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Multi-Response Optimization in Machining: Exploration of TOPSIS and Deng's Similarity Based Approach

Thesis Submitted in Fulfillment of the Requirements for the Award of the Degree of

Master of Technology (M. Tech.)

In

Production Engineering

By

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CERTIFICATE OF APPROVAL

This is to certify that the thesis entitled **MULTI-RESPONSE OPTIMIZATION IN MACHINING: EXPLORATION OF TOPSIS AND DENG'S SIMILARITY BASED APPROACH** submitted by ***Bedamati Nayak*** has been carried out under my sole supervision in fulfillment of the requirements for the award of the Degree of ***Master of Technology (M. Tech.)*** in ***Production Engineering*** at **National Institute of Technology**, **Rourkela**, and this work has not been submitted elsewhere before for any other academic degree/diploma.

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Bedamati Nayak

Abstract

Machining deals with removal of unwanted material from the work piece in the form of chips in order to get required dimension. Consumption of energy, wastage of material, requirement of skilled person etc. make the process expensive. Hence, machining industries have to face the inevitable challenge to reduce cost as well as to machine material within the tolerance limit which can be accepted by the customers. The output characteristics like Material Removal Rate (MRR), surface roughness, tool wear, tool life, cutting temperature, cutting force etc. are greatly influenced by the input cutting parameters like speed, feed rate, depth of cut etc. Therefore, selection of cutting parameter plays an important role for a sound production. Optimization techniques are quite helpful for selection of appropriate cutting parameters through offline check. The industries have to concern about a number of performance characteristics simultaneously because focus on a single objective may appear as loss for rest of the objectives, and, hence, multi-objective optimization techniques may be suitable. In the present work, turning operation of aluminum was carried out using a HSS tool on a lathe machine. Cutting parameters: speed, feed rate, and depth of cut was varied at five different levels; Taguchi method was employed for designing a L_{25} orthogonal array. The output performances viz. MRR, surface roughness, cutting temperature, and cutting forces were recorded for each run. Deng’s similarity based method and TOPSIS (integrated with Taguchi method) were explored for determining appropriate process environment (parameter setting) for simultaneous optimization of multiple process-performance-yields.

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Chapter 1

Introduction

1.1 Aspects of Machining

Machining has been regarded as one of the most fascinating topic for the researchers. It is one of the frequently used manufacturing operations to get permissible dimension in tolerance zone, good surface finish as well as required complicated geometry. The growing demand of machining leads the researcher to investigate and eradicate several problems during the operation and insists them to make the process economic. As per the definition machining deals with the removal of unwanted material from the work piece surface in the form of chips to get the desired dimension. Several technologies have been developed for removal of material. The suitability of each technology for the process depends on factors like material property of tool and work piece, economic and favorable cutting conditions, cutting environment etc. The machining process is broadly classified as traditional and nontraditional. The traditional method involves removal material due the relative motion between tool and work piece and metal removes due to the plastic deformation of work piece material caused by the shear force. Whereas, non-traditional method involves use of energy sources like electric energy, heat energy, laser ray, electron bombardment etc. for removal of material.

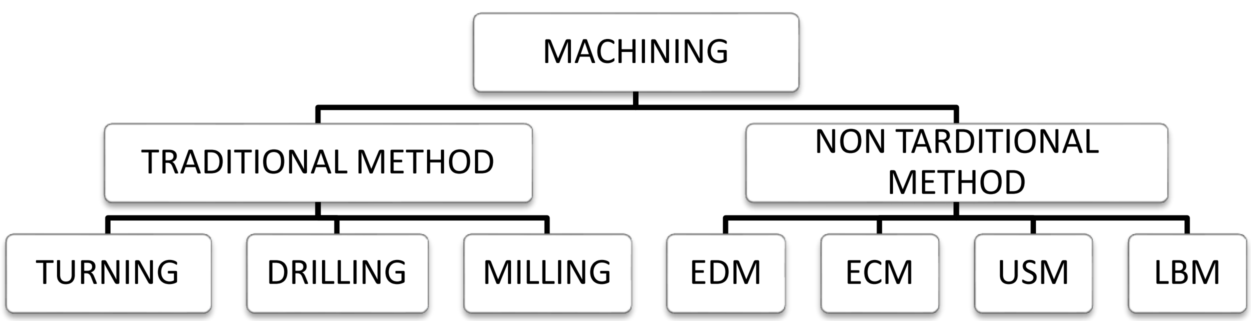

Fig 1: Classification of machining

The nontraditional methods are quite costly as well as their metal removal rate is also low. Hence its application is limited to the materials having low machinability and finishing operations. In tradition method metal removal rate is comparatively higher. The concept behind metal cutting is that the metal gets compressed by the tool and deforms both elastically and plastically at the shear zone and then removed by shear from parent material. The separation of the material from the work piece surface occurs due to the yielding or fracture depending upon the cutting conditions. The effectiveness of the process is measured in the form of material removal rate, surface finish, tool wear rate, cutting forces etc. known as qualities. Hence it is necessary to study about the quality in order to enhance the productivity.

1.2 Quality and Productivity Requirements in Machining

Quality can be defined as the combination of characteristics or features in a product, which gain the customer satisfaction. To face the tough competition of market, every industry needs loyal customer, which is possible only through improved product quality. Quality makes the customer to buy a product again and again. The quality characteristics in a product may be in the form of dimensional accuracy, aesthetic, sensory, functional, reliability (time oriented quality characteristic) etc.

Productivity is related to profit of the industries and mathematically expressed as the ratio of output by input. Higher will be the output, higher will be productivity which leads to reduce in cost. In order to gain good productivity one has to extract output as much as possible from given input.

Quality and productivity are inter-related to each other. By improving quality, the productivity also increases because higher quality leads to less rework which saves time. In the machining industries quality refers to material removal rate, surface roughness, cutting force, tool wear, tool life etc. Some of these qualities are described below.

1.2.1 Material Removal Rate (MRR)

Material removal rate has been counted as one of most important output characteristics for the quality measurement and represents the volume of metal removed per unit time. Higher material removal rate is always desirable in a machining operation as it increases the productivity. Mathematically it can be expressed as:

$$\text{MRR} = \frac{\text{Weight before machining} - \text{Weight after machining}}{\text{Density of workpiece} * \text{machining time}}$$

For turning operation it also can be expressed as: MRR = V * f * d

Here V = cutting speed, f = feed rate, d = depth of cut.

1.2.2 Surface Roughness

Surface roughness can be described as the unevenness of surface. In a machining industry, surface roughness is measured in the form of height of the texture from the normal surface level. Availability of roughness increases the friction tendencies, which enhance the wear rate. However, controlled surface roughness is desirable as minimum surface roughness results slippery surface, which will be hard to handle. The surface roughness can be represented in several ways.

- *Arithmetic average (R_a)*: It is calculated as the mean of the absolute deviation of the textures from the surface. Mathematically it can be expressed as :

  $R_a = \frac{1}{n}\sum_{i=1}^{n} |h_i|$

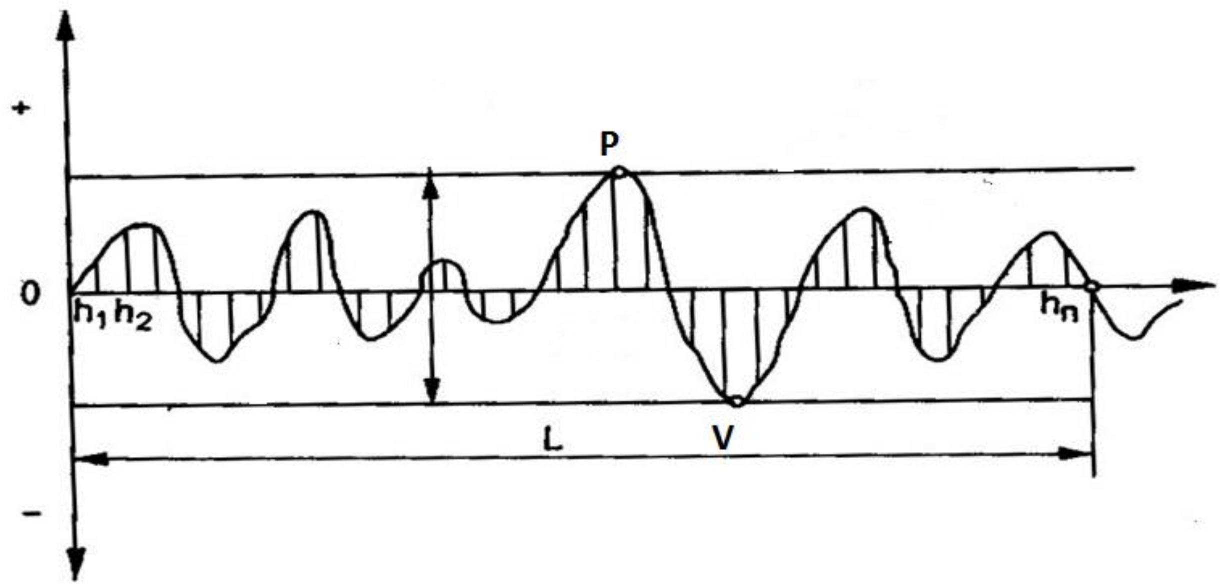

Fig 2: Surface texture for the measurement of surface roughness

- *Root mean Square (R_q):* It is calculated by taking the root of mean of square of the deviations and mathematically represented as:

  $R_q = \sqrt{(\frac{1}{n}\sum_{i=0}^{n} h_i^2)}$

- *Maximum valley depth (R_v):* It can be defined as the maximum valley depth and mathematically expressed as $R_v = \min h_i$
- *Maximum peak height (R_p)*: It is expressed as the maximum peak height and mathematically described as $R_p = \max h_i$

- *Maximum height of the profile (R_t)* : It is expressed as the difference between the maximum peak height and minimum valley depth and represented as $R_t = R_p - R_v$
- *R_{zDIN}*: it is refered as the average distance between the hirghest peak and lowest valley throughout the sampling spaces taken in to consideration. Mathematically it is expressed as:

  $R_{zDIN} = \frac{1}{s}\sum_{i=0}^{s} R_{ti}$

For the measurement of surface roughness, instruments like talysurf, surface tester, profilometer etc. are frequently used. The sensitive stylus of the instrument traces the disorder on the surface.

1.2.3 Cutting Forces

During the machining operation generally three types of forces like radial force, thrust force and cutting force comes into picture. As these cutting forces are directly related to the rate of power consumption, minimum cutting forces are desirable. Cutting forces are measured through dynamometer. The cutting forces are dependent on cutting conditions, material property of work piece, tool geometry etc. But control through cutting condition is easier and economical.

1.2.4 Tool-Tip Temperature

When the tool is pressed in to the work piece, temperature arises due to the plastic deformation of the work piece and the rubbing action between the tool and chip. This temperature is highly undesirable because it leads to tool wear, reduces tool life and forms built up edge. In order to reduce the temperature coolant and lubricants can be provided. Tool tip temperature is also controlled through cutting parameters. The temperature can be measured by using thermocouple, infrared thermometer etc.

1.2.5 Tool Wear

Tool wear is one of barrier of productivity and quality. It is the failure caused by tool due to removal of material from the tool surface. It can be classified as flank wear and crater wear. Basically tool wear refers to the flank wear which is caused due to the abrasion action between the flank and chip which results the geometrical disorder and increases the tendency greater surface roughness, larger cutting force, decreased tool life. Tool wear can be controlled by adjusting the input parameter, proper lubrication, coating etc. Tool wear can be observed through optical microscope.

From the previous research, it has been proved that input cutting parameters have strong influence on the output characteristics, which are the measure of quality and productivity. Hence, it is indeed required to control the input parameter to enhance quality and productivity. Therefore, selection of optimum cutting parameter is necessary. Optimization techniques are quite helpful in order to get the optimum values. Several researches have been carried out and several optimization techniques have been employed to get the optimum cutting conditions. Some of the previous research outcomes are described below.

1.3 Literature Review

Lee and Tang (2000) determined optimal cutting parameters for maximizing production rate in multistage turning operations using a machining model based on a polynomial network, which established the relationships between cutting parameters like cutting speed, feed rate, and depth of cut and cutting performances like surface roughness, cutting force, and tool life through a self-organizing adaptive modeling technique. **Zuperl and Cus (2000)** proposed a neural network based approach, which could be used for the complex optimization of cutting parameters. The authors used the technique to determine cutting parameter values for production rate, operation cost, cutting quality. **Wang et al. (2002)** used deterministic optimization approach; a realistic optimization strategy based on the criteria typified by the minimum production time per component, which allowed many practical constraints for single pass turning on CNC machine. Their study demonstrated the suitability of the developed computer program for on-line applications in computer-aided manufacturing systems. **Singh and Kumar (2006)** carried out the turning operation of EN 24 steel using TiC coated carbide tool and employed Taguchi combined with utility concept in order to obtain optimum cutting conditions. **Srikanth and Kamala (2008)** used real coded genetic algorithm to minimize the surface roughness of the machined product, in the form of nonlinear objective function of cutting parameters like speed feed rate, depth of cut, nose radius. **Khidhir and Mohamed (2009)** proposed the way for selection of cutting parameters from prediction model of cutting force for turning Nickel based Hastelloy C-276 using response surface methodology. **Aruna and Dhanalakshmi (2010)** carried out finish turning operation of Inconel 718 with cermet tools using Taguchi's design of experiment (DOE) and response surface methodology. **Lan (2010)** considered the fuzzy Taguchi deduction optimization and TOPSIS (Technique for Order

Preference by Similarity to Ideal Solution) to optimize multiple attribute performance characteristics (the surface roughness, tool wear, material removal rate) of finish CNC turning operation, considering for four parameters like speed, feed rate, depth of cut, tool nose runoff. **Yang and Natarajan (2010)** implemented multi-objective differential evolution (MODE) algorithm and non-dominated sorting genetic algorithm (NSGA-II) for a turning operation of EN 24 steel using WC tool in order to minimize tool wear, maximize metal removal rate. The authors had taken depth of cut, speed and feed rate as machining parameters and given constraints of surface roughness and temperature. Finally regression models were developed for tool wear, temperature, and surface roughness and performance of both methods were compared. **Jurkovic et al.(2010)** investigated the effect of machining parameters of turning on surface quality of machined product. The authors designed the experiment using central composite design and orthogonal array and the results were optimized and analyzed through the classical mathematics, analytic method, Taguchi principle and ANN in order to obtain the optimal cutting condition. Finally the effectiveness of the processes was compared. **Yang and Natarajan (2010)** implemented multi-objective differential evolution (MODE) algorithm and non-dominated sorting genetic algorithm (NSGA-II) for a turning operation of EN 24 steel using WC tool in order to minimize tool wear, maximize metal removal rate. The authors had taken depth of cut, speed and feed rate as machining parameters and given constraints of surface roughness and temperature. Finally regression models were developed for tool wear, temperature, and surface roughness and performance of both methods were compared. **Jurkovic et al.(2010)** investigated the effect of machining parameters of turning on surface quality of machined product. The authors designed the experiment using central composite design and orthogonal array and the results were optimized and analyzed through the classical mathematics, analytic method, Taguchi principle and ANN in order to obtain the optimal cutting condition. Finally the effectiveness of the processes was compared. **Ranganathan and Senthilvelan (2011)** applied grey relation theory for the optimization of output responses namely tool life, surface roughness and material removal rate, varying the machining parameters namely feed rate, depth of cut, workpiece temperature and speed throughout the turning operation of stainless steel. The authors found the optimum level of process parameter from the grey relation grade, which was again analyzed using ANOVA and the result presented the dominating effect of cutting speed and feed rate. **Sastry and Devi (2011)** carried out turning operation of aluminium using HSS tool in a CNC lathe machine to obtain the best parametric combination to enhance the MRR and reduce the surface roughness. The authors employed RSM for designing the experiment and analyzing the effect of parameters on responses. Finally results were verified through confirmation test. **Kazancoglu et al. (2011)** proposed Taguchi combined Grey relation analysis to determine the best parametric combination which will enhance the quality and productivity of turning operation. MRR, cutting forces and surface roughness were considered as performance characteristics. The multi response optimization method provided the grey relation grade after the evaluation of all the responses. Finally the GRG was analyzed through ANOVA and confirmation test was performed for final verification. **Thirumalai and Senthilkumaar (2011)** proposed an approach for selection of machining parameters by using an intelligent technique to optimize the cost and quality of the machining process. Using the experimental responses mathematical models were developed for objective functions as well as constraints in the multi-objective optimization. The Multiple Attribute Decision Making (MADM) method was used to evaluate and rank the machining conditions. **Golshan et al. (2011)** found the superiority of Non-dominated Sorting Genetic algorithm (NSGA-II) over micro genetic algorithm (MGA) upon the parameters like cutting speed, feed rate, depth of cut and tool geometry as inputs in order to optimize the surface finish and tool life criteria. **Abhang and Haemeedullah (2012)** adopted grey relation analysis combined with factorial design (8 added center points) to optimize surface roughness and chip thickness, taking speed, feed, nose radius and concentration of solid liquid lubricant as input process parameters and found that concentration of lubrication had dominant influence followed by feed rate cutting speed and nose radius. **Pansare and Kavade (2012)** obtained optimum turning parameters for minimum surface roughness value by using ant colony optimization (ACO) algorithm in multi pass turning operation. Also the relationship between the parameters and the performance measures were determined using multiple linear regressions; the mathematical model was used to determine optimal parameters. **Koushik et al. (2012)** discussed neural network and multiple objective optimizations. The optimization techniques discussed was found advantageous as it was complementing the model by new input parameters without modifying the existing model structure. **Sai et al. (2012)** determined the optimal machining parameters for continuous profile machining with respect to the minimum production time, subjected to a set of practical constraints, cutting force, power and dimensional accuracy and surface finish. Due to complexity of the machining optimization problem, a genetic algorithm (GA) was used to resolve the problem and the results obtained. **Vignesh and Selvaraj (2013)** found the effect of machining parameter on surface texture and temperature aspects during turning of 6063 Aluminium alloy. The authors designed the experiment using central composite design and analyzed the quality through RSM and also developed mathematical model for prediction of quality characteristics. **Quazi et al.(2013)** implemented

Taguchi principle to optimize the machining parameters of turning operation. The authors explored orthogonal array to design the experiment and analyzed data using ANOVA and S/N ratio. **Makhfi et al. (2013)** implemented artificial neural network (ANN) in order to determine cutting force components throughout hard turning of bearing steel by means of CBN cutting tools. The authors had considered feed rate, cutting speed, workpiece hardness and cutting depth as controlling parameters for the ANN model. **Rajesh et al. (2013)** used Taguchi based grey relationship coupled with PCA (principal component analysis) and carried out turning operation of red mud based aluminum metal matrix composite using uncoated carbide tool on a CNC turning machine in dry condition to optimize surface roughness, power consumption and vibration. **Savadamuthu et al. (2012)** provided fuzzy control scheme designed by the Taguchi-genetic method to study the performance characteristics for turning operations of AISI 1030 steel bars using TiN coated tools by employing orthogonal array, the signal-to-noise ratio, the analysis of variance (ANOVA), then Adaptive Neuro Fuzzy Inference System (ANFIS) and genetic algorithm was applied to search for the optimal control parameters of both the predictor and the fuzzy controller. **Doriana and Teti (2013)** determined the optimal machining parameters using genetic algorithm based method during a turning process that minimize the production time without violating any imposed cutting constraints multi-object optimization, minimizing machining time while considering technological and material constrains. **Krishnamurthy and Venkatesh (2013)** employed orthogonal array, the S/N ratio and analysis of variance to find out the inter relationship between the performance characteristics like surface roughness and material removal rate and the cutting factors speed, feed, depth of cut. **Warhade et al. (2013)** compared Taguchi analysis, ANOVA, RSM to get relationship between the parameters speed, feed, depth of cut and machining time power consumption, machining time, material removal rate**. Suresh and Krishnaiah (2013)** obtained the optimal setting of process parameters and the percentage of each process parameter in turning for maximizing the material removal rate of the manufactured component employing Taguchi's Design of Experiments, (orthogonal array), ANOVA. **Doddapattar and Batakurki (2013)** studied the independent effects of input process parameters (speed, feed, depth of cut, nose radius) on the output parameters (material removal rate, surface roughness, machining time) using Taguchi method, which provided the optimum input parameter minimizing surface roughness.

1.4 Motivation and Objectives

From the literature review, it was found that many researches have employed different optimization techniques to find out the optimum cutting condition for turning operation. So many advanced multi-objective optimization techniques like micro genetic algorithm, Neuro fuzzy interference system, ant colony method etc. are employed and proved their effectives to find out the optimum values. But less work has been done using the concept of similarity based method. The present work is based on study of cutting condition of turning operation of cylindrical aluminum rod. The objectives of the present work are:

- To find out the optimum condition of the turning operation using TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution).
- To find out the optimum condition of the turning operation using Deng's similarity based method.
- To check the effectiveness of TOPSIS and Deng's similarity based method.

Chapter 2

Multi-Response Optimization in Machining: Exploration of TOPSIS

2.1 The Concept of TOPSIS

The Technique for Order of Preference by Similarity to Ideal solution (TOPSIS) is a multi-criteria decision analysis method, based on the concept that the chosen alternative should have the longest geometric distance from the negative ideal solution and the shortest geometric distance from the positive ideal solution. TOPSIS provides a more realistic form of modeling as it allows trade-offs between criteria, where a poor result in one criterion can be negated by a good result in another criterion. Steps involved in TOPSIS are described below **[Safari et.al (2013)]:**

Step1: The decision matrix can be established for ranking in matrix format as:

$$X = \begin{bmatrix} x_{11} & x_{12} & . & x_{1j} & x_{1n} \\ x_{21} & x_{22} & . & x_{2j} & x_{2n} \\ . & . & . & . & . \\ x_{i1} & x_{i2} & . & x_{ij} & . \\ . & . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mj} & x_{mn} \end{bmatrix} \tag{1}$$

Step 2: The normalized decision matrix can be found out by determining the normalized value x'_{ij} as:

$$x'_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

$$X' = \begin{bmatrix} x'_{11} & x'_{12} & . & x'_{1j} & x'_{1n} \\ x'_{21} & x'_{22} & . & x'_{2j} & x'_{2n} \\ . & . & . & . & . \\ x'_{i1} & x'_{i2} & . & x'_{ij} & . \\ . & . & . & . & . \\ x'_{m1} & x'_{m2} & . & x'_{mj} & x'_{mn} \end{bmatrix} \tag{2}$$

Step 3: The weighted normalized decision matrix can be determined as:

$$\boldsymbol{Y = w_j x'_{ij}}$$

$$Y = \begin{bmatrix} y_{11} & y_{12} & . & y_{1j} & y_{1n} \\ y_{21} & y_{22} & . & y_{2j} & y_{2n} \\ . & . & . & . & . \\ y_{i1} & y_{i2} & . & y_{ij} & . \\ . & . & . & . & . \\ y_{m1} & y_{m2} & . & y_{mj} & y_{mn} \end{bmatrix} \tag{3}$$

Step 4: The positive ideal solutions and negative ideal solutions are determined as:

Positive ideal solution

$$A^+ = \left\{ \left(\max_i \ y_{ij} \middle| j \in J \right), \left(\min_i \ y_{ij} \middle| j \in J' \middle| i = 1, 2, ..., m \right) \right\} \qquad \text{(Best criteria)}$$

$$= \left\{ y_1^+, y_2^+, ..., \ y_j^+, ... \ y_n^+ \right\} \tag{4}$$

Negative ideal solution

$$A^- = \left\{ \left(\min_i \ y_{ij} \middle| j \in J \right), \left(\max_i \ y_{ij} \middle| j \in J' \middle| i = 1, 2, ..., \ m \right) \right\} \qquad \text{(Worst criteria)}$$

$$= \left\{ y_1^-, y_2^-, ..., \ y_j^-, ... \ y_n^- \right\} \tag{5}$$

Here J is associated with the positive criteria and J' is associated with the negative criteria.

Step 5: The separation measures are calculated by using the n-dimensional Euclidean distance. The separation of each alternative from the positive-ideal solution is given as:

Separation from positive ideal solution:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_j^+\right)^2}$$

Separation from negative ideal solution

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_j^-\right)^2} \qquad i = 1, 2, \ldots\ldots\ldots, m \tag{6}$$

Step 6: The relative closeness to the ideal solution is calculated. The relative closeness of the alternative Ai with respect to A+ is defined as:

$$C_i^+ = \frac{D_i^-}{D_i^+ + D_i^-}, \quad i = 1, 2, \ldots\ldots\ldots, m; 0 \le C_i^+ \le 1 \tag{7}$$

Step 8: Ranking is done in descending order of the relative closeness value. Larger relative closeness value indicates a good performance of the alternative $\boldsymbol{A_i}$

Now summarizing the total methodology of TOPSIS we can represent steps in a process chart as described below:

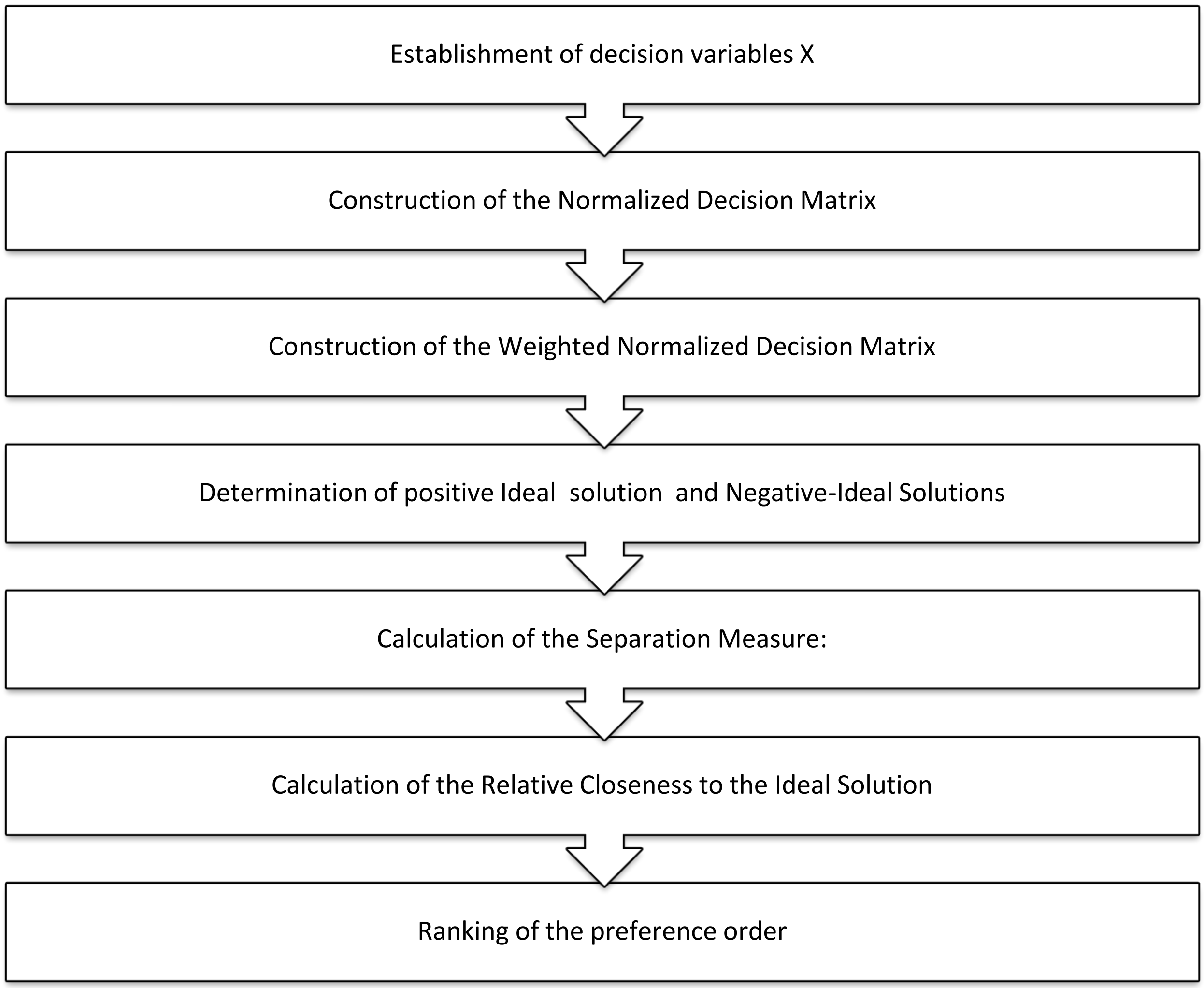

Fig. 3: Step by step process of TOPSIS

2.2 Experimentation

The turning operation has been carried out using lathe HMT NH26. The research aims at assessing the effect of machining parameters on surface roughness, cutting forces, tool-tip temperature (during machining) and MRR of turned aluminum bar. The work attempts to determine an optimal machining condition to minimize surface roughness, cutting forces and tool-tip temperature as well as to maximize MRR. Sample of aluminum bars having dimension of diameter 50 mm and length of 150 mm has been used as work piece material. Single point HSQ tool of 3-X 10% cobalt has been used during experiments.

Fig. 4: Experimental setup

Taguchi's philosophy is mainly explored for designing the experimental procedure to investigate the effects of the entire machining parameters through limited number of experimental runs. Taguchi's orthogonal array design of experiment is economic as well as less time consuming. In this study, three governable process parameters: spindle speed, feed and depth of cut have been selected and varied in five different levels **(Table 1).**

Table 1: Domain of Experiments

Factors	Unit	Level 1	Level 2	Level 3	Level 4	Level 5
Spindle Speed (N)	RPM	275	357	465	605	787
Feed Rate (f)	mm/rev	0.08	0.12	0.16	0.20	0.24
Depth of Cut (d)	mm	0.6	0.9	1.2	1.5	1.8

Here, L_{25} orthogonal array has been chosen for this experimental procedure and furnished in **Table 2.** Here, only the main effects of machining parameters i.e. spindle speed, feed rate and depth of cut has been considered for assessing the optimal condition and their interaction effects has been considered as negligible.

Table 2: Design of Experiment (DOE)

Sl. No.	N [rpm]	f [mm/rev]	d [mm]
1	275	0.08	0.6
2	275	0.12	0.9
3	275	0.16	1.2
4	275	0.20	1.5
5	275	0.24	1.8
6	357	0.08	0.9
7	357	0.12	1.2
8	357	0.16	1.5
9	357	0.20	1.8
10	357	0.24	0.6
11	465	0.08	1.2
12	465	0.12	1.5
13	465	0.16	1.8
14	465	0.20	0.6
15	465	0.24	0.9
16	605	0.08	1.5
17	605	0.12	1.8
18	605	0.16	0.6
19	605	0.20	0.9
20	605	0.24	1.2
21	787	0.08	1.8
22	787	0.12	0.6
23	787	0.16	0.9
24	787	0.20	1.2
25	787	0.24	1.5

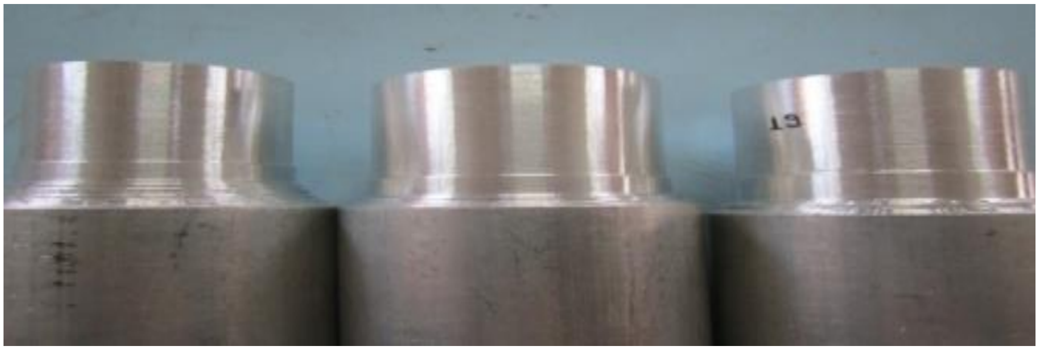

Fig 5: Machined work piece

Material Removal Rate (MRR), surface roughness (R_a), maximum tool-tip temperature (during operation) and cutting forces have been considered as manufacturing goals (performance features) for turning operations.

Material removal rate (MRR) is a key criterion to characterize any industrial machining process, can be defined as the volume of material removed divided by the machining time. Corresponding MRR values have also been computed by using following equation:

$$MRR = \frac{W_i - W_f}{\rho \times t_m} mm^3 / \min \qquad (8)$$

$W_i =$ Initial weight of the work piece, $W_f =$ Final weight of the work piece after machining, $\rho =$ Density of the work material, and $t_m =$ Machining time.

Surface roughness considered as quality aspects in manufacturing environment can be defined as measure of the level of unevenness of the part's surface. Here, surface roughness tester SJ-210 (Make: Mitutoyo) has been used to measure the roughness average value based on carrier modulating principle. Cutting tool dynamometer (Computerized Lathe Tool Dynamometer, Make: MEDILAB ENTERPRISES, Chandigarh, INDIA) has been used while performing turning for assessment of cutting forces in all three directions (F_X, F_Y and F_Z). During the machining process, temperature arises at machined surface because of plastic deformation of the work piece surface, the friction of the chip on the tool tip and the friction between the tool and the work piece interface. Tool-tip temperature has been measured by using non- contact infrared thermometer (Model: AR882 and temperature range -18 to 15000C), supplied by Real Scientific Engineering Corporation, New Delhi

Fig 6: Experimental setup with computerized dynamometer

The experimental results of six output responses Material removal rate, surface roughness, tooltip temperature, radial force, thrust force and cutting force are recorded through different instruments stated above and tabulated in **Table 3.**

Table 3: Experimental data

Sl. No.	Tool-tip Temperature (^oC)	F_x (N)	F_y (N)	F_z (N)	R_a (μ-m)	MRR (mm^3/min)
1	30	44.90	31.79	109.65	3.482333	4444.444444
2	33.7	72.50	52.93	112.42	4.741	7407.407407
3	40	206.34	131.05	270.51	17.22433	22962.96296
4	39.8	337.80	248.27	536.54	31.86533	32592.59259
5	49.5	499.07	379.80	808.09	28.76167	50370.37037
6	40.9	153.57	97.46	221.91	18.08233	22222.22222
7	39.5	91.30	74.43	129.72	5.391667	8888.888889
8	30.6	110.73	173.34	406.26	12.24533	14814.81481
9	31.2	223.15	154.99	328.43	16.276	17777.77778
10	35.3	95.72	64.80	128.47	12.74267	8888.888889
11	32.9	64.12	52.30	83.17	4.055	8148.148148

12	42.1	108.91	141.03	300.52	5.885333	15555.55556
13	32.4	158.93	129.54	240.14	8.232	20000
14	30.1	69.94	42.85	85.76	9.801333	7407.407407
15	32.7	143.69	81.43	183.02	13.058	11851.85185
16	34.5	71.09	48.22	106.75	9.080667	12592.59259
17	38.4	149.25	117.18	209.27	21.14767	175555.5556
18	31.7	65.89	47.23	82.27	6.228667	10370.37037
19	32.4	103.37	76.79	173.34	8.611333	15079.36508
20	37.2	174.35	112.38	267.39	12.52167	23703.7037
21	35.5	66.63	30.22	97.74	12.75567	17777.77778
22	48.1	52.50	93.43	61.95	4.482667	15555.55556
23	37.2	95.15	68.99	122.25	18.13867	21367.52137
24	37.2	90.61	87.08	176.2	20.47787	28703.7037
25	39.2	149.41	176.14	271.00	23.23933	28888.88889

2.3 Data Analysis

In course of data analysis, the normalized values are determined as it adjusts the values measured on different scales to a notionally common scale and normalized matrix is determined as shown in **(Eq. 2)*.*** The normalized values are tabulated in **Table 4.**

Table 4: Normalized data

Sl. No.	TEMP	FX	FY	FZ	SR	MRR
01	0.162889	0.053571	0.048041	0.079837	0.045871	0.021992
02	0.182979	0.086501	0.079988	0.081854	0.06245	0.036654
03	0.217185	0.246189	0.198044	0.196961	0.226886	0.113627
04	0.216099	0.403037	0.375189	0.39066	0.419744	0.161277
05	0.268767	0.595452	0.573958	0.588377	0.378861	0.249246
06	0.222072	0.183228	0.147283	0.161575	0.238188	0.109962
07	0.21447	0.108932	0.11248	0.09445	0.071021	0.043985
08	0.166147	0.132114	0.261954	0.295802	0.161301	0.073308
09	0.169404	0.266245	0.234223	0.239133	0.214394	0.087969
10	0.191666	0.114206	0.097927	0.09354	0.167852	0.043985
11	0.178635	0.076503	0.079036	0.060557	0.053414	0.040319
12	0.228587	0.129943	0.213126	0.218811	0.077524	0.076973
13	0.17592	0.189623	0.195762	0.174848	0.108435	0.098965
14	0.163432	0.083447	0.064755	0.062443	0.129107	0.036654
15	0.177549	0.17144	0.123058	0.133258	0.172006	0.058646
16	0.187322	0.084819	0.072871	0.077726	0.119614	0.062312
17	0.208498	0.178073	0.177084	0.152371	0.278566	0.868697

18	0.172119	0.078615	0.071375	0.059902	0.082047	0.051315
19	0.17592	0.123333	0.116046	0.12621	0.113432	0.074617
20	0.201982	0.208021	0.16983	0.194689	0.164941	0.117292
21	0.192752	0.079498	0.045669	0.071165	0.168023	0.087969
22	0.261165	0.062639	0.141193	0.045106	0.059048	0.076973
23	0.201982	0.113526	0.104259	0.089011	0.23893	0.105732
24	0.201982	0.108109	0.131596	0.128293	0.269743	0.142034
25	0.212842	0.178264	0.266185	0.197318	0.306119	0.14295

Based on the impact on machining yield, the priority weight has been assigned to each response. Here, equal weight (0.167) has been assigned to each performance characteristic and weighted (normalized) decision-making matrix has been shown in **Table 5.**

Table 5: Weighted normalized decision making matrix

Sl. No.	TEMP	FX	FY	FZ	SR	MRR
01	0.027148	0.008929	0.008007	0.013306	0.007645	0.003665
02	0.030496	0.014417	0.013331	0.013642	0.010408	0.006109
03	0.036198	0.041031	0.033007	0.032827	0.037814	0.018938
04	0.036017	0.067173	0.062531	0.06511	0.069957	0.02688
05	0.044794	0.099242	0.09566	0.098063	0.063144	0.041541
06	0.037012	0.030538	0.024547	0.026929	0.039698	0.018327
07	0.035745	0.018155	0.018747	0.015742	0.011837	0.007331
08	0.027691	0.022019	0.043659	0.0493	0.026883	0.012218
09	0.028234	0.044374	0.039037	0.039855	0.035732	0.014662
10	0.031944	0.019034	0.016321	0.01559	0.027975	0.007331
11	0.029772	0.01275	0.013173	0.010093	0.008902	0.00672
12	0.038098	0.021657	0.035521	0.036469	0.012921	0.012829
13	0.02932	0.031604	0.032627	0.029141	0.018073	0.016494
14	0.027239	0.013908	0.010793	0.010407	0.021518	0.006109
15	0.029591	0.028573	0.02051	0.02221	0.028668	0.009774
16	0.03122	0.014137	0.012145	0.012954	0.019936	0.010385
17	0.03475	0.029679	0.029514	0.025395	0.046428	0.144783
18	0.028687	0.013102	0.011896	0.009984	0.013674	0.008553
19	0.02932	0.020556	0.019341	0.021035	0.018905	0.012436
20	0.033664	0.03467	0.028305	0.032448	0.02749	0.019549

21	0.032125	0.01325	0.007611	0.011861	0.028004	0.014662
22	0.043528	0.01044	0.023532	0.007518	0.009841	0.012829
23	0.033664	0.018921	0.017376	0.014835	0.039822	0.017622
24	0.033664	0.018018	0.021933	0.021382	0.044957	0.023672
25	0.035474	0.029711	0.044364	0.032886	0.05102	0.023825

Then the positive ideal solutions and negative ideal solutions are determined using **(Eq. 4-5).** As higher MRR is desirable (as it corresponds to Higher-is-Better, HB criterion), maximum value among the recorded values are considered as positive ideal solution and minimum value referred as negative ideal solution. Whereas for rest of the responses like surface roughness, cutting forces, tool-tip temperature, lower values are desirable (as they correspond to Lower-is-Better, LB criterion). Hence, minimum value of the recorded value is regarded as positive ideal solution and maximum value represents the negative ideal solution. The positive ideal solution and negative ideal solution are determined and tabulated in **Table 6.**

Table 6: Positive ideal solution and negative ideal solution

A+	0.027148	0.008929	0.007611	0.007518	0.007645	0.144783
A-	0.044794	0.099242	0.09566	0.098063	0.069957	0.003665

Now the separation distance is measured from both positive ideal solution and negative ideal solution using **(Eq. 6)** and then the relative closeness index is calculated using **(Eq. 7)** and tabulated in **Table 7.**

Table 7: Ranking of the alternative

Run No.	s+	s-	c_i	Ranking Order
1	0.141237	0.164977	0.538764	5
2	0.139103	0.15766	0.531265	7
3	0.138366	0.113622	0.450902	20
4	0.166097	0.061869	0.271397	24
5	0.19534	0.038484	0.164585	25
6	0.135079	0.126604	0.483805	17
7	0.138785	0.1508	0.520745	11
8	0.145466	0.115179	0.4419	22
9	0.144953	0.105694	0.421685	23
10	0.139902	0.146529	0.511568	14

11	0.138283	0.161203	0.538266	6
12	0.139064	0.129661	0.482504	18
13	0.134829	0.12804	0.487086	16
14	0.139521	0.157571	0.530376	9
15	0.139439	0.135531	0.492893	15
16	0.135306	0.15554	0.534785	7
17	0.052837	0.187253	0.779927	1
18	0.136526	0.160142	0.539803	4
19	0.134546	0.144472	0.517787	12
20	0.133538	0.123252	0.479974	19
21	0.131941	0.156906	0.543215	2
22	0.133943	0.15807	0.541312	3
23	0.132274	0.143991	0.521206	10
24	0.128773	0.138066	0.517413	13
25	0.137869	0.112097	0.44845	21

From the above table, it is clearly visible that run 17 is getting the 1st rank. Hence, the corresponding input parameter i.e. spindle speed of 605 rpm, feed rate of 0.12 mm/ rev and depth of cut of 1.8 mm is found to be the optimum combination. In the present scenario we have 3 cutting parameter which are varied up to 5 levels. Hence 3^5 numbers of combinations are possible. But only 25 combinations we have taken into consideration. Therefore, there is a possibility that the optimum condition may lie in rest of the combinations. So to find out the optimum combination the concept of S/N ratio can be adopted. Higher will be the relative closeness more optimum will be the result. Higher-is-Better (HB) criterion is accepted and the corresponding S/N ratio values are determined by using the following formula.

$$\text{S/N ratio} = -10 \log \frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2} \tag{9}$$

The S/N ratio values are tabulated in **Table 8.**

Table 8: S/N ratio values for TOPSIS

Sl. No.	N [rpm]	f [mm/rev]	d [mm]	ci	SNRA1
1	275	0.08	0.6	0.53876	-5.372
2	275	0.12	0.9	0.53127	-5.4938
3	275	0.16	1.2	0.4509	-6.9184

4	275	0.2	1.5	0.2714	-11.328
5	275	0.24	1.8	0.16459	-15.672
6	357	0.08	0.9	0.48381	-6.3066
7	357	0.12	1.2	0.52075	-5.6675
8	357	0.16	1.5	0.4419	-7.0935
9	357	0.2	1.8	0.42169	-7.5002
10	357	0.24	0.6	0.51157	-5.8219
11	465	0.08	1.2	0.53827	-5.3801
12	465	0.12	1.5	0.4825	-6.33
13	465	0.16	1.8	0.48709	-6.2479
14	465	0.2	0.6	0.53038	-5.5083
15	465	0.24	0.9	0.49289	-6.145
16	605	0.08	1.5	0.53479	-5.4364
17	605	0.12	1.8	0.77993	-2.1589
18	605	0.16	0.6	0.5398	-5.3553
19	605	0.2	0.9	0.51779	-5.717
20	605	0.24	1.2	0.47997	-6.3757
21	787	0.08	1.8	0.54322	-5.3006
22	787	0.12	0.6	0.54131	-5.3311
23	787	0.16	0.9	0.52121	-5.6598
24	787	0.2	1.2	0.51741	-5.7232
25	787	0.24	1.5	0.44845	-6.9657

The main effect plots for each cutting parameter are plotted in order to get the optimum combination. **Fig 7** shows the main effect plot. From the above graph, we can conclude that the optimum combination is spindle speed of 605 rpm, federate of 0.12 mm/rev and depth of cut of 0.6.

Although TOPSIS is providing optimum results, it has been proved to be ineffective to choose the preference in some cases because the measured distance may create confusion while choosing the best alternative. As we can see from the **Fig 8**, it is difficult to find out the preferable alternative and quite confusing to rank them.

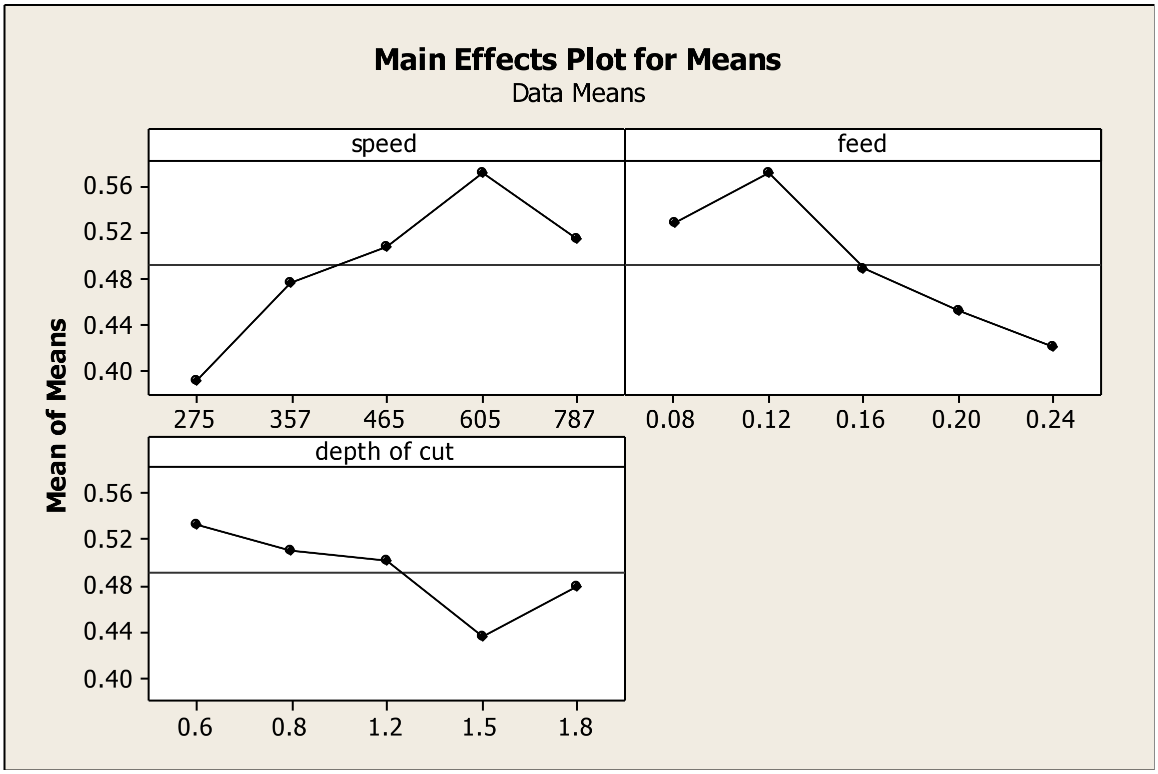

Fig 7: Evaluation of optimal parametric combination by using TOPSIS

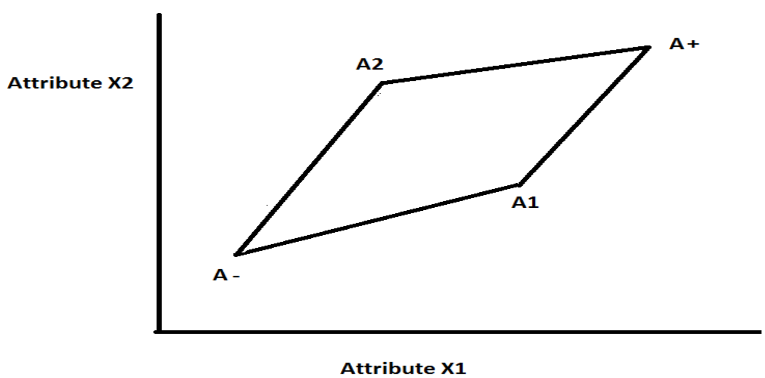

Fig 8: Separation distance of alternatives from positive and negative ideal solution

To avoid this type of circumstances **Hepu Deng (2007)** proposed another method called as Deng's similarity based method which is explored in the later phase of this work.

Chapter 3

Multi Response Optimization in Machining: Exploration of Deng's Similarity Based Method

3.1 Deng's Similarity Measure Approach

Hepu Deng (2007) proposed a new approach to find out the best alternative of the multi-criteria decision problem. In some cases, TOPSIS was found inefficient, because, comparing the distance between two alternatives was not sufficient. Deng discovered that, the comparison would be more effective, if magnitude and conflict between the alternative and ideal solution are taken in to consideration. Gradients of the variables indicate the conflicts and from the rank of conflict index, the best alternative can be identified.

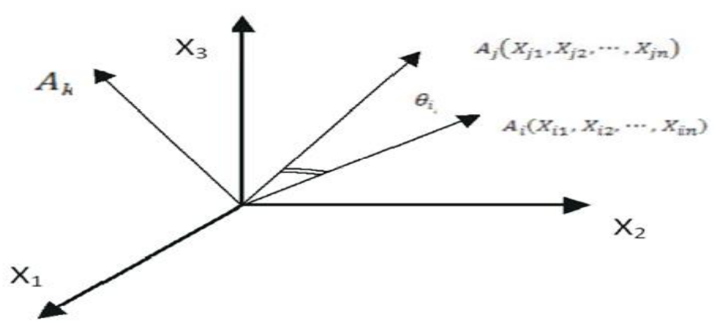

Fig 9: Degree of conflict by gradient

The steps for the method are similar to TOPSIS up to *step 4*. Further steps can be expressed as **[Safari et.al (2013)]:**

Step 5: Degree of conflict between each alternative and positive ideal solution and negative ideal solution can calculated as follow

Conflict between the alternative and positive ideal solution can be obtained as:

$$\cos\theta_i^+ = \frac{\sum_{j=1}^{m} y_{ij}\, y_j^+}{\left(\sum_{j=1}^{m} y_{ij}^{\;2}\right)^{0.5}\left(\sum_{j=1}^{m} y_{ij}^{+2}\right)^{0.5}}$$

Conflict between the alternative and negative ideal solution can be obtained as:

$$\cos \theta_i^- = \frac{\sum_{j=1}^{m} y_{ij} y_j^-}{\left(\sum_{j=1}^{m} y_{ij}{}^2 \right)^{0.5} \left(\sum_{j=1}^{m} y_j^{-2} \right)^{0.5}} \tag{10}$$

Here, the value of θ lies between 0° and 90°

Step 6: The degree of similarity and conflict between the alternatives and positive and negative ideal solution is calculated as:

Degree of conflict:

$$\left| C_i \right| = \cos \theta_i^{-+} \times \left| A_i \right| \tag{11}$$

Degree of similarity:

$$S_i^{-+} = \frac{\left| C_i \right|}{\left| A^{-+} \right|} = \frac{\cos \theta^{-+} \times \left| A_i \right|}{\left| A^{-+} \right|} = \frac{\cos \theta^{-+} \times \left(\sum_{j=1}^{m} y_{ij}^2 \right)^{0.5}}{\left(\sum_{j=1}^{m} y_j^{-+2} \right)^{0.5}} \tag{12}$$

Step 7: The overall performance index for each alternative is calculate as:

$$P_i = \frac{S_i^+}{S_i^+ + S_i^-}, \; i = 1,2,........, \; n$$

Step 8: Ranking according to Deng's similarity based method

Now summarizing the total methodology of Deng's similarity based method we can represent steps in a process chart as described below:

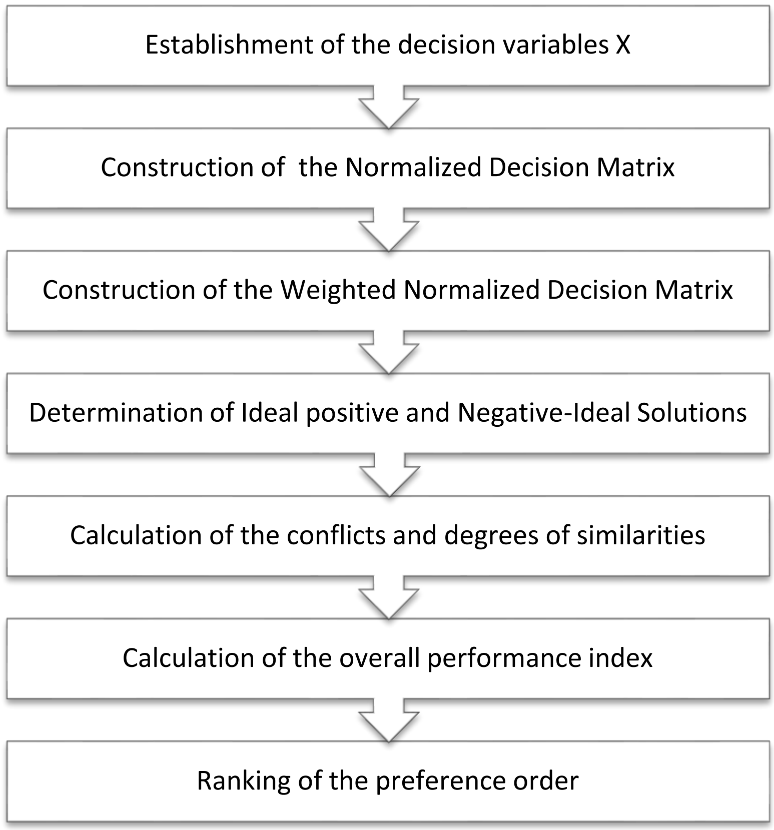

Fig 10: Step by step process of Deng's similarity based method

3.2 Experimental Data Analysis

In relation to the experimentation as discussed in **Section 2.2** of **Chapter 2**, the experimental data (Refer **Table 3**) are analyzed using Den's similarity based method in conjugation with Taguchi's optimization philosophy. Now the conflict angle, degree of conflict are calculated by using the above mentioned formulae and the values are tabulated in **Table 9.**

Table 9: Degree of conflicts of the alternatives

Run No.	COSθ+	COSθ-	C^+	C^-
01	0.314626	0.745175	0.010575	0.025047
02	0.353323	0.805229	0.014341	0.032682
03	0.394943	0.940899	0.032924	0.078437
04	0.336211	0.972178	0.04704	0.136019
05	0.356369	0.979455	0.067931	0.186702
06	0.419199	0.892354	0.031207	0.066431

07	0.350655	0.822394	0.01718	0.040292
08	0.304468	0.947968	0.024472	0.076194
09	0.326687	0.980365	0.028046	0.084165
10	0.329988	0.85252	0.017237	0.044532
11	0.379336	0.766074	0.014439	0.029159
12	0.361572	0.898035	0.025164	0.0625
13	0.415691	0.943147	0.027482	0.062354
14	0.343361	0.804724	0.013992	0.032792
15	0.342926	0.92437	0.020355	0.054869
16	0.426061	0.791767	0.019031	0.035366
17	0.947203	0.441188	0.154838	0.07212
18	0.419546	0.780515	0.016227	0.030188
19	0.426651	0.896494	0.0218	0.045807
20	0.436783	0.932792	0.03188	0.068082
21	0.478136	0.720201	0.02345	0.035322
22	0.433391	0.66383	0.023239	0.035596
23	0.451473	0.793586	0.028229	0.04962
24	0.494924	0.806304	0.034918	0.056887
25	0.417238	0.908728	0.038153	0.083095

Then the degree of similarity is calculated from eq.12. Finally overall performance index is calculated and tabulated in **Table 10.** Rank is provided to the index in a descending order such that the highest value of the index will get the first rank.

Table 10: Degree of similarity and ranking of alternatives

S^+	S^-	**P**	**Rank**
0.071377	0.13288	0.349448	17
0.096791	0.173387	0.358248	14
0.222217	0.416124	0.348116	18
0.317493	0.721612	0.305544	23
0.458492	0.990494	0.316423	22
0.21063	0.35243	0.37408	10
0.115955	0.213759	0.351683	16

0.165171	0.404223	0.290082	25
0.189296	0.446514	0.297725	24
0.11634	0.23625	0.329958	20
0.097452	0.154694	0.38649	8
0.169844	0.331577	0.338725	19
0.18549	0.330801	0.359275	13
0.094436	0.173968	0.351842	15
0.137387	0.29109	0.32064	21
0.128448	0.187624	0.406388	6
1.045065	**0.382614**	**0.732003**	**1**
0.109521	0.160154	0.406124	7
0.147138	0.243017	0.377127	9
0.215169	0.36119	0.373325	11
0.158274	0.187391	0.457883	2
0.156852	0.188844	0.453728	3
0.19053	0.263246	0.419876	5
0.235677	0.301797	0.438491	4
0.257508	0.440836	0.368741	12

From the above table, it is clearly visible that run 17 is getting the 1^{st} rank. Hence, the corresponding input parameter i.e. spindle speed of 605 rpm, feed rate of 0.12 mm/ rev and depth of cut of 1.8 mm is found to be the optimum combination. Finally, the Taguchi method has been implemented on the overall performance coefficient (OPI) for evaluating the optimal machining parameter by using S/N ratio plot of OPI. Higher the value of overall performance index, the corresponding parameter combination is said to be close to the optimal solution. The S/N ratio values are calculated using eq.9 and tabulated in **Table 11.**

Table 11: S/N ration of overall performance index (OPI)

Sl. No.	N [rpm]	f [mm/rev]	d [mm]	OPI	S/N ratio
1	275	0.08	0.6	0.349448	-9.1323
2	275	0.12	0.9	0.358248	-8.9163
3	275	0.16	1.2	0.348116	-9.1655

4	275	0.2	1.5	0.305544	-10.2985
5	275	0.24	1.8	0.316423	-9.9946
6	357	0.08	0.9	0.37408	-8.5407
7	357	0.12	1.2	0.351683	-9.077
8	357	0.16	1.5	0.290082	-10.7496
9	357	0.2	1.8	0.297725	-10.5237
10	357	0.24	0.6	0.329958	-9.6308
11	465	0.08	1.2	0.38649	-8.2572
12	465	0.12	1.5	0.338725	-9.4031
13	465	0.16	1.8	0.359275	-8.8915
14	465	0.2	0.6	0.351842	-9.073
15	465	0.24	0.9	0.32064	-9.8796
16	605	0.08	1.5	0.406388	-7.8212
17	605	0.12	1.8	0.732003	-2.7097
18	605	0.16	0.6	0.406124	-7.8268
19	605	0.2	0.9	0.377127	-8.4702
20	605	0.24	1.2	0.373325	-8.5583
21	787	0.08	1.8	0.457883	-6.7849
22	787	0.12	0.6	0.453728	-6.8641
23	787	0.16	0.9	0.419876	-7.5376
24	787	0.2	1.2	0.438491	-7.1608
25	787	0.24	1.5	0.368741	-8.6656

Fig.10 shows the optimal parametric combination obtained by the methodology and it is noticed that predicted S/N ratios values for these optimal combination appears as the highest than that obtained for corresponding S/N ratios in **Table 11** for all run numbers.

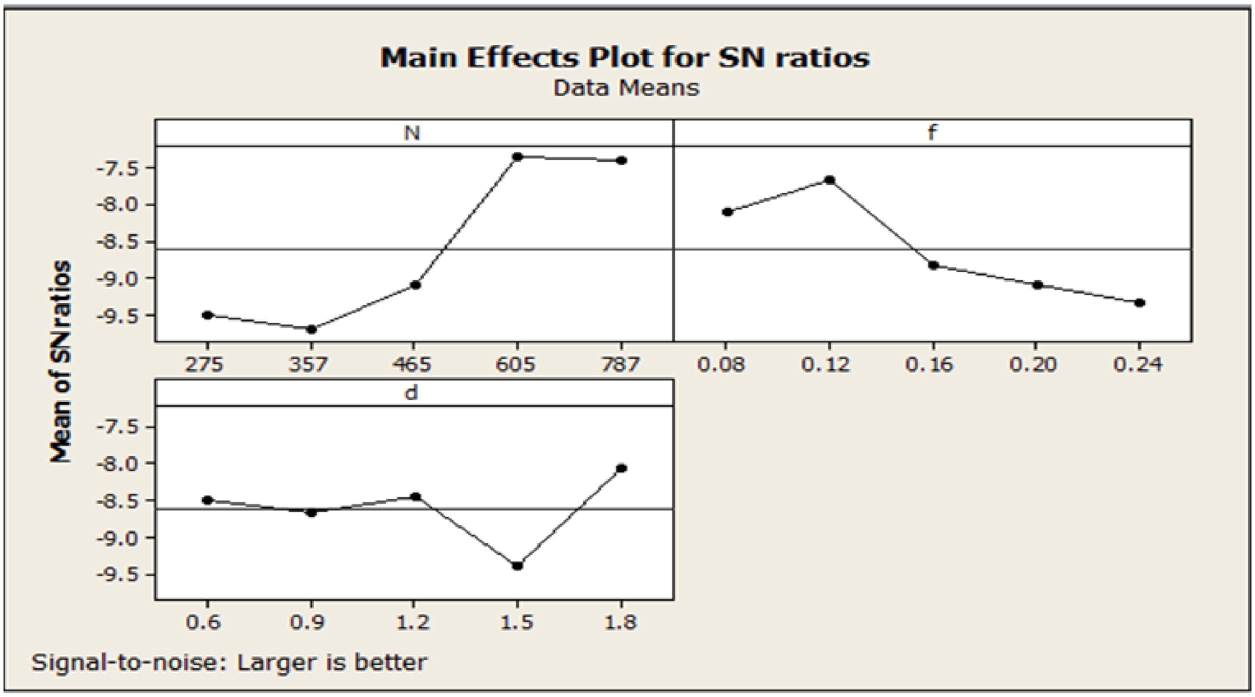

Fig 11: Evaluation of optimal parametric combination by using Deng's similarity based Taguchi approach

From the S/N ratio results, it is observed that the optimum spindle speed for Deng's similarity based method integrated with Taguchi's philosophy is 605 rpm, feed is found to be 0.12 mm/rev and depth of cut is found to be 1.8 mm.

Chapter 4
Summary and Conclusion

Aluminum is the most widely used non-ferrous metal due to having special properties like low density, good conductivity, excellent reflectivity, ductility, corrosion resistance etc. Again it is theoretically 100% recyclable without any loss of its natural qualities. Hence, it has a wide application in the field of transportation, aerospace, packaging, construction, household items, electrical transmission line for power distribution etc. Therefore, it is required to study the challenges regarding machining of aluminum, for enhancing the productivity as well as for reducing cost and processing time with improved product quality. Turning is one of the most common machining process in which material is removed due to the relative motion between the rotating work piece and linearly moving single point cutting tool. For the process to be efficient, high MRR (Material Removal Rate), good surface roughness (low R_a), low cutting force, low cutting temperature etc. are indeed desired; which can be obtained by manipulating the input parameters like speed (cutting speed or spindle speed), feed rate, depth of cut. In this study, material removal rate, surface roughness, cutting tool-tip temperature and cutting forces during turning of aluminum was experimentally investigated, to compare TOPSIS, Deng's Similarity Based Method combined with Taguchi's robust optimization philosophy. The experiments were designed based on Taguchi L25 orthogonal array at five different levels of cutting speed, feed rate and depth of cut. During the experiments, cutting force components, weight of material, tool tip temperature and surface roughness were recorded. The results were analyzed by using S/N ratio. In TOPSIS, the Euclidian distance between ideal solution and corresponding alternative provides the closeness between them which was practically found difficult to provide precise results. Hence Deng's similarity based method was introduced, where the closeness of the alternatives and ideal solution was found by comparing the magnitudes and conflicts between them. Finally, the optimum input factors (process control parameters) and their corresponding levels were found out using S/N ratio concept. TOPSIS and Deng's similarity based method was found efficient to provide optimum cutting parameters for turning operation in order to maximize the MRR and minimize surface roughness, cutting tool tip temperature and cutting forces as well.

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