FUZZY SET BASED OPTIMIZATION FOR GRINDING Al/SiC MMC; AN APPROACH TO MAXIMIZE *MRR* SATISFYING DESIRED SURFACE ROUGHNESS

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Abstract: Optimization of machining process for economic production of components is one of the most widely researched topics by the researchers. In the area of machining only fewer literatures are available on grinding of aluminum based metal matrix composites. Optimizing process parameters for maximizing metal removal rate (MRR) satisfying desired surface quality of jobs is an important requirement for manufacturing industries. This work employ application of fuzzy set theory is employed for optimizing cylindrical grinding of Al/SiC metal matrix composite (MMC). The fuzzy set based optimization (FSO) approach employs linguistic sub division of search domain and finding the optimal with the help of 'if-then' rules. The wheel velocity (V_s), work piece velocity (V_w), feed (f) and depth of cut (d) are considered as process parameters, on which the surface roughness depends. The optimization approach provides optimum zone which provides multiple number of solutions for alternative selection, if needed. The proposed optimization approach shows improved result in comparison with published work. The procedure is found effective where an approximate solution is desired, less number of variables are involved and suitable for problems in which the system does not change abruptly.

Key words: Optimization, cylindrical grinding, fuzzy set theory, MRR, surface roughness

1. INTRODUCTION

Metal matrix composites are widely used in various applications particularly in automotive and aerospace industries due to its improved properties like high strength, hardness, wear resistance and strength to weight ratio and it replaces non-reinforced alloys [1]. Among the various types of MMCs, aluminium alloy matrix based composites with SiCp as reinforcement particles are found popular in manufacturing industries. The applications of these materials demands for optimization of the process parameters in various machining process. A number of studies have been presented in machining Al-SiCp MMC using different cutting tools such as carbide, coated carbide and diamond in turning, drilling, reaming and threading of MMC materials employing approaches like Taguchi, RSM and ANN and fuzzy logics [2, 3]. Large number of literatures was found on machining optimization of turning, milling and drilling. In the area of machining only fewer literatures are available on grinding of aluminum based metal matrix composites. Grinding is one of the popular finish machining process to acquire high dimensional accuracy and surface roughness. The hard reinforcement particles present in Al/SiCp MMCs makes the grinding process very difficult. Previous literatures on grinding of MMCs have shown that Al/SiCp composites exhibit an improved grindability compared with non-reinforced aluminium alloys, and provides better surface finish with lower tendency to clog the wheel. Gopal and Rao [4] optimized grinding for maximizing material removal rate with surface finish and damage as constraints. Shaji and Radhakrishnan [5] performed grinding experiments and carried out Taguchi optimization to minimize the grinding force and surface roughness. The process parameters were speed, feed, and depth of cut. The results have been compared with the results obtained in the conventional coolant grinding following the same method. Mohanasundara raju and Sivasubramanian [6] used Artificial Neural Network-Taguchi approach to optimize grinding parameters while machining Al/SiC composites for obtaining desired roughness. They found that the combination of ANN model with Taguchi technique helps to predict optimal conditions for obtaining required roughness value more accurately. The application of soft computing based techniques such as ANN, fuzzy logic, genetic algorithm, particle swarm optimization, ant colony optimization, cuckoo search optimization, etc., have become popular for modeling and optimization of machining processes. L. A. Zadah published his first paper on the fuzzy set theory which has been applied for modeling of engineering problem [7].
The main advantage of fuzzy modeling is that it takes care of uncertainty. Apart from modeling and

control problem, the application of fuzzy set is also used in the area of optimization. Luhandjula [8] reviewed fuzzy optimization problems as two different parts as flexible programming and mathematical programming problems with fuzzy parameters. Flexible programming is capable of tolerating some flexibility in the formulation of goals and constraints of the mathematical program. Ekel et al. [9] has proposed a general approach to solving a wide class of fuzzy optimization problems containing fuzzy coefficients in objective functions and constraints. The authors have also provided some references describing the application of fuzzy optimization in power engineering. Fuzzy optimization have been found very convenient in handling multi-objective problems, where instead of weighted combination of various objective functions, overall membership grade of the combination of various incommensurable and conflicting goals is maximized. Dixit et al. [10] used this approach in the conceptual design of a laboratory cold rolling mill with a view to maximize mill-speed and possible reduction of sheet thickness, and minimize the rolling power. Chandrasekaran et al. [11] applied fuzzy set theory as a general optimization tool. They employed fuzzy set based optimization (FSO) and demonstrated the methodology using standard test function. They applied FSO to multipass turning process and found that the result obtained is similar with published literatures. They also discuss the merits and demerits of the approach. John and Vinayagam [12] applied Sugeno fuzzy neural system for optimizing the nonlinear characteristics of ball burnishing process in CNC milling using aluminium alloy (Al 63400) as work piece material and tungsten carbide as tool. They considered force (50-350 N), table feed (100-200 mm/min), step over (0.1-0.3 mm), ball diameter (8-12 mm)and number of passes (2-4) as input parameters and surface roughness along feed direction, surface roughness across feed direction and surface micro-hardness as output responses. The minimum surface roughness obtained by Sugeno fuzzy neural system is 0.032 µm along feed direction, 0.23 µm across tool path and micro hardness of 91.63HV. The obtained result is further correlated with the Pearson product moment and found the model is better correlated with experimental results. Prabhu et al., [13] proposed a surface roughness model for electrical discharge machining (EDM) of AISI D2 tool steel material using ANFIS approach. They considered dielectic, electrode current, pulse current, pulse duration and pulse voltage as input parameters to developed the model. They concluded that the developed ANFIS model show good predictive capability with an accuracy of 99.70%. Prabhu et al., [14] also used fuzzy logic analysis coupled to optimize the precision and accuracy of EDM process during machining of AISI D2 tool steel. They optimize the machining parameters for obtaining minimum surface roughness and micro-cracks using with or without CNT (carbon nanotube) based dielectric fluid. The minimum surface roughness and micro cracks obtained is 3.78 µm and 4.51 nm respectively. They found that fuzzy logic model improves the predictive capability of responses accurately and precisely. Rezgui et al., [15] developed fuzzy model for predicting microhardness of composite: Ni-Al2O3. They found that the developed model shows an average predictive error 3.88%, and, gives an accuracy of 96.12%. This shows good agreement between the fuzzy predictive results and experimental results. Piotr & Alfred [16] also used fuzzy logic in decision support for the monitoring and diagnostic of cutting tool wear. Application of fuzzy logic significantly increases the accuracy of the decision making and monitoring the condition of tool during manufacturing.

The objective of the present work is to demonstrate the potential of fuzzy set theory as a general optimization tool. Fuzzy set based optimization (FSO) is applied to optimize cylindrical grinding parameters in machining Al/SiCp MMC components. The objective is to maximize metal removal rate (MRR) satisfying the desired surface roughness of the component to be produced.

2. FUZZY SET BASED OPTIMIZATION (FSO)

The optimization of machining process aims to obtain optimum process parameters for economic manufacturing of the product. Researchers have used a number of traditional and non-traditional optimization techniques for obtaining optimum parameters in single and multipass machining processes. The results of conventional offline optimization have many limitations and need to be fine-tuned in the shop floor depending on the rigidity of machine tool, deviation in the properties of material and a number of random causes. The fuzzy set based optimization algorithm follows the following procedure: (i) Divide the search domain into linguistic subdivision (i.e., as number of cells). Identify the cutting conditions at centroid of the cells and evaluate the function value (i.e., decision variable); (ii) Fuzzify the decision variable with number of fuzzy subsets. Consider a membership of grade 1 at the centroid of the cell and 0 at the centroid of the adjacent cells and evaluate membership value as mentioned in [17]; (iii) Develop the rule base otherwise, generate fuzzy rules; (iv) Based on the rule base, desired objective and constraints, identify the cells where the optimum may lie; (v) Refine the search by choosing the cell having the highest strength of the rule amongst the identified cells.

Depending on the result, either move on to the next identified cell or refine further or stop. Figure 1 shows the general procedure and steps of fuzzy set based optimization. In the present work, the fuzzy set based optimization is used for optimizing cylindrical grinding process.

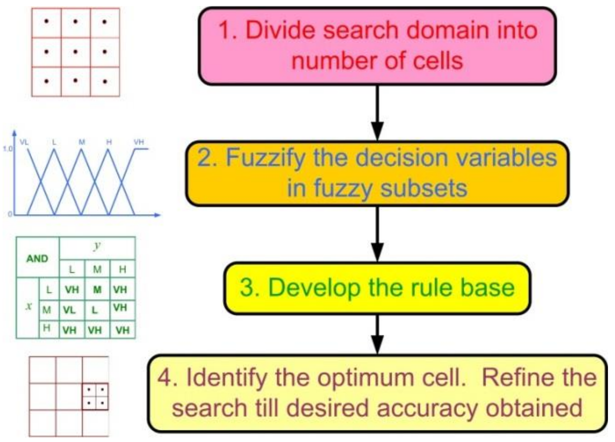


Fig.1. Procedure and steps of fuzzy set based optimization [15].

3. APPLICATION OF FSO FOR GRINDING PROCESS

The application of FSO approach is optimize grinding parameters by maximizing metal removal rate (MMR) while satisfying the desired surface roughness of the component to be produced. The experiments and modeling carried out by Thiagarajan et al. [18] is considered in this work. The grinding experiments are conducted on Al/SiCp MMC based on the full factorial design (3^4), a total of 81 experiments. Figure 2 shows schematic diagram of cylindrical grinding process with different process parameters. The wheel velocity (V_w), work piece velocity (V_s), feed (f) and depth of cut (d) are considered as process variables and the process response are surface roughness (R_a) and metal removal rate (MRR).

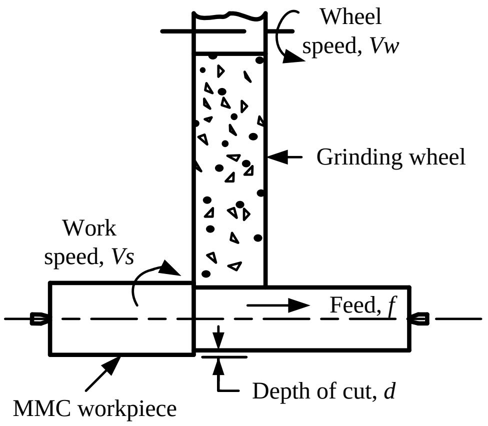


Fig.2 Schematic diagram of cylindrical grinding

The experimental data are used to develop mathematical model for surface roughness using multiple regression analysis (*MRA*). The surface roughness is a function of process parameters and is represented by

$$Y = \phi(Vs, Vw, f, d)$$

where V_s=wheel velocity in (m/s),V_w=work piece velocity in (m/min), f=feed in (m/min) and d=depth of cut in (µm). The surface roughness model is developed as given by

$$R_a = C \times V_s{}^p \times V_w{}^q \times f^r \times d^s \quad (2)$$

The above equation (2) is represented in linear mathematical form as follows:

$$R_a = \ln C + p \ln V_s + q \ln V_w + r \ln f + s \ln d \quad (3)$$

Thiagarajan et al. [13] have developed R_a model considering individual variables and is obtained as

$$R_a = 424.113 (V_s)^{-0.855} (V_w)^{-0.339} (f)^{0.342} (d)^{0.402} \quad (4)$$

The metal removal rate is evaluated using an empirical relation and is given by the equation (5).

$$\text{MRR (mm3/mm/min)} = \text{fd} \quad (5)$$

3.1 Problem formulation

Consider optimization of cylindrical grinding of a component to obtain maximum allowable or desired surface roughness (R_a). In order to satisfy surface roughness the researchers consider the surface roughness constraint as actual R_a produced is less than or equal to desired surface roughness. But the lower value of surface roughness requires low feed for which the MRR will be lower. Hence in order to maximum MRR satisfying surface roughness it is desired between upper and lower limits. Incorporating some statistical variation in surface roughness Chandrasekaran et al., [19] considered actual surface roughness ($R_{a_{act}}$) to be produced should be within upper and lower limits and it is considered in this work. The formulation of the problem is as follows.
Optimization objective: Maximize MRR.
Subjected to:

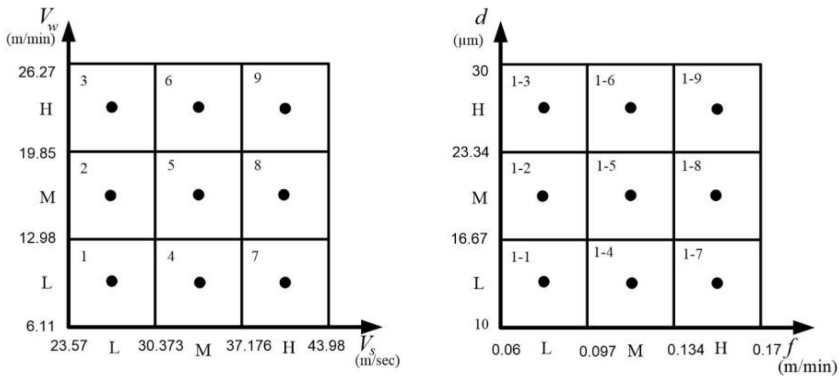
$$\begin{gathered} 0.64 R_a \le R_{a_{act}} \le 0.96 R_a \\ V_{s_{\min}} \le V_s \le V_{s_{\max}} \\ V_{w_{\min}} \le V_w \le V_{w_{\max}} \\ f_{\min} \le f \le f_{\max} \\ d_{\min} \le d \le d_{\max} \end{gathered} \quad (6)$$

The maximum and minimum limits of grinding process variables (i.e., V_s, V_w, f and d) forms search space. The search domain is divided into number of cells with linguistic division as low, medium and high. The decision variable (MRR) is evaluated at all centroidal cutting conditions. The surface roughness and MRR are obtained using equation (4) and equation (5). Now centroidal points have to be identified that satisfy surface roughness constraints. Fuzzify the decision variable into number of fuzzy subsets and evaluate its membership grade (range: 0−1). The highest value of membership grade yield optimum cell satisfying all constrains.

Further initiate the search in the optimum cell to obtain the zone where the variation of function value is maximum or within the desired accuracy limit. This is known as optimum cell and the centroidal cutting condition gives optimum solution.

3.2 Illustrative example

Let optimum grinding parameters for producing a component with desired surface roughness of 0.3µm is to be considered. The surface roughness is the function of V_s, V_w, f and d and is evaluated using equation 4. The problem objective is to maximize MRR satisfying the surface roughness such that $0.19 \leq R_{a_{act}} \leq 0.29$. The FSO is initiated by dividing the search domain: 25.37 $\leq V_s \leq$43.98; 6.11 $\leq V_w \leq$ 26.72; 0.06 $\leq f \leq$ 0.17; and 10 $\leq d \leq$ 30; into number of cells with linguistic subdivision of low, medium and high cells. The optimization is four dimensional problem. Thus search domain is initially divided into 9×9=81 cells as shown in Figure 3. The centroidal point corresponding to each cell is considered as different cutting conditions. The first cutting condition is $V_s - V_w - f - d$: 26.97− 9.54− 0.078− 13.34;the actual R_a and MRR obtained are 0.4226µm and 1.0468mm^3/mm/min respectively. Similarly the surface roughness and MRR are evaluated at all cutting centroidal points.



S.No.	Cell Number	Cell position (V_s–V_w–f–d)
1	1-1	L–L–L–L
2	1-2	L–L–L–M
--	- -	- - - - - - - -
--	- -	- - - - - - - -
81	9-9	H–H–H–H

Fig.3 Linguistic sub-division o fsearchd omainas 9×9=81cells

Now identifying the centroidal points that satisfy the surface roughness constraint and evaluate function values (i.e., MRR). Table 1 shows the cell points that satisfy the surface roughness and evaluated function values. There are 7 cells that satisfy surface roughness constraint. The function values vary between $MRR_{\min}$ = 1.04 mm^3/mm/min and $MRR_{\max}$ = 2.03 mm^3/mm/min.

The output variable is now fuzzified using triangular membership function with 5 fuzzy subsets *viz.*, very low, low, medium, high, very high and is shown in Figure 4. Evaluate membership grade values. Table 2 depicts the rule base along with the strength of the rules in the search domain.

Table 1. Function values at cell centroids with $0.19 \leq R_{a(act)} \leq 0.29$

Cell number	Cell position				Centroidal cutting condition				Actual surface roughness $(R_{a(act)})$ (µm)	Function value(i.e., MRR) (mm^3/mm/min)
	V_s	V_w	f	d	V_s	V_w	f	d		
6-1	M	H	L	L	33.7745	23.285	0.0785	13.335	0.2576	1.0468
8-1	H	M	L	L	40.578	16.415	0.0785	13.335	0.2479	1.0468
9-1	H	H	L	L	40.578	23.285	0.0785	13.335	0.2203	1.0468
9-2	H	H	L	M	40.578	23.285	0.0785	20.005	0.2593	1.5704
8-4	H	M	M	L	40.578	16.415	0.1155	13.335	0.2830	1.5402
9-4	H	H	M	L	40.578	23.285	0.1155	13.335	0.2514	1.5402
9-7	H	H	H	L	40.578	23.285	0.152	13.335	0.2761	2.0269

As the goal is to obtain very high value of MRR, the seventh rule corresponds to cell number (9-7) may be fired. Firing of seventh rulethe search domain gets reduced 37.176 $\leq V_s \leq$ 43.98; 19.85 $\leq V_w \leq$ 26.72; 10 $\leq f \leq$ 16.67; and 0.134 $\leq d \leq$ 0.17. The search domain corresponding to cell number 9-7 is now divided into less number of cells (i.e., say 4) with low and high linguistic value shown in Figure 5 (a & b). Each decision variable now gets divided into ‘low’ and ‘high’. The output variable is fuzzified into four fuzzy subsets *viz*., very low, low, high and very high. Table 3 shows the function values at the cell centroids and corresponding rule base with its strength.

Table 2. Rule base and its strength

Cell Number	Rule base	Function value	
		Grade	Membership strength
6-1	M−H−L−L	Very low	0.97
8-1	H−M−L−L	Very low	0.97
9-1	H−H−L−L	Very low	0.97
9-2	H−H−L−M	High	0.14
8-4	H−M−M−L	Medium	0.98
9-4	H−H−M−L	Medium	0.98
9-7	H−H−H−L	Very high	0.99

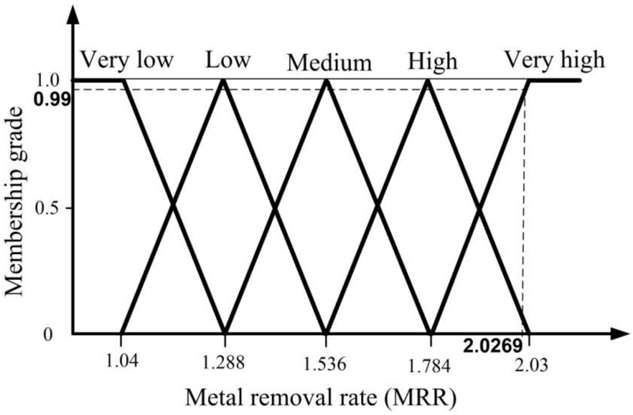


Fig. 4 Fuzzification of function values

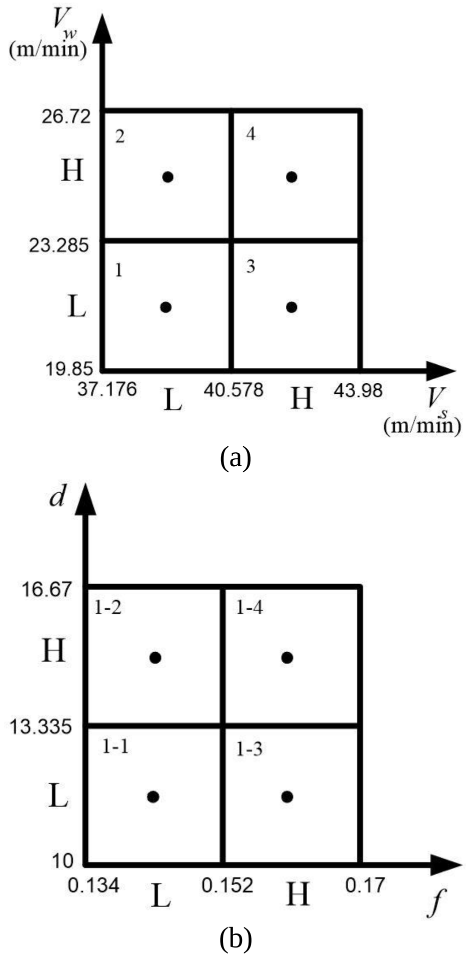


Fig.5. Refined search domain

Table 3. Rule base for refined search domain

Cell No.	Cell Centroids (V_s-V_w-f-d)	Rule No.	Rule base (V_s -V_w- f- d-MRR)	Strength	Surface roughness [R_a]	Function value
1-1	38.87-21.56-0.143-11.6	1	L-L-L-L-VL	0.9	0.273	1.668
1-2	38.87-21.56-0.143-15.0	2	L-L-L-H-M	0.43	0.302	2.145
1-3	38.87-21.56-0.161-11.6	3	L-L-H-L-L	0.82	0.284	1.878
1-4	38.87-21.56-0.161-15.0	4	L-L-H-H-H	0.02	0.314	2.415
2-1	38.87-25.00-0.143-11.6	5	L-H-L-L-VL	0.9	0.259	1.668
2-2	38.87-25.00-0.143-15.0	6	L-H- L-H-M	0.43	0.287	2.145
2-3	38.87-25.00-0.161-11.6	7	L-H- H-L-L	0.82	0.270	1.878
2-4	38.87-25.00-0.161-15.0	8	L-H- H-H-H	0.02	0.299	2.415
3-1	42.27-21.56-0.143-11.6	9	H-L- L-L-VL	0.9	0.254	1.668
3-2	42.27-21.56-0.143-15.0	10	H-L- L-H-M	0.43	0.281	2.145
3-3	42.27-21.56-0.161-11.6	11	H-L- H-L-L	0.82	0.264	1.878
3-4	42.27-21.56-0.161-15.0	12	H-L- H-H-H	0.02	0.293	2.415
4-1	42.27-25.00-0.143-11.6	13	H-H- L-L-VL	0.9	0.242	1.668
4-2	42.27-25.00-0.143-15.0	14	H-H- L-H-M	0.43	0.267	2.145
4-3	42.27-25.00-0.161-11.6	15	H-H- H-L-L	0.82	0.252	1.878
4-4	42.27-25.00-0.161-15.0	16	H-H- H-H-H	0.02	0.278	2.415

For obtaining maximum MRR rule sixteen is fired being highest function value and the corresponding cell domain is optimum zone. It is given by: $40.587 \leq V_s \leq 43.98$; $23.285 \leq V_w \leq 26.72$; $0.152 \leq f \leq 0.17$; and $13.335 \leq d \leq 16.67$. It is optimum zone and provides number of optimal solutions. The function values at different 9 different points of the cell are evaluated and it varies from 2.027 mm^3/mm/min to 2.834 mm^3/mm/min. Figure 6 depicts the function value at various co-ordinate positions in the optimum fuzzy domain. The MRR corresponds centroid of the fuzzy domain may be considered as optimum and the corresponding cutting parameters are: V_s=42.28 m/s; V_w=25 m/s; f=0.16mm; d=0.28mm. The surface roughness and the function value at this combination is 0.278µm and 2.415mm^3/mm/min respectively. The result is compared with [13] and shows improved which give maximum *MRR* of 2.336 mm^3/mm/min. The results are compared with previously published literature and found that it is satisfied.

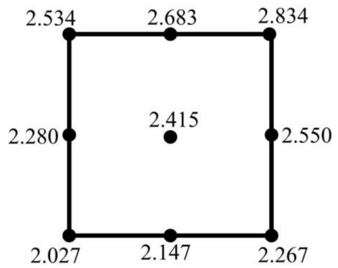


Fig.6 Optimum fuzzy domain with minimum variation of function value (i.e. *MRR*)

Table 4. Comparison of optimum result

Sl. No.	Desired surface roughness [µm]	Optimal parameters (V_s− V_w−f−d)	Actual surface roughness obtained [µm]	Maximum *MRR* [mm^3/mm/min]	Maximum *MRR* [16] [mm^3/mm/min]
1	0.3	(43.13-25.86-0.17-15.84)	0.279	2.621	2.336

4. CONCLUSIONS

In this work fuzzy set based optimization (FSO) approach is proposed for optimizing parameters in cylindrical grinding of Al/SiC metal matrix composites. Wheel velocity (V_s), work piece velocity (V_w), feed (f) and depth of cut (d) are considered as process parameters. The optimization objective is to obtain optimum grinding condition by maximizing metal removal rate (MMR) satisfying the desired surface roughness of the component to be produced. The procedure employs linguistic sub-division of search space and finds the optimum using *if-then* rules. The following are the conclusions obtained.

1. The optimization procedure is simple and follows rule base derived from the experimental outcome. The method is found effective in solving optimization problems where usually an approximate solution is desired.
2. The procedure provides an 'optimum zone' instead of a single combination of optimum parameters, which provides number of optimal solutions. This facilitates the selection of alternate optimum condition, if desired.
3. The procedure shows an improved result while compared with previously published literature. It shows the efficiency of proposed optimization approach applicable for cylindrical grinding process. It also can be implemented for on-line optimization of the machining processes.
4. The limitation of the procedure is that it takes more time and not suitable for high accuracy of function value is required.

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