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PREDICTION AND CONTROL OF SURFACE ROUGHNESS FOR END MILLING PROCESS USING ANFIS

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Abstract: *In this paper, we have applied an Adaptive Neuro-Fuzzy Inference System (ANFIS) approach to the prediction of workpiece surface roughness for end milling process. A small number of fuzzy rules are used for building an ANFIS model with the help of the subtractive clustering method (ANFIS-Subtractive clustering model). The predicted values are found to be in an excellent agreement with the experimental data with average error values in the range of 3.47-3.49%. Also, we have compared the proposed ANFIS model to other Artificial Intelligence (AI) approaches. The results show that the proposed model has high accuracy in comparison to the other AI approaches in literature. Therefore, we can use the ANFIS model to predict and control workpiece surface roughness for end milling process.*

Key Words: *ANFIS, Surface Roughness, Computer Numerical Control (CNC) Machine*

1 Introduction

Nowadays, accuracy is one of the most important characteristics of current manufacturing, which is manifested not only in the dimensions of a workpiece, but also in the surface roughness of the workpiece to be manufactured. The workpiece surface roughness has been an important factor in predicting the performance measure of any machining process (Chandrasekaran, Muralidhar, Krishna, & Dixit, 2010). Artificial Intelligence (AI) techniques can be used in the machining area for prediction and control of the performance parameters as well as for optimization of the process (Chandrasekaran, et al., 2010). For instance, researchers have attempted to control surface roughness by using artificial neural networks (Khorasani & Yazdi, 2017; Markopoulos, Manolakos, & Vaxevanidis, 2008), fuzzy logic (Kovac, Rodic, Pucovsky, Savkovic, & Gostimirovic, 2013) and ANFIS (Dong & Wang, 2011; Ho, Tsai, Lin, & Chou, 2009; Lo, 2003; Maher, Eltaib, Sarhan, & El-Zahry, 2014; Sharkawy, 2011), mostly for end milling operations (Lo, 2003; Tangjitsitcharoen, Thesniyom, &

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Ratanakuakangwan, 2017). In milling, the surface roughness is influenced by machining parameters such as spindle speed, feedrate, depth of cut, etc. These parameters can be considered as inputs to model the workpiece surface roughness.

Lo (Lo, 2003) used an ANFIS model to predict workpiece surface roughness after end milling process. Spindle speed, feed rate, and depth of cut were considered as input variables. The triangular and trapezoidal functions were used to describe the membership degree of these inputs. The number of the membership functions was three for each input and, in total, 27 rules were obtained to define their relationship with surface roughness. The average error of the surface roughness prediction by the ANFIS with the triangular membership function was only 4%, reaching an accuracy of 96%. In contrast, the average error by the ANFIS with the trapezoidal membership function was relatively higher at 6.7%, with a lower accuracy of 93.3%.

Ho et al. (Ho, et al., 2009) also used the ANFIS with the GA algorithm to control workpiece surface roughness. Based on the same experimental data of Lo (Lo, 2003), a total of 48 samples were used for training purpose, and other 24 samples were used for testing stage. The results show that their approach using the Gaussian membership function gives similar results as the ANFIS model with the triangular membership function obtained by Lo (Lo, 2003) (average error was 4.06%). Sharkawy (Sharkawy, 2011) used three types of AI approaches to model surface roughness in the end milling process with the same dataset presented in (Lo, 2003) (Ho, et al., 2009). Three models were built using radial basis function neural network RBFNs, ANFIS, and genetically evolved fuzzy inference systems G-FISs. The average error of the surface roughness prediction by these three models was in the range of 4-5%. A later work by (Paturi, Devarasetti, Fadare, & Narala, 2018) used ANN model and response surface methodology (RSM) in modeling of surface roughness. The outcome of their study demonstrates that both statistical and AI modeling can make a potential alternative to time-consuming experimental work, while minimizing costly machining test trials. Clearly, using a neural network involves a moderately tedious trial and error effort for obtaining the network structure, especially involving the middle layer nodes. Instead, the nodes and the hidden layers can be determined precisely by the fuzzy inference techniques in the ANFIS approach.

Dong et al. (Dong & Wang, 2011) used the ANFIS with a leave-one-out cross-validation (LOO-CV) approach to predict workpiece surface roughness. Based on the same experimental data, the predictive result of their ANFIS model outperforms the models reported recently in the literature with average error of 3.62%. Therefore, the ANFIS can be taken as an alternative promising method for future modeling and control of surface roughness for end milling process.

The ANFIS model construction requires the division of the input-output data into rule patches. This can be achieved by using a number of methods such as grid partitioning, subtractive clustering method and fuzzy c-means (FCM) (Guillaume, 2001). According to Jang (Jang, 1993), the grid partition is only suitable for problems with a small number of input variables (e.g. fewer than 6). In this paper, the proposed models have three inputs. It is reasonable to apply the ANFIS-Grid partition method. A model with three inputs with three fuzzy sets per input produces a complete rule set of 27 rules as in above-mentioned studies. It is important to note that an effective partition of the input space can decrease the number of rules and thus increase speed in both the learning and the application phases. Therefore, using the subtractive clustering with the ANFIS can be regarded as knowledge extraction from the experimental data. This is important since knowledge can be easily gathered in linguistic terms as a collection of "IF-THEN" rules. This is significant because the learning strategies can start from the point where the risk of entrapment in a local minimum is reduced in comparison to that when the initial parameters are chosen at random (which is often the case for ANNs).

The goal of this work is to make the intelligent system readily applicable to predict and control workpiece surface roughness with minimal effort. In this article, the ANFIS will be used for building two surface roughness prediction models: ANFIS by dividing the data space into rectangular sub-spaces (ANFIS-Grid) and ANFIS by using the subtractive clustering method (ANFIS-SCM). This combined methodology can help us improve robustness of the proposed model, and reduce the number of rules. Data needed for development of the ANFIS models are obtained from the literature. Comparisons of the predicted surface roughness with that using other AI techniques have also been made in this paper. This paper is organized as follows: in the next section, i.e. Section 2, the theoretical background of ANFIS is described. Section 3 shows the data we use for our investigations. In Section 3.2, we test and validate the proposed models in Section 3.1. Finally, conclusions and further research aspects are discussed in Section 4.

2 Adaptive Neuro Fuzzy Inference System (ANFIS)

The Adaptive Neuro Fuzzy Inference System (ANFIS), was first introduced by Jang (Jang, 1993). According to Jang, the ANFIS is a neural network that is functionally the same as the Takagi-Sugeno type inference model. The ANFIS is a hybrid intelligent system that takes advantages of both the ANN and the fuzzy logic theory in a single system. By employing the ANN technique to update the parameters of the Takagi-Sugeno type inference model, the ANFIS is given the ability to learn from training data, the same as ANN. The solutions mapped out onto a Fuzzy Inference System (FIS) can therefore be described in linguistic terms. In order to explain the concept of ANFIS structure, five distinct layers are used to describe the structure of an ANFIS model. The first layer in the ANFIS structure is the fuzzification one; the second layer acts as the rule base layer; the third layer performs the normalization of membership functions (MFs); the fourth and fifth layers are the defuzzification and summation ones, respectively. More information about the ANFIS structure is given in (Jang, 1993). Fig. 1 shows basic structure of the ANFIS with two inputs.

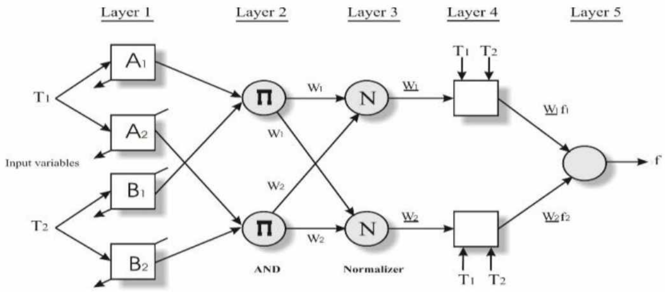

Fig. 1 Basic structure of ANFIS model

2.1 Extraction of the initial fuzzy model

In order to start the modeling process, an initial fuzzy model has to be derived. This model is required for selecting input variables and for input space partitioning (or clustering), for choosing the number and type of membership functions of the inputs as well as for creating fuzzy rules, their premise and conclusion parts. For a given dataset, different ANFIS models can be constructed using different identification methods such as grid partitioning and fuzzy subtractive clustering (Guillaume, 2001).

A. The ANFIS-Grid partition method is the combination of grid partition and ANFIS. The data space is divided into rectangular sub-spaces using axis-paralleled partitions based on a pre-defined number of MFs and their types in each dimension (Haddad & Al Kobaisi, 2012). The limitation of this method is that the number of rules rises rapidly as the number of input variables increases. For example, if the number of input sensors is n and the partitioned fuzzy subset for each input sensor is m, then the number of possible fuzzy rules is m^n. While the number of variables raises, the number of fuzzy rules increases exponentially; this requires a large computer memory. According to Jang (Jang 1993), the grid partition is only suitable for problems with a small number of input variables (e.g. fewer than 6).

B. The ANFIS-Subtractive clustering method combines the subtractive clustering method and the ANFIS. The subtractive clustering initially proposed by Chiu (Chiu, 1994) considers data points as candidates for the centre of clusters and computes the density at each point. One of the important aspects of the subtractive clustering algorithm is the determination of the cluster radius (R) which defines the number of clusters and, consequently, the number of rules. A small radius leads to many smaller clusters in the data space, which results in more rules. After clustering the data space, the number of fuzzy rules is determined and so is that of premise fuzzy MFs. Then the linear squares estimate is used to determine the consequence in the output MFs, resulting in a valid FIS.

In order to obtain a small number of fuzzy rules, a fuzzy rule generation technique that integrates ANFIS with the subtractive clustering method can be used, where the SCM is used to systematically identify the fuzzy MFs and the fuzzy rule base for the ANFIS model. In this paper, to identify premise membership functions, two afore-mentioned methods are used and compared.

3 Results and discussion

In order to build the proposed ANFIS models, spindle speed (Sp), feed rate (Fe), and depth of cut (Dep) are considered as input variables (see Table 1, Figs. 2 and 3, respectively). Fig. 2 shows experimental data used for training stage (48 samples), and Fig. 3 shows separate experimental data used for testing stage (24 samples). In this Section, the aim is to use the structure of the data-driven models described in the previous subsections in order to predict workpiece surface roughness. Moreover, comparison will be made between the estimates provided by the proposed models and the other models presented in literature. Based on the same experimental data of Lo (Lo, 2003), the available data set in Table 2 is divided into two sets; one is used for the ANFIS training (48 samples, about 66%, see Fig. 2), while the other for testing performance (24 samples, about 34%, see Fig.). The optimized ANFIS models are selected based on the minimal Root-Mean-Square Error (RMSE) value as will be discussed in the next section.

Table 1: The symbols used in the tables

Parameter	Definition	Unit
Sp	Spindle speed	Revolutions per minute (rpm)
Fe	Feed rate	Inch per minute (ipm)
Dep	Depth of cut	Inch (in)
Ra	Roughness	Micro inch (µin.)

Table 2: Experimental data (Lo, 2003)

Experimental results (training data set)					Experimental results (training data set)				
T no	Sp	Fe	Dep	Ra	T no	Sp	Fe	Dep	Ra
1	750	6	0.01	65	1	750	9	0.01	109
2	750	6	0.03	63	2	750	9	0.05	95
3	750	6	0.05	72	3	750	15	0.03	122
4	750	12	0.01	144	4	750	15	0.05	104
5	750	12	0.03	102	5	750	21	0.01	178
6	750	12	0.05	94	6	750	21	0.03	163
7	750	18	0.01	185	7	750	21	0.05	150
8	750	18	0.03	147	8	1000	9	0.01	92
9	750	18	0.05	121	9	1000	15	0.03	108
10	750	24	0.01	187	10	1000	21	0.01	149
11	750	24	0.03	170	11	1000	21	0.03	145
12	750	24	0.05	172	12	1000	21	0.05	112
13	1000	6	0.01	58	13	1250	15	0.01	106
14	1000	6	0.03	78	14	1250	15	0.03	96
15	1000	6	0.05	62	15	1250	21	0.01	125
16	1000	12	0.01	130	16	1250	21	0.03	100
17	1000	12	0.03	84	17	1250	21	0.05	105
18	1000	12	0.05	92	18	1500	9	0.03	73
19	1000	18	0.01	138	19	1500	15	0.01	106
20	1000	18	0.03	124	20	1500	15	0.03	83
21	1000	18	0.05	86	21	1500	15	0.05	99
22	1000	24	0.01	163	22	1500	21	0.01	118
23	1000	24	0.03	153	23	1500	21	0.03	102
24	1000	24	0.05	142	24	1500	21	0.05	113
25	1250	6	0.01	50					
26	1250	6	0.03	63					
27	1250	6	0.05	71					
28	1250	12	0.01	101					
29	1250	12	0.03	99					
30	1250	12	0.05	85					
31	1250	18	0.01	115					
32	1250	18	0.03	92					
33	1250	18	0.05	95					

34	1250	24	0.01	155
35	1250	24	0.03	109
36	1250	24	0.05	121
37	1500	6	0.01	37
38	1500	6	0.03	56
39	1500	6	0.05	56
40	1500	12	0.01	88
41	1500	12	0.03	82
42	1500	12	0.05	94
43	1500	18	0.01	119
44	1500	18	0.03	87
45	1500	18	0.05	104
46	1500	24	0.01	119
47	1500	24	0.03	103
48	1500	24	0.05	109

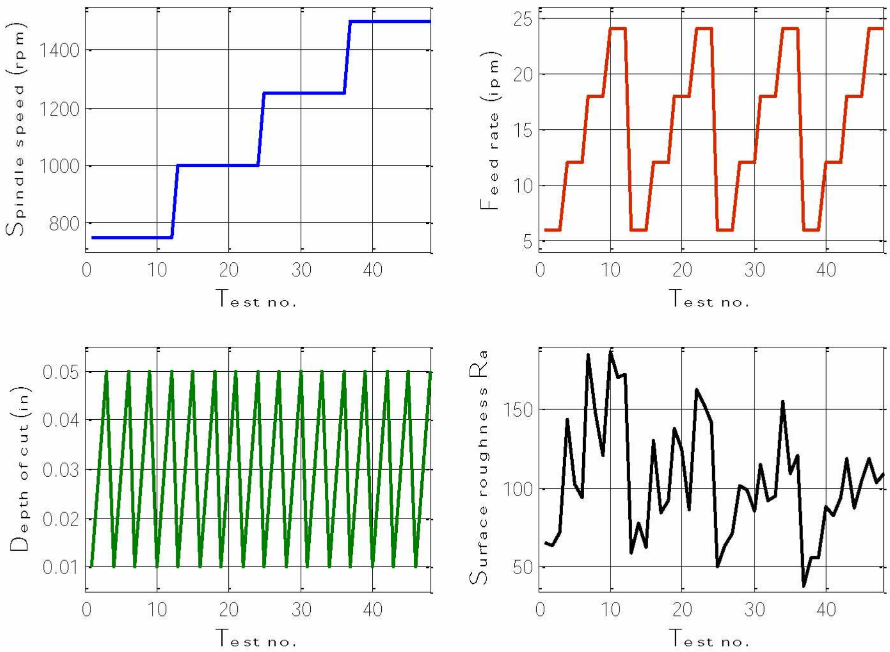

Fig. 2: Experimental results for training data

3.1 Development of the ANFIS models

In the ANFIS-Grid partition model structure, we can only use the Sugeno fuzzy rules, where the output is a linear combination of inputs. Different ANFIS models are evaluated using the RMSE in order to measure the deviation between the measured and the predicted values. By testing various ANFIS structures with a different number of MFs, we have obtained the optimal structure with 2 MFs for the spindle speed variable, 2 MFs for the feed rate variable, and 3 MFs for depth of cut variable, which adds up to the total of 12 rules. Also, we have tested all types of MFs such as Bell, Sigmoid, Triangle, Trapezoid and Gaussian. The Bell membership function in comparison with the others has the least error value. It is also observed that after using 5 epochs, the performance does not improve any further. The final ANFIS architecture used in this study is illustrated in Table 3. The corresponding rules of the optimal model are provided in Table 4.

Table 3: ANFIS-Grid model parameters

Parameters	ANFIS model
Type	Sugeno/ANFIS-Grid
Inputs/Outputs	3-1
Number of input membership function	2×2×3 for Sp, Fe and Dep, respectively
Number of output membership function	12
Input membership function Types	Bell
Output membership function Types	Linear
Rules Weight	1
Number of fuzzy rules	12
Number of epochs	5

Table 4: Linguistic rules

Linguistic rules
1. If (Sp is Low) and (Fe is Low) and (Dep is Low) then (Ra is out1mf1)
2. If (Sp is Low) and (Fe is Low) and (Dep is Medium) then (Ra is out1mf2)
3. If (Sp is Low) and (Fe is Low) and (Dep is High) then (Ra is out1mf3)
4. If (Sp is Low) and (Fe is High) and (Dep is Low) then (Ra is out1mf4)
5. If (Sp is Low) and (Fe is High) and (Dep is Medium) then (Ra is out1mf5)
6. If (Sp is Low) and (Fe is High) and (Dep is High) then (Ra is out1mf6)
7. If (Sp is High) and (Fe is Low) and (Dep is Low) then (Ra is out1mf7)
8. If (Sp is High) and (Fe is Low) and (Dep is Medium) then (Ra is out1mf8)
9. If (Sp is High) and (Fe is Low) and (Dep is High) then (Ra is out1mf9)
10. If (Sp is High) and (Fe is High) and (Dep is Low) then (Ra is out1mf10)
11. If (Sp is High) and (Fe is High) and (Dep is Medium) then (Ra is out1mf11)
12. If (Sp is High) and (Fe is High) and (Dep is High) then (Ra is out1mf12)

Next, different ANFIS models are constructed using the subtractive clustering method. In the ANFIS-SCM model, it is essential to obtain an optimal number of clusters. For this purpose, several ANFIS models can be constructed with a different number of cluster radiuses (R). The ANFIS model with R=0.8 is found to exhibit the lowest error after 5 epochs. The characterization of the ANFIS model is illustrated in Table 5. The corresponding rules of the optimal model are provided in Table 6.

Table 5: ANFIS-SCM model parameters

Parameters	ANFIS model
Type	Sugeno
Inputs/Outputs	3-1
Number of input membership function	8 for all inputs
Number of output membership function	8
Input membership function Types	Gaussian
Output membership function Types	Linear
Rules Weight	1
Number of fuzzy rules	8
Number of epochs	5

Table 6: Linguistic rules for ANFIS-SCM

Linguistic rules
1. If (Sp is SpCluster1) and (Fe is FeCluster1) and (Dep is DepCluster1) then (Ra is RaCluster1)
2. If (Sp is SpCluster2) and (Fe is FeCluster2) and (Dep is DepCluster2) then (Ra is RaCluster2)
3. If (Sp is SpCluster3) and (Fe is FeCluster3) and (Dep is DepCluster3) then (Ra is RaCluster3)
4. If (Sp is SpCluster4) and (Fe is FeCluster4) and (Dep is DepCluster4) then (Ra is RaCluster4)
5. If (Sp is SpCluster5) and (Fe is FeCluster5) and (Dep is DepCluster5) then (Ra is RaCluster5)
6. If (Sp is SpCluster6) and (Fe is FeCluster6) and (Dep is DepCluster6) then (Ra is RaCluster6)
7. If (Sp is SpCluster7) and (Fe is FeCluster7) and (Dep is DepCluster7) then (Ra is RaCluster7)
8. If (Sp is SpCluster8) and (Fe is FeCluster8) and (Dep is DepCluster8) then (Ra is RaCluster8)

3.2 Validation of the proposed models

In this section, the aim is to use the structure of the ANFIS models described in the previous section to predict the surface roughness. With the purpose of evaluating the prediction performance of the models, the remaining data set (testing data set) is used for running the proposed models. The performance of the models used in this study is computed using percentage error E_i and average percentage error E_{av} defined in equations (1) and (2), respectively, as follows:

$$E_i\% = \frac{\left|Ra_{Exp} - Ra_{Pre}\right|}{Ra_{Exp}} \times 100$$

$$E_{av}\% = \frac{1}{m}\sum_{i=1}^{m} E_i$$

where 'Ra_{Exp}' and 'Ra_{Pre}' stand for experimental values and predicted values, respectively; *m* is the samples number to be predicted.

It is observed from Table 6 that for the best models obtained by Lo (Lo, 2003), Ho et al. (Ho, et al., 2009), and Dong et al. (Dong & Wang, 2011), the maximum average errors are approximately 4.65% (for Triangular MF) and 7.31% (for Trapezoidal MF), 4.06%, and 3.62%, respectively; therefore, the error values are in the range of 3.62-7.31%. For the best ANFIS configuration obtained in this study, the maximum average errors are approximately 3.47% (for an ANFIS-Grid model, see Fig. 3) and 3.49% (for ANFIS-SCM model, see see Figure 4), respectively; therefore, the average error values are in the range of 3.47-3.49%.

From these results, it is clear that the surface roughness prediction by using the proposed ANFIS models outperforms the models presented in (Lo, 2003) (Ho, et al., 2009) (Dong & Wang, 2011), with the benefit of lower rules.

In this work, it can be clearly seen that the ANFIS model structure demonstrates several advantages. It provides a natural framework to include expert human being knowledge in the form of linguistic fuzzy "IF-THEN" rules. This knowledge can be easily gathered with the rules, which are automatically obtained from the data sets that describe the system. Therefore, the two main objectives to be addressed in this article are interpretability and accuracy. Generally speaking, the ideal model should satisfy both the criteria (interpretability and accuracy) to a high degree but since they are contradictory issues, this is generally impossible. Under the circumstances, one of them can be selected depending on the nature of the problem to be solved.

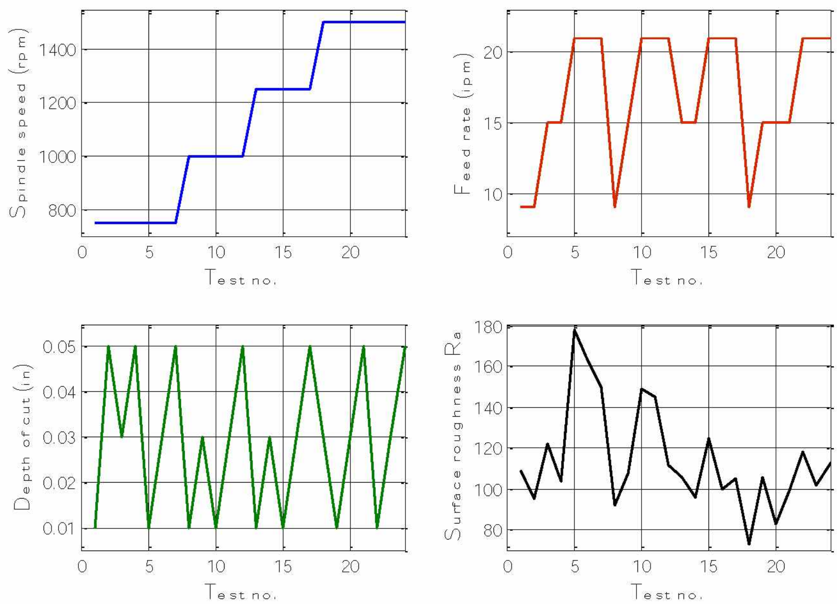

Fig. 3: Experimental results for testing data

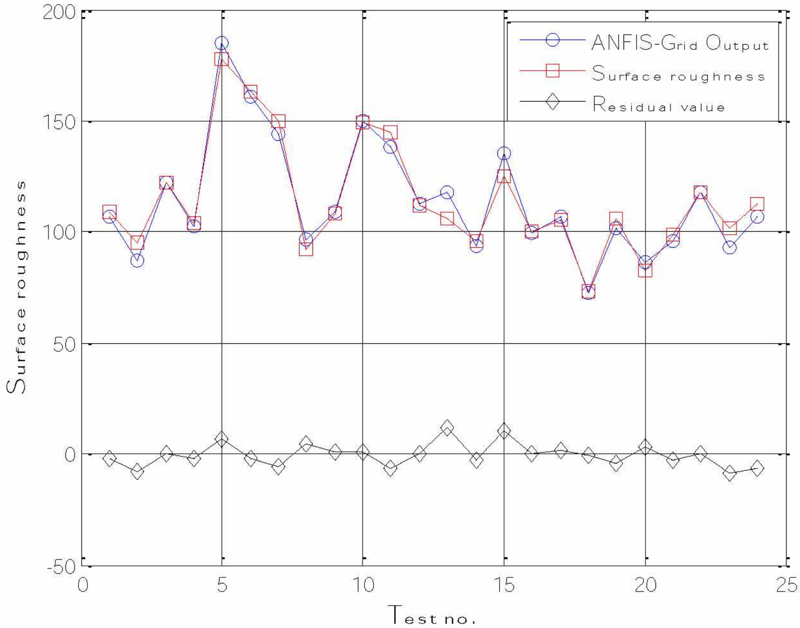

Fig. 4: The measured Ra and predicted Ra for testing dataset using ANFIS-Grid

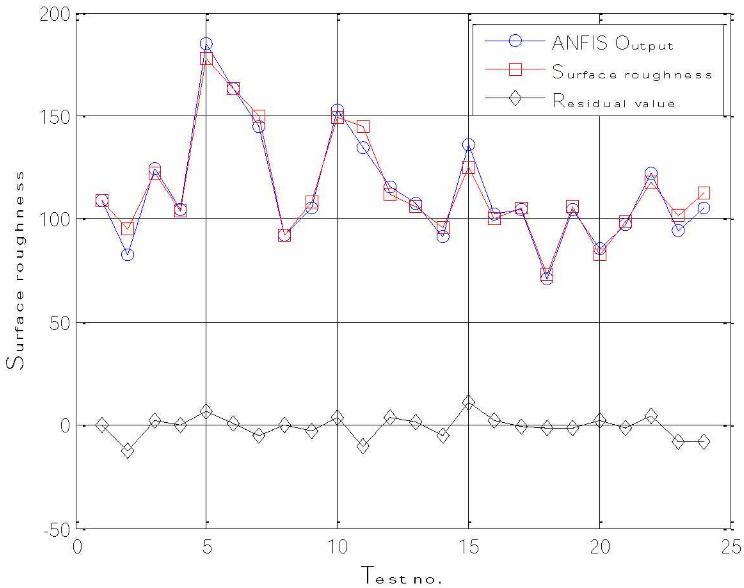

Fig. 5 The measured Ra and predicted Ra for testing dataset using ANFIS-SCM

4 Conclusions

In this paper, an adaptive Neuro-Fuzzy inference system for the modeling and control of workpiece surface roughness for end milling process is presented. The comparison between the experimental and the predicted values of the proposed ANFIS models shows that there is an excellent agreement between the predicted surface roughness and the experimental results with average error values in the range of 3.47-3.49%. This means that the proposed model can simulate workpiece surface roughness for end milling process with an excellent level of accuracy and lower rules. The results obtained with the proposed ANFIS models are superior to the Lo (Lo, 2003), Ho et al. (Ho, et al., 2009), and Dong et al. (Dong & Wang, 2011) models. Further work is required to validate the model using disparate cycles on multiple machines.

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