Multi-Objective Tooling Optimization for Sustainable Manufacturing

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ABSTRACT

Process planning is an activity for designers to evaluate manufacturability and manufacturing cost in the early design stage of mechanical parts production where important parameters that affect the machining process should be analyzed in detail. This paper deals with the systematic determination of the detailed methods involved in the manufacturing of parts from raw materials to a finished product using fuzzy optimization to minimize its impact on the environment. The focus of this study is to develop a fuzzy optimization model for environmental supportive process planning while minimizing the factors such as machining cost, machining time and environmental impact for turning operation. A multi-objective non-linear programming model is also developed and its results are compared with the fuzzy model.

Keywords **–environmental impact, fuzzy logic, multi-objective optimization, process planning, sustainable manufacturing.**

I. INTRODUCTION

Process planning is an activity for designers to evaluate manufacturability, manufacturing cost in the early design stage of mechanical parts production where important parameters that affect the machining process should be analyzed in detail. The environmental impact of the manufacturing processes has been emphasized on and given importance in recent research. Mathematical model-based techniques have been used for decades for analysis of parameters and decision making in the planning process [1]. Significant development has been made in the math-model based control techniques for process planning[2][3]. Mathematical non linear model concepts have yielded successful results in process planning along with the consideration of the environmental issues [4][5][6]. These conventional methods are primarily deterministic or heuristic and can be successfully implemented where it is possible to gather precise and reliable amounts of data [7]. Environment conscious process planning is knowledge intensive and the information available is often imprecise, inaccurate and vague. Conventional methods fail when the real life problems come into consideration. Thus there emerged a need to develop a concept that takes these limitations into account and delivers an optimal solution.

Fuzzy set theory has emerged as one of the prominent solution for dealing with these kinds of vagueness and uncertainty since Zadeh introduced it in 1965 [8]. The use of fuzzy set theory allows the uncertainties and complexities in the knowledge to be incorporated, and thus capture and model the impreciseness in human reasoning in set-up planning [9]. Fuzzy concepts have yielded successful results in process planning [10][11]. Environmental issues also have been considered into the process-planning problem [12]. Environmental issues are getting ample attention from all parts of the society, but gathering the precise data on these issues is not that easy. It needs subjective decisions during the process planning. In this paper, the authors deal with the systematic determination of the detailed methods involved in the manufacturing of parts from raw materials to a finished product using fuzzy optimization to minimize its impact on the environment. Along with the development of a non-linear multi-objective programming, a fuzzy inference system based model is also developed to compare the effectiveness of the fuzzy model with the non-linear programming model.

II. METHODOLOGY

2.1 Problem Description

Machine variables are various and their selection affects the ease with which a given material may be worked with a cutting tool. Common machine variables affecting the manufacturing process as given by Dorzda and Wick are work piece material, tool material, type of operation performed, cutting speed, dimension of cut, tool form, cutting fluid, rigidity of work holding device, nature of engagement of tool with work, and environmental impact [7]. The parameters which do not vary much in relation to the chosen objective can be considered as constants. Here some variables like, machine tool, rigidity of work holding device, nature of engagement of tool, are assumed to be constant as they do not influence the process much and hence the prime concern is about the tool type, cutting speed, dimensions of cut, cutting fluid and environmental impact. These characteristics are explained in detail below. Some other factors that we will be considering that affect the turning operation are cutting speed, feed rate, depth of cut and the environmental impact. These factors are explained below.

- **Work piece material**: The use of material is the prime factor in selecting the work piece material as each product can be used for different purpose depending on the material used. Here, the work piece material chosen is cast iron. The Wrought-Medium (Ductile) Leaded type cast iron is used.

- **Type of operation:** Here in this paper the type of manufacturing process to be optimized is the turning operation.

- **Type of tools:** Tool materials can be chosen according to the type of work piece material and the type of operation to be performed. Some tool materials that can be used to machine the cast iron work piece and run the turning operation are 1) High speed steels, 2) Coated carbide tools, and 3) Ceramics. These are the materials that we shall consider throughout this work for optimal tool material selection for the turning process while minimizing the environmental impact.

- **Cutting speed:** Cutting speed has to be determined considering the power of the machine tool, type of material, tool type, and type of operation performed. The cutting speed or speed is expressed in feet per minute (fpm) or surface feet per minute (sfpm).

- **Feed rate and depth of cut:** Feed rate can be defined as the distance the tool advances into or along the work piece each time the tool point passes a certain position in its moving over the surface. Feed rate and depth of cut also affect the machining time and cost along with the cutting speed. When the feed rate is increased along with the cutting speed, the tool life increases to a certain point after which the tool life decreases. As the feed rate is increased, the tool presses against more material, more work is done, and the temperature at the interface increases. However, increasing the feed rate has a small effect on the temperature than increasing the cutting speed. This increase in the temperature will affect the tool life as tool life decreases due to an increase in interface temperature. Also when both the cutting speed and feed are increased there is an increased probability of tool wear, which might lead to a breakdown of the cutting edge. Therefore cutting fluids must be used to reduce the temperature at the interface of the tool and work piece. The cost of the cutting fluid must therefore be taken into account when determining the optimal feed rate. High cutting speed and high feed rate may also lead to machine tool vibration. Strong vibration can lead to chatter and also the surface finish considerably drops. Hence it becomes necessary to obtain an optimal feed rate.

- **Cutting fluids:** Cutting fluids as mentioned are used to reduce the temperature at the work-tool interface. Sometimes the use of cutting fluids can be helpful in removing the chip at the interface. When both the cutting speed and the feed are higher, then the cutting fluid flow will also be higher. The feed should be chosen such that the tool cost, the cutting fluid cost, and the cutting cost is minimal. Based on the feed and cutting speed, the cutting fluid flow has to be selected. The following table gives the approximate values of cutting fluid flow on the assumption that total force, rigidity, and the surface finish are constant. Since the data are qualitative, the cutting speed and feed are assumed to be qualitative for selecting the cutting fluid flow.

Before proceeding further, it is important to assume that the factors, like, the power of the machine tool, the rigidity, and the surface finish, are made constant. Range of cutting speed for a tool life of 1-2 hrs is between 80-160 fpm.

Table 1: List of Notation Used

Notation	C_r	c_d	c_m	c_o	c_{cf}	c_s	c_t	c_{tc}
Meaning	Material cost	Direct labor cost	Machining cost	Overhead cost	Cost of cutting fluid	Setup cost	Tool cost	Tool change cost
Notation	d	f	l	N	ev	v	f_{cf}	f_i
Meaning	diameter of the work-piece in mm	feed rate in mm/rev	length of cut in mm	number of tools	environmental score per tool	cutting speed in mm/min	cutting fluid flow	feed rate of tool *i*
Notation	t_m	t_s	t_{tc}	T	t_m /T	T_T	k_t	k_o
Meaning	machining time	Setup time	Tool change and adjusting time	tool life in min	number of cutting edges needed per work-piece	total time needed to machine one part	Cost of a cutting edge	Overhead cost per unit time

2.2 Multi Objective Programming Model

A mathematical non-linear model is developed to obtain the optimized cutting conditions. This model is applicable when there are enough data available for the respective parameters. Parameters like cutting speed, feed rate, depth of cut and material hardness are considered and other parameters like , machine capability, machine power, surface finish, etc are held constant. There are a few formulas that are used repeatedly throughout the model which will be discussed followed by the model itself.

$$c_s = c_d * t_s \qquad (1)$$

$$c_m = c_d * t_m \qquad (2)$$

$$c_{tc} = t_{tc} * c_d * (t_m/T) \qquad (3)$$

$$c_o = k_o * T_T \qquad (4)$$

$$c_t = k_t * (t_m/T) \qquad (5)$$

where, $T_T = t_s + t_m + t_{tc} * (t_m/T)$ ……… (6)

For the turning operation, t_m is given by

$$t_m = \frac{\pi dl}{1000vf} \qquad (7)$$

The environmental score per tool *ev* is calculated from the software Eco-Scan. The total environmental score (*EV*) for a part is given by multiplying the number of tools with the EV per tool.

$$EV = ev * N \qquad (8)$$

where,

N = number of tools

The objective function of the mathematical model is

$$\text{Min } Z = (Z_1, Z_2, Z_3) \qquad (9)$$

where Z_1 represents manufacturing time, Z_2 represents manufacturing cost, and Z_3 represents environmental impact.

$$Z_1 = \sum \frac{\pi dl}{1000 v_i f_i}\left(1 + \frac{t_{tci}}{T_i}\right) \qquad (10)$$

$$Z_2 = \sum \frac{\pi dl}{1000 v_i f_i}\left(c_d + (c_{t_i} * t_{tc_i} * T_i) + (c_0 * (1 + \frac{t_{tc_i}}{T_i}) \right) + \sum \frac{\pi dl}{1000 v_i f_i}\left((c_{cf} * f_{cf}) + (c_d * (\frac{t_{tc_i}}{T_i}) \right) \quad \text{.......(11)}$$

$$Z_3 = \sum \frac{\pi dl}{1000 v_i f_i}\left(\frac{ev_i}{T_i} \right) \quad \text{.......(12)}$$

where,

v_i= cutting speed of tool *i*, ev_i = environmental impact value of tool *i*

Decision Variable: *i* = type of tool selected

Constraints:

$v_i \geq v_{\min}$ and $v_i \leq v_{\max}$

$f_i \geq f_{\min}$ and $f_i \leq f_{\max}$

$d_i \geq d_{\min}$ and $d_i \leq d_{\max}$

$f_{\min}, f_{\max}$ = minimum and maximum values of feed rate for tool *i* respectively.

$v_{\min}, v_{\max}$ = minimum and maximum values of cutting speed for tool *i* respectively.

$d_{\min}, d_{\max}$ = minimum and maximum values of depth of cut for tool *i* respectively.

The other parameters like, overhead cost, direct labor cost, cutting fluid cost, diameter of the work-piece, length of cut, are held constant as these parameters are not dependent on the type of the tool selected. The tool cost, tool change cost, are dependent on the type of tool selected and they are taken into the consideration through the coefficient of tool life constant. The cutting fluid flow depends on the cutting speed, feed rate as well as the depth of cut applied. This in turn depends on the type of tool selected. The cutting fluid flow is determined qualitatively as per the guidelines given in the Machining data handbook [13]. Although the tool cost and tool change time are constant, they change depending on the type of tool selected. The values of some constants are given in Table 2. All the data for the performance parameters are taken from the Machining data handbook, the cost of direct labor from the US government information on labor and wages. Turning operation is considered for all calculations and the data are from the Machining data handbook [13].

Table 2: Values of Constraints

Cost of direct labor	**Diameter of work piece**	**Length of cut**	**Overhead cost**	**Cutting fluid cost**
$13	20 mm	10 mm	$14	$10/gal

2.3 Normalization of the Objective

The output values obtained from this model are normalized using equation (13):

$$Z = \frac{Z(X) - Z_{MIN}(X)}{Z_{MAX}(X) - Z_{MIN}(X)} \quad \text{.......(13)}$$

where,

Z = rescaled objective function

Z(X) = objective function before rescaling

$Z_{MAX}(X)$ = maximum possible value of the objective function

$Z_{MIN}(X)$ = minimum possible value of the objective function

2.4 Assigning Weights to the Objectives

We are dealing with a multi objective problem in this paper since we have three objective functions that are machining cost, machining time and the environmental impact. In order to incorporate the importance of each of the objectives, a certain weight has to be given to the objectives depending on the requirements. Each objective is given a weight ranging from 0-1 such that the total weight of all three objectives has to be equal to 1. If we assume the weight for the cost function to be W_1, the time function to be W_2 and the environmental function to be W_3, the objective function can be written as

$Z = Min\ (W_1*Z_1,\ W_2*Z_2,\ W_3*Z_3)$ ……………….. (14)

where,

$0 \le W_1 \le 1;\ 0 \le W_2 \le 1;\ 0 \le W_3 \le 1;$

$W_1 + W_2 + W_3 = 1$……………………………….(15)

2.5 Front End Tool

From the mathematical model described above the tool type and the optimal cutting parameters for each tool type can be obtained. This involves very complex time consuming calculations. There was the need for a tool which could enable even the common worker to get the required tool type and cutting parameters. This tool was developed using Visual Basic for the front end and the calculations were done in the back end with the help of software What's Best.

The tool needs the maximum and minimum values of cutting speed, feed rate to be entered. Weights can be assigned for each objective as the weight can change according to the situation based on company preferences. A visual of how the tool looks is given below.

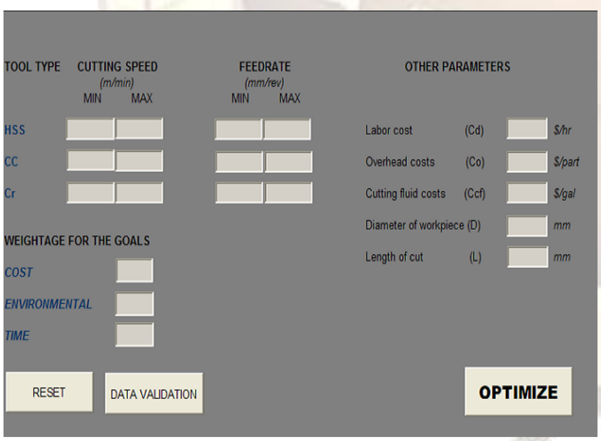

Figure 1: Front end tool

III. Development of Fuzzy Inference Model

The uzzy model is based on the relationship between hardness, cutting speed, feed rate and the depth of cut. A method proposed by Mamdani [14] is used to build the fuzzy inference system. The range of input parameters is taken from the machining data handbook [15]. There are two ways to define the membership functions for the fuzzy set namely numerical and functional. We opt for the functional type which defines the membership function of a fuzzy set in analytic expression which allows the membership grade for each element to be calculated within the defined universe of discourse. Here in this paper we have chosen triangular form membership function to represent the input and output variables. Fuzzy logic is a concept where the numerical variables are expressed as linguistic or fuzzy variables. This process is the initial step in the rule discovery method of fuzzy inference system. We use Wang-Mendel's rule discovery method which consists of the following steps:

- Data generation
- Normalization of data
- Fuzzification of data
- Converting into fuzzy variables
- Rule generation
- De-normalization

All the data required is obtained from the Tool and Manufacturing Engineers hand book and the fuzzy inference model development is explained step by step.

3.1 Data Generation

For data generation the input and output variables have to be defined beforehand. Here the input variables are material hardness, depth of cut, feed rate, cutting speed and the output parameters are machining cost, machining time and environmental impact. Since these parameters are assumed to follow triangular membership, they can be linguistically expressed as

- Material hardness – soft, medium, and hard
- Depth of cut – low, medium, and high
- Feed rate – low, medium, and high

- Cutting speed – low, medium, and high

The table 3 shows the parameters divided in three levels from which the output variables can be determined using the formulae discussed in the previous topic. All the possible combinations have to be carried out and the test has to be repeated three times for each level to ensure robust data generation.

Table 3: Input Parameter Range

Material hardness (RA)	Depth of cut (mm)	Feed rate (mm/rev)	Cutting speed (m/min)
85	1	0.20	40-50
	8	0.50	30-40
	16	0.75	24-30
90	1	0.18	112-150
	8	0.60	87-112
	16	1.0	50-87
95	1	0.13	215-250
	4	0.25	185-215
	8	0.40	150-185

3.2 Data Normalization

Normalization is done to make all the parameters have the same dimensions or dimensionless. We use the formula in eq. 13 for rescaling the objectives. Here care should be taken in selecting $Z_{MAX}(X)$ and $Z_{MIN}(X)$. The maximum and minimum value should be chosen considering all the types of tools. For example the hardness of a HSS tool is around 85 R_A and of the Ceramic tool it is around 95 R_A. So the range of hardness should be taken is 85-95 R_A. Table 4 gives the minimum and maximum values of each parameter. It is not easy to figure out the minimum and maximum values for output parameters. So while calculating the range of an output parameter, the weight given to other output parameters has to be kept as zero and the optimization model has to be run for minimizing and maximizing the output. For example when calculating the range of machining time the weight given to the machining time should be one and the weights given to machining cost and environmental impact should be zero. The same is repeated for the other parameters.

Table 4: Maximum and Minimum Value for Data Normalization

Parameters	Minimum Value	Maximum Value
Material hardness (RA)	85	95
Depth of cut (mm)	1	16
Cutting speed (m/min)	24	250
Feed rate (mm/rev)	0.13	1
Machining time (min)	0.0027	0.2227
Machining cost ($)	0.303	26.2239
Environmental impact (mPt)	0.0599	5.9538

3.3 Fuzzification of Data

Fuzzification comprises of transforming the crisp normalized values in to grades of membership for linguistic terms of fuzzy sets. Here, as we have discussed a triangular membership is assumed where in all the parameters are expressed as low, medium, high. A method proposed by Nozaki et al [7] to fuzzify a crisp value into a fuzzy value is used in this paper. Here it is assumed that the domain interval of the i^{th} input variable is divided in to K_i fuzzy sets, low, medium and high. We employ the symmetric triangular fuzzy sets with the following membership function explained in the equation:

$$\mu_{ij_i}(x) = \max\{1 - \left| x - a_{j_i}^{K_i} \right| / b^{K_i}, 0\} \quad \text{………………………………………(16)}$$

where

$$j_i = 1,2,...,K_i$$

$$a_{j_i}^{K_i} = (j_i - 1)/(K_i - 1)$$

$$b^{K_i} = 1/(K_i - 1)$$

Since we have assumed the triangular membership functions, the K_i value is set to 3. Hence the value of a_i and b_i are calculated from the above formulae and the following Table 5 shows their respective values.

Table 5: Fuzzy Partition Values

Membership function	a_i	b_i
Low	0	0.5
Medium	0.5	0.5
High	1	0.5

3.4 Converting To Linguistic Variables

After the data fuzzification process the subset which has the maximum value is selected, noted down and the crisp values can be expressed as linguistic variables by using the following "if-then" rules:

- If Maximum value of $\mu_{ij_i}(x)=\max\{1-|x-a_{j_i}^{K_i}|/b^{K_i},0\}$ falls in the column "low" the linguistically it can be expressed as "low".
- If Maximum value of $\mu_{ij_i}(x)=\max\{1-|x-a_{j_i}^{K_i}|/b^{K_i},0\}$ falls in the column "medium" then linguistically it can be expressed as "medium".
- If Maximum value of $\mu_{ij_i}(x)=\max\{1-|x-a_{j_i}^{K_i}|/b^{K_i},0\}$ falls in the column "high" then linguistically it can be expressed as "high".

3.5 Fuzzy Rule Based System

Fuzzy rules are linguistic IF-THEN- constructions that have the general form "IF A THEN B" where *A* and *B* are (collections of) propositions containing linguistic variables. *A* is called the premise and B is the consequence of the rule. In a more explicit form, if there are *i* rules each with *K* premises in a system, the i^{th} rule has the following form. If a_1 is $A_{i,1}$ Θ a_2 is $A_{i,2}$ Θ ...... Θ a_k is $A_{i,k}$, then B_i. In the above equation *a* represents the crisp inputs to the rule and *A* and *B* are linguistic variables. The operator can be *AND* or *OR* or *XOR*.

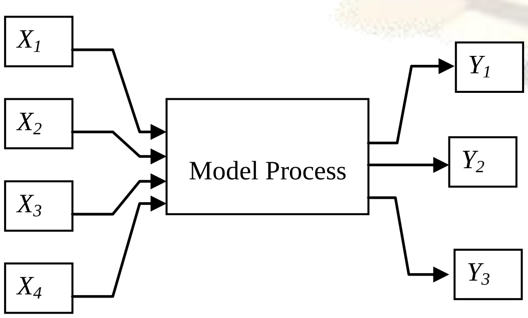

Figure 2: Fuzzy Inference Model

3.6 Effectiveness Rule Selection Method

A method of rule selection is the effectiveness rule selection method. It can be expressed by the formula

$$Max\left(\mu_{ij}(x_1)\times\mu_{ij}(x_2)\times\cdots\times\mu_{ij}(x_n)\times\mu_{ij}(y_1)\times\mu_{ij}(y_2)\times\cdots\times\mu_{ij}(y_n)\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(17)$$

The maximum fuzzy membership numbers of all the input and output parameters multiplied and whichever output combination gets the maximum of the product, then that corresponding rule is selected. Using this formula the generated rules are filtered. There are total 81 rules generated from the data and some of the rules are listed below.

- Rule 1: If (Hardness is low) and (Depth is low) and (Feed is low) and (Cutting speed is low) Then (Machining time is high) and (Machining cost is high) and (Environmental value is high).
- Rule 2: If (Hardness is low) and (Depth is low) and (Feed is medium) and (Cutting speed is low) Then (Machining time is low) and (Machining cost is low) and (Environmental value is low).
- Rule 3: If (Hardness is low) and (Depth is low) and (Feed is high) and (Cutting speed is low) Then (Machining time is low) and (Machining cost is low) and (Environmental value is low).
- Rule 4: If (Hardness is low) and (Depth is medium) and (Feed is low) and (Cutting speed is low) Then (Machining time is medium) and (Machining cost is medium) and (Environmental value is medium).
- Rule 5: If (Hardness is low) and (Depth is medium) and (Feed is medium) and (Cutting speed is low) Then (Machining time is low) and (Machining cost is low) and (Environmental value is low).

IV. COMPARISON OF THE TWO MODELS

The models developed are now checked for optimal output using a random collection of data for different values of the parameters for turning operation. The data are obtained from the Tools and Manufacturing Engineers handbook [15].

Table 6: Random Data for Model Comparison

Hardness (RA)	Depth of cut (mm)	Feed (mm/rev)	Speed (m/min)
85	1	0.14	26
85	8	0.7	40
85	15	1	50
90	9	0.6	100
90	14	0.9	150
95	4	0.2	175
95	6	0.3	200
95	8	0.4	250

Based on the input parameters four different scenarios are used for the process based on varying objective importance as shown in Table 7. And the corresponding output values are noted for each case. The input parameters selected for each case are then given as input to the fuzzy inference model and the output results of both the models are verified and the differences are analyzed. The Table 8 shows the output values of both the models for each case

Table 7: Input Parameters of Four Cases

Input Parameter	CASES			
	CASE 1	CASE 2	CASE 3	CASE 4
W1	1	0	0	1/3
W2	0	1	0	1/3
W3	0	0	1	1/3
Material	Ceramics	Ceramics	Cobalt Carbides	Cobalt Carbides
Depth of cut (mm)	8	8	9	9
Feed (mm/rev)	0.40	0.40	0.60	0.60
Cutting speed (m/min)	250	250	100	100

Table 8: Output Values of the Two Model

Case	Non-linear model			Fuzzy model		
	Time	Cost	Environmental Impact	Time	Cost	Environmental Impact
1	0.0089	0.8782	0.7372	0.0236	2.7631	0.6178
2	0.0089	0.8782	0.7372	0.0236	2.7631	0.6178
3	0.0108	1.2357	0.0999	0.0191	2.2446	0.5020
4	0.0108	1.2357	0.0999	0.0191	2.2446	0.5020

Table 8 shows that the value of the two models does not differ drastically considering the maximum and minimum values of each parameter. The fuzzy model tries in producing meaningful information rather than producing an accurate result, which in many cases is not so important. The accuracy of the fuzzy model depends on the type of methods incorporated in the model such as And method, Or method, Aggregation method, and Defuzzification.

Out of all these methods, it is the defuzzification method that has the greatest impact on the result. There are lots of ways of defuzzification such as Centroid method, Bisector method, MOM method, IOM method, and SOM method.

The Table 9 shows the average mean square error of each defuzzification method. All the different methods are tried out and the average mean square error of each model is derived by comparing it with the non-linear model. It is found that the MOM method has the least square error and hence it is chosen as the method of defuzzification.

Table 9: Mean Square Error of Defuzzification Methods

Methods/parameters	Time	Cost	Environmental Impact
Centroid	0.0007	11.23	0.7406
Bisector	0.0005	9.17	0.6198
MOM	0.0003	5.58	0.3448

V. CONCLUSION AND RESULTS

The fuzzy system only needs a few input numbers and produces meaningful information. As all the input needed to make a decision cannot be made often, fuzzy system proves to be efficient way of handling this problem. The fuzzy method proves to be a more general method than the non-linear method which is made for a specific purpose. One another advantage of the fuzzy inference model is that the desired outputs can be given as input data and the necessary cutting parameters can be calculated from the fuzzy inference model. Assigning weights to the objective function may not convey the importance of the objectives or in some cases the weights cannot be assigned to the objective functions. The fuzzy model does not need any weights to be given to the model;

instead it takes in qualitative information, which is much easier than assigning weights. The fuzzy model requires input declared in the range [0, 1] and the outputs obtained are also in the range [0, 1]. The outputs generated for some different scenarios are given in the table 10.

Table 10: Generating Inputs through Fuzzy Model

Case	Desired output	Inputs generated			
		Hardness (RA)	Depth (mm)	Feed (mm/rev)	Speed (m/min)
1	[0.2, 0.3, 0.4]	93.5	6.93	0.26	137
2	[0.3, 0.1, 0.5]	94	8.43	0.22	135.86
3	[0.5, 0.5, 0.9]	94.5	1.75	0.17	35.3
4	[0.7, 0.8, 0.2]	90	7	0.26	57.9

The fuzzy inference model also enables to infer the relationship between the input and output variables in graphs. The correlation between any two inputs and an output can be obtained as a 3-D graph. The Figure 3 shows the relation between the input and output parameters. It can be inferred from the graphs that the depth of cut does not influence any change in environmental impact as wells as the machining time and the machining cost. The Fig 3a shows that the hardness of the material affects the environmental score and it can be seen from the graph that the environmental impact score increase along with the increase in the hardness of the material. Also it can be inferred from Figure 3c that the change in feed rate and the depth of cut does not influence the change in machining time much. But the speed selected depends on the feed and the depth of cut. All these parameters are dependent on the type of material chosen, or the hardness of the material. So the appropriate selection of all these parameters is important

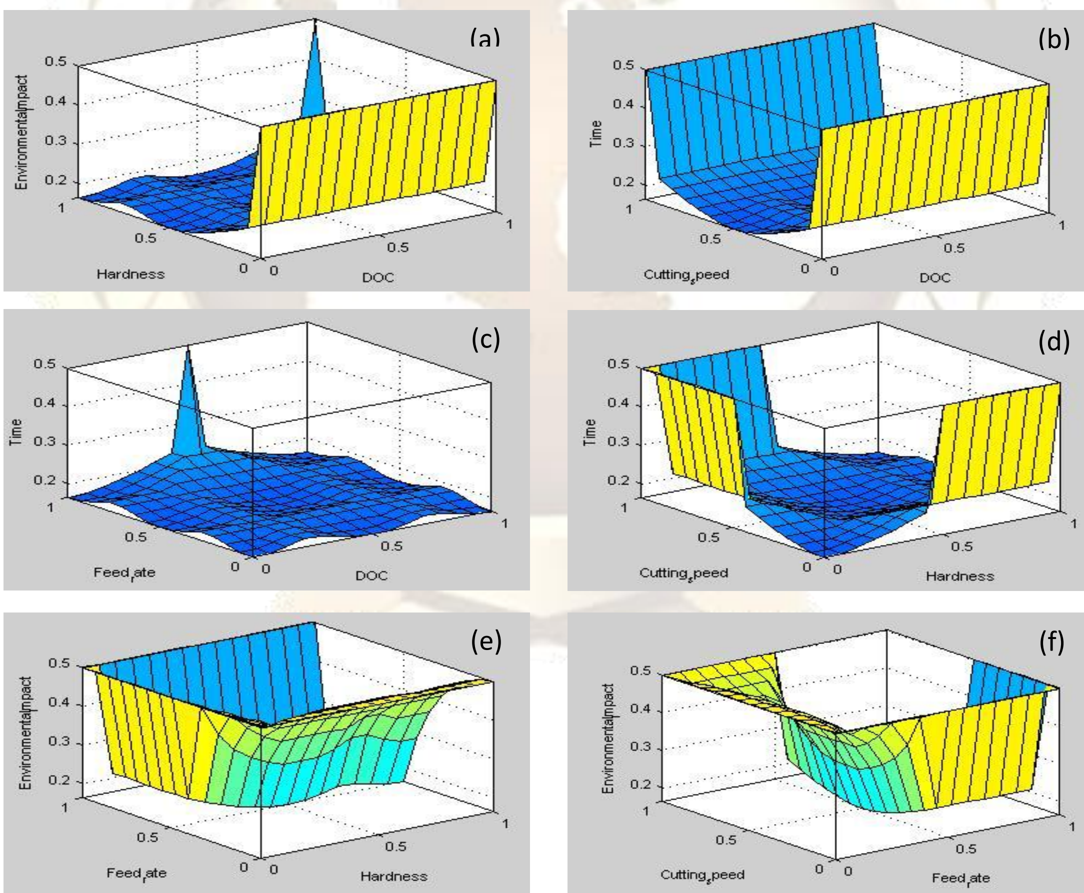

Figure 3: Correlation Chart among various parameters, (a) Environmental Impact, Hardness, and DOC, (b) Cutting Speed, Time, and DOC, (c) Feed Rate, Time, and DOC, (d) Cutting Speed, Time, and Hardness, (e) Feed Rate, Environmental Impact, and Hardness, and (f) Cutting Speed, Environmental Impact, and Feed Rate

VI. FUTURE RESEARCH

Here in this research the number of fuzzy sets has been assumed to be low, medium, and high. The number of fuzzy sets can be increased to more than three, like very low, low, medium, high and very high and it will give more accurate results. Also now we have focused on the range of parameters which are fixed. For example, we can only process in the speed range of 24-250 m/min, in future attempts can be made to incorporate the model to moving domains.

Fuzzy methods can be used as a start up plan when a rough estimation is needed like for example, in the stages of starting a new process to foresee the outcome of the process. It can also be developed into a global fuzzy inference system or fuzzy expert system. Instead of developing a model for the single process, the whole machine shop floor can be fed into the fuzzy model provided all the required data are available and the model can be formed into robust one, like fuzzy expert system or global fuzzy optimization. Also optimized input parameters can be obtained by selecting the output parameters for various preferences of the decision maker. From this optimal solutions for each variable can be obtained and these values can be fed into the fuzzy inference system and the corresponding value of output parameters, i.e. the objective functions are obtained, this value could be the best optimal solution of the fuzzy model.

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