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Determination and Analysis of Spindle Load in Boring Machining Operation on Cast Iron using Mathematical Models

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***Abstract*— Boring process in Grey Cast Iron Casting (GCIC) materials are widely used in machinery industries and particularly in automotive industries. However, improved mechanical properties of these materials limits us due to high cost of processing these materials. Spindle Load is one of the most important factors in machining operations of such materials and it is mainly affected by cutting conditions including the cutting speed, depth of cut, insert material and cooling environment along with length and diameter of the tool body. Machining manufacturing process are now moving towards automations. Therefore, Spindle Load monitoring is important to achieve an efficient manufacturing process. In this study, a tool wear prediction model during the boring machining operation of gray cast iron is studied. It is based on the monitoring of tool performance in controlled machining tests with measurements of tool life, surface finish, bore size variation, cutting time and load on spindle in terms of % current under different combinations of cutting parameters (cutting speed, depth of cut, tool nose radius, length & diameter of tool, tool material and coolant pressure & concentration). The influence of cutting parameters on the tool life was studied experimentally by performing more than 128 cutting tests. A prediction model was then developed to predict tool wear. The basic steps used in generating the model adopted in the development of the prediction model are: collection of data; analysis, pre-processing and feature extraction of the data, design of the prediction model, training of the model and finally testing the model to validate the results and its ability to predict tool wear.**

The evolution of boring machining operation properties using different parameters is a complex phenomenon. There are many factors (like cutting speed, depth of cut, insert material and cooling environment along with length and diameter of the tool body) affecting the performance of cast iron boring machining operation resulting to more load on spindle. This paper presents an experimental investigations and Sequential classical experimentation technique has been used to perform experiments for various independent parameters. An attempt of mini-max principle has been made to optimize the range bound process parameters for minimizing Spindle Load during cast iron boring machining operation. The test results proved that Spindle Load was significantly influenced by changing important four dimensionless π terms. The process parameters grouped in π terms were suggested the effective guidelines to the manufacturer for minimizing Spindle Load by changing any one or all from the available process parameters.

***Index Terms*— Gray cast iron, Spindle load, Boring machining process, Regression Analysis, RSM, Dimensional Analysis, Optimization, Buckingham's π terms.**

I. INTRODUCTION

Machine manufacturing process can be defined as the process of converting raw materials into products, including the product design, selection of raw materials and the sequence of the manufacturing procedure, Kalpakjian and Schmid [1]. In today's highly competitive market, the quality of manufactured products must be assured in all manufacturing stages Kalpakjian [2]. This has increased the demand for efficient manufacturing processes with optimum manufacturing cost, high quality and environmental sustainability considerations Deiab I., Assaleh K. and Hammad F [3]. There are two main concepts in modern manufacturing: machining automation and advanced engineering materials. Automation of manufacturing process could be the ideal solution to today's development revolution in terms of the new materials, cutting tools, and machining equipment. Automation will help in achieving an economical implementation of resources in the manufacturing process (materials, labor, electric power, etc.) without compromising the high levels of quality and productivity. In addition, the change in market demands and product specification requires faster production rates and consistency and uniformity of the manufactured parts Kalpakjian and Schmid [1]. Achieving these requires changing the tool just at the right time to get these benefits Choudhury S.K and Ratch S [4] and Lee et al [5]. The other main issue of modern manufacturing is the use of new advanced engineering materials. New industrial applications require materials with modified properties for products' particular requirements with reliable and economical manufacturing processes. Such advanced engineering materials are used in automobile, aerospace, electronics, medical applications and others industries Ezugwu [6] [7]. The modified properties will improve the quality of these materials and help meet certain mechanical, electrical, or chemical requirements. Typical properties of interest include: tensile strength, hardness, thermal, conductivity, and corrosion and wear resistance Dandekar [8], Ezugwu at al [9] and Yang [10]. Despite of all the advantages of the advanced engineering materials, they are difficult to cut and results in high processing cost.

II. BORING PROCESS

Metal cutting is one of the most extensively used manufacturing process. In metal cutting process, a sharp cutting tool removes material from internal surface of work peace to achieve desired product. The most common types of machining process are Turning, milling and drilling Kalpakjian [2]. Boring is the process of producing circular internal profiles in hollow work pieces by removing material from internal diameter surface of the work peace. In this process a boring bar with one or multiple cutting edges is rotating with some desired speed while the work peace is moving in and out with certain velocity. It is mainly used to generate the specific hole size with high accuracy. The boring process is carried out on a horizontal machines or vertical machines and the automatic boring process is carried out by CNC (Computerized Numerical Control) machines.
The boring process illustrated in Fig.1

a. b.

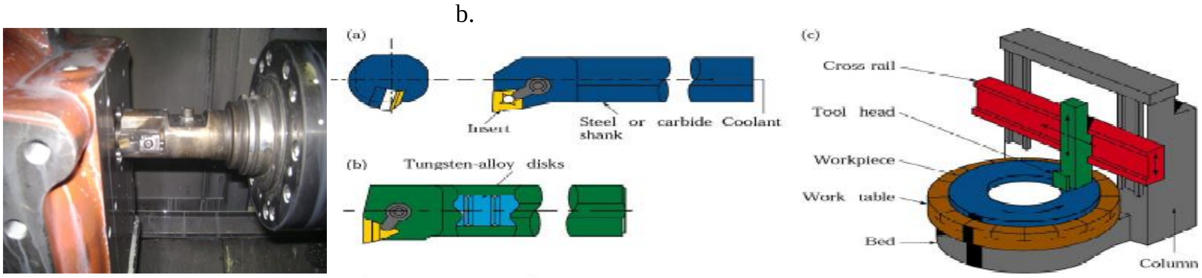


Fig no 1: a. Shows the boring process on horizontal machining centre. b. Shows the boring process tools and boring process on vertical machining centre.

Machining process is very common in manufacturing technology. These operations are applied in manufacturing of the almost every mechanical part. Boring is also one of the important machining process.

Because of their frequent use, these processes have to be efficient and economical. But in real practice this boring process is more expensive. On the way to lower manufacturing costs, there are many parameters that need to be considered. Tool wear is one of the most important considerations in machining operations as it affects surface quality, productivity and cost etc. To study the effect of cutting parameters on Spindle Load Mr. W.H. Yang [10] suggested the use of Taguchi Method. In his work he studied the optimal cutting parameters for improving the Spindle Load for turning operation Yang W.H [10]. In a Boring operation, it is an important task to select cutting parameters for achieving high cutting performance. Usually, the desired cutting parameters are determined based on experience or by use of a handbook. But one can select the optimal cutting parameters using optimization techniques. Therefore, considerable knowledge and experience are required for using this modern approach. Furthermore, a large number of cutting experiments were performed and analysed in order to build the mathematical models. Thus the required model building is very costly in terms of time and materials. Mr. Y. Sahin [11] also suggested the use of Taguchi method. In his work he studied the comparison of tool life in turning process with desired cutting parameters Sahin Y. [11]. The tool wears process illustrated in Fig.2

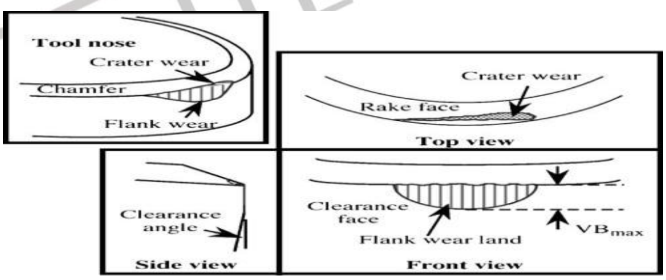


Fig no 2: shows the Tool wear obtained after the machining several components.

III. FORMULATION OF GENERALIZED EXPERIMENTAL DATA BASED MODELS

In view of forgoing it is obvious that one will have to decide what should be the optimum cutting speed required, nose radius, length, diameter and material of the cutting tool, cutting fluid pressure and concentration and depth of cut to be supplied to the system for maximizing the Spindle Load and to generate accurate sizes on the work peace in minimum time. By knowing this one can establish casting machining properties. It is well known that such a model for optimizing the Spindle Load in casting machining operation cannot be formulated applying logic Modak et al.[12], [13].The only option with which one is left is to formulate an experimental data based model, Hilbert Sc.Jr.[14]. Hence, in this investigation it is decided to formulate such an experimental data based model. In this approach all the independent variable are varied over a widest possible range, a response data is collected and an analytical relationship is established. Once such a relationship is established then the technique of optimization can be applied to deduce the values of independent variables at which the necessary responses can be minimized or maximized, Singiresu [15] and Yang [10]. In fact determination of such values of independent variables is always the puzzle for the operator because it is a complex phenomenon of interaction of various independent variables and dependant variables for optimizing the Spindle Load in casting machining operation is shown in table 1.

Table 1: Dependent and Independent variable of cast iron boring machining operation

S.N.	Variables	Unit	$M^0L^0T^0$	Dependant/ Independent	Variable /Constant
1	SL=Spindle Load	% Amp	$M^0L^0T^0$	Dependant	Response Variable
2	L=Length of tool	mm	L	Independent	Variable
3	D=Diameter of tool	mm	L	Independent	Variable
4	Dpc=Depth of cut	mm	L	Independent	Variable
5	Nr=Nose radius	mm	L	Independent	Variable
6	Vc=Cutting speed	mm/sec	LT^{-1}	Independent	Variable
7	Pc_c=Coolant pressure	N/mm^2	$ML^{-1}T^{-2}$	Independent	Variable
8	Cc=Coolant concentration	N/mm^3	ML^3	Independent	Variable
9	I=Insert material	N/mm^2	$M^0L^0T^0$	Independent	Variable
10	g_c=Acceleration due to gravity	m/sec^2	LT^{-2}	Independent	constant

IV. Experimental setup

Boring machining processes shown in fig.1 is utilized for producing circular internal profiles in hollow work pieces by removing material from internal diameter surface of the work peace. The process of formulation of mathematical model for optimizing the Spindle Load in casting machining operation and its analysis is mentioned this paper. For experimentation purpose two levels for each independent parameter is taken. In Spindle Load optimization process, the objective of the experiment is used to gather information through experimentation for formulation of mathematical model for cast iron machining operation. During cast iron machining operations, the measurement of tool life, surface finish, bore size variation, operation time and spindle load is measured using meter scale, surface finish tester, digital dia. test plug gauges, digital stopwatch and current in % amp shown in fig. 3. These process parameters were listed in Table 2 (a) and used in experimental design for the investigation of process parameters like cutting speed, nose radius, length, diameter and material of the cutting tool, cutting fluid pressure and concentration and depth of cut for casting machining operation. The observed values for tool life, surface finish, bore size variation, operation time and spindle load are recorded for formulation of mathematical model shown in Table 2(b). Different instruments for measurements illustrated in Fig.2.

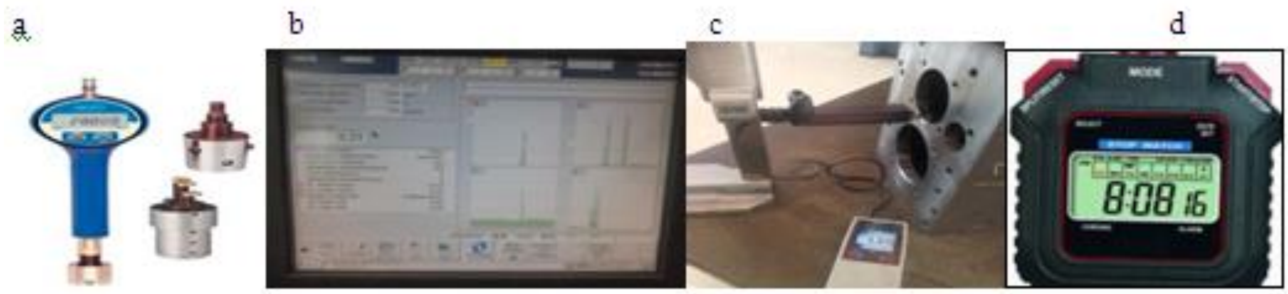


Figure 2 (a) Digital diatest gauge for measuring bore size variation; (b) Am meter for measuring spindle load in % current; (c) Portable surface roughness tester for measuring surface roughness; (d) Digital stop watch

Table2: a) Test envelope, test points

Pi term	Equation	Test envelope	Test Points	Independent variables with its own range
Π_1	Tool geometry Parameters: $(LDpcNR/D^3)$	(0.000162 to 0.0012096)	0.000162 0.000227 0.00025 0.00028 0.000324 0.00035 0.000392 0.000432 0.000454 0.0005 0.00056 0.000605 0.0007 0.000784 0.000864 0.00121	L, mm-175,270 Dpc, mm-0.5,0.7 NR, mm – 0.4, 0.8 D, mm- 50,60
Π_2	Cutting speed:	(0.46923	0.469237	g, mm/sec^2-9810,

	$(Vc/(Dg)^{0.5})$	to 0.706782)	0.514024 0.645201 0.706782	D, mm- 50,60, Vc-mm/sec^2-360,495
Π_3	Coolant concentration & Pressure: $(g.Cc/Pc.D^5)$	(4.21E-06 to1.88E-05)	4.21E-06 5.05E-06 6.31E-06 7.57E-06 1.05E-05 1.26E-05 1.57E-05 1.88E-05	g, mm/sec^2-9810, Pc-N/mm^2-10,15, D,mm-50,60, Cc, N/mm3- 5, 6
Π_4	Material Hardness: (Hm/Pc)	(1831.2 to 4414.5)	1831.2 2746.8 2943 4414.5	Hm, N/mm^2- Tn Carbide-27468, CBN-44145, Pc, N/mm^2-10,15

Table2: b) Sample of Reading according to plan of experimentation

-1	270	60	0.7	0.4	495	15	6	CBN							
1	175	50	0.5	0.8	360	10	5	Carbide			1.5 to 7.5	2 to 12	40 to 150	4 to 20	10 to 30
	mm	mm	mm	mm	mm/s	N/mm2	N/mm3	_			%	mm	mm	mm	sec
	L	D	DOC	Nr	Vc	Pc	Cc	Im			Amp(SL)	Ra	TL	Bv	T
	Length	Diameter	Depth of cut	Nose Radius	Cutting Speed	Coolant Pressure	Coolant Concen.	Insert Material	Material Hardness in N/mm2	g	Spindle Load	Surface Finish	Tool Life	Bore Variation	Cutting Time
unOrder	A	B	C	D	E	F	G	H							
1	270	60	0.7	0.4	360	10	6	CBN	44145	9810	5.1	4.9	80	0.008	26
2	175	60	0.7	0.8	360	10	6	CBN	44145	9810	2.6	2.1	105	0.003	26
3	270	50	0.7	0.8	495	15	5	Carbide	27468	9810	9.9	9.3	45	0.012	16
4	270	60	0.7	0.8	495	15	6	Carbide	27468	9810	5.4	5.6	60	0.009	16
5	270	50	0.7	0.4	360	15	6	CBN	44145	9810	9.6	8.1	95	0.006	26
6	270	60	0.5	0.4	360	10	6	Carbide	27468	9810	4.1	3.9	65	0.006	26
7	175	60	0.7	0.4	360	10	5	CBN	44145	9810	2.9	3.1	115	0.003	26
8	270	60	0.7	0.8	495	10	5	Carbide	27468	9810	9.8	9.9	41	0.013	16
9	270	50	0.5	0.4	360	10	5	Carbide	27468	9810	8.2	7.2	70	0.007	26
10	175	50	0.7	0.8	360	10	6	Carbide	27468	9810	3.2	4.1	82	0.003	26

V. DESIGN OF EXPERIMENTS

In this study, 128 experiments were designed on the basis of sequential classical experimental design technique that has been generally proposed for engineering applications, Hilbert Schank [14]. The basic classical plan consists of holding all but one of the independent variables constant and changing this one variable over its range. The main objective of the experiments consists of studying the relationship between 09 independent process parameters with the 05 dependent responses for Spindle Load optimization. Simultaneous changing of all 09 independent parameters was cumbersome and confusing. Hence all 09 independent process parameters were reduced by dimensional analysis. Buckingham's π theorem was adapted to develop dimensionless π terms for reduction of process parameters .This approach helps to better understand how the change in the levels of any one process parameter of a π terms affects 05 dependant responses for cast iron boring machining operation. Out of five response/dependant variables one dependant variables Spindle Load is detailed discussed in this paper. A combination of the levels of parameters, which lead to maximum, minimum and optimum response, can also be located through this approach. Regression equation models of Spindle Load were optimized by mini-max principle, Modak et al [12] [13] & Rao [15].

V-I : Formulation of Approximate Generalized Experimental Data Base Model By Dimensional Analysis

As per dimensional analysis, Sakhale at al. [16] Spindle Load S_L was written in the function form as :-

$$S_L = f\,(L, V_c, D_{pc}, N_R, D, P_c, C_c, H_m, g) \qquad (1)$$

By selecting Mass (M), Length (L), and Time (T) as the basic dimensions, the basic dimensions of the forgoing quantities were mentioned in table 1:

According to the Buckingham's - theorem, (n- m) number of dimensionless groups are forms. In this case n is 11 and m=3, so π1 to π9 dimensionless groups were formed. By choosing 'Pc', 'g' and 'D' as a repeating variable, eleven π terms were developed as follows:

$$(S_L) = f\left\{\left(\frac{L}{D}\right)\left(\frac{D_{pc}}{D}\right)\left(\frac{N_R}{D}\right)\left(\frac{V_c}{\sqrt{g.D}}\right)\left(\frac{g.C_c}{P_c.D^5}\right)\left(\frac{H_m}{P_c}\right)\right\} \qquad (2)$$

V-II : Reduction of independent variables/dimensional analysis

Deducing the dimensional equation for a phenomenon reduces the number of independent variables in the experiments. The exact mathematical form of this dimensional equation is the targeted model. This is achieved by applying Buckingham's π theorem When n (no. of variables) is large, even by applying Buckingham's π theorem number of π terms will not be reduced significantly than number of all independent variables. Thus, much reduction in number of variables is not achieved. It is evident that, if we take the product of the π terms it will also be dimensionless number and hence a π term. This property is used to achieve further reduction of the number of variables. Thus few π terms are formed by logically taking the product of few other π terms and final mathematical equations are given below:

$$\left\{\left(\frac{L}{D}\right)\left(\frac{D_{pc}}{D}\right)\left(\frac{N_R}{D}\right)\right\} = \left\{\left(\frac{L.D_{pc}.N_R}{D^3}\right)\right\} \qquad (3)$$

V-III : Test planning

This comprises of deciding test envelope, test points, test sequence and experimentation plan for deduced set of dimensional equations. Table 2 (a) shows Test envelope, test points for boring operation.

V-IV : Model Formulation

The relationship between various parameters was unknown. The dependent parameter Π_{01} i.e. relating to S_L was be an intricate relationship with remaining terms (ie. π_1 to π_4) evaluated on the basis of experimentation. The true relationship is difficult to obtain. The possible relation may be linear, log linear, polynomial with n degrees, linear with products of independent πi terms. In this manner any complicated relationship can be evaluated and further investigated for error. Hence the relationship for S_L was formulated as:

$\pi_{01}=k_1 x(\pi_1)^{a1} x(\pi_2)^{b1} x(\pi_3)^{c1} x(\pi_4)^{d1}$ (4)

Equation is modified as: Obtaining log on both sides we get,

$\text{Log}\pi_{01}=\log k1+a_1\log\pi_1+b_1\log\pi_2+c_1\log\pi_3+d_1\log\pi_4$ (5)

This linear relationship now can be viewed as the hyper plane in seven dimensional spaces. To simplify further let us replace log terms by capital alphabet terms implies,

Let, $Z_1= \log \pi_{0\,1,}$ $K_1 = \log k1,$ $A = \log \pi_{1,}$ $B = \log \pi_2$ $C = \log \pi_{3,}$ $D= \log \pi_4,$

Putting the values in equations 5, the same can be written as

$Z_1 = K_1+ a_1 A+ b_1 B + c_1 C+ d_1 D$ (6)

This is true linear relationship between A to D to reveal π_{01}, i. e. log S_L. Applying the theories of regression analysis, the aim is to minimize the error (E) = Ye – Yc. Yc is the computed value of π_{01} using regression equation and Ye is the value of the same term obtained from experimental data with exactly the same values of π_1 to π_4. The comparison of computed (Model) and Experimental data is shown in figure 3 for general and clubbed model. Table 3 shows the Statistical comparison between computed (Model) and Experimental data.

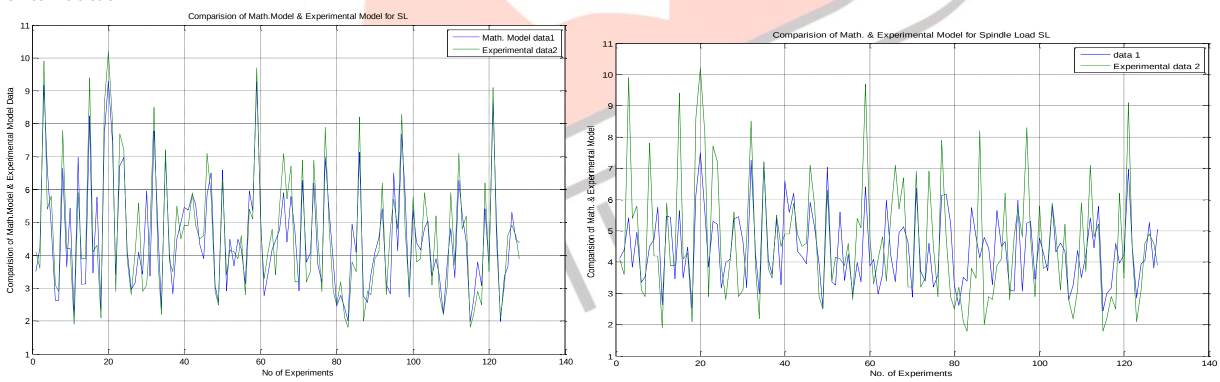


Figure 3: Comparison between Model and Experimental Data of SL Model

Table3: Statistics of SL General and clubbed model

	Data	General Model		Clubbed Model	
		Experimental	**Model**	**Experimental**	**Model**
min	1	1.8	1.975	1.8	2.447
max	128	10.2	9.259	10.2	7.506
mean	64.5	4.644	4.572	4.644	4.431
median	64.5	4.2	4.284	4.2	4.285
mode	1	2.9	1.975	2.9	2.447
std	37.09	1.91	1.678	1.91	1.155
range	127	8.4	7.314	8.4	5.06

Thus, Model formulation 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. Mathematical model for cast iron boring machining operation is shown below:

Π_{01}= Mathematical Equation for Spindle Load S_L:

$$S_L(\pi_{01}) = 117.1925489\left\{\left(\frac{L.D_{pc}.N_R}{D^3}\right)^{0.7271}\left(\frac{V_c}{\sqrt{g.D}}\right)^{0.4662}\left(\frac{g.C_c}{P_c.D^5}\right)^{-0.1603}\left(\frac{H_m}{P_c}\right)^{0.0879}\right\} \quad (7)$$

V-V : Clubbed Mathematical Term

In this type of model all the Pi terms i.e. π_1,π_2,π_3 and π_4 are multiplied (clubbed) together and then using regression analysis mathematical model is formed. The mathematical clubbed model for cast iron boring machining operation is shown below:

$$S_L - Clubbed\ (\pi_{01}) = 87.9225\left\{\left(\frac{L.D_{pc}.N_R}{D^3}\right)\left(\frac{V_c}{\sqrt{g.D}}\right)\left(\frac{g.C_c}{P_c.D^5}\right)\left(\frac{H_m}{P_c}\right)\right\}^{0.2528} \quad (8)$$

V-VI: R^2 = Co-efficient of Determination for Ra model

A statistical method that explains how much of the variability of a factor can be caused or explained by its relationship to another factor. Coefficient of determination is used in trend analysis. It is computed as a value between 0 (0 percent) and 1 (100 percent). The higher the value, the better the fit. Coefficient of determination is symbolized by r2 because it is square of the coefficient of correlation symbolized by r. The coefficient of determination is an important tool in determining the degree of linear-correlation of variables ('goodness of fit') in regression analysis. Also called r-square. It is calculated using relation shown below:
$R^2 =1- \sum Yi-fi)^2/\sum(Yi-Y)^2$
Where, yi= Observed value of dependent variable for i^{th} Experimental sets (Experimental data), fi=Observed value of dependent variable for i^{th} predicted value sets (Model data), Y= Mean of Yi and R^2 = C0-efficient of Determination
From calculation the value of R^2 for general Model is 0.83 and clubbed model is 0.40. A value of General Model indicates a nearly perfect fit, and therefore, a reliable model for future forecasts. A value of clubbed model, on the other hand, would indicate that the model fails to accurately model the dataset. This shows that General Model gives better accuracy results as compared to clubbed model.

VI. Reliability of Model

Reliability of model is established using relation Reliability =100-% mean error and Mean error $=\left(\frac{\sum xi \times fi}{\sum xi}\right)$ where, xi is % error and fi is frequency of occurrence. Therefore the reliability of General model and Clubbed Model are equal to 85.89063% and 74.78125% respectively. Figure shown 4 graphs between % of Error and frequency occurrence of error for general and clubbed model.

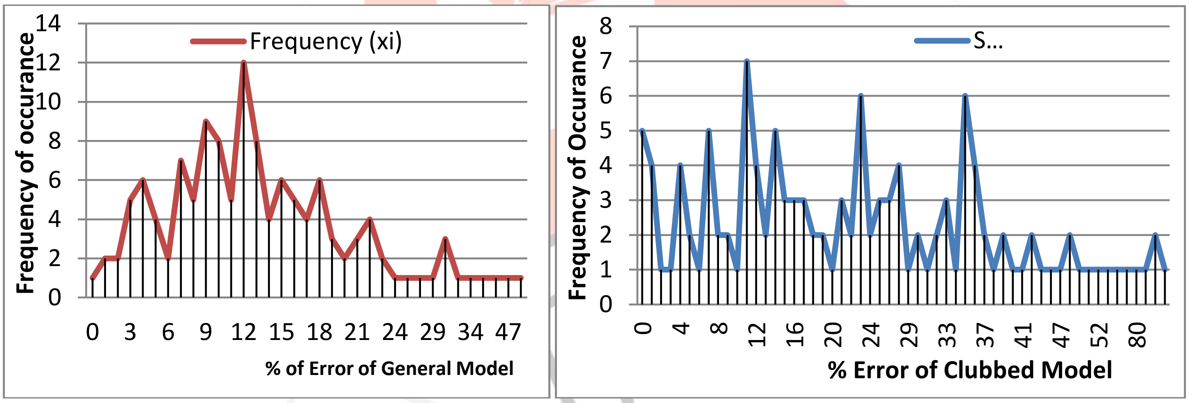


Figure 4: Graph between % of Error and frequency occurrence of error for general and clubbed model.

VII. Estimation of Limiting Values Of Response Variables

The ultimate objective of this work is to find out best set of variables, which will result in maximization/minimization of the response variables. In this section attempt is made to find out the limiting values of eight response variables viz.cutting speed, nose radius, length, diameter and material of the cutting tool, cutting fluid pressure and concentration and depth of cut. To achieve this, limiting values of independent π term viz. π1, π2, π3, π4, are put in the respective models. In the process of maximization, maximum value of independent π term is substituted in the model if the index of the term was positive and minimum value is put if the index of the term was negative. The limiting values of these response variables are compute for cast iron boring machining operation is as given in Table 4.

Table 4: Limiting Values of Response Variables (Spindle Load : Amp)

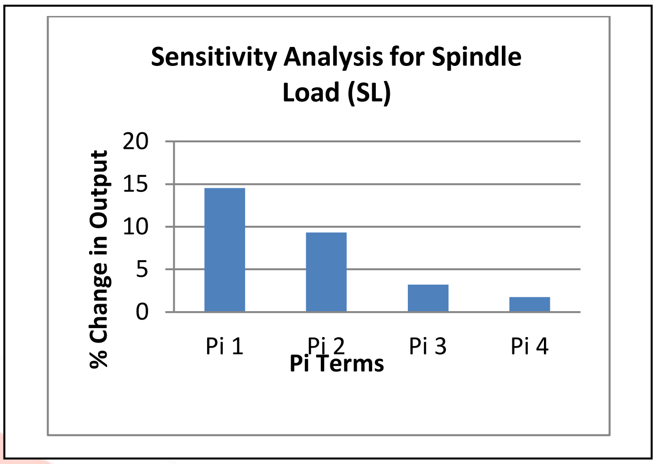
Max and Min. of Response π terms	Boring Operation
	SL- SPINDLE LOAD (Π_{01})
Maximum	11.4714188
Minimum	1.599301788

VIII. SENSITIVITY ANALYSIS

The influence of the various independent π terms has been studied by analyzing the indices of the various π terms in the models. The technique of sensitivity analysis, the change in the value of a dependent π term caused due to an introduced change in the value of individual π term is evaluated. In this case, of change of ± 10 % is introduced in the individual independent π term independently (one at a time).Thus, total range of the introduced change is 20 %. The effect of this introduced change on the change in the value of the dependent π term is evaluated .The average values of the change in the dependent π term due to the introduced change of ± 10 % in each independent π term. This defines sensitivity. Nature of variation in response variables due to increase in the values of independent pi terms is given in table 5.

Table 5: Sensitivity Analysis for Boring Operation

Pi 1	Pi 2	Pi 3	Pi 4	Spindle Load (SL)
0.000506	0.583811	1.00851E-05	2983.875	**4.674689582**
0.000556	0.583811	1.00851E-05	2983.875	**5.010134659**
0.000455	0.583811	1.00851E-05	2983.875	**4.329946257**
			% Change	**14.55045068**
0.000506	**0.583811**	1.00851E-05	2983.875	**4.674689582**
0.000506	**0.642192**	1.00851E-05	2983.875	**4.887086738**
0.000506	**0.52543**	1.00851E-05	2983.875	**4.45062123**
			% Change	**9.336780562**
0.000506	0.583811	**1.00851E-05**	2983.875	**4.674689582**
0.000506	0.583811	**1.10936E-05**	2983.875	**4.603811462**
0.000506	0.583811	**9.0766E-06**	2983.875	**4.754312266**
			% Change	**3.219482298**
0.000506	0.583811	1.00851E-05	**2983.875**	**4.674689582**
0.000506	0.583811	1.00851E-05	**3282.263**	**4.714017542**
0.000506	0.583811	1.00851E-05	**2685.488**	**4.631596253**
			% Change	**1.763139308**



IX. MODEL OPTIMIZATION

In this case there is model corresponding to Spindle Load for boring operations. This is the objective functions corresponding to these models. These models have nonlinear form; hence it is to be converted into a linear form for optimization purpose. This can be achieved by taking the log of both the sides of the model. The linear programming technique is applied which is detailed as below for cast iron boring machining operation.

$$S_L(\pi_{01}) = 0.109900583(D)\left\{\left(\frac{L.D_{pc}.N_R}{D^3}\right)^{-0.1547}\left(\frac{V_c}{\sqrt{g.D}}\right)^{-0.1573}\left(\frac{g.C_c}{P_c.D^5}\right)^{0.1253}\left(\frac{H_m}{P_c}\right)^{0.357}\right\} \quad (9)$$

Taking log of both the sides of the Equation 9, we get

$$S_L(\pi_{01}) = 117.1925489\left\{\left(\frac{L.D_{pc}.N_R}{D^3}\right)^{0.7271}\left(\frac{V_c}{\sqrt{g.D}}\right)^{0.4662}\left(\frac{g.C_c}{P_c.D^5}\right)^{-0.1603}\left(\frac{H_m}{P_c}\right)^{0.0879}\right\} \quad (10)$$

Taking log of both the sides of the Equation 9, we get

$\text{Log}(\Pi_{01})=\log(K)+0.7271.\log\left(\frac{L.D_{pc}.N_R}{D^3}\right)+0.4662.\log\left(\frac{V_c}{\sqrt{g.D}}\right)-0.1603.\log\left(\frac{g.C_c}{P_c.D^5}\right)+0.0879\ \log\left(\frac{H_m}{P_c}\right)$ (11)

$Z = K+ K_1+ a \times X_1+ b \times X_2+ c \times X_3+d \times X_4$ and

$Z = \log(117.1925489) + 0.7271.\log\ (\pi_1)+0.4662\ \log(\pi_2)-0.1603.\log(\pi_3)+0.0879.\log\ (\pi_4)$ (12)

Z (Spindle load: Π_{01} max) = $2.0689+ 0.7271 X_1+ 0.4662 X_2-0.1603 X_3+ 0.0879 \times X_4$ (13)

Subject to the following constraints

$1 \times X_1+ 0 \times X_2 + 0 \times X_3 + 0 \times X_4 \le -2.91736$
$1 \times X_1+ 0 \times X_2 + 0 \times X_3 + 0 \times X_4 \ge -3.79039$
$0 \times X_1+ 1 \times X_2 + 0 \times X_3 + 0 \times X_4 \le -0.15071$
$0 \times X_1+ 1 \times X_2 + 0 \times X_3 + 0 \times X_4 \ge -0.32861$
$0 \times X_1+ 0 \times X_2 + 1 \times X_3 + 0 \times X_4 \le -4.72503$
$0 \times X_1+ 0 \times X_2 + 1 \times X_3 + 0 \times X_4 \ge -5.37621$
$0 \times X_1+ 0 \times X_2 + 0 \times X_3 + 1 \times X_4 \le 3.644882$
$0 \times X_1+ 0 \times X_2 + 0 \times X_3 + 1 \times X_4 \ge 3.262736$

(14)

On solving the above problem by using MS solver we get values of X_1,X_2,X_3,X_4 and Z. Thus Π_{01min} = Antilog of Z and corresponding to this value of the Π_{01min} the values of the independent pi terms are obtained by taking the antilog of X_1,X_2,X_3,X_4 and Z. Similar procedure is adopted to optimize the models for Π_{01min}. The optimized values of Π_{01max} are tabulated in the following table 6.

Table 6: Optimize values of response variables for cast iron boring machining operation

	Spindle Load : Π_{01} min	
	Log values of π terms	Antilog of π terms
Z	**0.203930423**	**1.5996**
X_1	-3.790385707	0.000162037
X_2	-0.328607628	0.469237132
X_3	-4.725029764	1.88352E-05
X_4	3.26273578	1831.2

X. DISCUSSION OF 3D AND 2D GRAPHS

In boring operation there are four independent π terms and two dependent π terms. It is very difficult to plot a 3D graph. To obtain the exact 3D graph dependent π terms is taken on Z-axis whereas from four independent π-terms, two are combined and a product is obtained which is presented on X-axis. Whereas remaining two independent π terms are combined by taking product and represented on Y-axis. Fig. 5 and fig.6 shows 3D and 2D graphs for three dependent terms i.e. Spindle Load. From 3D and 2D graphs it is observed that the phenomenon is complex because of variation in the dependent Π terms are in a fluctuating form mainly due to cutting speed and diameter of the tool body. This in turn is due to linearly varying cutting speed, nose radius, length, diameter and material of the cutting tool, cutting fluid pressure and concentration and depth of cut.

For Spindle Load there are 7 peaks in graph of torque i.e. SL vs. X (shown in fig.6(a)). There must be in all 14 mechanisms responsible for giving these 14 peaks. Whereas, in graph of SL vs. Y, there are 13 peaks. Hence there must be in all 26 mechanisms are responsible for giving these13 peaks. This is based on reasoning given as regards deciding number of physical mechanisms prevalent in any complex phenomenon in a course work, [16] Research Methodology in Engineering and Technology by Modak J.P. [12].

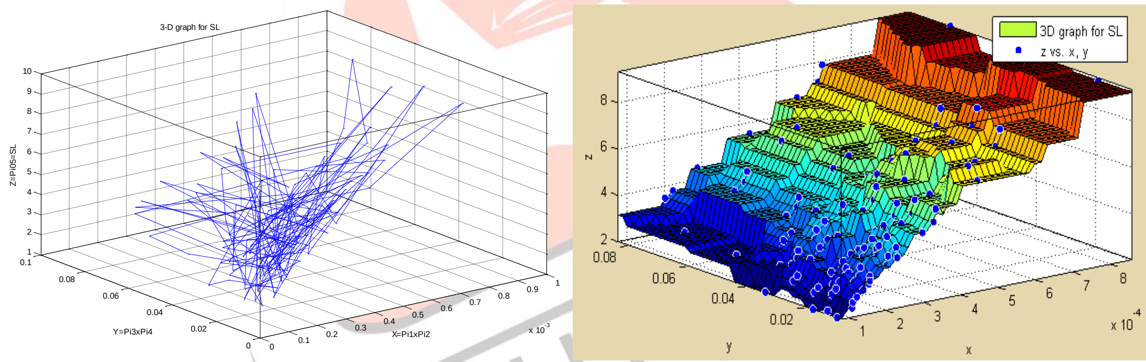


Figure 5: 3 D Graph of SL (X=Pi1xPi2, Y=Pi3xPi4 vs Z=S_L)

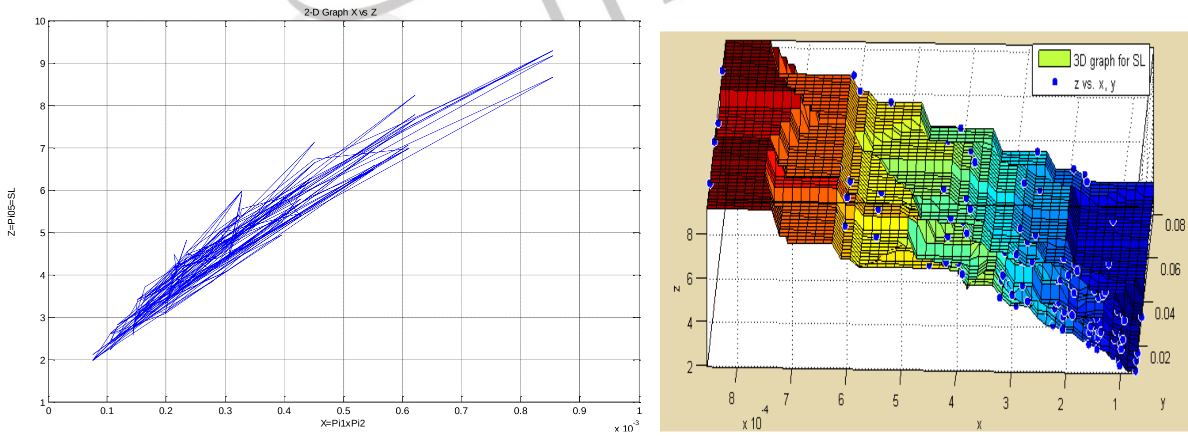


Fig. 6.a) X=Pi1xPi2 vs Z=S_L

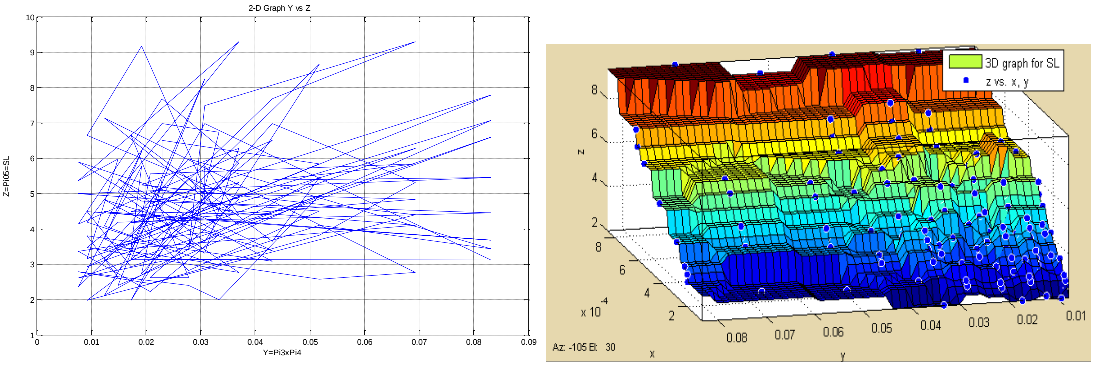


Fig. 6.b) Y=Pi3xPi4 vs Z=S_L

Figure 6: 2 D Graph of S_L

XI. Computation of The Predicted Values By 'ANN '

In this research the main issue is to predict the future result. In such complex phenomenon involving non-linear system it is also planned to develop Artificial Neural Network (ANN). The output of this network can be evaluated by comparing it with observed data and the data calculated from the mathematical models. For development of ANN the designer has to recognize the inherent patterns. Once this is accomplished training the network is mostly a fine-tuning process.

An ANN consists of three layers (representing the synapses) and the output layer .It uses nodes to represent the brains neurons and these layers are connected to each other in layers of processing. The specific mapping performed by ANN depends on its architecture and values of synaptic weights between the neurons .ANN as such is highly distributed representation and transformation that operate in parallel and has distributed control through many highly interconnected nodes. ANN were developed utilizing this black box concepts. Just as human brain learns with repetition of similar stimuli, an ANN trains itself within historical pair of input and output data usually operating without a priory theory that guides or restricts a relationship between the inputs and outputs. The ultimate accuracy of the predicted output, rather than the description of the specific path(s) or relationship(s) between the input and output, is the goal of the model .The input data is passed through the nodes of the hidden layer(s) to the output layer, a nonlinear transfer function assigns weights to the information as it passes through the brains synapses. The role of ANN model is to develop a response by assigning the weights in such a way that it represents the true relationship that really exists between the input and output. During training, the ANN effectively interpolates as function between the input and output neurons. ANN does not an explicit description of this function. The prototypical use of ANN is in structural pattern recognition. In such a task, a collection of features is presented to the ANN; it must be able to categories the input feature pattern as belonging to one or more classes. In such cases the network is presented with all relevant information simultaneously. The results of ANN are shown in fig. 7 and 8.

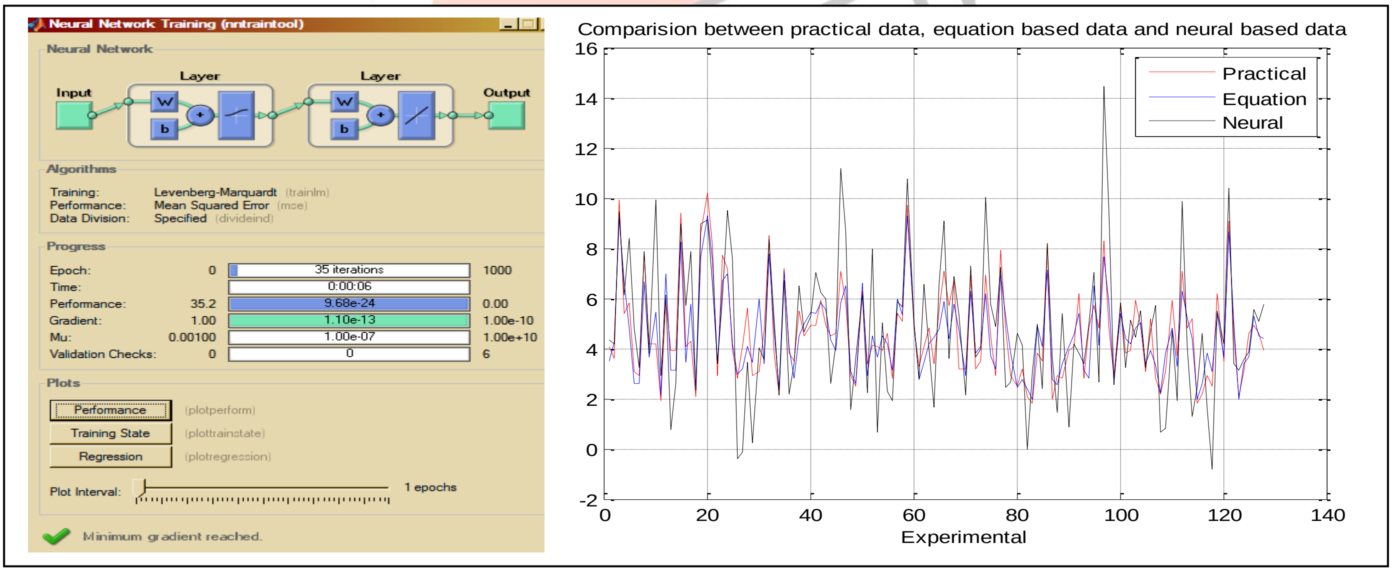


Figure 7. (a) Neural Network Model (b) Comparison of results of Experimental, Model and ANN

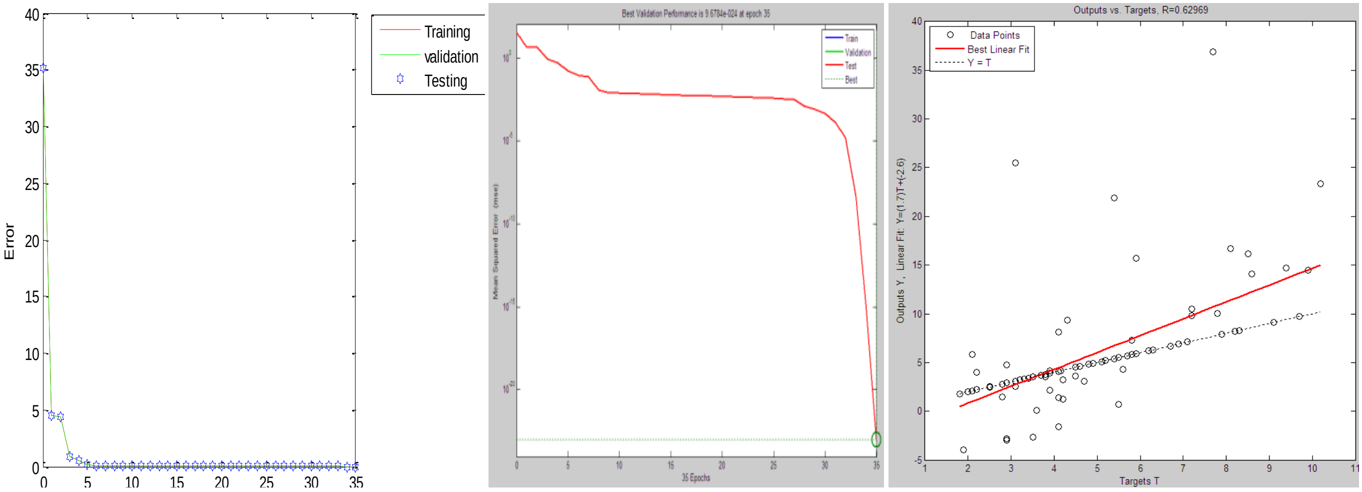


Figure 8 (a) Training and validation of ANN (b) Best fit curve for boring operation (for Π_{01})

XII. ANALYSIS OF SPINDLE LOAD MODELS-DEPENDENT TERM Π_{01}

Π_{01}= Mathematical Equation for Spindle Load S_L:

$$S_L(\pi_{01}) = 117.1925489\left\{\left(\frac{L.D_{pc}.N_R}{D^3}\right)^{0.7271}\left(\frac{V_c}{\sqrt{g.D}}\right)^{0.4662}\left(\frac{g.C_c}{P_c.D^5}\right)^{-0.1603}\left(\frac{H_m}{P_c}\right)^{0.0879}\right\} \qquad (15)$$

The following primary conclusions appear to be justified from the above model.

1] The absolute index of π_1 is highest index of Π_{01} viz. 0.7271. The factor 'π_1' is related to tool geometry parameters is the most influencing term in this model. The value of this index is positive indicating involvement of tool geometry parameters has strong impact on $\Pi_{01.}$

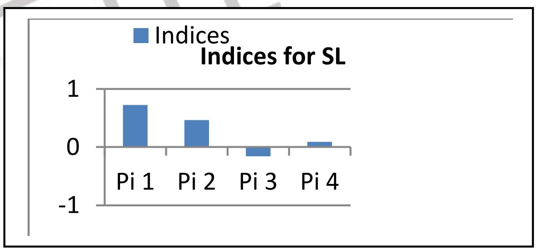
2] The absolute index of $\pi_{4,}$ is lowest index of Π_{01} viz. 0.0879. The factor 'π_4' is related to Material Hardness is the least influencing term in this model.

3] The negative index of $\pi_{3,}$ is lowest index of Π_{01} viz. -0.1603. The factor 'π_3' is related to Coolant concentration & Pressure is the least influencing term in this model. The value of this index is negative indicating inversely varying.

3] The indices of dependent terms are shown in Fig.9 and table 6. The negative indices are indicating need for improvement. The negative indices of Π_{01} are inversely varying with respect to π_2 respectively.

Table 7. Constant and Indices of Response variable $\Pi_{01,}$ Spindle Load (S_L)

Pi terms	**Spindle Load**
K	2.0689
Π_1	0.7271
Π_2	0.4662
Π_3	-0.1603
Π_4	0.0879



4] From above it is cleared that value of constant is more than 1 for model $\Pi_{01,}$ hence it has magnification effect in the value computed from the product of the various terms of the model.

5] Sensitivity analysis (from table 5) of cast iron boring machining operation indicates tool geometry parameters is most sensitive and Material Hardness is least sensitive for model Π_{01} and hence needs strong improvement.

The comparison of experimental, mathematical model and ANN models cast iron boring machining operations are shown in the table 6.

Table 8 Error Estimation for cast iron boring machining Operation

Mean /Error	**Spindle Load**
meanexp	4.6441
meanann	4.8232
meanmath	4.5719
mean_absolute_error_performance_function	1.4409
mean_squared_error _performance_function	3.5360
perf	347.5989

XIII. Response Surface Methodology for the boring operation for calculation of Spindle Load

This section describes the use of response surface methodology in the Boring Machining operation.

XIII.I: "Response Surface Methodology approach"

This section describes the basic of response surface methodology.

Surface Response Method: The response surface methodology, or RSM, is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influence by several variables and the objectives is to optimize this response

The equation for the RSM is

$$y = f(x1, x2) + \varepsilon \qquad (16)$$

where, x1 , x2 are process parameters and ε represents error observed in the response y.

if we denote the expected responses by

$$E(y) = f(x1, x2) = \eta \qquad (17)$$

Then the surface represented by

$\eta = f(x1, x2)$ is called a response surface.

In most RSM applications, the form of relationship between the response and the independent variables is unknown. Thus the first step in RSM is to find a suitable approximation for the true functional relationship between y and the set of independent variables. Usually a low order polynomial in some region of independent variables is employed. If the response is well modeled by a linear function of independent variables, then the approximating function is the first order model.

$$y = \beta 0 + \beta 1x1 + \beta 2x2 + \text{----------------} + \beta k\, xk + \varepsilon \qquad (18)$$

If there is a curvature in the system, then the polynomial of higher degree must be used such as the second order model.

$$y = \beta 0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum \sum_{i<1}^{k} \beta_{ij} x_i x_j + \varepsilon \qquad (19)$$

The response surface analysis is then performed using the fitted surface. If the fitted surface is an adequate approximation of the true response function then the analysis of the fitted surface will be approximately equivalent to the analysis of the actual data.

XIII.II: Response Surface Design

As per the dimensional analysis, seven π terms are developed. These π terms are dimensionless hence it is very easily possible to convert into three groups. These three groups are converted into 3 dimensions in space to develop response surface. Hence

$$X = \pi_1 \times \pi_2, Y = \pi_3 \times \pi_4, Z_1 = \pi_{01} \qquad (20)$$

The ranges of input X , Y and output Z are more variant . Hence by using scaling principle, the above X , Y and Z values are scaled as follows :

$$x = X / \max(X),\ y = Y / \max(Y),\ \text{and } z = Z / \max(Z) \qquad (21)$$

XIII.III: RSM Model Development

The 128 experiments were conducted, with the process parameter levels set as given in experimental table to study the effect of process parameters over the output parameters.

The experiments were designed and conducted by employing response surface methodology (RSM). The selection of appropriate model and the development of response surface models have been carried out by using statistical software, "MATLAB R2009a". The best fit regression equations for the selected model were obtained for the response characteristics, viz., Spindle Load. The response surface equations were developed using the experimental data and were plotted (Fig.9) to investigate the effect of process variables on various response characteristics.

For Response variable Spindle Load, response surface equation is

$$f(x,y) = S_L = -0.1178 + 3.728\ .x + 0.6025\ .y - 8.535\ x^2 - 6.856\ .xy + 2.056\ .y^2 + 17.93\ .x^3 - 7.482\ x^2y + 22.38\ xy^2 - 14.49\ y^3 - 25.13\ x^4 + 48.19\ x^3y - 53.52\ x^2y^2 + 7.525\ xy^3 + 16.24\ y^4 + 12.18\ x^5 - 26.88\ x^4y + 9.798\ x^3 * y^2 + 22.11\ x^2y^3 - 13.33\ xy^4 - 5.334\ y^5$$

SSE: 0.7758, R-square: 0.8258, Adjusted R-square: 0.7933, RMSE: 0.08515 (22)

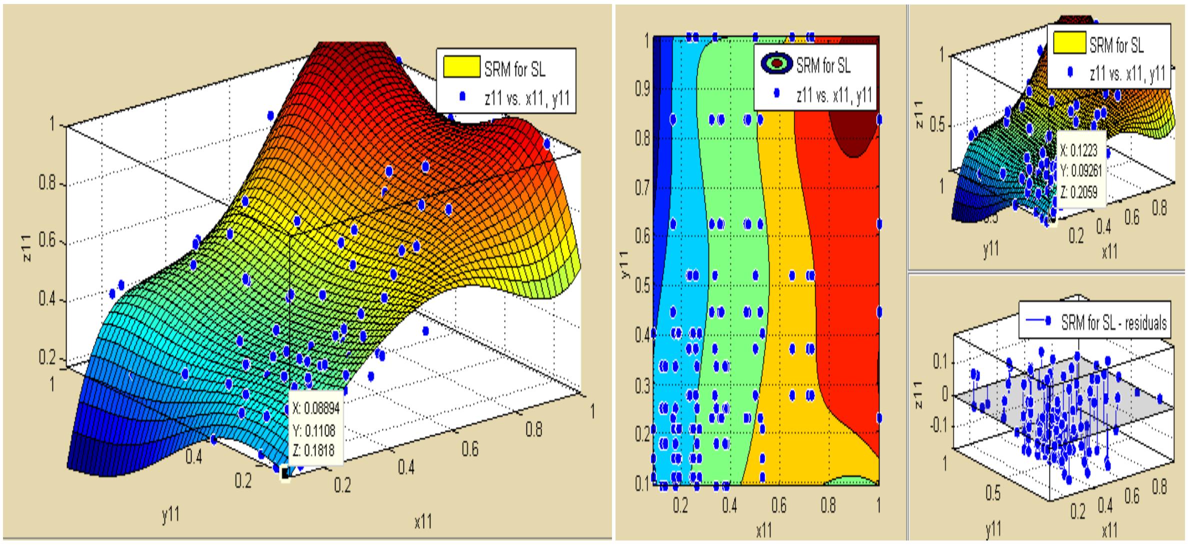


Figure 9 : a) RSM model b) Contour plot for Spindle Load

XIV. CONCLUSIONS

1. The dimensionless π terms have provided the idea about combined effect of process parameters in that π terms. A simple change in one process parameter in the group helps the manufacturer to maintain the required S_L values so that to get decreased Spindle Load.
2. The mathematical models developed with dimensional analysis for different combinations of parameters for cutting speed, nose radius, length, diameter and material of the cutting tool, cutting fluid pressure and concentration and depth of cut can be effectively utilized for cast iron boring machining operations.
3. The computed selection of cast iron boring machining operation parameters by dimensional analysis provides effective guidelines to the manufacturing engineers so that they can minimize Spindle Load for higher performances.

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