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Mathematical Models of Material Removal Rate & Power Consumption for Dry Turning of Ferrous Material using Dimensional Analysis in Indian Prospective

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Abstract

Material Removal Rate (MRR) & Power Consumption (PC) prediction models using Dimensional Analysis (DA) have been developed to examine the effects of machining field parameters. En1A, En8 and S.S.304 were considered as a ferrous material for the dry turning process. The DA models of MRR & PC have been developed with machining field parameters. The parameters were the operator performing the turning operation, the cutting tool used to remove the material, the work piece, the cutting process parameters, such as cutting speed, feed rate, depth of cut etc., and lathe machining specifications and the turning environmental parameters, such as humidity, atmospheric temperature, air circulation, noise level, and light illumination etc. The experiments were planned according to a random plan of experimentations and the seasonal conditions in India. The mathematical models with few variables can be easily formulated with traditional methods, such as Response Surface Method (RSM). But it is seen that for large numbers of variables the traditional modelling tools could not be unproblematic in very less time. For this, an attempt has been made to formulate the model by using dimensional analysis techniques followed by the analysis, i.e., optimization and sensitivity analysis.

In order to develop DA model, the Buckingham's pi theorem (BPIT) was used to group the variables. The linear programming using Ms-solver was used to perform the optimization and the sensitivity analysis for the model developed. The results reveal that the cutting condition and the lathe machine parameters have significant effects on the material removal rate and the power consumption, while the tool and the environment have the least effect. The developed DA models can be used for selecting the best set of input parameters which improve MRR and reduce PC.

Keywords: *Material Removal Rate, Power Consumption, Dry Turning, Dimensional Analysis, Ms-solver, Optimization, Sensitivity Analysis.*

1. Introduction

Material Removal Rate (MRR) and Power Consumption (PC) are the most significant parameters to assess the productivity of machining industry as well as machined tools. Hence, achieving the maximum MRR and minimizing the PC are of great importance for the performance analysis of the machining industry. MRR and PC are used as an indicator for the machining process and have an influence on several performance parameters, such as human utilization, use of the machine and productivity measures. In today's manufacturing industry, a special attention is given to cost, time, dimensional accuracy and surface finish. From an Indian perspective, convectional turning is a crucial and most essential operation in most of the production processes industry. The turning operation produces the components, which have critical features that require specific surface finish. Due to inadequate technical knowledge and factors affecting the MRR & PC in turning operation to improve the productivity, an improper decision may cause more machining time, higher production costs and lower machining quality. The proper selection of the operator, the cutting tools machine, the process parameters and the suitable environment for achieving a higher cutting performance, i.e., MRR & PC, in a dry turning operation is a critical task. Hence a proper estimation of different parameters affecting the MRR and PC is the focus of the present study. Researchers have developed various mathematical models to predict the surface roughness in terms of various process parameters during the turning of different materials. The model development by Response Surface Method (RSM), suggested by Montgomery, was an easy and convenient

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method for the industry, which requires less experiments to be conducted, thus, reducing the cost and time of the experimentations. However, the RSM-based models have been restricted to a small range of independent input parameters only, and hence are not suitable for actual highly complex and non-linear processes. The man machine system use in the convectional machining environment, in the Indian context, is very complex and nonlinear in nature; hence it is very difficult to study and formulate the mathematical model for this system on the basis of RSM. In the past, with the developments in Artificial Neural Network (ANN), the researchers paid a great deal of attention to the solution of non-linear problems. A study was presented by S. S. Panda *et al.* [1] to predict the flank wear of the drill beat using back propagation neural network in drilling of mild steel work pieces. A neural network method was used by L. A. Dobrzanski *et al.* to study the mechanical properties of structured steel after heat treatment [2]. J. Paulo Davim *et al.* developed a model for the surface roughness parameters (R_a & R_t) with cutting condition as the cutting speed, the feed and the depth of the cut [3]. The objective of the ANN model development and prediction of the response is to replicate human brain so as to implement functions such as accuracy, association, self-organization and general. However, the different theoretical models do not take into account all the uncontrollable parameters.

A neural network was used by C. Natarajan *et al.* to predict the surface roughness [4]. ANN model was deliberated through back propagation network using MATLAB 7 software. Comparison of the observed data and ANN response proved that there was no significant difference and ANN was used assertively. A network method was used by Ilhan Asilturk to study the possessions of cutting parameters such as speed, feed, and depth of cut on surface roughness of AISI 1040 steel [5]. A full factorial experimental design was implemented to increase the assurance limit and dependability of the experimental data. ANN and multiple regression approaches were used to model the surface roughness of AISI 1040 steel. The ANN was likely to be competent for solving a convoluted crisis in a very proficient manner by distributing the acquaintance over the neurons and conducting parallel dispensation on information.

M.Cema Cakir *et al.* examined the special effects of cutting parameters (cutting speed, feed rate and depth of cut) onto the surface roughness through the mathematical model developed by using the data gathered from a series of turning experiments performed [6]. A further investigation was agreed upon in order to assess the weight of two well-known coating layers onto the surface roughness. For this purpose, the experiments were repetitive for two CNMG 120408 (with an ISO designation) carbide inserts having finally the same geometry and substrate but diverse coating layers, in a manner that indistinguishable cutting conditions would be ensured. S. M. Ali *et al*. developed ANN model for the prediction of tool wear and surface roughness as a function of cutting parameters [7;10]. The model proved to be booming in terms of agreement with investigational results. The planned model can be used in the optimization of the cutting process for proficient and profitable production by forecasting the tool wear and surface roughness in turning operations.The multilayer feed forward network consisting of four inputs, 25 hidden neurons (tangent sigmoid neurons) and four outputs (network architecture represented as 4-25-4 was found to be the optimum network for the model developed in this study. The back propagation learning algorithm was used in the developed feed forward single hidden layer network. A superior performance of the neural network was achieved with coefficient of determination (R^2) between the model prediction and the experimental values, which were 0.9915, 0.9906. M. F. F. Ab. Rashid *et al.* has developed a model using multiple regressions and artificial neural network model for artificial intelligent technique. Spindle speed, feed rate, and depth of cut have been selected as predictors in order to predict surface roughness [8; 9]. 27 samples were run by using FANUC CNC Milling α-T14E. The experiment was executed by using full factorial design. Analysis of variances shows that the most considerable parameter was feed rate followed by spindle speed and lastly depth of cut. Komanduri R. and Hou ZB reviewed the various techniques for the measurement of heat and the temperatures generated in various manufacturing processes and tribological applications [13]. They observed that the proper technique for a given thermal problem depended on the situation under consideration, such as the effortlessness of accessibility of the sensor to the location of the subject, spot size, dynamics of the situation, accuracy needed, cost of instrumentation, advancements in sensor technology, and data collection and analysis.

K. Kadirgama focused on the optimization of the surface roughness when milling Mould Aluminium alloys (AA6061-T6) with carbide coated insert to reduce cost and time for machining mould [14]. The approach was based on Response Surface Method (RSM) and Radian Basis Function Network (RBFN). This network was used to predict thrust force and surface roughness in drilling. In this effort, the objectives were to find the optimized parameters, and to find out the most prevailing variables (cutting speed, federate, axial depth and radial depth). The optimized value was used to develop a blow mould. Both RSM and RBFN model divulge that feed rate was the most significant design variable in determining surface roughness response as compared to others. With the model equations obtained, a designer can subsequently select the best amalgamation of design variables for achieving optimum surface roughness. This ultimately will reduce the machining time.

D. Dinakaran focused on an ultrasonic system to monitor the tool wear in the turning operation. This system reflected the wear region of flank wear [15]. Adaptive Neuro Fuzzy Inference System (ANFIS) was used to identify the tool wear. The experimental validation runs show the system can predict the tool wear with average error the Decision Making Algorithm (DMA) was presented to determine the status of wear. Ajay Goyal *et al.* [18] modified the previous author's coding at MATLAB® with small changes to determine the temperature rise distribution at chip side due to primary deformation zone. The modified MATLAB coding was simple to gain temperature rise contour in a few seconds early during the turning operation. The author validated the result with the already obtained results of scientists at the time. The developed coding was used for EN31 Steel only when the work piece turned with MTCVD coated carbide inserts. The experimental data were used to generate temperature rise contour graphs for every experiment from developed coding. From the findings, it was observed that the cutting parameters were directly proportional to the developed forces and temperature rise during machining. Influence of Cutting Velocity was most and Depth of Cut was least.

Ajay Goyal *et al.* [19] tested mathematical model(s) which serve(s) the purpose in a better way. The developed mathematical model(s) was/were practical and profitable as compared to the experimental methods for the set of the machining parameters. A numeral of mathematical methods was developed, and the results were compared with authenticity. In the present paper, the author has taken the efforts to review and systemize the study of all the most important analytical methods that have been developed through history to identify the prospect scope of research. Further, a qualified study of the virtues and the demerits of the experimental methods for measurement of temperature rise that were developed in the past are focused on. Ajay Goyal *et al.* [20] developed and tested from instance to instance, but none was established perfectly; some were improved at certain circumstances but failed at others. The apposite practice for a given problem depends on the situation under consideration, such as the ease of accessibility, situation dynamics, desired accuracy, spot size, and economics. These techniques were largely categorized in three categories, namely analytical, experimental, and finite element methods. The experimental was more matter-of-fact, and more correct among these three anchors. In the present paper, all experimental techniques for the measurement of tool, chip, and work piece temperatures distribution are considered in depth and exist in a user-friendly concise behavior.

2. Dimensional Analysis

2.1. Parameters under Study

The formulation of a dimensional equation is the first step to formulate the model of convectional dry turning process. The variables to be predicted are called the dependent variables and the variables predicting the responses are called the independent variables (Ref. Table 1). The functional relationship amongst the inputs and responses (MRR & PC), affecting the convectional dry turning process, is formulated using dimensional analysis. Following are the two methods for dimensional analysis:

- Buckingham's – theorem
- Rayleigh's method

These two methods provide the same results in most cases, but they have a slightly different approach of formulation. Buckingham's method of dimensional analysis is used in this work and it expresses a functional relationship of inputs and responses in the form of an exponential equation. The present work is concerned with the following input and output parameters. Input parameters and output parameters related with the convectional turning process are identified as the inputs and responses [10-12].

Inputs: machine operator, single point cutting tool, work piece, cutting process, lathe machine and the machining environment.

Responses: material removal rate and power consumption. The lists of variables are as shown in Table 1.

Table 1. List of Variables under Investigation

S.N.	Specification	Parameter	Unit	Estimated by
1	Anthropometric of the operator.	AN	-	Operator body
2	Weight of the operator.	W_p	Kg	Operator weight
3	Age of the operator.	AGP	Year	Operator
4	Experience	EX	Year	Operator
5	Skill rating	SK	-	Surface finished
6	Educational qualifications	EDU	-	Operator
7	Psychological Distress	PS	-	Test
8	Systolic Blood pressure	SBP	-	B.P. Meter
9	Diastolic Blood pressure	DBP	-	B.P. Meter
10	Blood Sugar Level during Working	BSG	mm of Hg	Gluco- meter
11	Oxygen consumption in the body	SPO2	-	Oximeter
12	Cutting Tool angles ratio.	CTAR	-	Protector
13	Tool nose radius	R	mm	Micrometer
14	Tool overhang length	Lo	mm	Micrometer
15	Approach angle	α	Degree	Protector
16	Setting angle	β	Degree	Protector
17	Single point cutting Hardness	BHNT	BHN	Hardness tester
18	Lip or Nose angle of tool	LP	mm	Protector
19	Wedge angle	WG	Degree	Protector
20	Shank Length	LS	mm	Micrometer
21	Total length of the tool	LT	mm	Micrometer
22	Tool shank width	SW	mm	Micrometer
23	Tool shank Height	SH	mm	Micrometer
24	Work piece hardness	BHNW	Kg	Micrometer
25	Weight of the raw work piece.	W	Kg	Hardness tester
26	Shear stress of the work piece	τ	N/mm^2	Laboratory
27	Density of the work piece material	DST	Kg/mm^3	Supplier
28	Length of the raw work piece	LR	mm	Micrometer
29	Diameter of the raw work piece	DR	mm	Micrometer
30	Cutting Speed	VC	m/min	Tachometer
31	Feed	f	mm/rev.	Machine
32	Depth of cut	D	mm	Micrometer
33	Cutting force	FC	Newton	Dynamometer
34	Tangential Force.	FT	Newton	Dynamometer
35	Spindle revolution	N	r.p.m.	Tachometer
36	Tool interface Temperature	TEMP	^oC	Temperature gun
37	Cutting tool vibration	VBTool	mm	Vibrometer
38	Machine Tool Vibration	VBMC	mm	Vibrometer
39	Machine Specification ratio	MSP	-	Manual
40	Power of the Machine motor	HP	HP	Manual
41	Weight of the machine	Wmc	Kg	Manual
42	Age of the machine	AGM	Year	Machine shop
43	Air flow	Vf	m/s	Anemometer

2.2. Reduction of Variables

According to the theories of engineering experimentation by H. Schenck Jr., the preference of primary dimensions requires at least three primaries, but the analyst is open to choose any reasonable set he wishes; the only requirement being that his variables must be expressible in his system [9]. Inspection of the above shows that the three quantities *D*, *VC*, and *FC* comprise a complete, dimensionally independent subset of the forty-nine independent variables. The dimension of any one of these three cannot be made up of the dimensions of the other. The dimensions of the remaining independent variables and the dependent variable MRR can be made up of those of *D*, *VC* and *FC* as follows:

MRR= f (AN, Wp, AGP, Ex, Sk, EDU, PS, SBP, DBP, BSG, CTAR,---------------------,DTO) (1)

PC= f (AN, Wp, AGP, Ex, Sk, EDU, PS, SBP, DBP, BSG, CTAR,……………….., DTO) (2)

The general form can be defined as: total number of variables = 49 (Ref. Table 1), all these variables can be expressed in terms of three primary dimensions, i.e., mass (*M*), Length (*L*) and Time (*T*). According to Buckingham's pi theorem, one should get = 49 – 03 = 46 dimensionless terms. Choosing *D*, *VC* and *FC* as repeating variables

Ø= f (AN, Wp, AGP, Ex, Sk, EDU, PS, SBP, DBP, BSG, CTAR,……………………, DTO, MRR, PC) (3)

$$\pi B1 = D^{a}\, VC^{b}\ FC^{c} AN$$

$$M^0\, L^0\, T^0\ =\ (L)^a\ (LT^{-1})^b\ (M^1\ L^1\ T^{-1})^c\ (M^0\ L^0 T^0)$$

For M : 0=1c +0 Hence c=0

For L: 0= 1a -1b + 1c + 0

Hence a = b=

For T: 0= -1b-1c+0

Hence a=0 and b=0

$\pi B_1 = AN$

Similarly for other *pi* terms are evaluated and dimensionless equations are formed

$$\emptyset(\pi B1, \pi B2, \pi B3, \pi B4, \pi B5, \pi B6 \ldots \pi B46) = 0 \quad (4)$$

2.3. Dimensional Similarity

Dimensional analysis provides a similarity law for the phenomenon under consideration. Similarity in this context implies certain equivalence between two physical phenomena that are actually different. All the formulated 46 pi terms are grouped according to the similarity of the function. The multiplication or division of the pi term is a dimensionless pi term. Hence, using the same logic for grouping all the formulated pi terms. The group's similarity is classified into the operator, cutting tool, work piece, cutting process, lathe machine and the machining environment. The pi terms related with the independent and dependent variables are given below:

1. Pi term related with the Machine Operator data.
$$\pi 1 = \frac{AN \times SBP \times Sk \times Ag \times Wp \times SPO2}{(DBP \times PS \times EDU \times Ex \times BSG \times\ D^3)} \quad (5.1)$$

2. Pi term related with the single point cutting tool data.
$$\pi 2 = \frac{AR \times r \times \beta \times BHNT \times LT \times LP \times LS}{(\alpha \times LO \times SW \times SH \times WG)} \quad (5.2)$$

3. Pi term related with the work piece data.
$$\pi 3 = \frac{BHNW \times Wraw \times LR \times \tau}{(D \times FC \times DST \times DR)} \quad (5.3)$$

4. Pi term related with the cutting process data.
$$\pi 4 = \frac{f \times FT \times N \times TEMP \times VBTool}{(VBMC \times FC \times VC)} \quad (5.4)$$

5. Pi term related with the lathe machine data.
$$\pi 5 = (SP \times HP \times WMc)/(AGM \times FC^2) \quad (5.5)$$

6. Pi term related with the machining environmental data.
$$\pi 6 = \frac{HUM \times DTO \times DB \times Vf \times VC \times FC}{(LUX \times D^3)} \quad (5.6)$$

7. Pi term related with the Material Removal Rate (MRR)
$$\pi D1 = MRR/(FC \times D^3) \quad (5.7)$$

8. Pi term related with the Power Consumption (PC)
$$\pi D2 = PC/(FC \times VC) \quad (5.8)$$

For multifactor experiments, two types of plans, viz. classical plan or full factorial and factorial plan, are available; in this experimentation, a conventional plan of experimentation is recommended. All the data were collected from total 330 experiments of three ferrous materials S.S.304, En1A and En8. The experimental plan is as shown in Table 2.

Table 2. Plan for CDT Experimentation

Machine	Operator1	Operator2	Operator3
M1	En1A	En8	S.S.304
M2	En8	S.S.304	En1A
M3	S.S.304	En1A	En8

2.4. Dimensional Analysis (DA) Model Formulation:

It is necessary to quantitatively correlate the 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 a situation. The mathematical model for step turning operations is as given in [16;17] below.

For the machining operation, six independent pi terms (π_1, π_2, π_3, π_4 , π_5 and π_6) and one dependent pi term (π_{D1} & π_{D2}) were decided during experimentation, and, hence, are available for the model formulation. Each dependent π term is the function of the available independent terms.

$$\pi D1 = f(\pi_1, \pi_2, \pi_3, \pi_4, \pi_5, \pi_6) \tag{6}$$

A probable exact mathematical form for the dimensional equations of the phenomenon could be assumed to be of exponential form. For example, the model representing the behavior of dependent pi term π_{D1} with respect to various independent pi terms can be obtained as:.

$$\pi D_1 = K_1 \times \pi_1^a \times \pi_2^b \times \pi_3^c \times \pi_4^d \times \pi_5^e \times \pi_6^f \tag{7}$$

The values of exponent (*a, b, c, d, e* and *f*) are established independently at a time on the basis of the data collected through classical experimentation. There are six unknown terms in equation (7). Curve fitting constant K_1 and indices *a, b, c, d, e* and *f* to get the values of these unknowns we need minimum a set of six set of all unknown dimensionless pi terms.

$$Z = A + bX + CY \tag{8}$$

Equation (7) can be brought in the form of equation (8) by taking log on both sides. Model of dependent *pi* term π_{D1} for *MRR* or *PC:*

$$\pi D_1 = K_1 \times \pi_1^a \times \pi_2^b \times \pi_3^c \times \pi_4^d \times \pi_5^e \times \pi_6^f \tag{9}$$

Taking log on the both sides of the equation for *πD1*:

$$\log \pi D_1 = \log K_1 + a \times \log \pi_1 + b \times \log \pi_2 + c \times \log \pi_3 + d \times \log \pi_4 + e \times \log \pi_5 + f \times \log \pi_6 \tag{10}$$

Let, $Z = \log \pi D1$, $K = \log k1$,
$A = \log \pi 1$, $B = \log \pi 2$
$C = \log \pi 3$, $D = \log \pi 4$,
$E = \log \pi 5$ and $F = \log \pi 6$

Putting the values in equations 4, the same can be written as:

$$Z = K + a \times A + b \times B + c \times C + d \times D + e \times E + f \times F \tag{11}$$

Equation (12) is a regression equation of *Z* on *A, B, C, D* and *E* in a dimensional co-ordinate system:

$$\begin{aligned}
\sum Z &= N \times K + a \times \sum A + b \times \sum B + c \times \sum C + d \times \sum D + e \times \sum E + f \times \sum F \\
\sum AZ &= K \sum A + a \times \sum AA + b \times \sum AB + c \times \sum AC + d \times \sum DA + e \times \sum AE + f \times \sum AF \\
\sum BZ &= K \sum B + a \times \sum BA + b \times \sum BB + c \times \sum BC + d \times \sum BD + e \times BE + f \times \sum BF \\
\sum CZ &= K \sum C + a \times \sum CA + b \times \sum CB + c \times \sum CC + d \times \sum CD + e \times \sum CE + f \times \sum CF \\
\sum DZ &= K \sum D + a \times \sum DA + b \times \sum DB + c \times \sum DC + d \times \sum DD + e \times \sum DE + f \times \sum FD \\
\sum EZ &= K \sum E + a \times \sum EA + b \times \sum EB + c \times \sum EC + d \times \sum DE + e \times \sum EE + f \times \sum EF \\
\sum AF &= K \sum F + a \times \sum AF + b \times \sum BF + c \times \sum FC + d \times \sum FD + e \times \sum FE + f \times \sum FF
\end{aligned} \tag{12}$$

The equation above is written in the form where *A,B,C,D,E* & *F* are the dimensionless constant and *a,b,c,d,e* & *f* are arbitrary exponents**.** Dimensional equation so obtained can be formulated into a model using a multiple-linear regression analysis. Multiple-linear-regression analysis is a statistical tool that utilizes the relation between two or more quantitative variables so that one variable can be predicted from another. By using this methodology the dimensional equation and model are formulated for the material removal rate. The formulated model is evaluated on the basis of correlation, solving these equations using 'MATLAB' is given below = 7 x 7 matrix multipliers of *k*, reliability and root mean square error between the computed values by model and the estimated values. In the set of equations above the values of the multipliers *k, a, b, c, d, e* and *f* are the set of equations calculated. After substituting these values in equation (12), one will get a set of five equations, which get the values of *k , a, b, c, d, e* and *f* . The equations above can be verified in a matrix form and further values of *k, a, b, c, d, e* and *f* can be obtained by the matrix:

$$X_1 = inv(W) \times P1 \tag{13}$$

a, b, c, d, e and *f*, P_1 = 7 x 1 matrix of the terms on *L H S* and X_1 = 7 x 1 matrix of values of *k, a, b, c, d, e* and *f*. After solving, we get the following models for the Dimensional Analysis (DA). Figure 2 shows the program use to formulate the DA model using regression analysis.

The geometry of the finish work piece is as shown in Figure 3a. The sample of work piece is as shown in Figure 3b. The chemical composition for the ferrous materials under investigation is as shown in Table 3.

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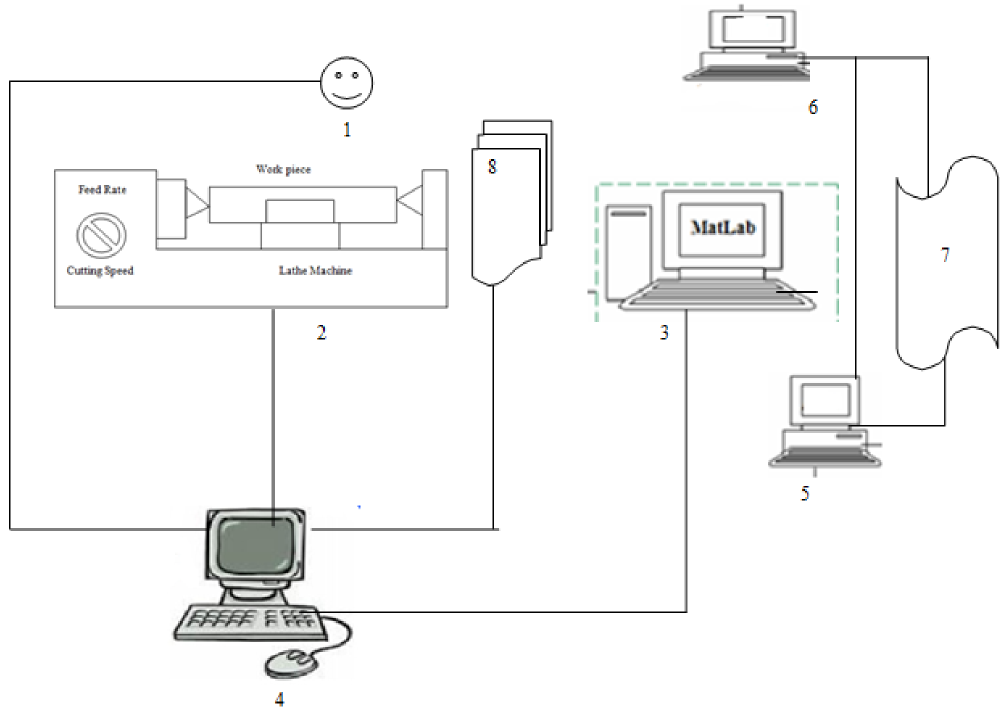

1) Camera 2) Machining set up 3) Data modelling system
4) Data Storage system 5) DA Module 6) Experimental module
7) Comparison module 8) Instrumentation system

Figure 1. Experimental plan for dry turning a ferrous material.

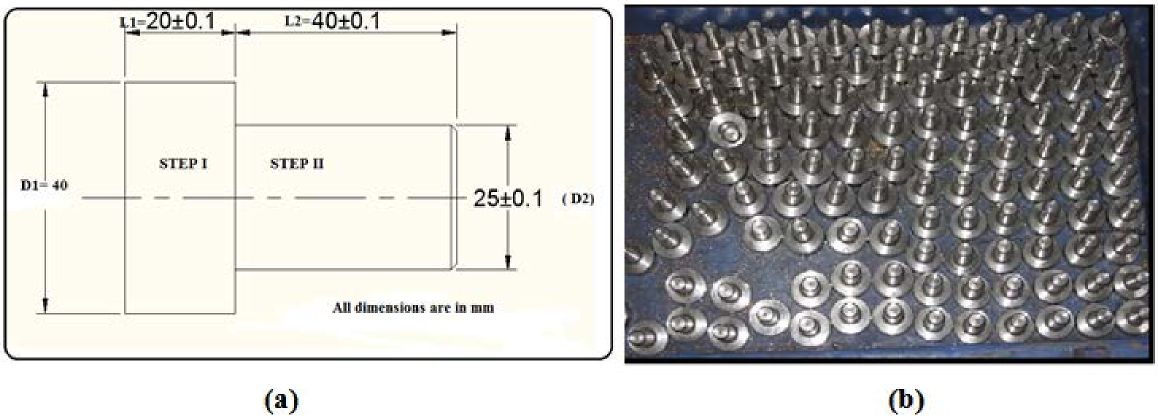

Figure 3. (a) Geometry of finish work-piece, (b) Sample of finish work -piece

Table 3. Chemical composition of the ferrous materials under investigation

Material	C %	Si %	Mn %	Ni %	Cr %	Mo %	S %	P %	Fe %
En1A	0.07-0.15	0.10 Max	0.8 – 1.2	-	-	-	0.2-0.3	0.07 Max	≥ 97.91
En8	0.35-0.45	0.1-0.35	0.6-1.0	-	-	-	0.05 Max	0.05 Max	≥ 97.91
S.S.304	0.08 Max	0.75 Max	2.0 Max	8.0-10.5	18.0-20.0	-	0.03 Max	0.045Max	66.345-74.00

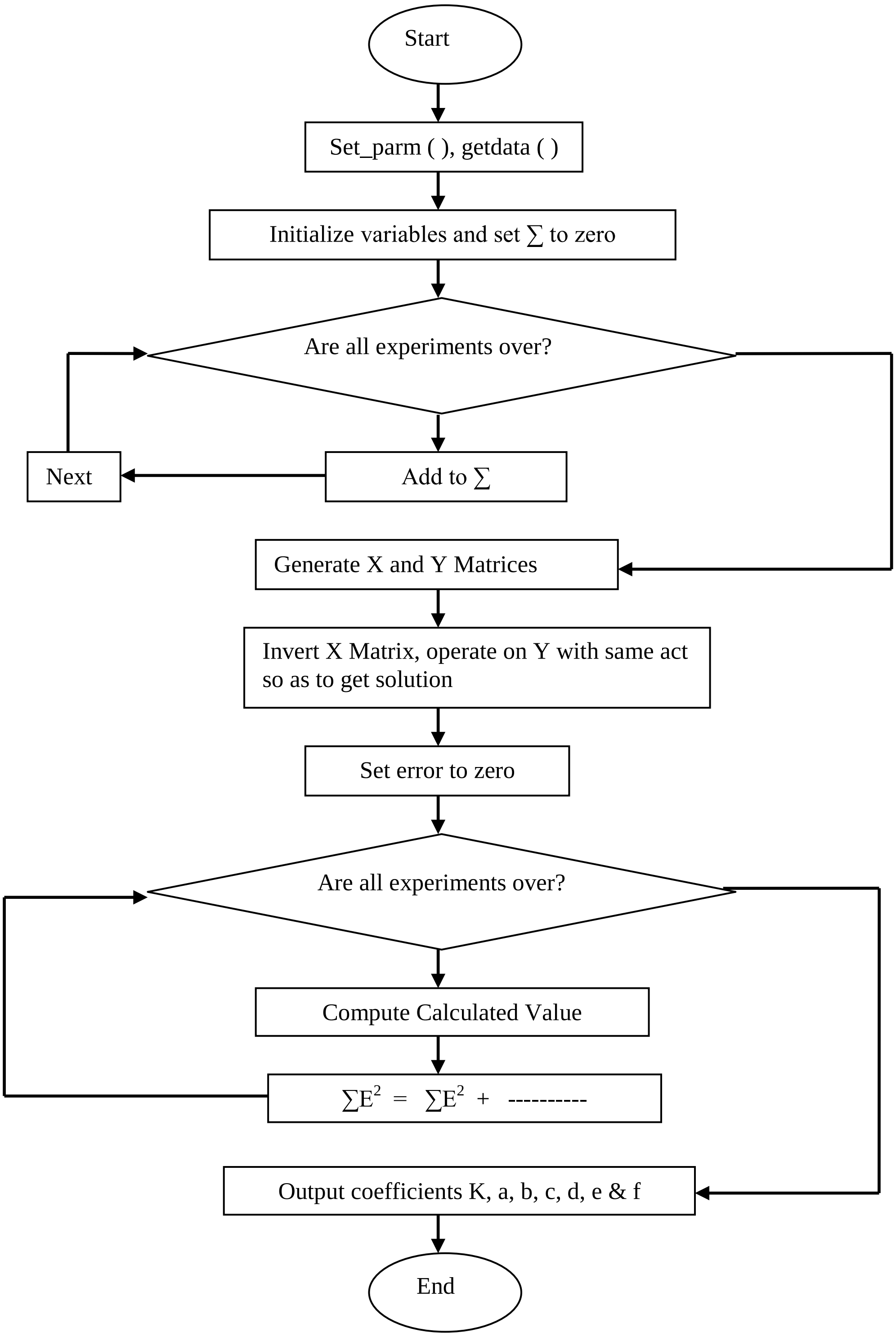

Figure 2. Flow Chart for regression Analysis

3. 3. Results and Discussion

The model for MRR is given below:

3.1. Model Formulation

Model: Material Removal Rate (MRR) Model

$$\pi D_1 = 0.00026743 \times \pi_1^{0.1408} \times \pi_2^{-0.0293} \times \pi_3^{0.324} \times \pi_4^{0.520} \times \pi_5^{-0.0415} \times \pi_6^{0.4412} \quad (14)$$

- Correlation Coefficient = 0.982915516
- Root Mean Square Errors=0.034305626
- Reliability = 98.25331313%

The *pi* term related to the cutting process has the most dominant effect on MRR, followed by the machining environment, work piece and machine operator. The pi term related to the cutting tool, lathe machine specification has an adverse effect on MRR in the turning of ferrous material. A high MRR is obtained with the combination of cutting process, machining environment and work piece material. Figure 4 shows the MRR values obtained by experimentation and the values predicted by the DA model. It is obvious that the predicted values by DA are very close to the experimental readings.

Model: Power Consumption (PC) Model

$$\pi D_2 = 9.65\,E^{-05} \times \pi_1^{-0.0545} \times \pi_2^{-0.0495} \times \pi_3^{0.5267} \times \pi_4^{-0.1369} \times \pi_5^{0.1072} \times \pi_6^{-0.1983} \quad (15)$$

- Correlation Coefficient = 0.98203603
- Root Mean Square =0.03476825
- Reliability = 98.1258013%

The pi term related to the work piece has the most dominant effect on PC, followed by the machine. The pi term related to the cutting tool, machine operator, cutting process and the machining environment has an adverse effect on PC in the turning of ferrous material. A high PC is obtained with the combination of work piece material and machine. Figure 5 shows PC values obtained by experimentation and values predicted by the DA model. It is obvious that the predicted values by DA are very close to the experimental readings.

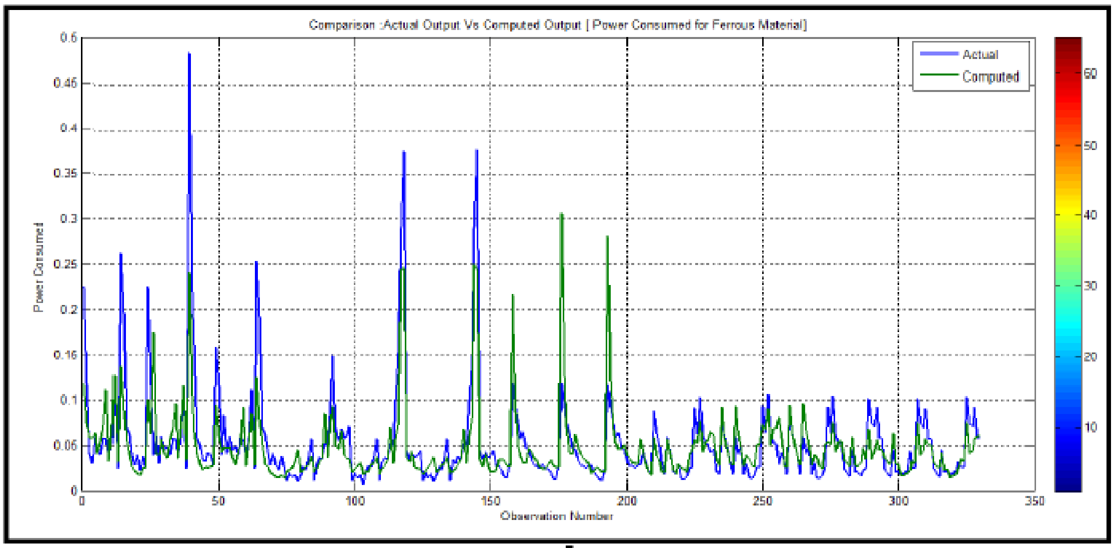

Figure 4. Comparison between actual and computed output for material removal rate

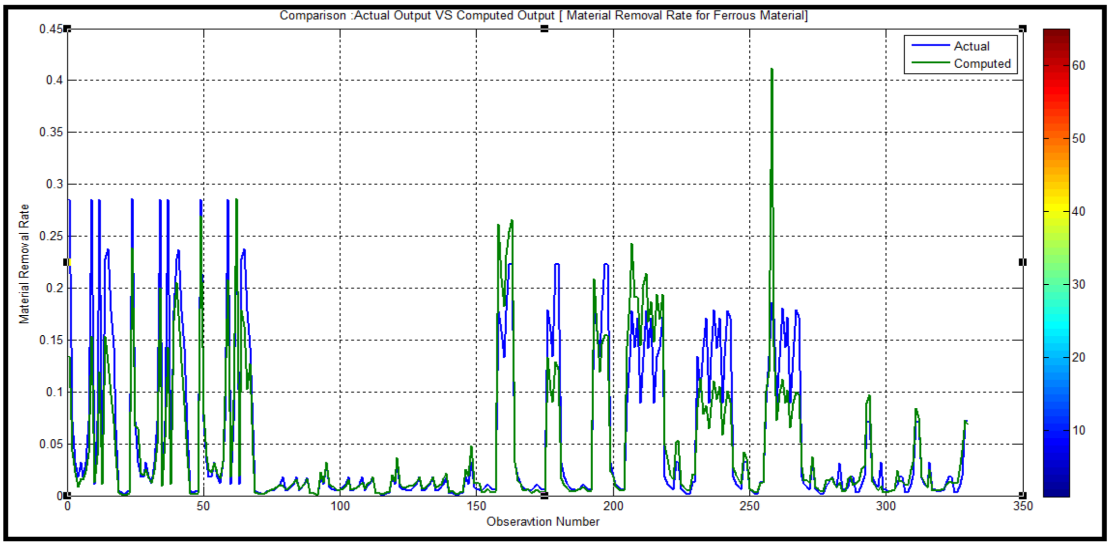

Figure 5. Comparison between actual and computed output for power consumption

3.2. Optimization of the Model

The generalized models have the non-linear form (Eq.16); hence, it is to be converted into a linear form for optimization purpose:

$$\pi D_1 = K_1 \times \pi_1^a \times \pi_2^b \times \pi_3^c \times \pi_4^d \times \pi_5^e \times \pi_6^f \quad (16)$$

This can be achieved by taking the log of both programming technique applied, which is detailed as below for a step turning operation. Taking log of both the sides of Equation 16, we get:

$$\begin{aligned} log\, \pi D_1 = log \quad K_1 + a \times log\, \pi_1 + b \times log\, \pi_2 + \\ c \times log\, \pi_3 + d \times log\, \pi_4 + e \times \\ log\, \pi_5 + f \times log\, \pi_6 \end{aligned} \quad (17)$$

The general linear equation can be written as equation 16:

$$\begin{aligned} Z = K_1 + [aX_1] + [bX_2] + [cX_3] + [d\, X_4\,] + \\ [\, e\, X\,_5] + [f\, X_6\,] \end{aligned} \quad (18)$$

Comparing Eq. 17 and Eq. 18, we get:

Z= Log (Π D1), *K= Log (K_1),*
X_1= Log (Π_1), *X_2 = Log (Π_2)*
X_3= Log (Π_3), *X_4= Log(Π_4),* (19)
X_5= Log (Π_5 *and X_6=Log (Π_6)*

Z_1 (Max MRR) = -8.228 +0.1408X_1 -0.0293 X_2 +0.324X_3 +0.5200 X_4 - 0.0415X_5 +0.4412X_6

Z_2 (Min PC) = -9.2455 -0.0545X_1 -0.0495 X_2 +0.5267X_3 -0.1369 X_4 +0.1072 X_5 -0.1983 X_6

Subject to the following constraints:

$$\begin{aligned}
1 \times X_1 + 0 \times X_2 + 0 \times X_3 + 0 \times X_4 + 0 \times X_5 + 0 \times X_6 &\le Max\, X_1 \\
1 \times X_1 + 0 \times X_2 + 0 \times X_3 + 0 \times X_4 + 0 \times X_5 + 0 \times X_6 &\ge Min\, X_1 \\
0 \times X_1 + 1 \times X_2 + 0 \times X_3 + 0 \times X_4 + 0 \times X_5 + 0 \times X_6 &\le Max\, X_2 \\
0 \times X_1 + 1 \times X_2 + 0 \times X_3 + 0 \times X_4 + 0 \times X_5 + 0 \times X_6 &\ge Min\, X_2 \\
0 \times X_1 + 0 \times X_2 + 1 \times X_3 + 0 \times X_4 + 0 \times X_5 + 0 \times X_6 &\le Max\, X_3 \\
0 \times X_1 + 0 \times X_2 + 1 \times X_3 + 0 \times X_4 + 0 \times X_5 + 0 \times X_6 &\ge Min\, 3 \\
0 \times X_1 + 0 \times X_2 + 0 \times X_3 + 1 \times X_4 + 0 \times X_5 + 0 \times X_6 &\le Max\, X_4 \\
0 \times X_1 + 0 \times X_2 + 0 \times X_3 + 1 \times X_4 + 0 \times X_5 + 0 \times X_6 &\ge Min\, X_4 \\
0 \times X_1 + 0 \times X_2 + 0 \times X_3 + 0 \times X_4 + 1 \times X_5 + 0 \times X_6 &\le Max\, X_5 \\
0 \times X_1 + 0 \times X_2 + 0 \times X_3 + 0 \times X_4 + 1 \times X_5 + 0 \times X_6 &\ge Min\, X_5 \\
0 \times X_1 + 0 \times X_2 + 0 \times X_3 + 0 \times X_4 + 0 \times X_5 + 1 \times X_6 &\le Max\, X_6 \\
0 \times X_1 + 0 \times X_2 + 0 \times X_3 + 0 \times X_4 + 0 \times X_5 + 1 \times X_6 &\ge Min\, X_6
\end{aligned}$$

On solving the above problem by using MS solver, we get values of X_1,X_2, X_3,X_4,X_5,X_6 and *Z*. Thus, actual *πD* =Antilog of *Z* and corresponding to this value of the *πD* the values of the independent π terms are obtained by taking the antilog of X_1,X_2,X_3,X_4,X_5,X_6 and *Z*. A similar procedure is adopted to optimize all the models. The optimum values are tabulated in the Table 5.

3.3. Sensitivity Analysis

The influence of the various independents π terms have been studied by analyzing the indices of the various π terms in the models. Through 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, change of ± 10% is introduced in the individual independent π term independently (one at a time). Thus, the 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 are due to the introduced change of ± 10% in each independent π term. This defines sensitivity. The total % change in output for ± 10% change in input is shown in Table 6. Figures 6 & 7 show the comparative sensitivity and the comparative indices for the MRR and PC models.

Table 4. Sample observation for the MRR and PC

Obcode	Opcode	Mccode	Wpcode	SeasCode	Shftcode	Operator (π_1)	Tool (π_2)	work piece (π_3)	Process (π_4)	Machine (π_5)	Environment (π_6)	MRR (mm^3/s)	Power (KW)
1	Op1	Mc1	S.S.304	Mansoon	Morning	0.6886	1016.0	8147567	0.2089	0.098522	101.406951	6687.2	0.211497984
2	Op1	Mc1	S.S.304	Mansoon	Morning	0.083474	1016.09	2250978	0.2650	0.02700719	25.1731387	6652.8	0.211497984
3	Op1	Mc1	S.S.304	Mansoon	Morning	0.024924	1016.09	1073961.	0.4476	0.01229538	7.34918536	6629.4	0.105748992
5	Op1	Mc1	S.S.304	Mansoon	Morning	0.010462	1873.85	600244.6	0.5516	0.00711519	1.15619304	6545.1	0.105748992
6	Op1	Mc1	S.S.304	Mansoon	Afternoon	0.015239	1873.85	1039858.	0.4880	0.01201961	4.2220951	6640.6	0.158623488
7	Op1	Mc1	S.S.304	Mansoon	Afternoon	0.006538	4761.77	587390.5	0.6535	0.00698965	5.16938300	6584.9	0.158623488
9	Op1	Mc1	S.S.304	Mansoon	Afternoon	0.015540	4761.77	1080320.	0.4862	0.01218562	9.38396014	6620.2	0.105748992
10	Op1	Mc1	S.S.304	Mansoon	Afternoon	0.050371	5957.80	2284609.	0.4573	0.02646216	15.9097311	6650.0	0.105748992
11	Op1	Mc1	S.S.304	Mansoon	Evening	0.491155	5957.80	9072891.	0.2933	0.10229096	106.770365	6710.6	0.052874496
12	Op1	Mc1	S.S.304	Mansoon	Evening	0.00414	5957.80	396160.6	0.6807	0.00456860	5.06548084	6535.5	0.158623488
13	Op1	Mc1	S.S.304	Mansoon	Evening	0.063057	5219.26	2214347.	0.4424	0.02635513	13.3453003	6665.0	0.105748992
14	Op1	Mc1	S.S.304	Mansoon	Evening	0.517613	5219.26	9219451.	0.3136	0.09988655	53.2685411	6720.7	0.105748992
15	Op1	Mc1	S.S.304	Mansoon	Evening	0.004156	5219.26	338673.6	0.6475	0.00453795	3.78798675	6489.2	0.105748992
-	-	-	-	-	-	0.055121	8363.14	321393.6	0.1543	0.03062768	6.22044499	-	-
129	Op3	Mc3	En8	Mansoon	Morning	0.023293	8363.14	184285.0	0.1545	0.01767357	5.21023595	6739.6	0.211497984
130	Op3	Mc3	En8	Mansoon	Afternoon	0.007859	8363.14	119021.5	0.1764	0.01156465	2.32077084	10159.	0.26437248
131	Op3	Mc3	En8	Mansoon	Afternoon	0.004685	8363.14	84231.84	0.1824	0.00813796	4.38177156	13504.	0.158623488
132	Op3	Mc3	En8	Mansoon	Evening	0.003702	8363.14	61412.14	0.1615	0.00604478	2.54547836	16914.	0.211497984
133	Op3	Mc3	En8	Mansoon	Evening	0.157719	8363.14	707981.7	0.1950	0.06523187	41.3166138	17122.	0.211497984
-	-	-	-	-	-	0.012485	182.257	172622.6	0.1826	0.01642545	0.80931012	-	-
135	Op3	Mc3	En1A	Mansoon	Morning	0.021488	182.257	290822.6	0.1229	0.03130714	1.95534777	9406.4	0.370121472
137	Op3	Mc3	En1A	Mansoon	Afternoon	0.005646	182.257	112619.6	0.1990	0.00954766	2.67833723	9233.5	0.26437248
138	Op3	Mc3	En1A	Mansoon	Evening	0.029860	182.257	301775.5	0.1830	0.02234496	4.56812758	9412.2	0.317246976
139	Op3	Mc3	En1A	Mansoon	Evening	0.097161	182.257	443645.4	0.2204	0.02725797	16.2099348	9459.3	0.211497984

Table 5. Optimization of *MRR* and *PC*

Variables	Material removal Rate		Power Consumption	
	Log Value	Antilog values	Log Value	Antilog values
Z	1.389751886	4.013854037	-7.41936344	0.000599531
X_1	0.09327963	1.097768661	0.09327963	1.097768661
X_2	6.06803321	431.8305258	9.38627043	11923.5466
X_3	17.1963836	29396424.23	10.4741287	35388.0227
X_4	0.132500464	1.141679546	0.132500464	1.141679546
X_5	-15.14558	2.64459E-07	-15.14558	2.64459E-07
X_6	7.96337577	2873.757742	7.96337577	2873.757742

Table 6. Sensitivity analysis of *MRR* and *PC* Model

Input Parameters	Material Removal rate		Power Consumption	
	Sensitivity	Indices	Sensitivity	Indices
Operator	2.823538892	0.1408	-1.093960304	-0.0545
Cutting Tool	-0.588052562	-0.0293	-0.993571142	-0.0495
Work piece	6.492296707	0.324	10.54629538	0.5267
Cutting Process	10.41236705	0.5200	-2.74915883	-0.1369
Lathe Machine	-0.832959484	-0.0415	2.150072782	0.1012
Environment	8.836869033	0.4412	-3.983530018	-0.1983

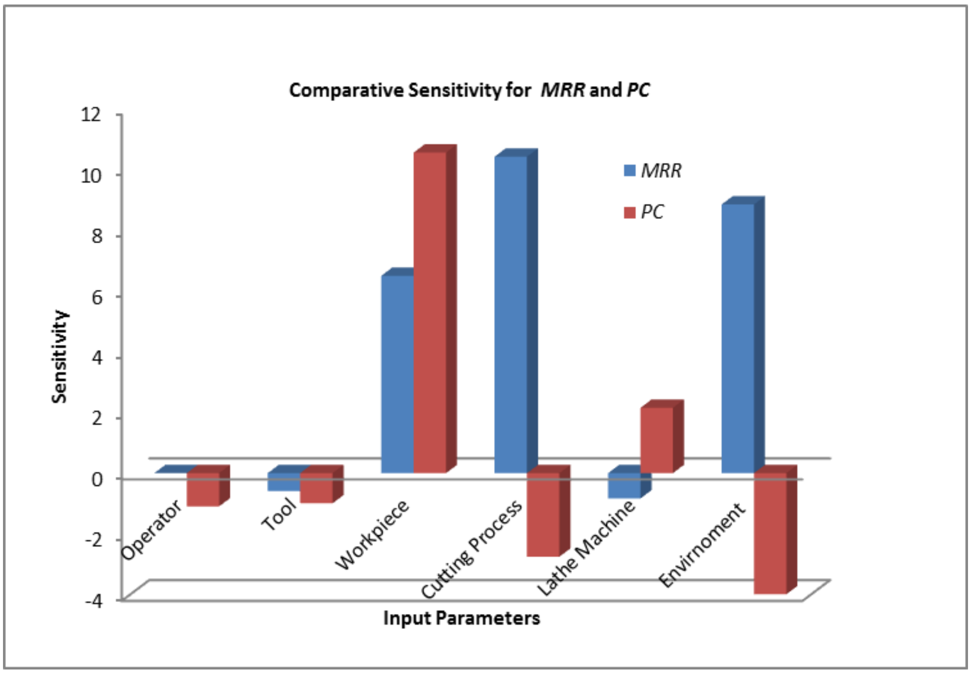

Figure 6. Sensitivity analysis for the formulated dimensional analysis models.

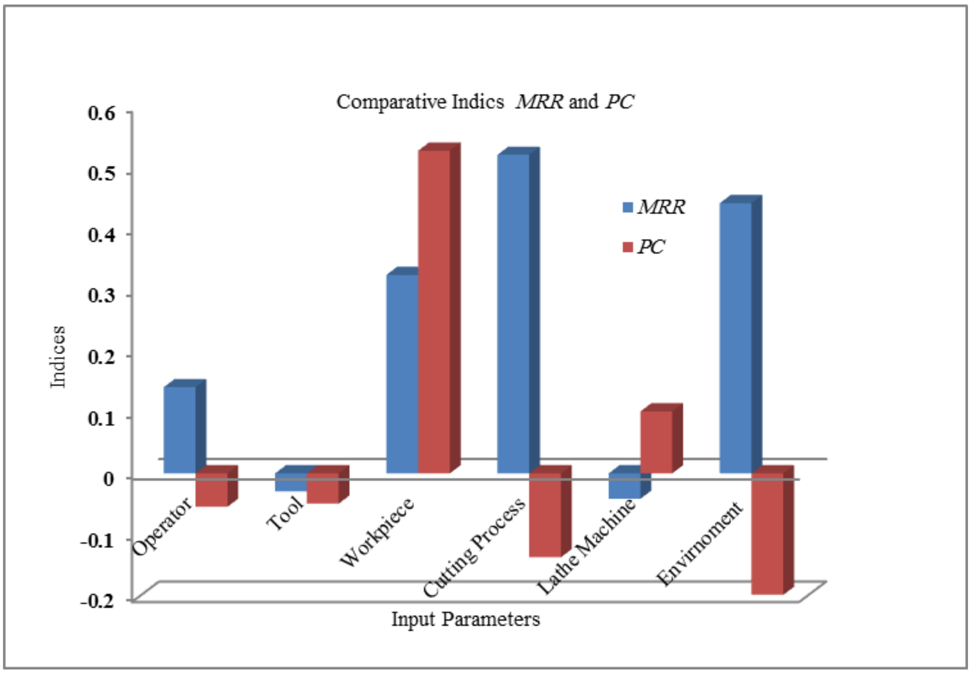

Figure 7. Comparative indices for the formulated dimensional analysis model.

4. Conclusion

Dimensional Analysis (DA) modelling has been found to be the easiest and a well-known technique to perform the analysis of MRR and the PC with respect to various independent parameters, such as operator data, cutting tool, work–piece data, cutting process data, lathe machine specification and the machining environmental parameters. The models developed by using DA approach have been found to accurately represent MRR and PC values with respect to the experimental results.

Both MRR and PC dimensional analysis models reveal that the feed rate is the most significant design variable in determining surface roughness response as compared to others. With the model equations obtained, a designer can subsequently select the best combination of design variables for achieving optimum surface roughness. This will eventually reduce the machining time and save the cutting tools.

With the model equations obtained, a researcher can subsequently select the most excellent combination of design variables for achieving optimum MRR and PC. Finally, this will improve productivity. The analysis of the DA model shows that the DA model can predict PC and MRR with a correlation of more than 0.98. Hence, the DA model is presented to correlate the large number of variables effectively and efficiently.

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