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Modeling and Simulation of Productivity in the Turning of Ferrous and Nonferrous Material using Artificial Neural Network and Response Surface Methodology

M. Mangesh R. Phate[1], Tatwawadi V.H.[2] and Modak J.P.[3]
[1]Dept. Of Mechanical Engg, TSSM's, PVPIT, Bavdhan, Pune, Maharashtra, INDIA
[2]Dr.Babasaheb Ambedkar College of Engg and Research, Nagpur, Maharashtra, INDIA
[3]Mechanical Engg, Dept, Priyadarshni College of Engineerig, Nagpur, INDIA

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Abstract

Traditional machining is a complex phenomenon which includes the workers who operates the machines and his working environment such as atmospheric parameters, work piece parameters, cutting process parameters, tool parameters and etc In the India and other country the majority of total machining operation are still executed manually which needs to be focused and develop a mathematical model referred as Field data based Model) to identify the strengths and weaknesses of the present method. The formulated field data based Model (FDBM) correlates the various input parameters with the output parameters . The present paper aimed to propose improvement in methods of performing these activities by developing mathematical simulation from data collected while the work was actually being executed in the field. Once the generalized model using all possible parameters developed, the weaknesses of the present method identified and improvement is possible. The main contribution of this paper is to develop the mathematical model for the turning of ferrous and nonferrous material. The validation of the formulated Field Data Based Mathematical model (FDBM) is achieved by comparing with the Artificial Neural Network and response surface model. The aim of the paper is to find out the mathematical model for the productivity i.e. machining time and the machining cost required for turning the ferrous and nonferrous work piece. Out of so many parameters mentioned above we would like to find out which of these are most important for increasing the productivity. Simultaneously it would be interesting to know influence of one parameter over the other.

Keywords: Artificial neural network, response surface methodology, field data based model, Turning, ferrous and nonferrous material and Simulation etc.

Introduction

H.S.Yoon et al. has proposed an orthogonal cutting force model based on slip-line field model for micro machining. Two material flow processes are being considered- chip formation process and ploughing. The paper takes into account the effects of parameters like effective rake angle, depth of deformation and minimum chip thickness. The edge radius effect is an important effect in machining processes. The tool can be scaled down to a large extent but the sharpness of the tool cannot be scaled down so drastically and proportionately. So, in micro machining ploughing force is a important factor instead of shearing force which is the dominant factor in conventional machining. Another important effect is the minimum chip thickness effect. When the un deformed chip thickness is below the minimum chip thickness, chip formation doesn't occur and there is only ploughing. However, when the unreformed chip thickness exceeds the minimum value, chip formation occurs. Some experimental analysis has shown that chip formation occurs only when the unreformed chip thickness is more than 30% of the tool edge radius. This paper is based on the assumption that the tool has a perfectly rounded tool edge. The cutting performed is assumed to be orthogonal. The material deforms plastically below the minimum chip thickness height. Another assumption is that the work material is not work-hardening. So, the shear stresses on all shear planes have the same values. The chip is also assumed to be a free body, such that the normal force on the shear plane is zero. The paper has also concentrated on the effect of the dead metal zones on micro machining. These zones act as stable built up edges on the tool, as stagnation zones where no material flow occurs. Several researchers have used this process for machining of wide variety of materials considering different process parameters. Suhail et al. optimizes the cutting parameters such as cutting speed, feed rate and depth of cut based on surface roughness and assistance of work piece surface temperature in turning process[1]. In machining operation the quality of surface finish is an important requirement for many turned work pieces. The work piece surface temperature can be sensed and used effectively as an indicator to control the cutting performance and improves the optimization process. So it is possible to increase machine utilization and decrease production cost in an automated manufacturing environment. Kirby optimizes the turning process toward an ideal surface roughness target. This study seeks an actual target surface roughness value, which may allow for a higher feed rate depending upon that specified target[2]. In using the variation of the nominal the-best signal to noise formula, variation about a specified (ideal) value is explored and sought to be minimized. Singh optimizes tool life of Carbide Inserts for turned parts. The experiments were carried to obtain an optimal setting of turning process parameters- cutting speed, feed and depth of cut, this may result in optimizing tool life[3]. The relative power of feed in controlling variation and mean tool life is significantly smaller than that of the cutting speed and depth of cut. Mahto et al. optimizes the process parameters in vertical CNC mill machines[4]. The study was conducted in machining operation in hardened steel DIN GX40CRMOV5-1. The processing of the job was done by Tin coated carbide inserted end-mill tool under semi-finishing and finishing conditions of high-speed cutting. The milling parameters evaluated was cutting speed, feed rate and depth of cut. Thamizhmanii et.al analyses the surface roughness by turning process[5]. The optimum cutting conditions were predicted to get lowest surface roughness in turning SCM 440 alloy steel. The study revealed that the depth of cut has significant role to play in producing lower surface roughness followed by feed. Also the cutting speed has lesser effect on the surface roughness. Petropoulos et al. developed a predictive model of cutting force in longitudinal turning of St37 steel with a Tin coated carbide tool using Taguchi and Response surface techniques[6]. The model is formulated in terms of the cutting conditions namely feed, cutting speed and depth of cut.

Field Data Based Model Formulation

Variables affecting the Turning Process: The term variables are used in a very general sense to apply any physical quantity that undergoes change. If a physical quantity can be changed independent of the other quantities, then it is an independent variable. If a physical quantity changes in response to the variation of one or more number of independent variables, then it is termed as dependent or response variable. If a physical quantity that affects our test is changing in random and uncontrolled manner, then it is called an extraneous variable. The variables affecting the effectiveness of the phenomenon under consideration are operator data, single point cutting tool, lathe machine, work piece, process parameters and the environmental parameters. The dependent or the response variables in this case of turning operation is human energy. The list of various process variables which affects the machining phenomenon is as shown in table 1.

Reduction of Variables by using Buckingham's Pi Therom: According to the theories of Engineering experimentation by H. Schenck Jr[7]. the choice of primary dimensions requires at least three primaries, but the analyst is free to choose any reasonable set he wishes, the only requirement being that his variables must be expressible in his system. There is really nothing basis or fundamental about the primary dimensions.

Table-1
List of Variable under Investigation

S.N	Description	Symbol	Dimensions
1	Anthropometric dimensions ratio of the operator.	An	$M^0 L^0 T^0 \theta^0 \Delta^0$
2	Weight of the operator.	W_p	$M^1 L^0 T^0 \theta^0 \Delta^0$
3	Age of the operator.	AGP	$M^0 L^0 T^1 \theta^0 \Delta^0$
4	Experience	EX	$M^0 L^0 T^1 \theta^0 \Delta^0$
5	Skill rating	SK	$M^0 L^0 T^0 \theta^0 \Delta^0$
6	Educational qualifications	EDU	$M^0 L^0 T^0 \theta^0 \Delta^0$
7	Psychological Distress	PS	$M^0 L^0 T^0 \theta^0 \Delta^0$
8	Systolic Blood pressure	SBP	$M^0 L^0 T^1 \theta^0 \Delta^0$
9	Diastolic Blood pressure	DBP	$M^0 L^0 T^0 \theta^0 \Delta^0$
10	Blood Sugar Level during Working	BSG	$M^1 L^{-3} T^0 \theta^0 \Delta^0$
11	Cutting Tool angles ratio.	CTAR	$M^0 L^0 T^0 \theta^0 \Delta^0$
12	Tool nose radius	R	$M^0 L^1 T^0 \theta^0 \Delta^0$
13	Tool overhang length	Lo	$M^0 L^1 T^0 \theta^0 \Delta^0$
14	Approach angle	A	$M^0 L^0 T^0 \theta^1 \Delta^0$
15	Setting angle	B	$M^0 L^0 T^0 \theta^1 \Delta^0$
16	Single point cutting tool Hardness	BHN	$M^0 L^0 T^0 \theta^0 \Delta^0$
17	Lip or Nose angle of tool	LP	$M^0 L^0 T^0 \theta^1 \Delta^0$
18	Wedge angle	WG	$M^0 L^0 T^0 \theta^1 \Delta^0$
19	Shank Length	LS	$M^0 L^1 T^0 \theta^0 \Delta^0$
20	Total length of the tool	LT	$M^0 L^1 T^0 \theta^0 \Delta^0$
21	Tool shank width	SB	$M^0 L^1 T^0 \theta^0 \Delta^0$
22	Tool shank Height	SH	$M^0 L^1 T^0 \theta^0 \Delta^0$
23	Work piece hardness	BHNW	$M^0 L^0 T^0 \theta^0 \Delta^0$
24	Weight of the raw work piece.	W	$M^1 L^0 T^0 \theta^0 \Delta^0$
25	Ultimate Shear stress of the workpiece material	σ_{sut}	$M^1 L^{-1} T^{-2} \theta^0 \Delta^0$
26	Density of the workpiece material	DST	$M^1 L^{-3} T^0 \theta^0 \Delta^0$
27	Length of the raw workpiece	LR	$M^0 L^1 T^0 \theta^0 \Delta^0$
28	Diameter of the raw workpiece	DR	$M^0 L^1 T^0 \theta^0 \Delta^0$
29	Cutting Speed	VC	$M^0 L^1 T^{-1} \theta^0 \Delta^0$
30	Feed	f	$M^0 L^1 T^0 \theta^0 \Delta^0$
31	Depth of cut	D	$M^0 L^1 T^0 \theta^0 \Delta^0$
32	Cutting force	FC	$M^1 L^1 T^{-2} \theta^0 \Delta^0$
33	Tangential Force.	FT	$M^1 L^1 T^{-2} \theta^0 \Delta^0$
34	Spindle revolution	N	$M^0 L^0 T^{-1} \theta^0 \Delta^0$
35	Machine Specification ratio	MSP	$M^0 L^0 T^0 \theta^0 \Delta^0$
36	Power of the Machine motor	HP	$M^1 L^2 T^{-3} \theta^0 \Delta^0$
37	Weight of the machine	Wm	$M^1 L^0 T^0 \theta^0 \Delta^0$
38	Age of the machine	AGM	$M^0 L^0 T^1 \theta^0 \Delta^0$
39	Atmospheric Humidity	Φ	$M^0 L^0 T^0 \theta^0 \Delta^0$
40	Atmospheric Temperature	DT	$M^0 L^0 T^0 \theta^0 \Delta^1$
41	Air Flow	Vf	$M^0 L^1 T^{-1} \theta^0 \Delta^0$
42	Light Intensity	LUX	$M^1 L^0 T^{-4} \theta^0 \Delta^0$
43	Sound level	DB	$M^0 L^0 T^0 \theta^0 \Delta^0$
44	Productivity in terms of cost and time	PROD	$M^0 L^1 T^0 \theta^0 \Delta^0$

For this case ,the variables are expressed in mass (M), length (L), time (T), temperature (θ) and angle (Δ).The final dimensionless pi term id as shown in table-2.

Formulation of FDBM By Regression Analysis: It is necessary to correlate quantitatively various independent and dependent terms involved in this very complex phenomenon. This correlation is nothing but a mathematical model as a design tool for such situation. The Mathematical model for step turning operations is as given below: For the machining operation Five independent pi terms (π1, π2, π3, π4 ,π5 and π6) and one dependent pi terms (πD1) were decided during experimentation and hence are available for the model formulation. Each dependent π term is the function of the available independent terms.

$$\Pi_{D1} = f(\Pi_1, \Pi_2, \Pi_3, \Pi_4, \Pi_5, \Pi_6) \quad (1)$$

A probable exact mathematical form for the dimensional equations of the phenomenon could be relationships assumed to be of exponential form Thamizhmanii et.al analyses[5]. For example, the model representing the behaviour of dependent pi term π_{D1} with respect to various independent pi terms can be obtained as under.

$$\Pi_{D1} = K_1 \times \Pi_1^a \times \Pi_2^b \times \Pi_3^c \times \Pi_4^d \times \Pi_5^e \, x \, \Pi_6^f \quad (2)$$

Table-2
Final Independent and Dependent dimensionless Pi term

S.N	Pi term	Dimensionless ratio	Nature of Basic Physical Quantities
1	π_1	An*SBP*SK*Ag*Wp *SPO2 / DBP*PS*EDU*EX*BSG*D^3	Machine operator data
2	π_2	AR * r * β * BHNT * LT*LP*LS / α * LO* SW * SH * WG	Single point cutting tool
3	π_3	BHNW * W raw* LR * τ / D * FC * DST * DR	Work piece material
4	π_4	f * FT * N * $Temp_{wp}$* VB_{Tool} / $VB_{Machine}$ * FC*VC	Cutting process parameters
5	π_5	SP * P_{HP} * $W_{m/c}$ / AGM* FC^2	Lathe Machine
6	π_6	HUM*DTO *V_f *DB*VC*FC/ LUX*D^3	Environmental data
7	π_{D1}	VC * TM * RS /D	Productivity in terms of cost and time

Model 1 for Ferrous and Non ferrous materials with all independent pi terms

$$\Pi_{D1} = 142.0365124 \times \Pi_1^{0.3586} \times \Pi_2^{0.0577} \times \Pi_3^{-0.1071} \times \Pi_4^{0.2382} \times \Pi_5^{0.1411} \times \Pi_6^{0.0236} \quad (3)$$

Correlation Coefficient = 0.739744651, Root Mean Square =0.377347, Reliability = 68.857819%

Model 2 for Ferrous Material with all independent pi terms

$$\Pi_{D2} = 5700.3300 \times \Pi_1^{0.0992} \times \Pi_2^{0.0757} \times \Pi_3^{0.7333} \times \Pi_4^{0.9274} \times \Pi_5^{0.0709} \times \Pi_6^{-0.1379} \quad (4)$$

Correlation Coefficient = 0.89656, Root Mean Square =0.22541, Reliability = 82.729933%

Model 3 for Non ferrous Material with all independent pi terms

$$\Pi_{D2} = 6.113641945 \times \Pi_1^{0.2772} \times \Pi_2^{0.0116} \times \Pi_3^{-0.3070} \times \Pi_4^{-0.7006} \times \Pi_5^{0.0389} \times \Pi_6^{0.2575} \quad (5)$$

Correlation Coefficient = 0.721978214, Root Mean Square =0.329422774, Reliability = 80.80630951%

The indices of various models are as shown in figure 1.

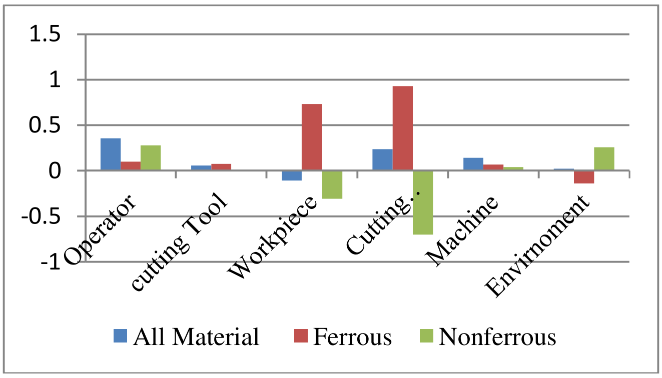

Figure-1
Comparing indices for the MRR Model for formulated model.

Table-3
Effect of change in independent parameters on dependent parameter (MRR)

Dependent pi terms (MRR)	**Sequence of independent pi terms according to intensity of influence (High to Low)**					
Ferrous and Nonferrous	Π_1	Π_4	Π_5	Π_2	Π_6	Π_3
Ferrous	Π_4	Π_3	Π_1	Π_2	Π_5	Π_6
Nonferrous	Π_6	Π_1	Π_5	Π_2	Π_4	Π_3

Formulation of Model by Artifical Neural Network

Artificial neural network is an information processing pattern or methodology. Neural Network is used to learn patterns and relationship in data.A neural network needs to be given only raw data related to the problem. The neural network sorts this information and produces an understanding of the factors impacting sales. The model can then be called upon to provide a prediction of future sales given a free cost of the key factors.

These advancements are due to the creation of neural network learning rules, which are the algorithms used to learn the relationship in data. The learning rules able the network to gain knowledge from available data and apply that knowledge to assist a manager in making key decision.

The development of ANN started 50 years ago. ANN are gross simplification of relationship of neurons. The methodology of neural network which began during the 1940's promises to be a very important tool for studying the structure function relationship of the human brain. Artificial neural network consists of many nodes i.e processing unit analogs to neuron in the brain.Each node has a node function associated with it which along with a set of local parameters determines the output of the nodes, given an input. The signals are transmitted by means of connection links. The links posses are associated weight, which is multiplied along with the incoming signal (net Input) for any typical neural net. The output signal is obtained by applying activation to the net input.

The field data based modelling has been achieved based on observed data for the seven dependent pi terms. Simulation consists of three layers. First layer is known as input layer. No. of neurons in input layer is equal to the no. of independent variables. Second layer is known as hidden layer. It consists of five number of neurons. The third layer is output layer. It contains one neuron as one of dependent variables at a time. Multilayer feed forward topology is decided for the network. MATLAB software is selected for developing ANN simulation. 6-5-1 topology is used for the ANN network the generated network are as shown in figure 3-5

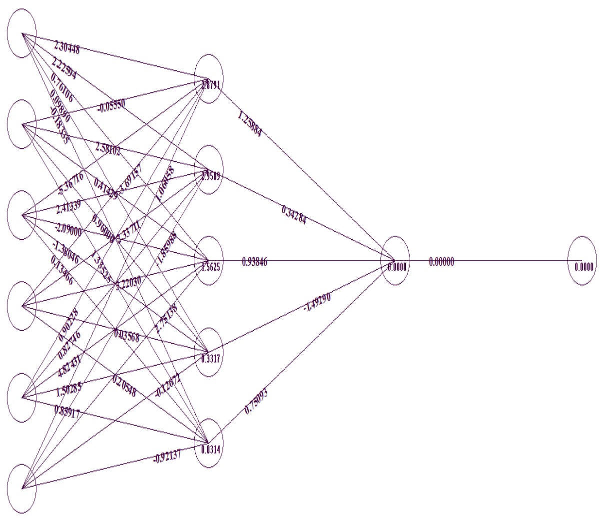

Figure-2
MRR 6-5-1 ANN network for ferrous and nonferrous material

Formulation of Model by ANN: Model 1: i. Correlation Coefficient = 0.893566574234881, ii. Root Mean Square =0.296727254798129, iii. Reliability = 78.06410256 %

Model 2: i. Correlation Coefficient = 0.927884856693157, ii. Root Mean Square =0.212223401732276, iii. Reliability =84.29393939 %

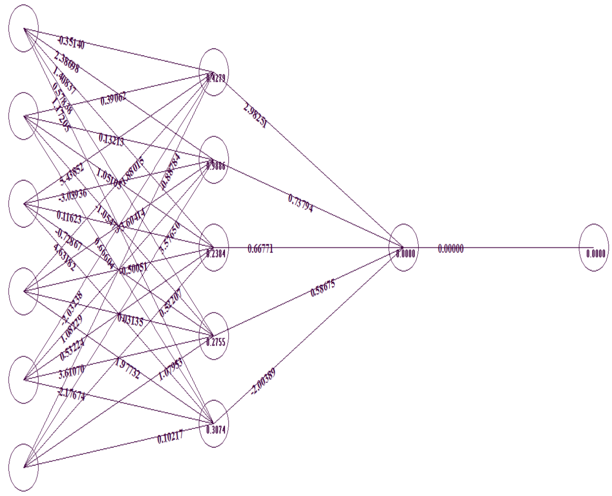

Figure-3
MRR 6-5-1 ANN network for ferrous material

Model 3: i. Correlation Coefficient = 0.826915533295339,. ii. Root Mean Square =0.372578866826212, iii. Reliability = 75.43796296 %

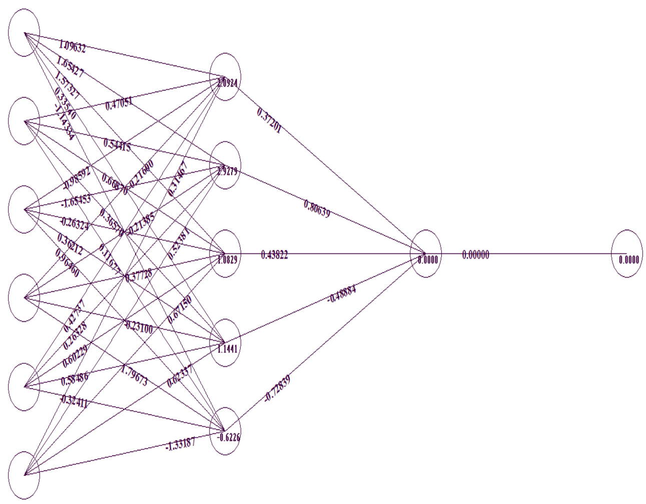

Figure-4
MRR 6-5-1 ANN network for nonferrous Material

Response Surface Model

Response surface methodology (RSM) is a collection of mathematical and statistical techniques for empirical model building. by careful design of experiments, the objective is to optimize a response (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response.

Originally, RSM was developed to model experimental responses and then migrated into the modelling of numerical experiments. The difference is in the type of error generated by the response. In physical experiments, inaccuracy can be due, for example, to measurement errors while, in computer experiments, numerical noise is a result of incomplete convergence of iterative processes, round-off errors or the discrete representation of continuous physical phenomena. In RSM, the errors are assumed to be random.

The RSM is practical, economical and relatively easy for use and it was used by lot of researchers for modelling machining processes[8] and (Hill and Hunter) reviewed the earliest work on response surface methodology. Response surface methodology (RSM) is a combination of experimental and regression analysis and statistical inferences. The concept of a response surface involves a dependent variable y called the response variable and several independent variables x1, x2,. .., xk. If all of these variables are assumed to be measurable, the response surface can be expressed as

$$y = f(x_1; x_2; x_1; ------- ; x_k) \tag{1}$$

Optimizing the response variable y, it is assumed that the independent variables are continuous and controllable by the experimenter with negligible error. The response or the dependent variable is assumed to be a random variable. In our experiments turning operation was selected, it is necessary to find a suitable combination of X1 (Product of Operator, tool and Work piece pi term) and Y (Product of Cutting process, machine and the environmental parameters). The observed response Z as a function of the X and Yan be written as

$$y = f(X; Y) + \varepsilon_i \tag{2}$$

Usually a best fit polynomial was fitted, The parameters of the polynomials are estimated by the method of least squares. The proposed relationship between the machining responses (cutting force) and machining independent variables can be represented by the following:

RSM Model 1 : For Turning of Ferrous and Nonferrous material

$$\begin{aligned} \Pi D1 = {} & 39.11 - 8.202*X + 9.74*Y + 0.4202*X^2 - 0.5332*X*Y \\ & - 0.1768*Y^2 - 0.004709*X^3 - 0.002989*X^2*Y \\ & + 0.03*X*Y^2 - 0.01886*Y^3 \end{aligned} \tag{6}$$

Goodness of fit: SSE: 67.82, R-square: 0.4847, Adjusted R-square: 0.476, RMSE: 0.3557
Correlation Coefficient = 0.696169, Root Mean Square =0.29838, Reliability = 73.235

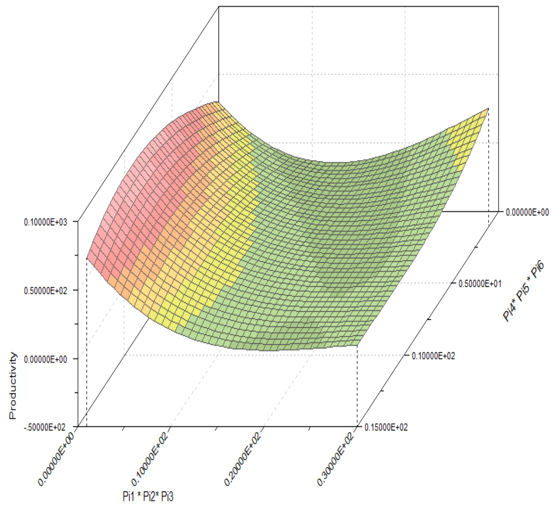

Figure- 5
Productivity Model Response Surface for Ferrous and Nonferrous Material

RSM Model 2: For Turning of Ferrous material

$$\begin{aligned} \Pi D1 = {} & -15.16 + 3.581*X - 2.598*Y - 0.132*X^2 - 0.07138*X*Y \\ & + 0.3388*Y^2 + 0.002323*X^3 - 0.003955*X^2*Y + \\ & 0.01412*X*Y^2 - 0.02209*Y^3 \end{aligned} \tag{7}$$

Goodness of fit: SSE: 24.3, R-square: 0.7235, Adjusted R-square: 0.7157, RMSE: 0.2756,
Correlation Coefficient = 0.850596, Root Mean Square =0.2527965, Reliability = 78.605067

RSM Model 3: For Turning of Nonferrous material

$$\begin{aligned} \Pi D1 = {} & -143.9 + 27.19*X - 17.83*Y - 1.585*X^2 + 1.813*X*Y \\ & - 0.2311*Y^2 + 0.03164*X^3 - 0.05882*X^2*Y + \\ & 0.04454*X*Y^2 - 0.02758*Y^3 \end{aligned}$$

Goodness of fit: SSE: 26.66, R-square: 0.3027, Adjusted R-square: 0.2722, RMSE: 0.3597 (8)

Correlation Coefficient = 0.62998, Root Mean Square =0.2367764, Reliability = 73.089067

Comparision between different approach outputs.

Dimensional analysis and regression approach of model formulation was adopted for the model formulation .The formulated model was simulated by the Artificial neural network and response surface approach. The results obtained is for ferrous and nonferrous, ferrous and nonferrous materials are comparing and the graphical representation of the results are as shown is in the following figures 8-10.

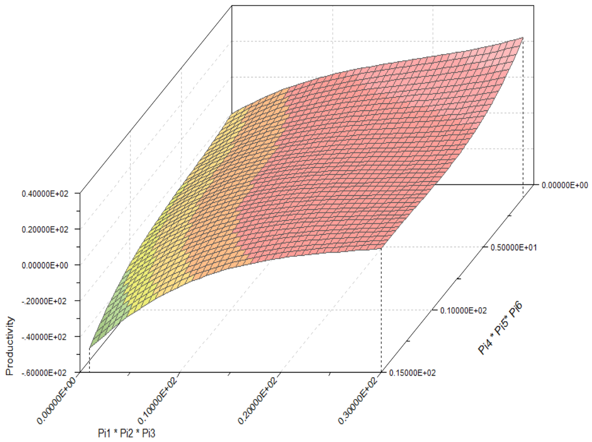

Figure-6
Productivity Model Response Surface for Ferrous Material

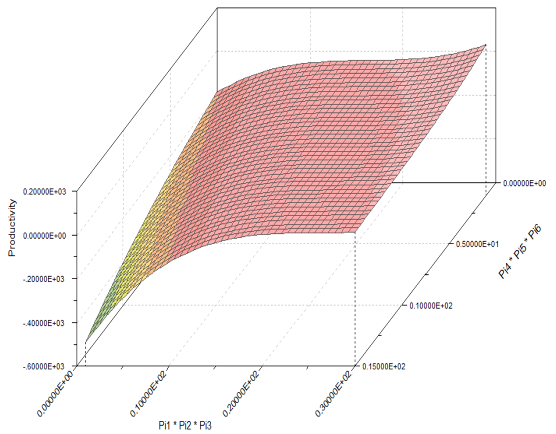

Figure-7
Productivity Model Response Surface for Nonferrous Material

Conclusion

In this study, From equation 3, the absolute index of $\pi1$ is highest 0.3586. The factor $\pi1$ is related to the machine operator. The value of this index is positive indicating involvement of this ratio has strong impact on productivity for machining of ferrous and nonferrous material. The sequence of the various π terms in the descending order of sensitivity was $\pi4$, $\pi5$, $\pi2$ and $\pi6$. The value of this index is positive indicate that productivity increases with increase in the ratio and or otherwise. The absolute index of $\pi3$ is lowest index -0.1071 This factor is related to the work piece data and is the least influencing term in this model. From equation 4, the absolute index of $\pi4$ is highest 0.9274. The factor $\pi4$ is related to the cutting process parameters. The value of this index is positive indicating involvement of this ratio has strong impact on productivity for machining of ferrous material. The sequence of the various π terms in the descending order of sensitivity was $\pi3$, $\pi1$, $\pi2$ and $\pi5$. The value of this index is positive indicate that productivity increases with increase in the ratio and or otherwise. The absolute index of $\pi3$ is lowest index -0.1379. This factor is related to the machining environment data and is the least influencing term in this model. From equation 5, the absolute index of $\pi6$ is highest 0.2575. The factor $\pi6$ is related to the environmental parameters. The sequence of the various π terms in the descending order of sensitivity was $\pi1$, $\pi5$, $\pi2$ and $\pi3$.The value of this index is positive indicating involvement of this ratio has strong impact on productivity for machining of ferrous and nonferrous material. The value of this index is positive indicate that productivity increases with increase in the ratio and or otherwise. The absolute index of $\pi4$ is lowest index -0.7006 This factor is related to the cutting process parameters and is the least influencing term in this model.

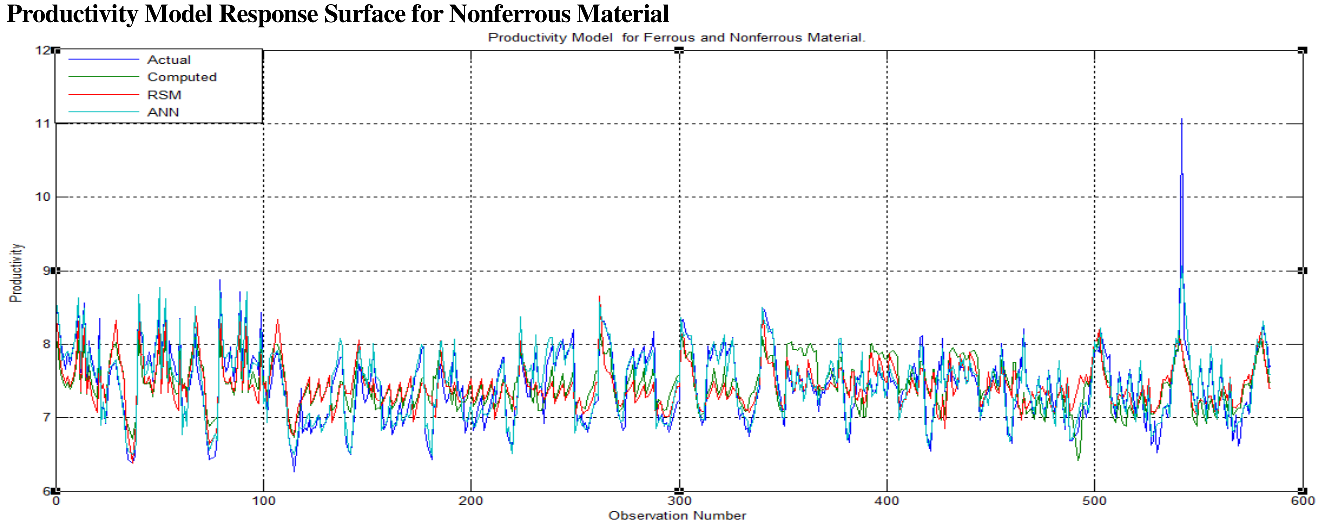

Figure-8
Comparison between Actual, Computed, RSM and ANN Output for ferrous and nonferrous Material

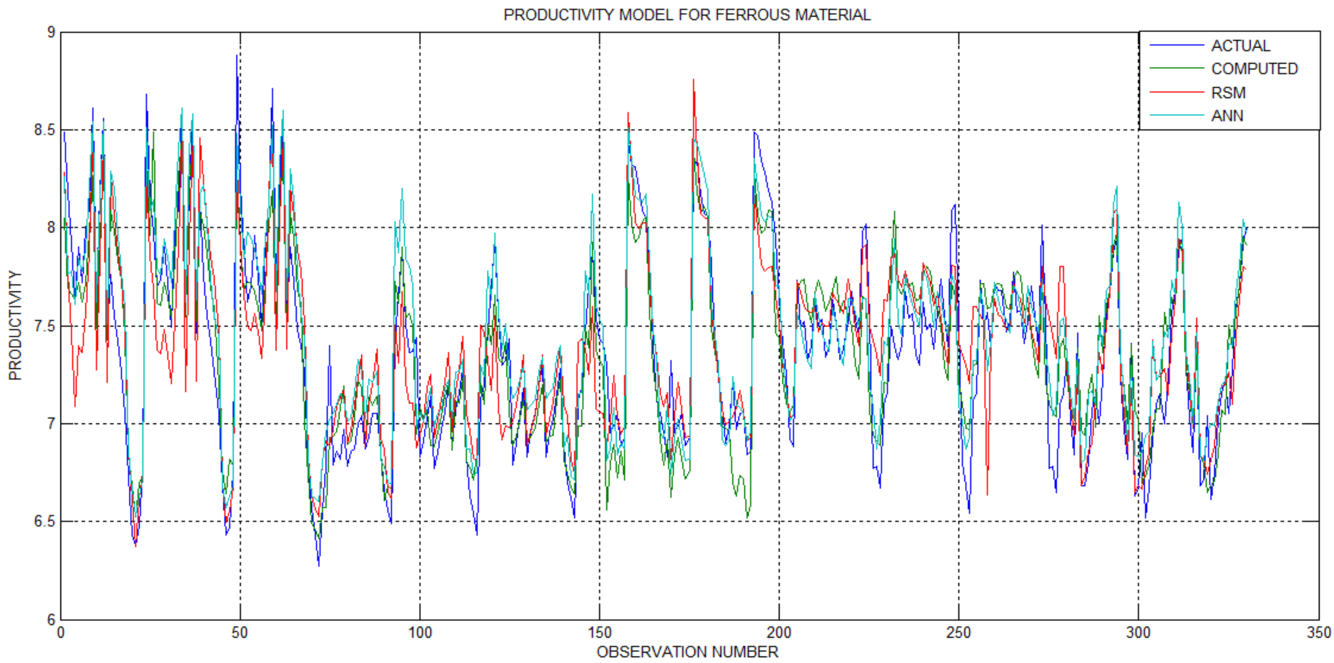

Figure-9
Comparison between Actual, Computed, RSM and ANN Output for ferrous Material

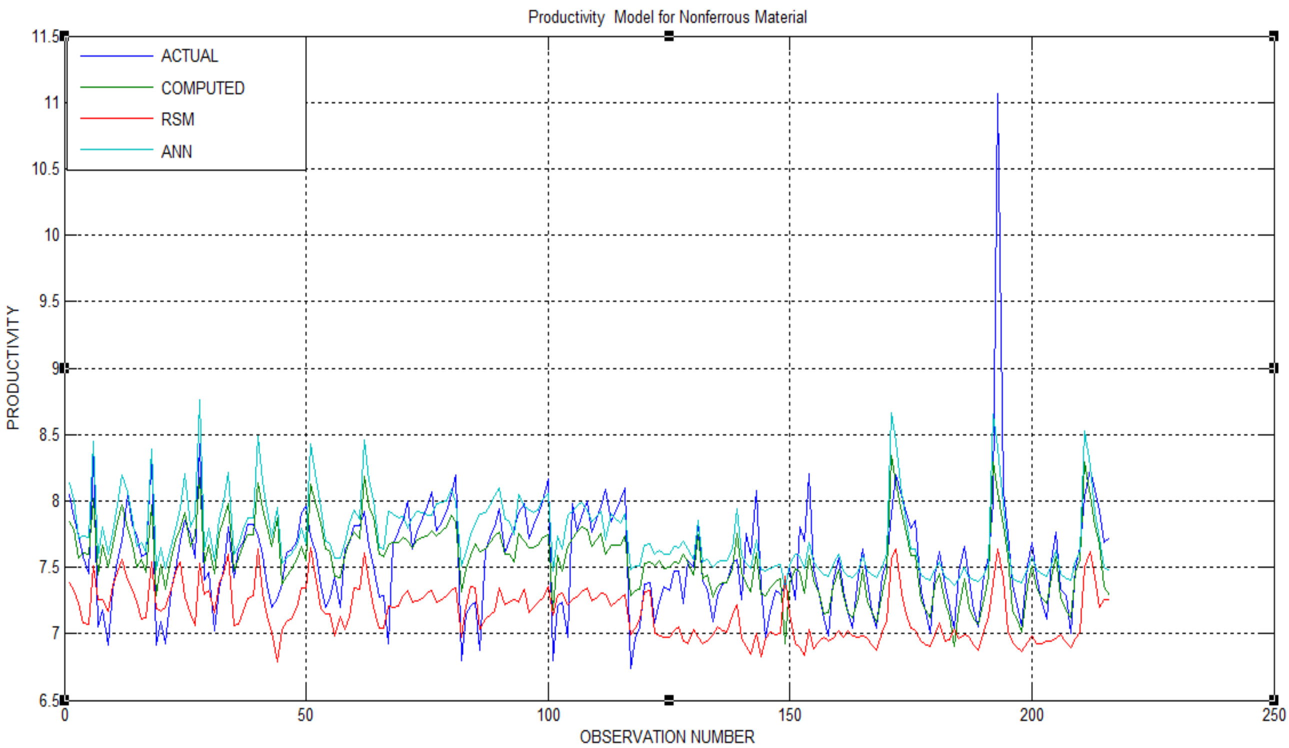

Figure-10
Comparison between Actual, Computed, RSM and ANN Output for nonferrous Material

The equations show magnification factors (K) or the curve fitting constant as 142.0365124,5700.3300 and 6.113641945 for productivity which collectively represents all extraneous variables (Uncontrollable variables) affecting the turning process.The equation 6-8 shows the response surface equation for the best fitted polynomial and fig 5-7 shows the nature of the response surface.

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