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Prediction of cutting and feed forces for conventional milling process using adaptive neuro fuzzy inference system (ANFIS)

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ABSTRACT

Due to the extensive use of highly automated machine tools in the industry, the manufacturing requires reliable models for the prediction of output performance of machining processes. The prediction of cutting forces plays an important role in the manufacturing industry. The focus of this paper is to develop a reliable method to predict cutting forces (force in X-direction and force in Z-direction) for milling process during conventional machining of mild steel. This paper implements an adaptive Neuro-fuzzy interface system (ANFIS) to actualize an efficient model for prediction of cutting forces during conventional milling. A set of three input machining parameters like speed, feed and depth of cut, which has a major impact on the cutting forces was chosen as input to represent the machining condition. Our result confirms that ANFIS model with Gaussian member function is a better predictive tool for prediction of milling forces with minimum average test error.

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1. INTRODUCTION

Milling is a process of machining the flat, curved and irregular surfaces. This process is done progressively by removing the predetermined amount of material from a work piece against the rotating multi-edge cutting tool. In addition to other conventional applications, milling is a strong contender for producing holes, cavities and surfaces which is used for turning, threading, etc. The characteristics feature of the milling operation is that, each milling cutter tooth cut out its share of the stock in the form of small individual chips. This milling process mainly preferred for the milling casting or forging applications with a very rough surfaces. There are two types of milling processes namely up milling and down milling according to relative motion of milling cutter and work piece. As there is excessive chip thickness and edge breakage in down milling, so we use up milling process to remove such type of remedies. When there is a large variation in working allowance, up milling is mainly preferred. In Up milling (conventional milling), there are high cutting forces which tend to push the cutter and work piece away from each other. Hence it is required to analyze the cutting forces in conventional milling process. In this process chip can easily be trapped between the insert and work piece, which results breakage in insert. To rectify this breakage the staggered-tooth design is used. This staggered-tooth design cutter prevents the chips, to interfere with the cutting action. This cutter also produces an exceptionally smooth cut with good surface finish and careful limit control with absorbing the shock of contact which mainly prevents the feasibility of tooth corner breakage.

In milling operation there are various machining parameters which can affect the cutting force (force in Z-direction or vertical force, Fz) and feed force (force in X-direction or horizontal force, Fx). These parameters are spindle speed, feed, depth of cut and others. So we need to carry out a number of experiments to compute the input output relationship for this prediction. In recent decay various mathematical modelling are used for prediction of output parameters of a process, which helps us to avoid the large number of experiments. Artificial intelligence is used as a prediction tool due to its significant advantages. Hongtao et al. predicted the mean cutting force of milling operation by taking two inputs such as feed and depth of cut by Artificial neural network (ANN) model [1]. As compared with other regression models in artificial intelligence, ANFIS has a better performance for modelling the nonlinear input-out relationship [2]. Natarajan et al analyzed the ANFIS model for flexible prediction of Surface roughness of end milled parts. After prediction they compared prediction results and mean square error with respect to MFNN model and finally conclude that the ANFIS is better than MFNN for regression. Also they observed that the convergence speed for proposed ANFIS model is higher than the Multi layer feed forward neural network (MFNN) [3]. ANFIS is also used for condition monitoring in milling to predict the flank wear of the tool [4]. Also this model was implemented for prediction of surface roughness of a typical die made by ball end milling operation. It compared with the theoretical model and response surface methodology by means of RMSE and MAPE and found that the proposed ANFIS model gives a very less amount of error for testing data [5]. Similarly MRR and WIWNU in CPM Process were modelled by introducing ANFIS which is an alternative method to neural network. It observed that ANFIS approach was perform better result than neural network [6]. Zhang Y et al proposed ANFIS and multiple models based an adopted generalized predictive control method for non-linear system. ANFIS model is adopted to estimate and compensate the unmodeled dynamics, which avoids some possible flames of a feed forward neural network. They concluded that ANFIS based prediction overcomes the uncertainty of neural networks and save the training time [7]. ANFIS is also used for modelling and control of (different process) a high performance drilling process in a networked application [8] [8]. The tool flank wear propagation in the up milling operations was more rapid than that in the down milling operations. It is believed that the thermal effect was a significant cause for the peak force variation within a single cutting pass, while the tool wear propagation was the major reason for the gradual increase of the mean peak force in successive cutting passes [9]. Prediction of cutting forces (F_x, F_y and F_z) in face milling influence by inclination angle, cutting speed, feed and depth of cut [10]. The first and second order cutting force equations are developed using the response surface methodology (RSM) to study the effect of four input cutting parameters (cutting speed, feed rate, radial depth and axial depth of cut) on cutting force. The received second order equation shows, that the most influential input parameter was the feed rate followed by axial depth, and radial depth of cut and, finally, by the cutting speed [11]. ANFIS also applied to determine the thermodynamic properties of refrigerants and the model gives slightly better result than ANN with the use of same data [12]. Juntaek Ryoo et al implemented adoptive network based fuzzy interface system to control convergence of a computational fluid dynamics algorithm. This interface system takes less number of iteration as compare to rule based fuzzy control to converge the computational fluid dynamics (CFD) algorithm [13]. Three cutting parameters like speed, feed, depth of cut are considered with constant nose radius and utilizing two computational methods that is Adaptive-neuro fuzzy inference system (ANFIS), modelling and Artificial neural network (ANN) to predict surface roughness of work piece for variety of cutting conditions in hard turning. The ANFIS model provided better prediction capabilities than Artificial Neural Networks model because they generally offer the ability to model more complex nonlinearities and interactions. The Adaptive Neuro Fuzzy-Inference System gives closed correlation with experimental value [14].

Those above-mentioned investigations were restricted studying the effect of various machining parameters for the cutting forces in conventional milling operation. Hence the present study attempts to investigate about the machining performance using different machining parameters like feed, spindle speed and depth of cut. For this analysis mild steel was taken as work piece. In this research by considering these machining parameters we develop a multi input multi output ANFIS model to predict the values of cutting force (Fz) and feed force (Fx) conventional milling operation. The three process parameters namely feed, depth of cut and spindle speed were varied to investigate the cutting force and feed force. The design of these parameters was done by full factorial design.

2. EXPERIMENTAL SCHEME

2.1. Experimental Set Up

In this study, the machine setup for the milling operation is a horizontal type FN2U. Figure 1 shows the schematic diagram for experimental set up of the up milling (conventional milling) process for present investigation. A staggered tooth milling cutter (Φ100mm and number of tooth=16nos.) was used as cutting tool and work piece as mild steel. Piezeo electric type dynamometer is attached in between work piece and table of milling machine also shown in Figure 1. During the machining process the dynamometer measures the required force in Z and X-direction. The experiment was carried out by setting of three machining parameters at different levels.

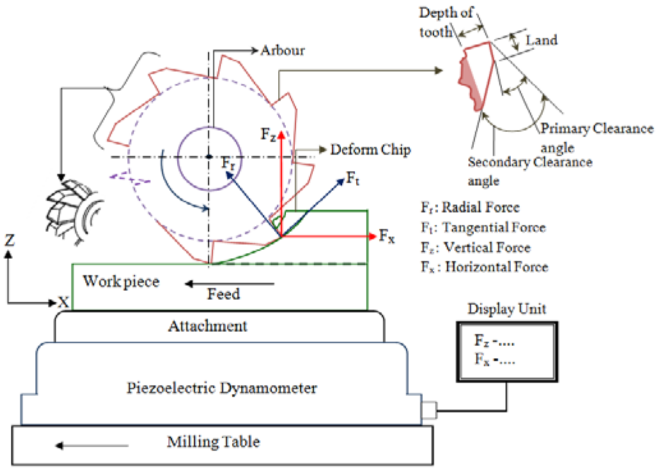

Figure 1. Schematic diagram or model of conventional milling operation set up

2.2. Setting of Experimental Parameters:

For determining the milling forces, a general full factorial design (multilevel factorial design) is adopted for setting of the experimental parameters. As there are several factors in an experiment therefore factorial design should be used and these design parameters are varied together. The present experimental process parameters are shown in Table 1. Here three factors, speed, feed and depth of cut are in different levels. Speed is in three levels (3^1), feeds in four levels (4^1) and depth of cut is in two levels (2^1). By combining all factors and their levels, it is a ($3^1 \ast 4^1 \ast 2^1$) design. According to this design the number of instances in the experiment is 24 as shown in Table 2.

Table 1. Experimental Process Parameters (Machining Process Parameters) with Levels

Machining parameters	Unit	Levels 1	2	3	4
Speed	m/min	14.14	17.59	23.3	
Feed	mm/min	16	20	25	32
Depth of cut	mm	0.1	0.3		

Table 2. Experimental Designs (Multilevel Factorial Design)

No. of expt.	Experimental process parameters (input parameters) Speed (m/min)	feed (mm/min)	depth of cut (mm)	Output parameters F_z (N)	F_x (N)
1	14.14	32	0.1	97	27
2	23.3	32	0.1	113	48
3	23.3	20	0.1	88	37
4	23.3	16	0.1	62	32
5	23.3	20	0.3	186	78
6	23.3	25	0.1	88	35
7	17.59	20	0.1	140	53
8	14.14	16	0.3	88	41
9	14.14	20	0.1	78	45
10	17.59	16	0.3	145	109
11	14.14	16	0.1	65	55
12	23.3	25	0.3	165	88
13	17.59	32	0.3	160	101
14	14.14	20	0.3	96	38
15	14.14	32	0.3	189	97
16	23.3	32	0.3	173	94
17	17.59	25	0.1	128	78
18	23.3	16	0.3	70	53
19	17.59	16	0.1	155	58
20	17.59	32	0.1	197	105
21	14.14	25	0.1	94	34
22	17.59	20	0.3	155	83
23	14.14	25	0.3	200	107
24	17.59	25	0.3	165	83

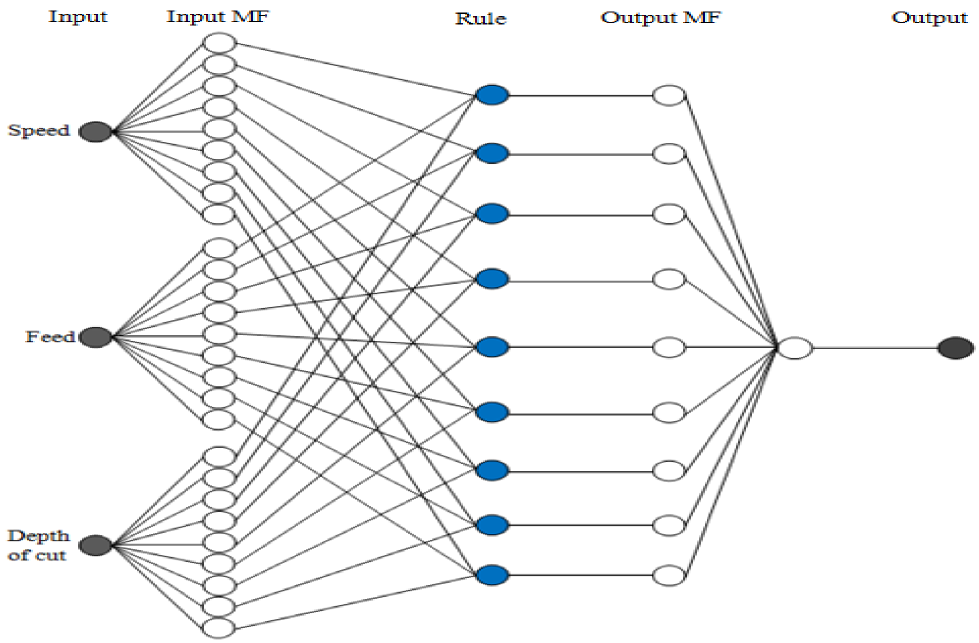

Figure 2. ANFIS architecture for prediction of forces for milling operation

3. ANFIS MODELLING

ANFIS is a class of adaptive network which act as the framework for adaptive fuzzy interface system. The architecture of ANFIS in figure 2 mainly composes of five different layers namely inputs, input membership functions, fuzzy based rules, output membership functions and output. The output of the nodes in each layers is mainly represented by y_i , where 'i' is represented as the i^th node of layer L. [15]
This layer-1 in ANFIS is mainly used to generate the membership functions corresponding to the different input variables. In this research we have taken three input variables namely speed, feed and depth of cut. So the output of layer-1 is given as

$$y_{1,i} = \mu_{a_{ik}}\left(x_i\right) \tag{1}$$

Where i=1,2..n are the number of inputs associated with the ANFIS model and $\mu_{a_{ik}}$ for k=1,2,3 are the number of input membership functions. Here we have used three membership functions and the $y_{1,i}$ in equation-1 corresponds to the output obtained from layer-1.
The membership function is a generalised bell shaped and mathematically expressed as

$$\mu_{a_{ik}}(x_i) = \frac{1}{1+[(\frac{x_i - c_{ik}}{a_{ik}})^2]^{b_{ik}}} \tag{2}$$

The equation-3 gives the concept about the generalized bell function which is used as membership function and the parameters such as a_{ik}, b_{ik}, c_{ik} are referred as the promising parameters associated with the fuzzy set.
In layer-2 of the ANFIS architecture we generate the firing strengths by multiplying the incoming signals from layer-1 with the fuzzy rules. The output of layer 2 is given by the mathematical expression as

$$y_{2,i} = w_l = \prod_{i=1}^{n} \mu_{a_{ik}}\left(x_i\right) \tag{4}$$

Where i=1, 2, 3 … L are the L number of fuzzy based rules.
In layer-3 the normalized the firing strengths are calculated by using the mathematical formulae as

$$y_{3,i} = \overline{w}_i = \frac{w_i}{\sum_{i=1}^{L} w_i} \tag{5}$$

The node function associated in level-4 in the ANFIS architecture is a linear function and the output of layer-4 is calculated as

$$y_{4,i} = \overline{w}_i \left(m_1 x_1 + m_2 x_2 + ...m_n x_n + p_i \right) \tag{6}$$

Where m_i and p_i are the consequent parameters associated with the fuzzy rule is based approach.
The overall output of ANFIS model is obtained at Layer-5 which is mathematically expressed as

$$y = \frac{\sum_{i=1}^{L} w_i y_{4,i}}{\sum_{i=1}^{L} w_{4,i}} \tag{7}$$

For training of the ANFIS model, we use hybrid learning algorithm. During the forward pass of the hybrid learning algorithm each of the node outputs go forward until the layer- 4 accomplished and the outputs are obtained by using the least-squares procedure. When the values of $\left\{ m_i, n_i, p_i \right\}$ in the equation-6 are remain fixed, the overall output can be expressed as a linear combination of these parameters, which is given as

$$\mathrm{y}_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f}{\sum_i w_i} \tag{8}$$

The corresponding value of ‘f’ is given as $f = \overline{w}_i \left(m_1 x_1 + m_2 x_2 + ...m_n x_n + p_i \right)$

4. RESULTS AND DISCUSSION

Here the proposed model is carried out by considering the 24 input output patterns. The proposed ANFIS modelling is carried out in MATLAB. The overall block diagram of input output relationship is given in figure 3. For model-1 out1 is Fx and for model-2 out1 is Fz. By considering 50% of the dataset as training and rest as testing for the ANFIS based nonlinear model, the X-direction and Z-direction milling forces are the function of the input parameters like speed, feed and depth of cut. Initially the ANFIS model is trained with the input output combinations and after training the test data is evaluated on the basis of optimised training performance. The training performance depends upon the training error and the surface plot which shows the variations of inputs with respect to training error.

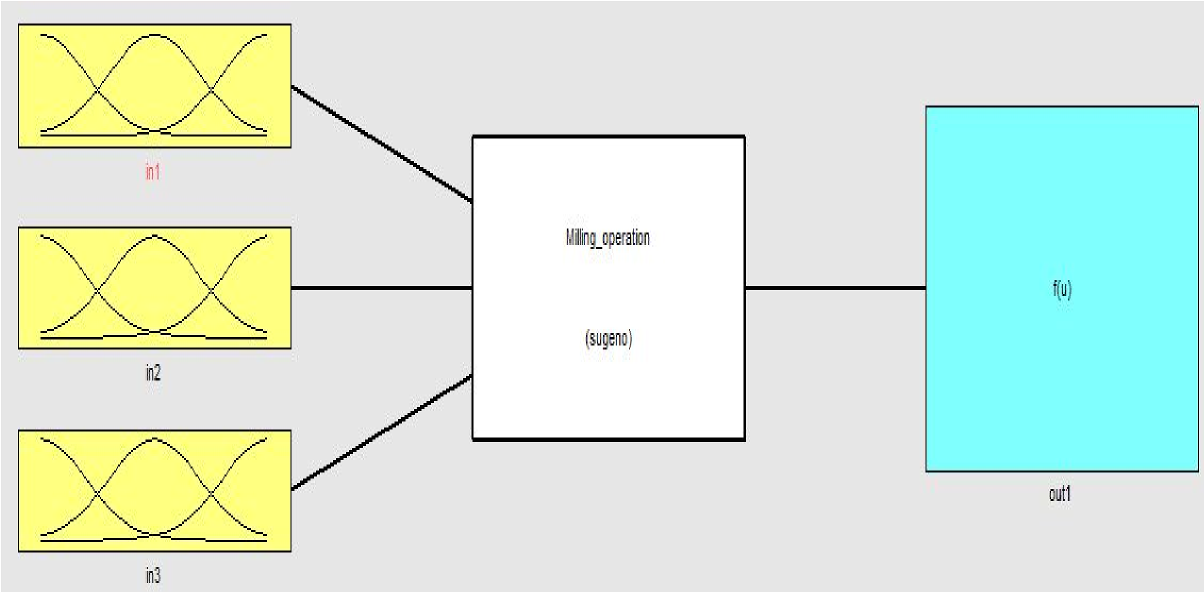

Figure 3. Fuzzy interface system (research model) for prediction of milling forces where in1, in2 and in3 are speed, feed and depth of cut respectively

4.1. Model-1 (X-direction Milling Force Prediction)

Considering the estimation of x-direction cutting force we use model-1, which consists of the input parameters combination as speed, feed and depth of cut. After training of the model-1, the optimised training parameter as the training error is found to be 2.0713×10^{-7}. The variation of training error with respect to number of iterations (epochs) for model-1 is shown in figure 4. Similarly the variation of force in X-direction with different inputs is also shown in figure 5, 6, and 7.

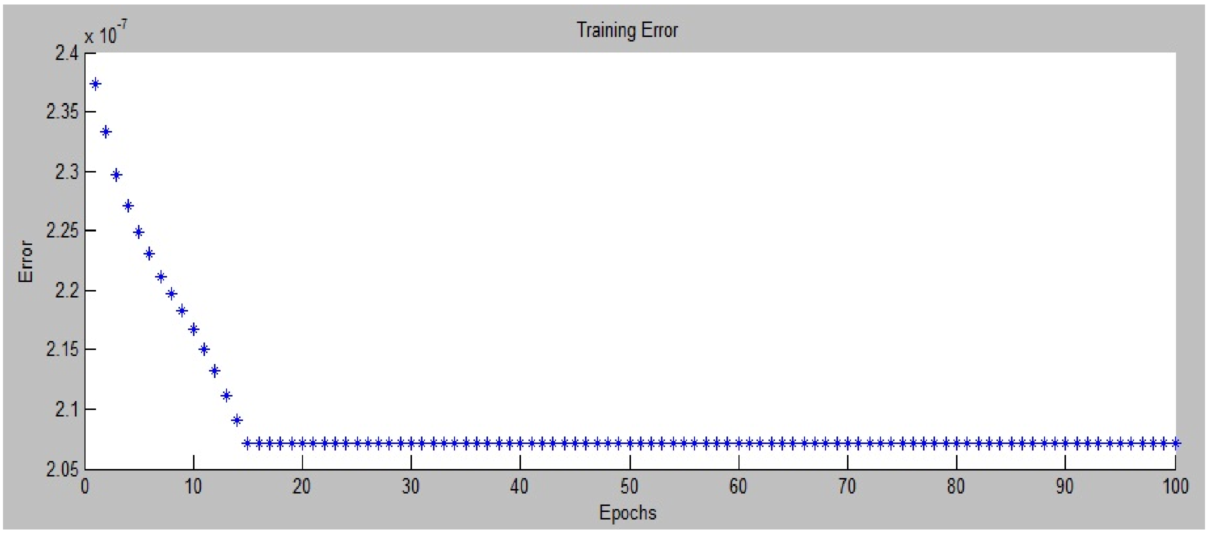

Figure 4. Variation of training with respect to iteration (epochs) for Fx

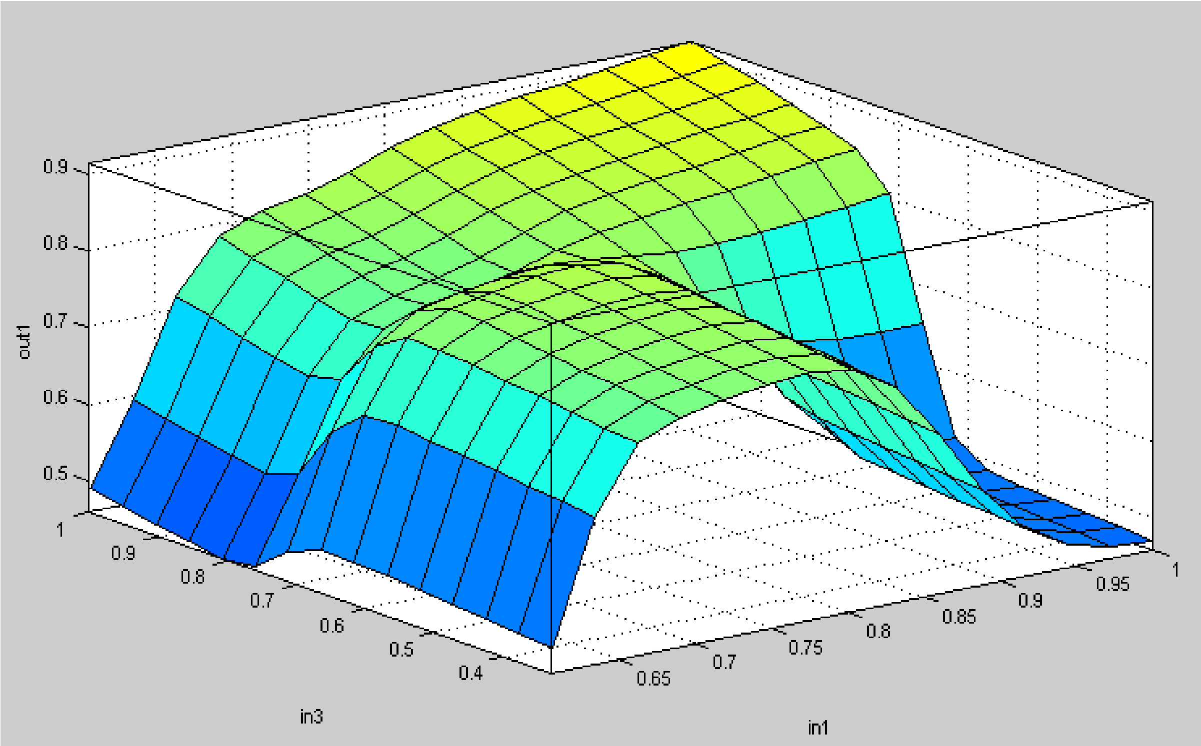

Figure 5. Force in X-direction (Fx) level is related to levels of speed (in1) and depth of cut (in3)

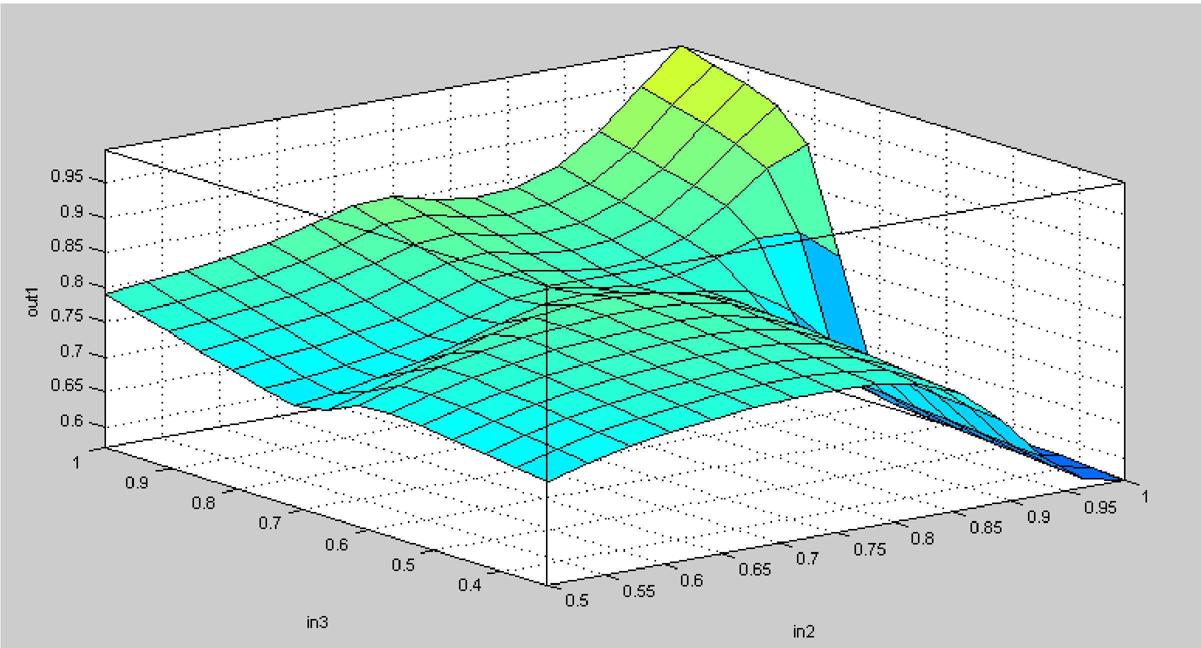

Figure 6. Force in X-direction (Fx) level is related to levels of feed (in2) and depth of cut (in3)

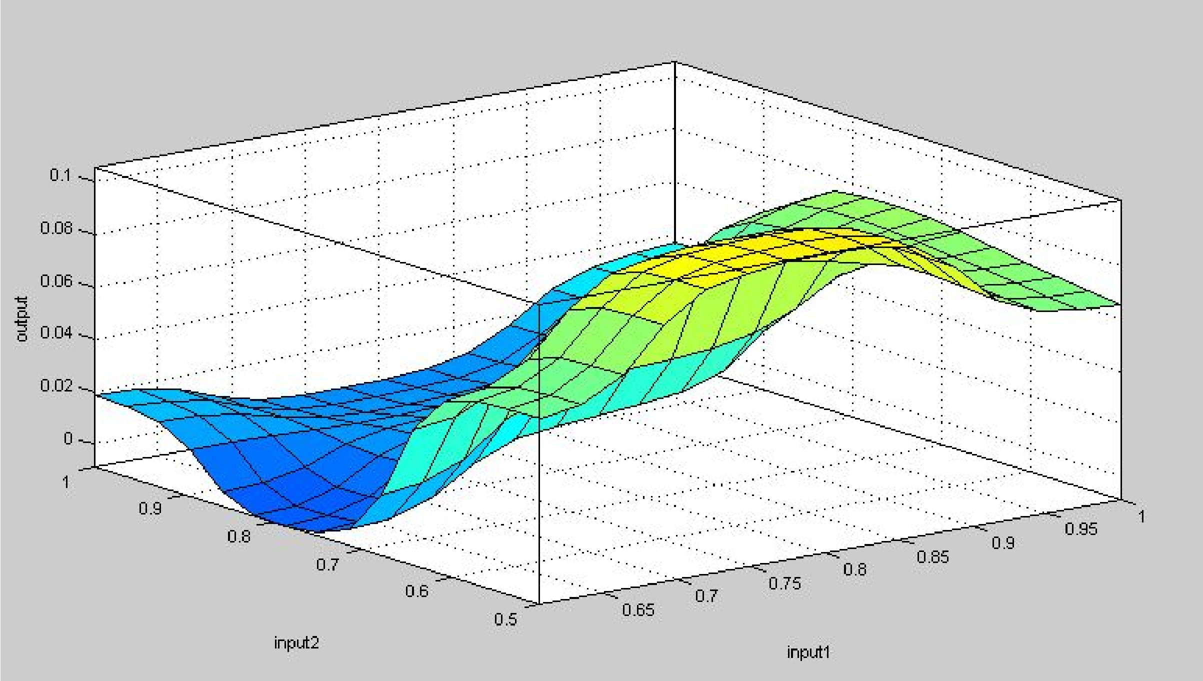

Figure 7. Force in X-direction (Fx) level is related to levels of speed (input1) and feed (input2)

The ANFIS based rules used for this optimised training is shown in figure 8. Hence the testing data is evaluated for model-1 by considering the optimised training performance and the average testing error found to be 0.30218.

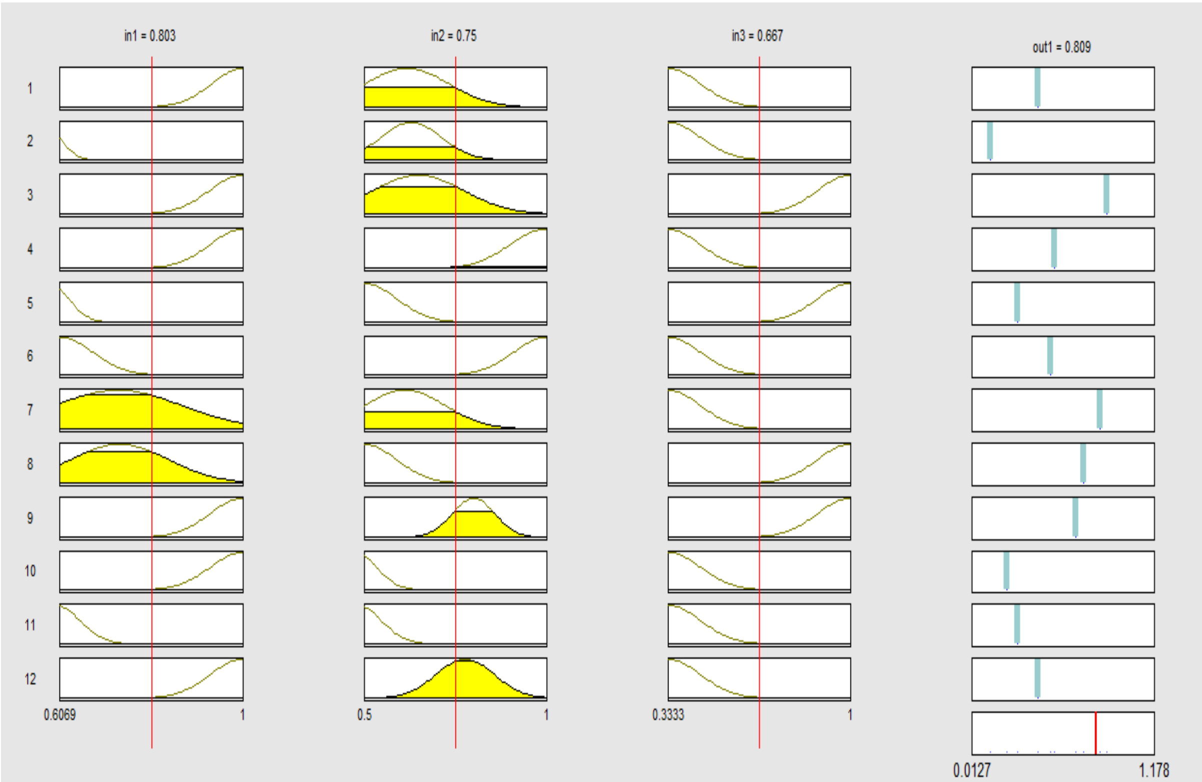

Figure 8. Rule viewer window for prediction of Fx

4.2. Model-2 (Z-direction Milling Force Prediction)

Similarly considering the estimation of z-direction cutting force we use model-2, which consists of the same input parameters combination as speed, feed and depth of cut. After training of the model-2, the optimised training parameter as the training error is found to be 3.7706×10^{-6}. The variation of training error with respect to number of iterations for model-1 is shown in figure 9. The variation of force in Z-direction with different inputs is also shown in figure 10, 11 and 12.

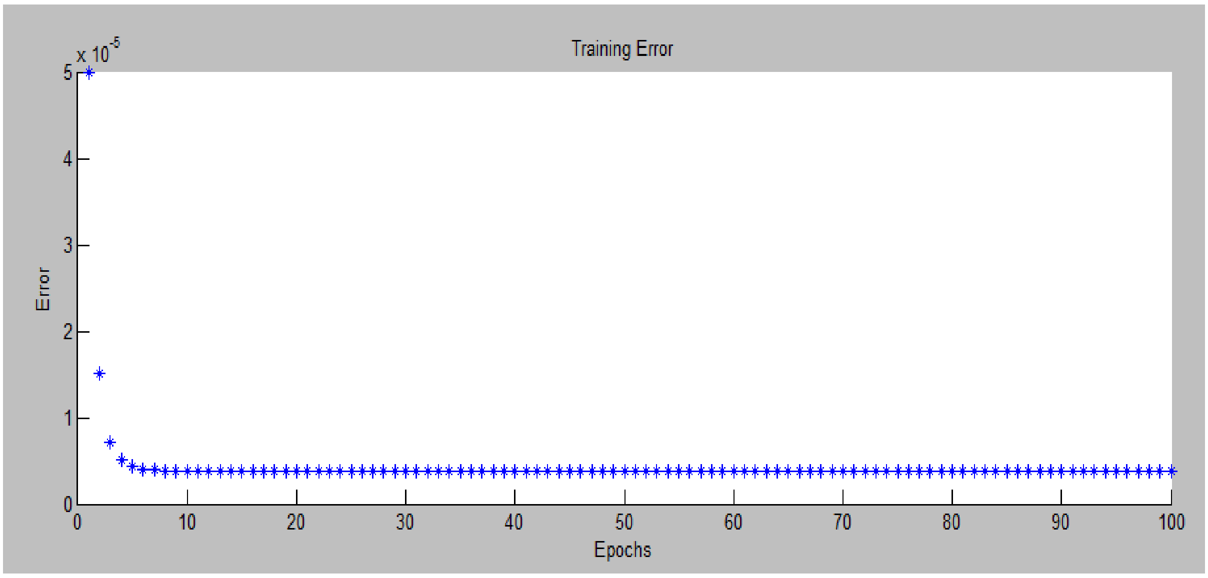

Figure 9. Variation of training with respect to iteration (epochs) for Fz

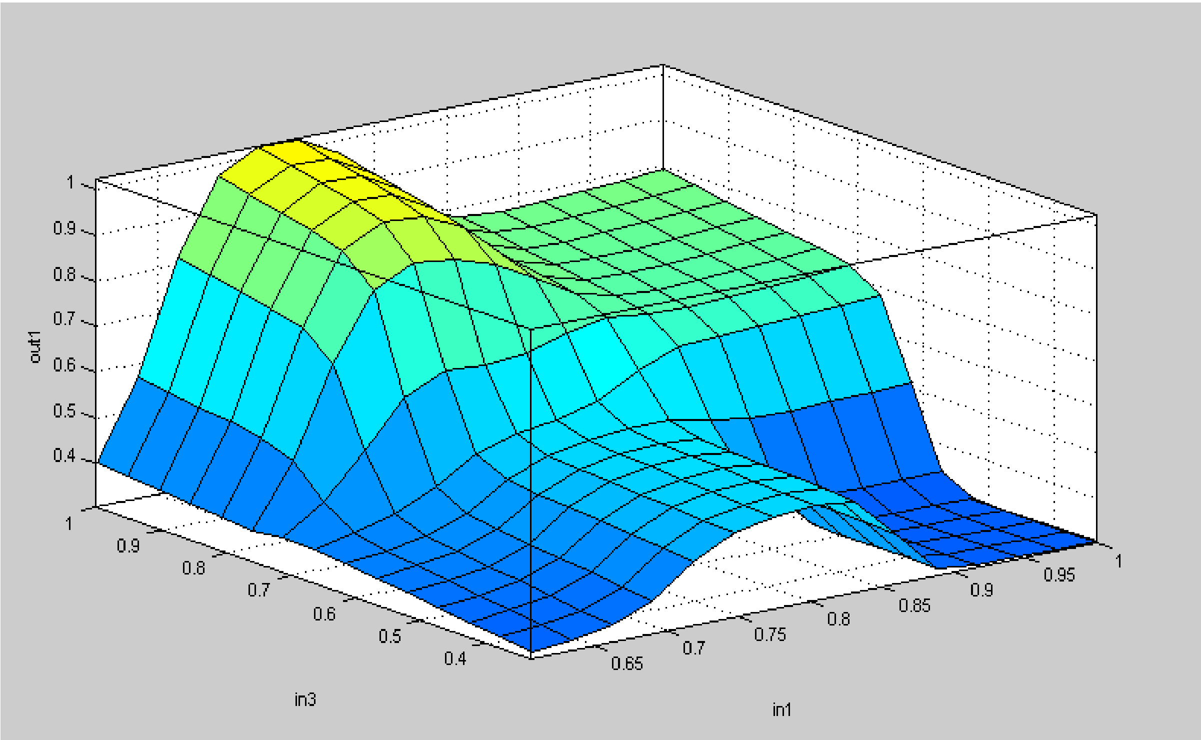

Figure 10. Force in Z-direction (Fz) level is related to levels of speed (in1) and depth of cut (in3)

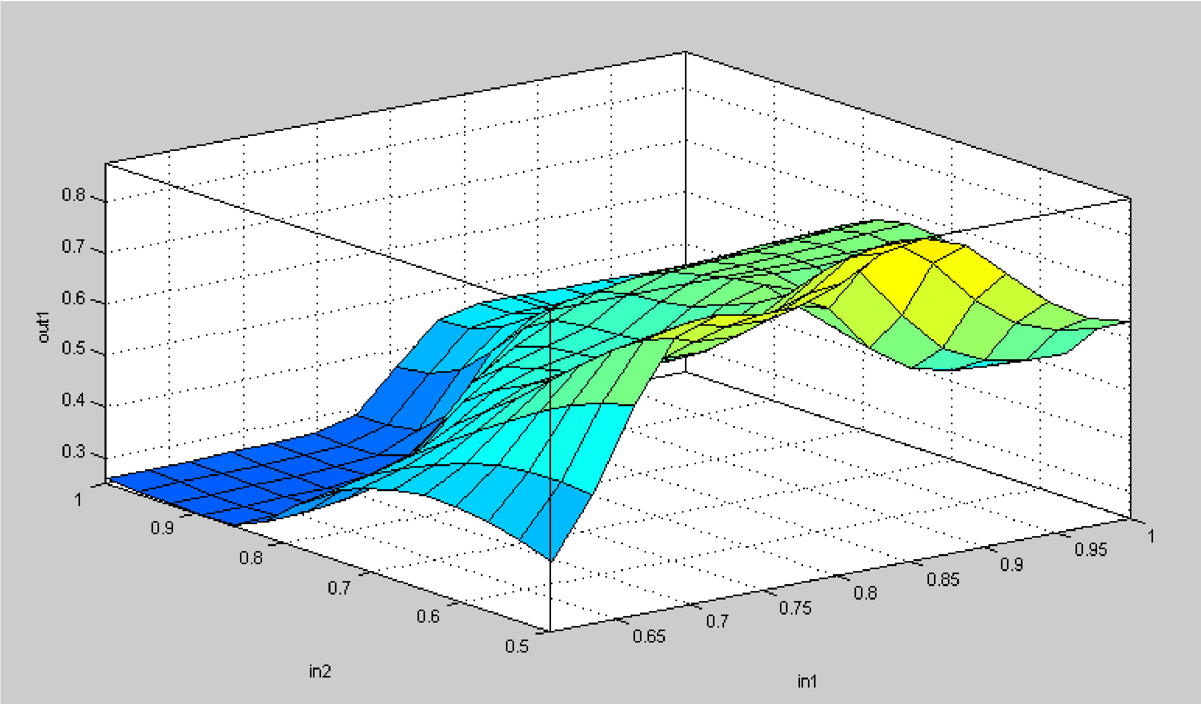

Figure 11. Force in Z-direction (Fz) level is related to levels of speed (in1) and feed (in2)

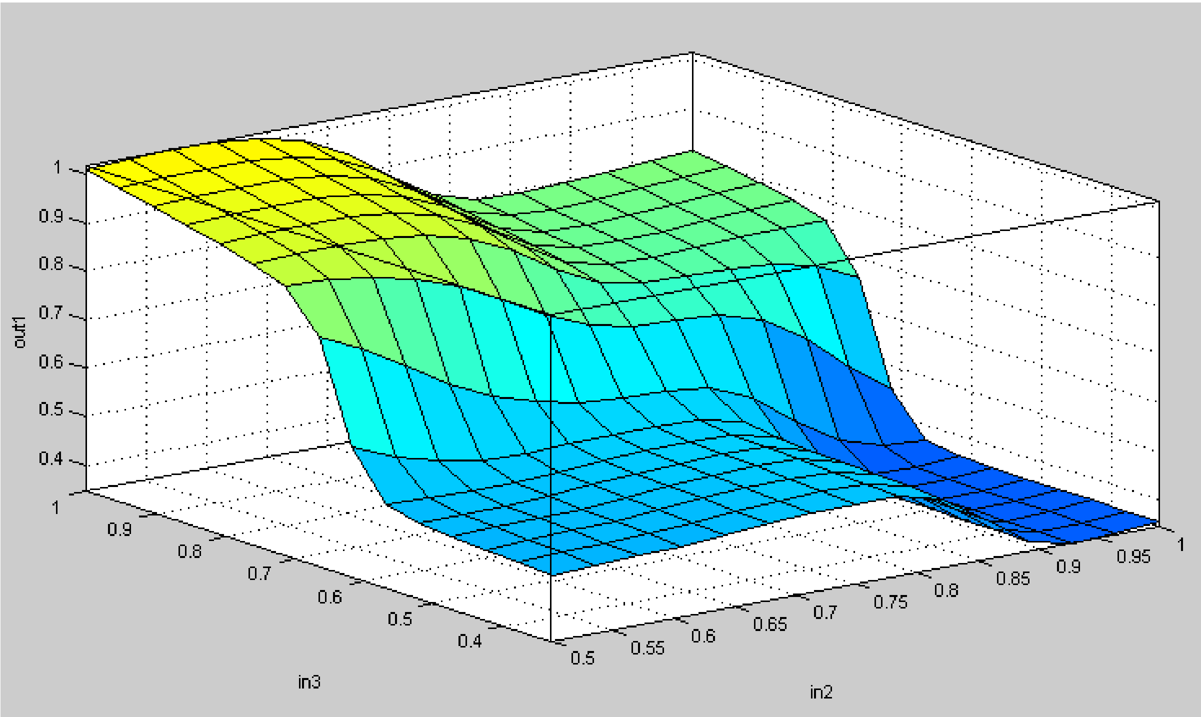

Figure 12. Force in Z-direction (Fz) level is related to levels of feed (in2) and depth of cut (in3)

As previously the ANFIS based rules used for this optimised training for model-2 is shown in figure 13. By considering the optimised training performance the testing data is evaluated for model-2 and the average testing error found to be 0.33945.

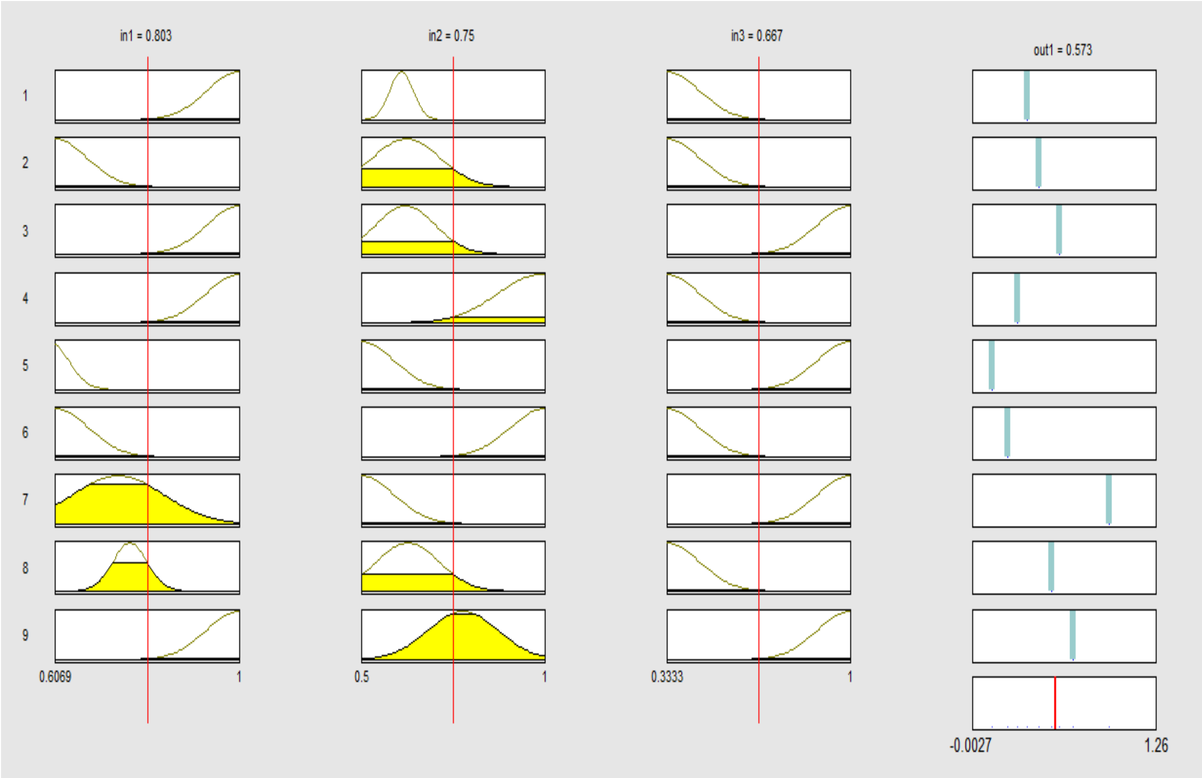

Figure 13. Rule viewer window for prediction of Fz

5. CONCLUSION

In this study ANFIS model was exploited for the prediction of cutting forces of conventional milling operation during machining of mild steel. The input parameters such as Cutting speed, feed and Depth used for the prediction of forces in X and Z-direction. After comparison of experimental output with ANFIS based predicted output, we conclude that ANFIS model is a better predictive tool with minimum average test error. Further this work can be extended by the uses of Advance machine learning algorithms like Support vector machine and relevance vector machine based regression analysis.

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