based Fuzzy Inference System (ANFIS) is widely used in complex system studies for modelling, control or parameter estimating. By using a hybrid learning algorithm which combines the gradient method and the least squares estimate to identify parameters. The ANFIS can construct an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and the stipulated input-output data pairs (Jang et al., 2004). However, ANFIS with multi-input and single-output used by many researchers for surface roughness prediction. Roy (2006) and Lo (2003) used ANFIS system to predict the workpiece surface roughness after the end milling process. The predicted values derived from ANFIS were compared with experimental data, and the comparison indicates that the adoption in ANFIS achieved very satisfactory accuracy.

The Hybrid Taguchi-Genetic Learning Algorithm (HTGLA) is applied in the ANFIS to determine the most suitable membership functions by Ho et al. (2009), and used to predict the workpiece surface roughness for the end milling process. The experimental results show that the optimal prediction error of the presented system is 4.06%.

An ANFIS system and computer vision were used to predict surface roughness in turning by Ho et al. (2002). The arithmetic averages of gray levels of the surface images with three cutting parameters were given, for a total of four inputs, to the ANFIS and the roughness value could then be obtained.

Metal cutting process parameters modelling (cutting temperature, cutting force, and quality of machined surface) presented by Tanikic et al. (2009), using artificial neural network, and ANFIS. The results show that ANFIS system gives slightly better performances, and have priority in the modelling of this type of data.

In this study based on considering the aforementioned literatures, multi ANFIS structure formed and presented using three ANFIS models in the first step to identify the initial values for the cutting parameters as (cutting speed, feed rate, and depth of cut) using the surface roughness (Ra) as a single input. Then, in the next step other three multi input single output ANFIS models were used to evaluate and verify the values of cutting parameters. Because of the non-linear behaviour of the machining process and to confirm that the set of the cutting parameters will lead to the desired output, the data contained the workpiece surface temperature (T) as a cutting performance factor obtained from the experimental work (in-process) were used for forming new MANFIS models to amend the final values of the cutting parameters. The workpiece surface temperature used by Suhail (2010), for in-process surface roughness prediction. The experimental results show that the workpiece surface temperature can be sensed and used effectively as an indicator of the cutting performance in turning operations.

MATERIALS AND METHODS

In this study, medium carbon steel AISI 1020 and 200 mm long with 50 mm diameter was used as work material for experimentation using a lathe turning machine. CNMG 432 TT5100 insert with Sandvik tool holder PCLNR 2525M/12 universal turning machine tool was used in the experiments. All tests were performed dry. Cutting speed, feed rate and depth of cut were selected as the machine parameters, surface roughness and workpiece surface temperature as cutting responses. The settings of cutting speed include 950, 1150 and 1400 rpm; those of feed rate include 0.05, 0.1, 0.15 mm rev^{-1}; the depth of cut is set at 0.5, 1.0 and 1.5 mm. Experimental planning was prepared by using cutting parameters and test conditions that were advised for a couple of tool-workpiece by tool manufacturer and the information available in the literature.

The amount of standard surface roughness parameter (Arithmetic average deviation from the mean line Ra) is carried out using the surface roughness tester model Mahr Perthometer (MarSurf PS1, produced by Mahr GMbH, Germany). Three measurements for workpiece surface roughness were made and averaged for each test.

For workpiece surface temperature measurement, handheld infrared thermometer type (OS534E) with a built-in laser circle to dot switchable and RS-232 output was used. A series of experiments was conducted to obtain the surface temperature of the workpiece by the aid of the infrared thermometer and surface roughness by the aid of a stylus type tester.

ANFIS

The acronym ANFIS derives its name from adaptive neuro-fuzzy inference system. Using a given input/output data set, ANFIS constructs a Fuzzy Inference System (FIS) whose membership function parameters are tuned (adjusted) using either a back-propagation algorithm alone or in combination with a least square type of method. This adjustment allows the Fuzzy inference systems to learn from the data they are modelling.

The parameters associated with the membership functions' changes through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the Fuzzy inference system is modelling the input/output data for a given set

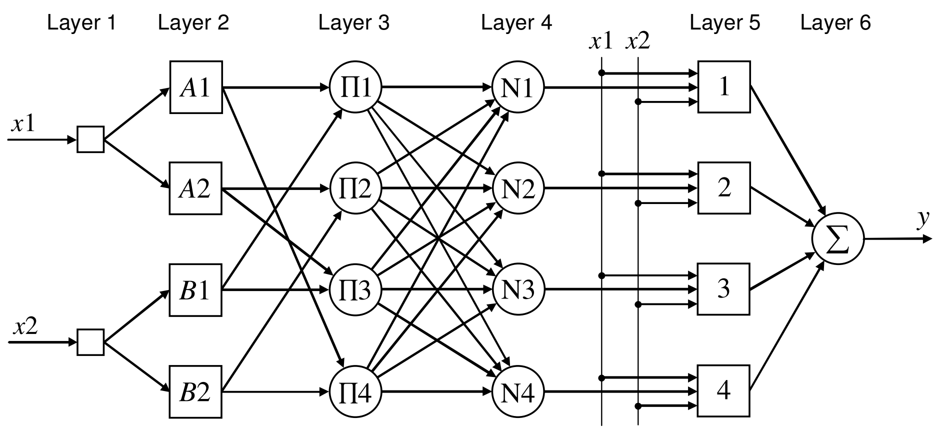


Figure 1. Architecture of ANFIS model.

of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure. This error measure is usually defined by the sum of the squared difference between actual and desired outputs (Mathworks, 2009). In the presented study ANFIS uses a combination of least squares estimation and back propagation (hybrid method) for membership function parameter estimation.

ANFIS model is one of the implementations of a first order Sugeno fuzzy inference system. A typical Sugeno Fuzzy rule is expressed in the following form:

IF x_1 is A_1 AND x_2 is A_2 . . . . . AND x_m is A_m THEN $y = f(x_1, x_2, . . . , x_m)$.

where $x_1, x_2, . . . , x_m$ are input variables; $A_1, A_2, . . . , A_m$ are fuzzy sets.

When y is a constant, we obtain a zero-order Sugeno fuzzy model in which the consequent of a rule is specified by a singleton, and when y is a first-order polynomial, that:

$$y = k_0 + k_1 x_1 + k_2 x_2 + . . . + k_m x_m \tag{1}$$

we obtain a first-order Sugeno fuzzy model.

The ANFIS model is shown in Figure 1. It is a multi-input, single-output model and a multi-output model can be designed by connecting few single output models. The architecture and learning rule of ANFIS had been described in detail by Jang et al. (1993), and can be summarized as follows:

Layer 1: is the input layer. Neurons in this layer simply pass external crisp signals to Layer 2.
Layer 2: is the fuzzification layer. Neurons in this layer perform fuzzification.
Layer 3: is the rule layer. Each neuron in this layer corresponds to a single Sugeno-type fuzzy rule. A rule neuron receives inputs from the respective fuzzification neurons and calculates the firing strength of the rule it represents.

$$y_i = \prod_{j=1}^{k} x_{ji} \tag{2}$$

$$y_{\Pi 1} = \mu_{A1} \times \mu_{B1} = \mu_1 \tag{3}$$

where the value of μ_1 represents the firing strength, or the truth value, of Rule 1.

Layer 4: is the normalisation layer. Each neuron in this layer receives inputs from all neurons in the rule layer, and calculates the normalised firing strength of a given rule.

The normalised firing strength is the ratio of the firing strength of a given rule to the sum of firing strengths of all rules. It represents the contribution of a given rule to the final result. Thus, the output of neuron i in Layer 4 is determined as,

$$y_i = \frac{x_{ii}}{\sum_{j=1}^{n} x_{ji}} = \frac{\mu_i}{\sum_{j=1}^{n} \mu_j} = \bar{\mu}_i \tag{4}$$

$$y_{N1} = \frac{\mu_1}{\mu_1 + \mu_2 + \mu_3 + \mu_4} = \bar{\mu}_1 \tag{5}$$

Layer 5: is the defuzzification layer. Each neuron in this layer is connected to the respective normalisation neuron, and also receives initial inputs, *x1* and *x2*. A defuzzification neuron calculates the weighted consequent value of a given rule as:

$$y_i = x_i[k_{i0} + k_{i1}x1 + k_{i2}x2] = \bar{\mu}_i[k_{i0} + k_{i1}x1 + k_{i2}x2] \tag{6}$$

where x_i is the input and y_i is the output of defuzzification neuron i in Layer 5, and k_{i0}, k_{i1} and k_{i2} is a set of consequent parameters of rule i.

Layer 6: is represented by a single summation neuron. This neuron calculates the sum of outputs of all defuzzification neurons and produces the overall ANFIS output y.

$$y = \sum_{i=1}^{n} x_i = \sum_{i=1}^{n} \bar{\mu}_i [k_{i0} + k_{i1}x1 + k_{i2}x2] \tag{7}$$

In the ANFIS training algorithm suggested by Jang, both antecedent parameters and consequent parameters are optimised. In the forward pass, the consequent parameters are adjusted while the antecedent parameters remain fixed. In the backward pass, the antecedent parameters are tuned while the consequent parameters are kept fixing.

The proposed MANFIS based method

A Multi-Input Multi-Output Adaptive Neural-Fuzzy Inference System (MANFIS) is developed for predicting the cutting parameters in turning operation. The architecture of the ANFIS models used in the proposed method is shown in Figure 2. The developed system has

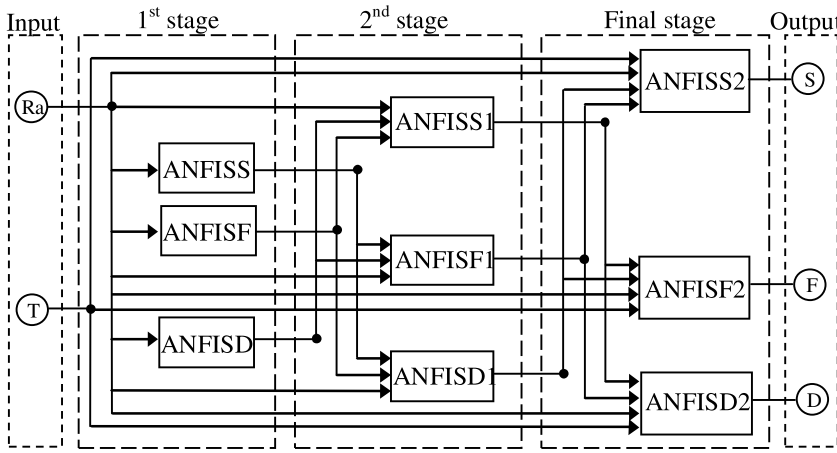


Figure 2. Architecture of multi adaptive neuro-Fuzzy inference system.

Table 1. Inputs and outputs for ANFIS models with notations.

Item	ANFIS Model	Input	Output	Notes
1	ANFISS	Ra	S	
2	ANFISF	Ra	F	Initial values
3	ANFISD	Ra	D	
4	ANFISS1	Ra, F, D	S	
5	ANFISF1	Ra, S, F	F	Primary values
6	ANFISD1	Ra, S, D	D	
7	ANFISS2	Ra, T, F, D	S	
8	ANFISF2	Ra, T, S, D	F	Final values
9	ANFISD2	Ra, T, S, F	D	

three stages; in the first stage three Fuzzy inference systems were built up using Fuzzy Subtractive Clustering Method (FSCM). This FSCM partitions the data into groups called clusters, and generates a FIS with the minimum number rules required to distinguish the Fuzzy qualities associated with each of the clusters. Then a single-input-single-output ANFIS model is used to train the FIS models to emulate the training data presented to it by modifying the membership function parameters according to a chosen error criterion. To achieve an accurate prediction gradient descent or back-propagation algorithm is used to tune the membership functions and the consequent parameters. The adjustment to these parameters is determined according to the gradient between the actual and expected output. The input for all models in this stage was the surface roughness, and the outputs were the initial values for cutting parameters as cutting speed (S), feed rate (F), and depth of cut (D).

The output of the first stage was used to generate other Fuzzy inference systems and then, multi-input-single-output ANFIS models were used to train these FIS models and find out the new cutting parameters' values. The interaction between S, F, and D controlled by the surface roughness (Ra) was examined in this stage. Then, these primary values of cutting parameters were used in the last stage with another performance measure (the workpiece surface temperature T) using another three multi-input-single-output ANFIS models, which were trained using the data obtained from the experimental work for verification purpose and predict out the final values of the cutting parameters.

The method of optimization used for training and learning is hybrid back propagation method, and numbers of training epochs were 40 for all ANFIS models. Table 1 shows the inputs and outputs for each ANFIS model with notations.

RESULTS

The experimental data of 27 turning experiments listed in Table 2 are utilized to training stages. FSCM was used to extract the new FIS models from the input-output of training data and then trained with ANFIS models. All program codes were generated by using MATLAB programme.

The trained ANFIS establishes the relationship between the surface roughness and each cutting parameter (S, F, and D) in the first stage represent the direct relationship (linear relationship). Under ANFIS environment the determination of the membership function was done, and the rules were automatically

Table 2. Experimental training data.

No.	S	F	D	RaEx	TEx
1	1400	0.05	0.5	0.750	66.54
2	1150	0.05	0.5	0.885	55.89
3	950	0.05	0.5	0.937	62.96
4	1400	0.10	0.5	0.899	65.31
5	1150	0.10	0.5	1.105	61.92
6	950	0.10	0.5	1.306	63.80
7	1400	0.15	0.5	1.056	55.86
8	1150	0.15	0.5	1.281	58.00
9	950	0.15	0.5	1.403	62.00
10	1400	0.05	1.0	0.930	75.87
11	1150	0.05	1.0	1.077	76.78
12	950	0.05	1.0	1.281	76.57
13	1400	0.10	1.0	1.124	69.18
14	1150	0.10	1.0	1.279	69.81
15	950	0.10	1.0	1.306	68.16
16	1400	0.15	1.0	1.200	60.80
17	1150	0.15	1.0	1.307	64.88
18	950	0.15	1.0	1.491	71.05
19	1400	0.05	1.5	0.982	84.00
20	1150	0.05	1.5	1.078	87.65
21	950	0.05	1.5	1.258	82.00
22	1400	0.10	1.5	1.036	85.00
23	1150	0.10	1.5	1.219	82.62
24	950	0.10	1.5	1.500	78.10
25	1400	0.15	1.5	1.036	87.00
26	1150	0.15	1.5	1.403	67.89
27	950	0.15	1.5	1.900	85.00

S: Cutting speed, F: Feed rate, D: Depth of cut, RaEx: Experimental surface roughness, TEx: Experimental workpiece surface temperature.

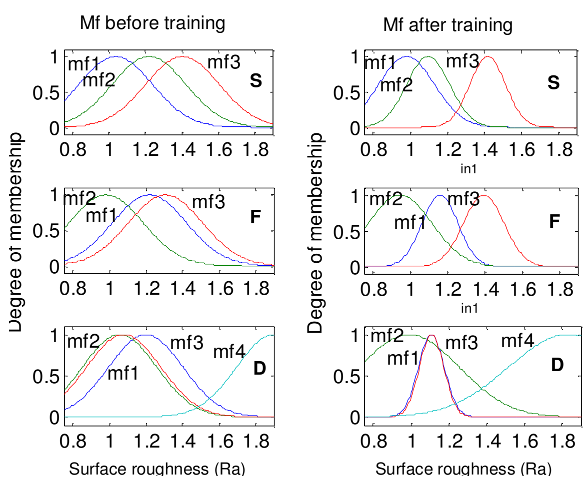


Figure 3. Initial stage membership functions before and after training.

generated. Figure 3 shows the Membership Functions (Mf) of the cutting parameters obtained in this stage before and after training, and the Gauss Mfs are used for all variables' models. In the same way, the effective

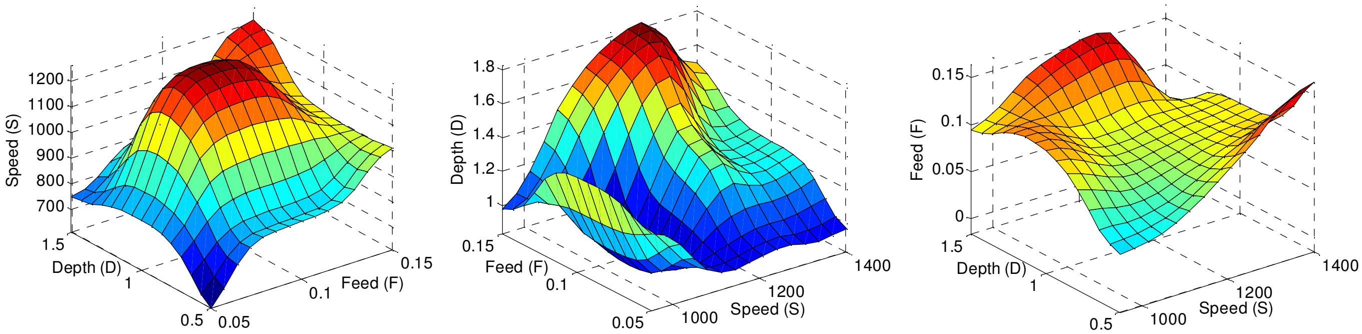
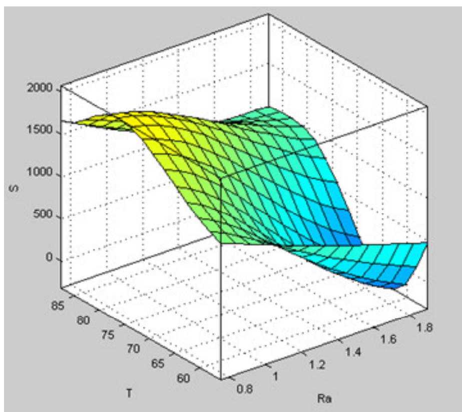
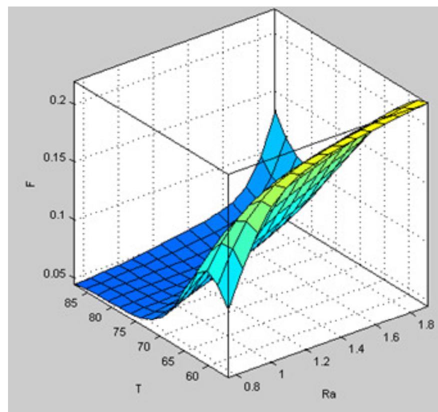


Figure 4. Primary stage output surface for cutting parameters.



a



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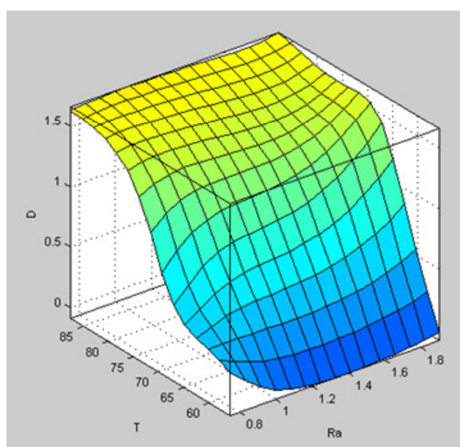

c

Figure 5. Final stage output surface for cutting parameters (a) Cutting speed, (b) Feed rate, (c) Depth of cut.

for the cutting parameters' interaction on the surface roughness was examined in the next step and more accurate cutting parameter values were obtained. New FIS models were established and trained using new sets of ANFIS models in this stage. The output of this stage is shown in Figure 4.

To further verify the prediction accuracy, another cutting response named workpiece surface temperature (T) was used in the last stage to amend the final values of the cutting parameters and the corresponding prediction errors are compared for each stage. Figure 5 shows the output surface for S, F, and D controlled by

Table 3. Summary of RMSE for each model stages.

Stages		RMSE		
		S	F	D
Stage 1	Initial before training	126.5087	0.0334	0.3433
	Initial after training	124.3610	0.0325	0.2938
Stage 2	Primary before training	37.8791	0.0168	0.1841
	Primary after training	27.2166	0.0136	0.0680
Stage 3	Final	9.32E-13	6.44E-17	1.97E-15

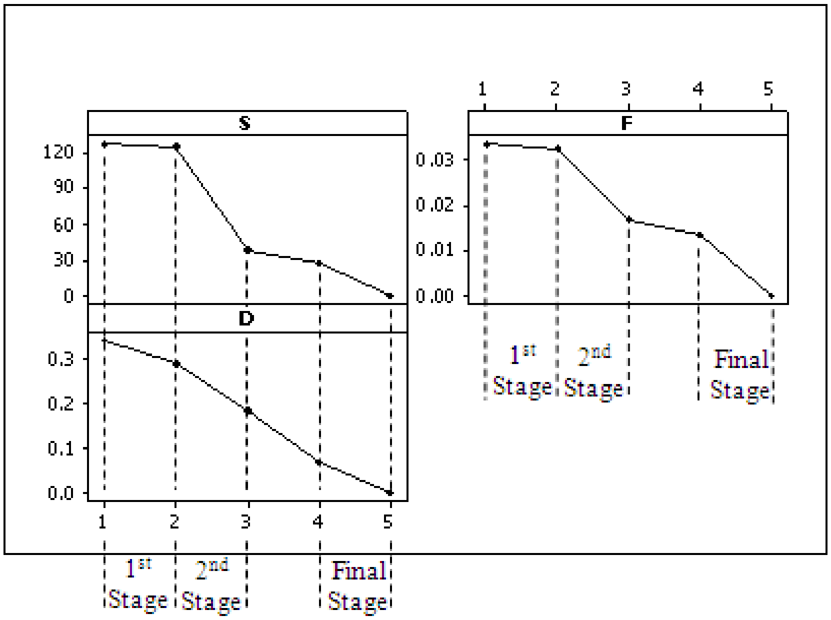

Figure 6. Error plots for ANFIS stages.

both, surface roughness and surface temperature.

To compare the accuracy between the stages, Root Mean Squared Error (RMSE) was computed before and after training for each stage and the results were summarized in Table 3. Furthermore, the error degradation is shown clearly stage by stage in Figure 6.

DISCUSSION

From Figure 3, it can be seen that for all cutting parameters of S, F and D, the Mfs, had considerable changes after training experience in the large and small areas, while the surface roughness was affected by feed rate (F) significantly according to the membership function shape and levels. This was followed by cutting speed (S) and lastly by depth of cut (D) which seems to affect the surface roughness in the low and high levels but not in the medium level. Both (F) and (S) both introduce three membership functions while (D) introduces four.

The surface graph in Figure 4 explains clearly the relationship between the cutting parameters controlled by surface roughness and shows the interaction between each parameter. It can be seen how ANFIS model guaranteed continuity of the output surface.

From Figure 5(a), it can be seen that the low Ra and high T give higher cutting speed (S) and vice versa, while low Ra and high T lead to lower feed rate (F) in Figure 5(b). Lastly, Figure 5(c) shows that depth of cut (D) can be predicted accurately by (T) but not by (Ra). All accords with the machine process theorem.

On the other hand, the RMSE decreases step by step after each stage as shown in Table 3, gives more prediction accuracy. As well as Figure 6 shows how that error decreases from high values in the first stage which depend on the linear relationship between Ra and the cutting parameters. While it decreases more by using the interaction effect of the cutting parameters in the second stage, reflect the role of the cutting parameters' interaction on the surface roughness. Finally, the error reaches near to zero in the last stage when another

Table 4. Experimental checking data.

No.	S	F	D	RaEx	Tex
1	1000	0.075	0.75	1.114	67.88
2	1000	0.125	0.75	1.354	67.49
3	1200	0.075	0.75	0.991	68.48
4	1200	0.125	0.75	1.172	66.47
5	1000	0.075	1.25	1.286	77.94
6	1000	0.125	1.25	1.558	78.81
7	1200	0.075	1.25	1.120	78.73
8	1200	0.125	1.25	1.285	79.06

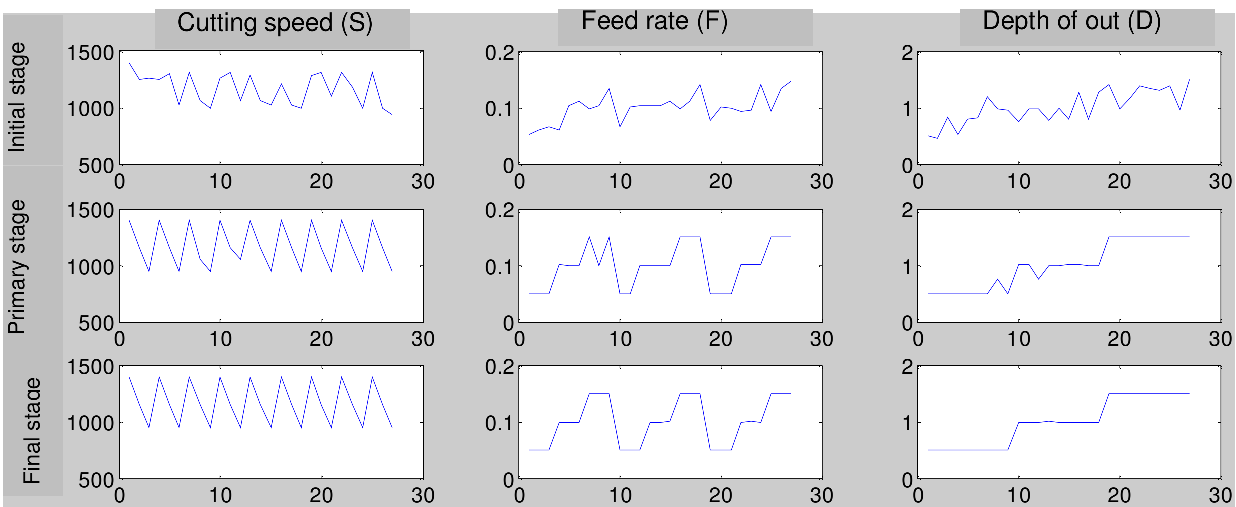

Figure 7. Predicted cutting parameters for each stages.

performance measure (T) used, shows the benefit of using multiple performance monitoring.

Model validation

Model validation is the process by which the input vectors from input/output data sets on which the FIS was not trained, are presented to the trained FIS model, to see how well the FIS model predicts the corresponding data set output values. The idea behind using a checking data set for model validation is that after a certain point in the training, the model begins over fitting the training data set. Over fitting is accounted for by testing the FIS trained on the training data against the checking data, and choosing the membership function parameters to be those associated with the minimum checking error if these errors indicate model over fitting. Experimental checking data of eight sets listed in Table 4 were used for model validation purpose.

To validate the presented model more, the predicted cutting parameters (S, F, and D) were plotted for each stage. As shown in Figure 7 the predicted S, F and D evaluated after each stage until the right cutting parameters values are reached. The results show that the designed MANFIS model is capable of learning and predicting machine parameters considerably accurate.

Conclusions

An artificial intelligence approach has been proposed in this paper using the MANFIS to effectively identify the cutting parameters in turning operation based in two performances measure (surface roughness and surface temperature). The proposed system consists of three stages, first stage for initial cutting parameters' prediction, second stage for modification and verification, and last stage for checking and amends the final cutting parameters' values. By directly minimizing the RMSE performance criterion stage by stage, the presented model proves the capability of ANFIS to learn and how it can be used successfully for machinability data selection. In other words, fewer numbers of training sets are required in MANFIS to achieve the same error of single

ANFIS. Therefore, faster and simpler solutions can be obtained based on MANFIS, and this model can improve to be a single-input-multi-output model.

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