OPTIMIZATION AND PREDICTION OF SURFACE ROUGHNESS ON CNC MILLING MACHINE BY USING ARTIFICIAL NUERAL NETWORK ON D2 STEEL

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ABSTRACT

Process optimization is a very important subject to several industrial sectors in confronting the growth on markets competition. However, due to the complexity of some processes, their optimization is not an easy task; therefore, to accomplish this objective, intelligent techniques should be used. The present paper is an attempt to predict the effective milling parameters on the final surface roughness of the work-piece made of D2 steel using artificial neural network. The required data were collected during the experiments conducted on the mentioned material. These parameters include cutting speed, feed per tooth and depth of cut.Modeling is done by ANN. It is best network model which gives minimum error between network output and real output. Prediction is done by ANN. Result of ANN and Taguchi methods are compared. Best method is used which gives the minimum error.

Keywords: Milling machining, D2 steel, surface roughness, ANOVA, ANN etc.

I. INTRODUCTION

As the machining process is non-linear and time dependent, it is difficult for the traditional identification methods to provide an accurate model. To address this difficulty, non-traditional techniques such as artificial neural networks (ANN) have been introduced. ANN can map the input/output relationships and possess massive parallel computing capability, have attracted much attention in research on machining processes. ANN provides significant advantages in solving processing problems that require real-time encoding and interpretation of relationships among variables of high-dimensional space. ANN has been extensively applied in modeling many metal-cutting operations such as turning, milling and drilling.Recent functionality requirements have led to development of components with varying free-form features. The ultimate goal of virtual machining process research is to identify process related issues and solve them before the costly physical trials in the shop. Modeling the process mathematically is necessary to achieve that goal in a Reasonable amount of time and the first step of process modeling is to model the mechanics of the operation that leads to the prediction of the cutting forces experienced by the cutting tool and the work-piece.

II. LITERATURE REVIEW

Eldon Y. Li et.al. (1994) proposed that artificial neural networks are increasingly popular in today's business fields. They have been hailed as the greatest technological advance since the invention of transistors. The paper reviewed the common characteristics of neural networks and discusses the feasibility of neural-net applications in business fields.

R. Peres et.al. (1999) proposed that process optimization is a very important subject to several industrial sectors in confronting the growth on markets competition. However, due to the complexity of some processes, their optimization is not an easy task; therefore, to accomplish this objective, intelligent techniques should be used. We are working on end-milling process optimization through combining analytic and fuzzy techniques.

J. F. Briceno et.al. (2002) proposed that two supervised neural networks are used to estimate the forces developed during milling. These two Artificial Neural Networks (ANNs) are compared based on a cost function that relates the size of the training data to the accuracy of the model.

J.A. Ghani et.al. (2004) proposed the Taguchi optimization methodology, which is applied to optimize cutting parameter in end milling when machining hardened steel AISI H13 with TiN coated P10 carbide insert tool under semi-finishing and finishing conditions of high speed cutting. The milling parameters evaluated is cutting speed, feed rate and depth of cut. An orthogonal array, signal-to-noise (S/N) ratio and Pareto analysis of variance (ANOVA) are employed to analyze the effect of these milling parameters. The analysis of the result shows that the optimal combination for low resultant cutting force and good surface finish are high cutting speed, low feed rate and low depth of cut.

S.Brevern et.al. (2009) proposed that the world of manufacturing has shifted its level to the era of space age machining. The purpose of this investigation is to develop Fuzzy based Graphical User Interface (GUI) for modeling of laser machining conditions.

M.S. Yazdi et.al. (2010) studied that the selection of optimal machining parameters (i.e., spindle speed, depth of cut and feed rate) for face milling operations was investigated in order to minimize the surface roughness and to maximize the material removal rate. Effects of selected parameters on process variables (i.e., surface roughness and material removal rate) were investigated using Response Surface Methodology (RSM) and artificial neural networks.

B. S.Reddy et.al. (2011) proposed that Pre-hardened steel (P20) is a widely used material in the production of moulds/dies due to less wear resistance and used for large components. In this study, minimization of surface roughness has been investigated by integrating design of experiment method, Response surface methodology (RSM) and genetic algorithm.

M. Bozdemir (2011) proposed that ANN modeling technique was developed with the results obtained from the experiments. For the training of ANN model, material type, cutting speed, cutting rate, and depth of cutting parameters were used. In this way, average surface roughness values could be estimated without performing actual application for those values. Various experimental results for different material types with cutting parameters were evaluated by different ANN training algorithms. So, it aims to define the average surface roughness with minimum error by using the best reliable ANN training algorithm.

S. Hossain et. al. (2012) proposed that Surface roughness is an index which determines the quality of machined products and is influenced by the cutting parameters. In this study the average surface roughness (Ra) value for Aluminum after ball end milling operation has been measured. 84 experiments have been conducted varying cutter axis inclination angle (ϕ degree), spindle speed (S rpm), feed rate (mm/min), radial depth of cut (feed f mm), and axial depth of cut (t mm) in order to find Ra. This data has been divided into two sets on a random basis; 68 training data set and 16 testing data set.

A. Joshi et.al. (2013) proposed the effects of various parameters of end milling process like spindle speed, depth of cut, feed rate have been investigated to reveal their impact on surface finish using

Taguchi Methodology. Experimental plan is performed by a Standard Orthogonal Array. The results of ANOVA indicate that the feed Rate is most influencing factor for modeling surface finish. The graph of S-N Ratio indicates the optimal setting of the machining parameter which gives the optimum value of surface finish.

A.Sahoo et.al. (2014) studied the performance of multilayer coated carbide insert in the machining of hardened AISI D2 steel (53 HRC) using Taguchi design of experiment. The experiment was designed based on Taguchi L27 orthogonal array to predict surface roughness. The S/N ratio and optimum parametric condition are analyzed. In regression model, the value of R2 being 0.98 indicates that 98 % of the total variations were explained by the model. It indicates that the developed model can be effectively used to predict the surface roughness on the machining of D2 steel with 95% confidence intervals.

III. EXPERIMENTAL DETAILS

End Milling

Among different types of milling processes, end milling is one of the most vital and common metal cutting operations used for machining parts because of its capability to remove materials at faster rate with a reasonably good surface quality. Also, it is capable of producing a variety of configurations using milling cutter. In end milling, the cutter, called end mill, has a diameter less than the work piece width. The end mill has helical cutting edges carried over onto the cylindrical cutter surface. End mills with flat ends (so called squire-end mills) are used to produce pockets, closed or end key slots, etc.

In end milling an end mill makes either peripheral or slot cuts, determined by the step-over distance, across the work piece in order to machine a specified feature such as a profile, slot, pocket, or even a complex surface contour. The depth of the feature may be machined in a single pass or may be reached by machining at a smaller axial depth of cut and making multiple passes.

Material Used

In this work hardened AISI D2 steel (hardness 50-70 HRC) will be used as the work piece material and Tungsten carbide preferably coated will be used as the tool material. Because increasing tool life is main concern of hard machining to decrease the cost of the machining process. A particular amount of maximum flank wear say 0.2 to 0.3 µm can be used as the tool life failure criterion. Flank wear can be measured using toolmaker's microscope. The chemical composition of AISI D2 tool steel is given in below Table 3.1.

Table 3.1 Chemical Composition of Steel

Carbon	Silicon	Manganese	Chromium	Molybdenum	Vanadium
1.55 %	0.30 %	0.35 %	12 %	0.75 %	0.90%

AISI D2 is recommended for tools requiring very high wear resistance, combined with moderate toughness (shock-resistance). AISI D2 can be supplied in various finishes, including the hot-rolled, pre-machined and fine machined condition forming Dies, Punches, Forming Rolls, Knives, Slitters, Shear blades.

Machine Used

Machining was carried out in CNC machine at CTR, Ludhiana.

Figure 1. CNC Milling Machine

Table 3.2 Specification of CNC Milling Machine

Table Size	915 * 356 mm
Table Load	341 KG
Power	3 phase, 60 Hz
Control	GE FANUC 211
X Axis Travel	560 mm
Y Axis Travel	406 mm
Z Axis Travel	508 mm
Spindle Speed	100 RPM Direct Drive
Spindle Diameter	65 mm
Spindle Taper	ISO-40
Tool Taper	BT-40
Magazine Capacity	22 Tools
Maximum Wt. of Tool Holder	50 KG
Maximum Tool Length	254 mm

Table 3.3 Levels of Input Control Parameters

Factors	***Levels***	***Factor Level values***
Speed (rpm)	3	500,750,1000
Depth of Cut (mm)	3	0.75,0.50,0.25
Feed (mm/min)	3	750,1000,1250

The optimum condition is identified by studying the main effects of each of the parameters. The main effects indicate the general trend of influence of each parameter. The knowledge of contribution of individual parameters is a key in deciding the nature of control to be established on a production process. Orthogonal Array is a statistical method of defining parameters that converts test areas into factors and levels. Test design using orthogonal array creates an efficient and concise test suite with fewer test cases without compromising test coverage. An orthogonal array is a "table" (array) whose entries come from a fixed finite set of symbols (typically, {1,2,..., n}), arranged in such a way that there is an integer t so that for every selection of t columns of the table, all ordered t-tuples of the symbols, formed by taking the entries in each row restricted to these columns, appear the same number of times. The number t is called the strength of the orthogonal array. The Table 3.4 shows the design matrix used in this work.

Table 3.4 Orthogonal Array L9

Sample No.	Spindle Speed (rpm)	Feed Rate (mm/min.)	Depth Of Cut (mm)
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

IV. EXPERIMENTAL PROCEDURES

- Checking and preparing the Centre Lathe ready for performing the machining operation.
- Firstly, the work-piece was cut according to above mentioned dimension i.e. 100*100*25 mm by cutter of diameter 32 mm.
- For developing models on the basis of experimental data three main machining parameters are considered to predict surface roughness of D2 material using carbide tool. Among the range of spindle speed, feed, and depth of cut available possible in the machine the following three levels are considered as shown in Table 3.3.
- The machining was carried out on end milling machine, the material work piece is clamped on vice mounted on the table of the machine. The machining process and work tool motion of the end milling process respectively.
- The machining is carried out by selecting proper spindle speed and feed rate during each experimentation. Experiment was carried out by varying the depth of cut.

Taguchi's designs aimed to allow greater understanding of variation than did many of the traditional designs. Taguchi contended that conventional sampling is inadequate here as there is no way of obtaining a random sample of future conditions. Taguchi suggests a three-stage process:

- System design,
- Parameter design,
- Tolerance design.

Artificial neural networks (ANNs) are non-linear data driven self-adaptive approach as opposed to the traditional model based methods. They are powerful tools for modeling, especially when the underlying data relationship is unknown. ANNs can identify and learn correlated patterns between input data sets and corresponding target values. After training, ANNs can be used to predict the outcome of new independent input data. ANNs imitate the learning process of the human brain and can process problems involving non-linear and complex data even if the data are imprecise and noisy. Thus they are ideally suited for the modeling of agricultural data which are known to be complex and often non-linear.

Development of an ANN model

The various steps in developing a neural network model are:

Variable Selection

Formation of Training, Testing and Validation Sets

Neural Network Architecture

Number of Hidden Layers

Number of Hidden Nodes

Number of Output Nodes

V. RESULTS AND DISCUSSION

End milling is one of the most fundamental and commonly encountered chip removal operations occurring in a real manufacturing environment. In this machining process, the surface finish is a key factor in evaluating and determining the quality of a part. In practice, a desired surface roughness value is usually designated, and the appropriate cutting parameters are selected to achieve the desired quality of a specified part. The single point incremental forming (SPIF) process is performed on three-axis CNC machine.

Table 5.1 Measured Surface Roughnesses

Pieces	*Speed (rpm)*	*Depth of Cut (mm)*	*Feed (mm/min)*	*Surface Roughness (μm)*
1	500	750	0.75	0.73
2	500	1000	0.50	0.77
3	500	1250	0.25	0.82
4	750	750	0.50	0.72
5	750	1000	0.25	0.49
6	750	1250	0.75	0.63
7	1000	750	0.25	0.42
8	1000	1000	0.75	0.72
9	1000	1250	0.50	0.55

Table 5.2 Measured Roughness Parameters

Pieces	*R_a (μm)*	*R_t(μm)*	*R_z(μm)*	*R_c(μm)*
1	0.73	3.94	2.97	1,91
2	0.77	4.22	3,34	2.45
3	0.82	4.46	3.62	2.88
4	0.72	3.87	2.94	1.87
5	0.49	2.14	1.82	1.21
6	0.63	3.41	2.69	1.64
7	0.42	2.02	1.71	1.16
8	0.72	3.89	2.95	1.88
9	0.55	2.87	1.98	1.34

5.1 Performance Analysis by ANN

Training a neural network to learn patterns in the data involves iteratively presenting it with examples of the correct known answers. The objective of training is to find the set of weights between the neurons that determine the global minimum of error function. This involves decision regarding the number of iteration i.e., when to stop training a neural network and the selection of learning rate (a constant of proportionality which determines the size of the weight adjustments made at each iteration) and momentum values (how past weight changes affect current weight changes.

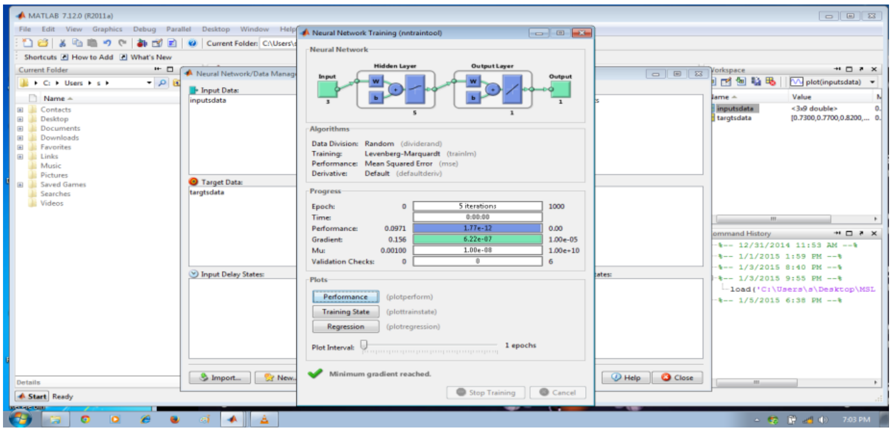


Figure 3 Neural Network Training

Best Model achieved in ANN is with feed forwarded back propagation neural network with Levenberg-Marquardt training function with three layers. [Network (3-5-1-1)]

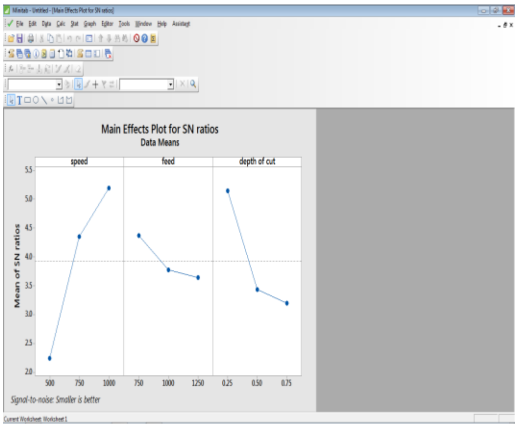
Table 5.3 Output from ANN Technique

Pieces	SR	Output (ANN)	Error (ANN)
1	0.73	0.73	0
2	0.77	0.77	0
3	0.82	0.75	-0.07
4	0.72	0.62	-0.1
5	0.49	0.49	0
6	0.63	0.63	0
7	0.42	0.42	0
8	0.72	0.72	0
9	0.55	0.55	0

5.2 Optimization by Taguchi Method

Since 1960, Taguchi methods have been used for improving the quality of Japanese products with great success. During the 1980's, many companies finally realized that the old methods for ensuring quality were not competitive with the Japanese methods. Performance characteristics are first converted into the S/N ratio using the Taguchi method. Using S/N quantity, optimal performance and minimal variance can be designed. The SR value is calculated for each trial from the basic data collected . The signal to-noise ratios of each experimental run are calculated based on the following equation, which are listed in corresponding tables with the data.

$$SNR = -10log\frac{1}{n}\sum y^2$$



Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
speed	2	13.8738	44.60%	13.8738	6.9369	1.46	0.407
feed	2	0.9118	2.93%	0.9118	0.4559	0.10	0.913
depth of cut	2	6.7995	21.86%	6.7995	3.3997	0.71	0.583
Error	2	9.5201	30.61%	9.5201	4.7600		
Total	8	31.1052	100.00%				

Figure 2-S/N ratio **Table 5.3 ANOVA**

Table 5.4 Comparison of Taguchi and ANN

Output Comparison of Taguchi Method and ANN Technique

Pieces	*SR*	*PSR (Taguchi)*	*Error (Taguchi)*	*Output (ANN)*	*Error (ANN)*
1	*0.73*	*0.79*	*0.06*	*0.73*	*0*
2	*0.77*	*0.81*	*0.04*	*0.77*	*0*
3	*0.82*	*0.71*	*-0.11*	*0.75*	*-0.07*
4	*0.72*	*0.61*	*-0.11*	*0.62*	*-0.1*
5	*0.49*	*0.55*	*0.06*	*0.49*	*0*
6	*0.63*	*0.67*	*0.04*	*0.63*	*0*
7	*0.42*	*0.46*	*0.04*	*0.42*	*0*
8	*0.72*	*0.61*	*-0.11*	*0.72*	*0*
9	*0.55*	*0.61*	*0.06*	*0.55*	*0*

Mean Absolute Percentage Error (MAPE) = $1 \div n \sum [|P_i - M_i|] \div M_i \times 100$

(Always take Error as Positive)

Where, P_i= predicted value

M_i= measured value

n= No. of Experiments

MAPE in Taguchi method = 10.77%

MAPE in ANN = 2.90%

So, ANN gives less MAPE as compared to Taguchi Method.

VI. CONCLUSION

1. The higher the cutting speed, the lower is the surface roughness.
2. The experimental results show that average surface roughness is low at lower depth of cut.
3. For achieving good surface finish on the D2 work piece, higher cutting speed, lower feed and lower depth of cut are preferred. The optimal parametric combination for AISI D2 Steel is speed3-feed1- depth of cut1.
4. ANOVA shows that the cutting speed is the most influencing parameter for surface roughness.
5. Mean Absolute Percentage Error is calculated in Taguchi method is 10.77% and Mean Absolute Percentage is Calculated in MATLAB is 2.90% so ANN technique gives us better results than Taguchi method .Error is minimized by ANN technique.
6. Best Model achieved in ANN is with feed forwarded back propagation neural network with Levenberg-Marquardt training function with three layers.

VII. REFERENCES

1. A.Behera, S.Behera, R.K Tripathy, S.C Mishra, "Least Square Support Vector Machine Alternative To Artificial Neural Network For Prediction Of Surface Roughness And Porosity Of Plasma Sprayed Copper Substrates", December, 2012.
2. A.Jameel, M. Minhat, Md. Nizam, "Using Genetic Algorithm to Optimize Machining Parameters in Turning Operation: A review", Volume 3, Issue 5, May 2013.
3. A.Joshi & P.Kothiyal, "Investigating Effect of Machining Parameters of CNC Milling on Surface Finish by Taguchi Method", Volume-2, Issue-2, 2013.
4. A.K Sahoo, "Application of Taguchi and regression analysis on surface roughness in machining hardened AISI D2 steel", International Journal of Industrial Engineering Computations 2014.
5. A.K Gupta, P.Chandna, P.Tandon, "Tool Life Optimization in 2.5d Milling By Coupling Regression Model And Genetic Algorithm", International Journal of Engineering and Technology Volume 1 No. 1, October, 2011.
6. A. Aggarwal and H. Singh, "Optimization Of Machining Techniques – A Retrospective and Literature Review" SadhanaVol. 30, Part 6, December 2005.
7. B.C Routara, S.D Mohanty, S.Datta, A. Bandyopadhyay and S.SMahapatra, "Optimization in CNC end milling of UNS C34000 medium leaded brass with multiple surface roughness characteristics" Vol. 35, Part 5, October 2010.
8. Clodeinir Ronei Peres, Rodolfo Elias Haber Guerra, Rodolfo Haber Haber, Angel Alique and Salvador Ros, "Fuzzy model and hierarchical fuzzy control integration: an
approach for milling process optimization", Computers in Industry 39 _1999. 199–207.
9. N. H. Razak, M.M. Rahman, M.M. Noor1 and K. Kadirgama, "ARTIFICIAL INTELLIGENCE TECHNIQUES FOR MACHINING PERFORMANCE: A REVIEW", National Conference in Mechanical Engineering Research and Postgraduate Studies (2nd NCMER 2010) 3-4 December 2010, Faculty of Mechanical Engineering, UMP Pekan, Kuantan, Pahang, Malaysia; pp. 39-53.
10. Ramezan Ali Mahdavinejad, Navid Khani and Mir Masoud Seyyed Fakhrabadi, "Optimization of milling parameters using artificial neural network and artificial immune system", Journal of Mechanical Science and Technology 26 (12) (2012) 4097~4104.

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