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Parametric optimization of end milling process under minimum quantity lubrication with nanofluid as cutting medium using pareto optimality approach

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ABSTRACT

In this paper a genetic algorithm based multi-objective optimization approach is applied in order to predict the optimal machining parameters for the end milling process of aluminium alloy 6061 T6 combined with minimum quantity lubrication (MQL) conditions using water-based TiO2 nanofluid as cutting fluid. The optimization is carried out employing a parametric model (in terms of input cutting parameters, i.e., cutting speed, feed rate, depth of cut, MQL flow rate and % volume concentration of nanofluid) and exploiting the capabilities of the MOGA-II algorithm applied to the constrained machining problem. The objective functions selected to optimize are: to minimize the surface roughness; to maximize the material removal rate; and to minimize the flank wear of the cutting tool. The output of the optimization includes several alternative optimal solutions, i.e., Pareto frontier, and the best compromised configuration of the cutting parameters is selected subject to weighted preference.

Keywords: MQL; MOGA; Pareto; bubble charts.

INTRODUCTION

The utilization of cutting fluids is integrated with the manufacturing processes. As the development of alternative manufacturing process technologies to replace machining is still a prohibitive task, preventing the negative environmental impact of machining can be achieved essentially by operating modifications to existing processes [1]. With increasing global eco-awareness, the application of sustainability indices in manufacturing units, and strict regulations due to the detrimental effects of cutting fluids on the environment and human exposure, the manufacturing world is in continuous pursuit of viable methods of economic dry machining. Only the near-dry machining process, also termed as minimum quantity lubrication (MQL), can offer a near-term solution to the problem [2-4]. Minimum quantity lubrication is a technique of sustainable manufacturing that incorporates all the issues related to machining [5, 6]. It aims to reduce the hazardous effects of coolants on the atmosphere and to minimize the resource consumption during a product life cycle which includes design, processing, production, packaging, transport, the use of the product and its disposal [7]. According to one study [8], the total cost of cutting fluids incurred during a machining process ranges from 7% to 17% of the total machining cost. Therefore a direct gauge of sustainable manufacturing is the reduction in the amount of cutting fluids during machining. MQL ensures safety of the environment and the worker and is a cost-effective technique [9]. The objective of MQL is to use the metal-working fluid in such a quantity that the final product, chip and machine remain in a dry and safe environment. This amount is usually three to four orders of magnitude less than is normally used in wet machining. The typical flow rate for MQL is about 50–500ml/hr [10-12]. Minimum quantity lubrication is also termed as near-dry lubrication [13] or microlubrication [14]. The idea of reduced lubrication emerged during the last two or three decades. In the recent past, there has been a general liking for dry machining [15]. To avoid the problems caused by cutting fluids, significant advances have been made during the last decade in the field of dry and near-dry machining [16]. In particular, MQL machining has been acknowledged as an alternative to dry and wet machining on account of its eco-friendly distinctiveness. A considerable number of researches in the mentioned field have also established its potential application in many practical machining operations [17]. Machining with MQL has been widely applied in many machining processes such as drilling [18-21], milling [7, 22-25], turning [11, 20, 26-28], and MQL grinding [29-31].

Minimum quantity lubrication (MQL) can be considered as a viable substitute for conventional cooling. In MQL a small amount of lubricant atomized in a compressed air flow is supplied to the cutting zone. Since the cooling capacity of the MQL flow largely depends on the air flow, complete replacement of the flood cooling medium with MQL is still considered complex [5, 32-36] and its application scope is still uncertain. Since a very minute amount of cutting fluid is used in MQL, its heat-carrying capacity and lubrication capability is inadequate [37]. Hence the heat-carrying capacity and lubricating ability of cutting fluids have to be improved. In order to achieve a high cooling and lubricating capability with minimum quantity lubrication, a fluid with high thermal conductivity must be utilized. Cooling is one of the most important challenges in the machining process [38]. High adhesion at high cutting speed ranges, high thermal loads, as well as work-hardening of the material present some other difficulties in machining. The conventional methods of enhancing the cooling rate have already been stretched to their limits [39-42]. The use of novel approaches is essential in order to achieve high performance cooling and lubrication. Nanofluids provide a potential way to fulfill this requirement.

Nanofluids belong to the novel group of potential heat transfer fluids with superior thermo-physical properties and heat transfer performance. The results of the latest researches with nanofluids in machining show the promising performance of these fluids as a replacement for conventional metal-working fluids accompanied with minimum quantity lubrication techniques. The applicability of nanofluids as coolants is mainly because of their enhanced thermal conductivity due to solid particles inclusions [43-46] and the convection heat transfer coefficient of the fluid can be greatly improved by nanoparticles suspensions [47-51]. Nanofluids can be conveyed to the cutting zone in a machining process through nozzles like flood cooling systems, but the higher manufacturing costs of nanofluids and large wastage during machining application [52-55] have prompted researchers to explore the greater potential of nanofluids incorporated with the principles of MQL. A lot of research on the application of nanocutting fluids has been reported in the literature about the use of nanoparticles as additives to traditional oil-based lubricants and the improved machining performance in terms of reduced wear and decreased friction. However, research on the application of nanoparticles as a water-based cooling / lubricating medium is very rare [56]. The application of water-based Al_2O_3 and diamond nanofluids in MQL grinding shows promising improvements in surface roughness, a reduction in the grinding force, and an improved G-ratio with high concentrations of nanofluids as compared to pure water application [57, 58]. Research was carried out to investigate the wheel wear and the tribological characteristics in wet, dry and MQL grinding of cast iron. The tribological properties and application performance of water-based TiO_2 nanofluid were investigated in the MSR 10D four ball tribotester and in bench drilling operations [56]. It was found that surface-modified TiO_2 nanoparticles can effectively reduce the load-carrying capacity, friction reducing and anti-wear properties of pure water. Water-based nanofluids can serve as more sustainable and environment-friendly cutting fluids, given the toxicity and non-biodegradability of oil-based fluids

With the advent of sustainability concepts in manufacturing, the major way to sustainability is not only by utilizing the minimum quantity of cutting fluids but also by optimizing the amount of cutting fluids, together with a proper selection of cutting fluid, that results in a reduction in cost and adds to the sustainability of the process. Practical manufacturing problems are often characterized by many non-compliant and often conflicting measures of performance, or objectives. Multi-objective optimization is different from single objective optimization in that single objective optimization is used to find the best design point or decision from among many, and usually this best design point is the global maximum or global minimization, depending on the type of optimization [59]. In the case of multiple objectives, however, it is not necessarily the case that a single solution is the best design with respect to all the objectives, due to incommensurability and conflict among objectives. For such problems where multiple objectives cannot be simply compared with each other, multi-objective optimization usually attempts to give a set of solutions. The problem usually has no exclusive, perfect (or single utopian) solution, but a set of non-dominated, alternative solutions, known as the Pareto-optimal solutions [60]. The aim of this research is to optimize the process of end milling of aluminium alloy 6061 T6 with minimum quantity lubrication using water-based TiO2 nanofluid. The process goals are to obtain better surface quality as well as higher productivity in terms of a higher material removal rate with the least damage or wear to the cutting tool. This is a problem of conflicting objectives and thus calls for the application of multi-objective optimization for the simultaneous achievement of all the process goals.

Table 1. Process control parameters and their ranges.

Factors	**Levels**				
	1	**2**	**3**	**4**	**5**
Cutting speed (rpm)	5200	5300	5400	5500	5600
Axial depth of cut (mm)	230	300	370	440	510
Feed rate f_z (mm/min)	0.75	1.50	2.25	3.00	3.75
MQL flow rate (ml/min)	0.31	0.48	0.65	0.83	1.00
% volume concentration of nanofluid	0.5	1.5	2.5	3.5	4.5

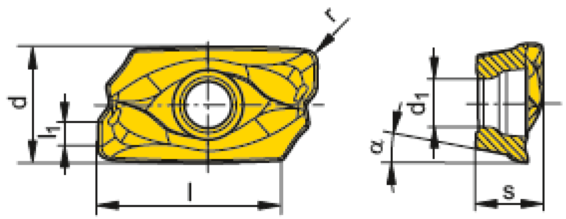
METHODS AND MATERIALS

Process Control Parameters and their Ranges

The process parameters used for this research are spindle speed, feed rate, depth of cut, minimum quantity lubricant flow rate and % volume concentration of nanofluid. Five levels of machining variables are selected, as shown in Table 1.

Workpiece and Cutting Tool Material

The material used for the study is aluminium alloy AA6061T6. The major alloying elements are Si, Cu and Mg. The tool is used for the purpose of machining. Specifications of the inserts used are listed in Figure 1. Inserts are commercially available tools as recommended by the supplier.



r (mm)	*d* (mm)	*l* (mm)	*a* (mm)	l_1 (mm)	d_1 (mm)	α	Composition: Co6.0%; WC balance Hardness: HV 1630
0.7874	4.9022	7.7978	3.175	1.0922	2.4892	15º	

Figure 1. Insert specifications used in the study (supplier: M/s CERATIZIT).

Parametric Models

The respective response surface models for surface roughness, material removal rate and tool wear (TW) are shown in Eq. (1)–(3).

$$\begin{aligned} R_a &= -354.926 + 0.133409\,x_1 - 0.04226\,x_2 - 2.66185\,x_3 + 23.985\,x_4 - 2.79369\,x_5 \\ &+ 0.0000100267\,x_1x_2 + 0.000591\,x_1x_3 + 0.003286\,x_1x_4 + 0.000578\,x_1x_5 + 0.00104404\,x_2x_3 \\ &- 0.0011128\,x_2x_4 + 0.0009795\,x_2x_5 + 0.4304348\,x_3x_4 + 0.084917\,x_3x_5 - 0.23.86\,x_4x_5 \\ &- 0.0000127\,x_1^2 - 0.0000192\,x_2^2 - 0.24485\,x_3^2 - 4.578106\,x_4^2 - 0.12485\,x_5^2 \end{aligned} \tag{1}$$

$$\begin{aligned} R_a &= 2818.918 - 0.61891\,x_1 - 17.3999\,x_2 + 9653.795\,x_3 + 12582.92\,x_4 - 9928.44\,x_5 \\ &+ 0.003967\,x_1x_2 - 1.58545\,x_1x_3 - 2.3067\,x_1x_4 + 2.042838\,x_1x_5 + 10.25198\,x_2x_3 \\ &+ 3.515217\,x_2x_4 - 1.25398\,x_2x_5 - 178\,x_3x_4 - 1139.972\,x_3x_5 - 162.442\,x_4x_5 \\ &- 0.000095\,x_1^2 - 0.00363\,x_2^2 - 42.7349\,x_3^2 - 856.153\,x_4^2 - 22.5884\,x_5^2 \end{aligned} \tag{2}$$

$$\begin{aligned} R_a &= 10281.08 - 3.73362\,x_1 - 0.22632\,x_2 - 32.481\,x_3 - 16.8907\,x_4 - 16.8058\,x_5 \\ &+ 0.000343\,x_1^2 + 0.000341\,x_2^2 + 7.806675\,x_3^2 + 14.59179\,x_4^2 + 3.466255\,x_5^2 \end{aligned} \tag{3}$$

where, R_a = Average surface roughness measured in µm; *MRR* = Material removal rate measured in mm^3/min; *FW* = Max. flank wear measured in µm; x_1 = Spindle speed measured in rpm; x_2 = Feed rate measured in mm/min; x_3 = Depth of cut measured in mm; x_4 = MQL flow rate measured in ml/min and x_5 = %volume concentration of nanofluid.

OPTIMIZATION MODELLING

The optimization problem in this study has the aim of finding the best compromised configurations of the end milling process parameters so as to achieve the trade-offs solutions for the three conflicting objective functions. The flow chart for the optimization process is shown in Figure 2. The designs of experiment used for the parametric modelling with central composite design methodology are used as the initial population for the multi-objective optimization algorithm with a 5-variables at 5-levels strategy resulting in 32 experiments. The algorithm is set to run for a total of 100 generations. The optimization problem is constrained using process-specific parametric constraints which are given as the upper and lower bounds on the design variables and the process objectives. The flow chart for the MOGA-II algorithm is shown in Figure 3.

Terms Used in Multi-objective Optimization Problem Formulation

The different terms and concepts used in multi-objective optimization are as follows:

1) Design variables or decisional parameters are the set of input parameters; best possible combinations of input variables are determined by optimization. In this study the input variables which are used for optimization are the axial depth of cut, spindle speed, feed rate, minimum quantity lubricant flow rate and % volume concentration of nanofluid.
2) Objective functions are the outputs or the goals of an optimization; surface roughness of the machined part, material removal rate and tool wear as obtained from SEM are used as the objective functions in this single-pass milling parameter optimization problem. Surface roughness is not only a quality indicator but also the final stage in controlling the machining performance and the operation cost [61]. Surface roughness is measured as Ra, which is the arithmetical mean deviation of all the measured values in the assessed profile from the mean line of that profile. A section of standard length (17 mm) determined from the capability of the Perthometer available, is sampled from the mean line on the roughness chart. The material removal rate (MRR) is taken as another objective function which serves as the basis of optimization. MRR is a measure of quantity, i.e., machining productivity. Therefore the two objectives, namely surface roughness and the material removal rate, are conflicting, i.e., one has to be compromised in order to achieve a gain in the other. The third objective function is to minimize the tool wear.
3) Design constraints are the specified requirements that must be satisfied by design variables and the functional constraints, i.e., that restrictions must be followed by the objective functions.

A multi-objective optimization problem is completely defined by a set of *k* parameters (design or decision variables), a set of *m* objective functions and a set of *n* constraints. The objective functions and the constraints are functions of the decision variables. The aim of optimization is to

$$minimize\ or\ maximize\ z = f(y) = (f_1(y), f_2(y), \ldots\ldots\ldots f_m(y)) \tag{4}$$

$$\text{satisfying the constraints}\quad c(y) = (c_1(y), c_2(y), \ldots\ldots\ldots c_n(y)) \le 0, \tag{5}$$

where $y=(y_1, y_2, \ldots\ldots\ldots y_k) \in Y, z=z_1, z_2, \ldots\ldots\ldots z_m) \in Z$. y is defined as the decision variable vector, z is given as the objective function vector, Y is the decision space and $Z_f = f(Y_f)$ is given as the objective space. The most feasible set Y_f is the set of decision variables vectors fulfilling the constraints $c(y) \leq 0$.

Each objective has been constrained within upper and lower limit boundary conditions: these are adopted from the experimental scope of the response variables. To achieve an effective optimization of a machining process, the machining constraints must be fully satisfied. These constraints work as boundary conditions within the experimental scope. The constraints considered in this study are given by Eq. (6)–(16).

Minimize surface roughness, $$Ra = fn(x_1, x_2, x_3, x_4, x_5) \tag{6}$$

Maximize material removal rate, $$MRR = fn(x_1, x_2, x_3, x_4, x_5) \tag{7}$$

Minimize flank wear $$FW = fn(x_1, x_2, x_3, x_4, x_5) \tag{8}$$

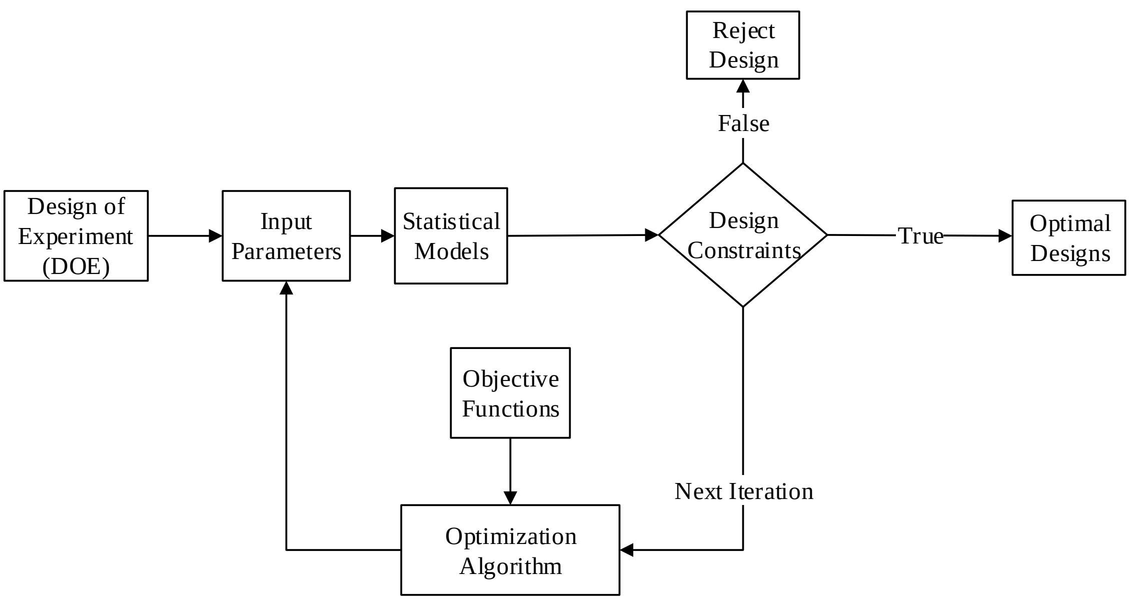


Figure 2. Optimization process flow chart.

Subject to:

$$x_{1\min} \leq x_1 \leq x_{1\max} \tag{9}$$
$$x_{2\min} \leq x_2 \leq x_{2\max} \tag{10}$$
$$x_{3\min} \leq x_3 \leq x_{3\max} \tag{11}$$
$$x_{4\min} \leq x_4 \leq x_{4\max} \tag{12}$$
$$x_{5\min} \leq x_5 \leq x_{5\max} \tag{13}$$

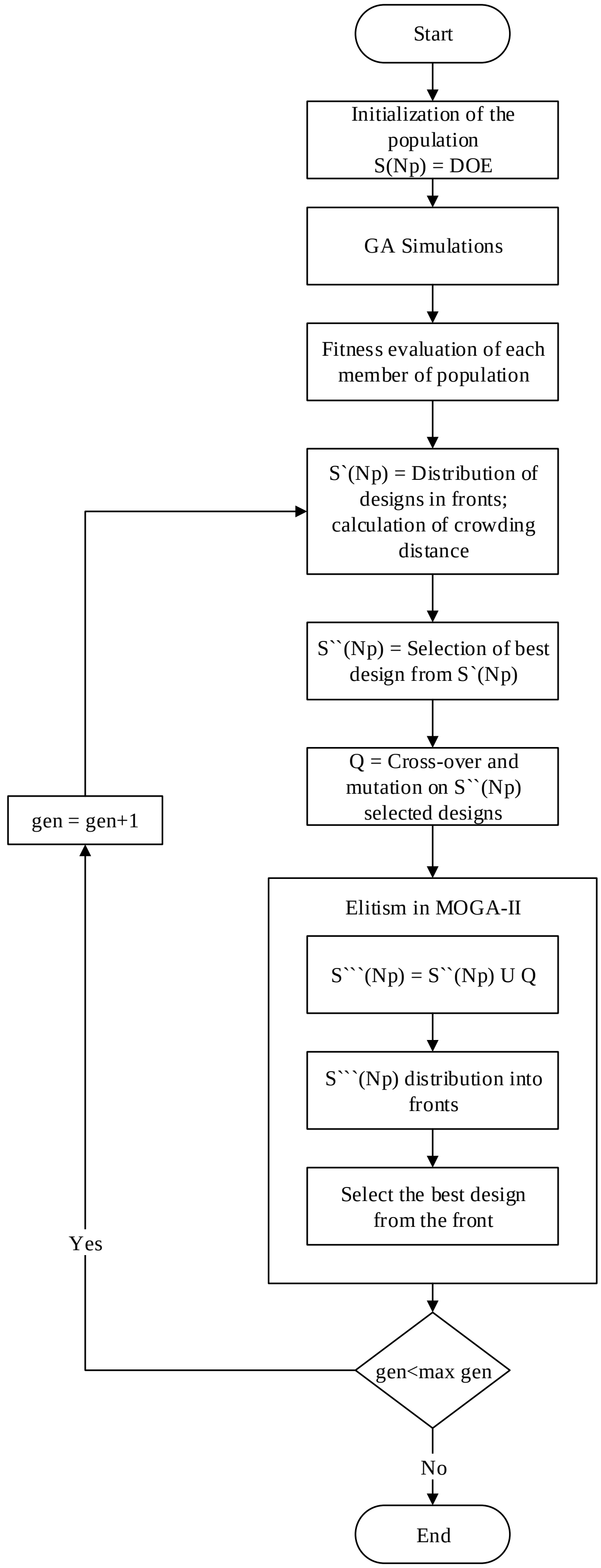


Figure 3. Flow chart for MOGA-II algorithm.

While

$$Ra_{\min} \leq Ra \leq Ra_{\max} \tag{14}$$

$$MRR_{\min} \leq MRR \leq MRR_{\max} \tag{15}$$

$$FW_{\min} \leq FW \leq FW_{\max} \tag{16}$$

Optimization Algorithm

In this research an algorithm called MOGA-II design environment is employed for multi-objective optimization. MOGA (Multi-objective genetic algorithm) while II designates the proprietary version. This is a genetic algorithm where designs of experiments serve as "*initial population*". The best individuals are evaluated, recombined and mutated to constitute a new population. MOGA was a first generation genetic algorithm [62], while MOGA-II is a second generation evolutionary algorithm with elitism. The multi-objective optimization performed using the MOGA-II algorithm results in 3232 overall designs including feasible and unfeasible designs. The number of feasible designs is 2963. From these 2963 designs, only 1156 Pareto designs are obtained and these are used to find the best compromised optimum design.

PARETO DESIGNS

The result from MOGA-II is a list of optimal feasible solutions depicting a trade-off among the three objectives. This set is called a Pareto set. Pareto designs are selected from among the feasible designs, thus the feasibility of these designs is ensured. The Pareto approach to optimization is aimed at identifying the set of parameters that characterize a design and beyond which no aspect of performance can be improved without compromising another.

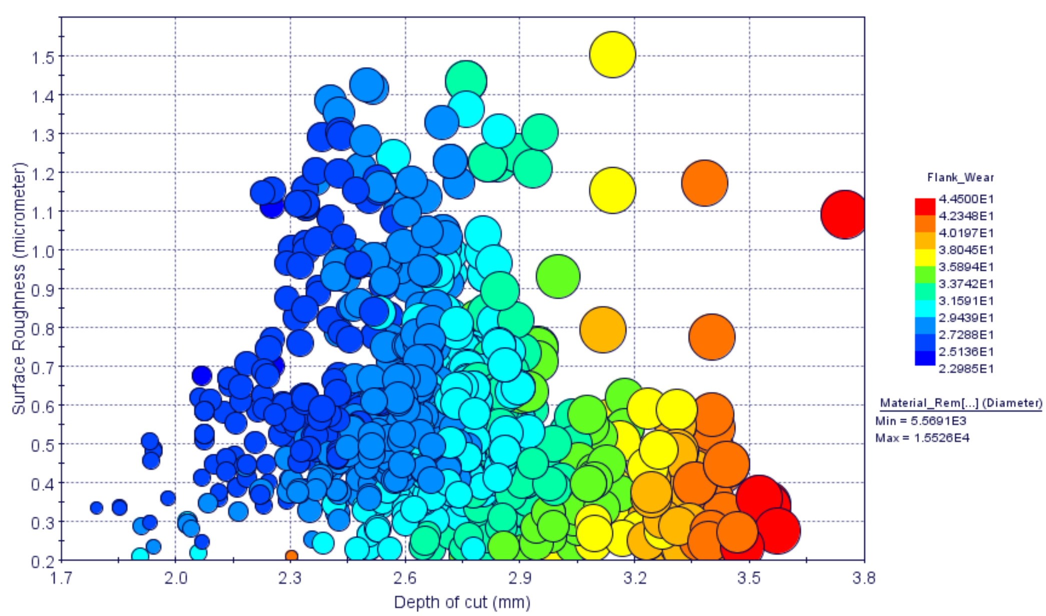


Figure 4. Pareto designs distribution with depth of cut.

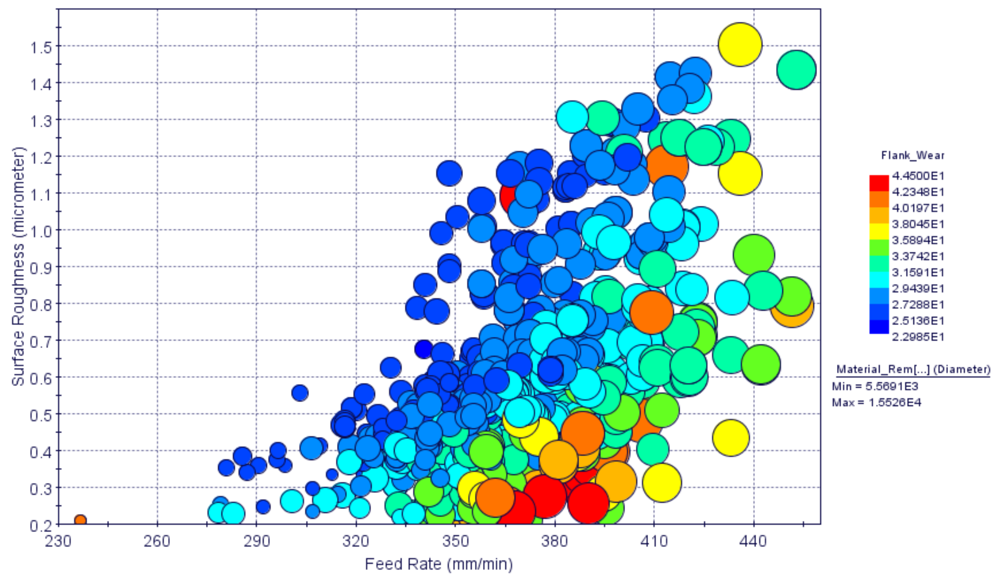


Figure 5. Pareto designs distribution with feed rate.

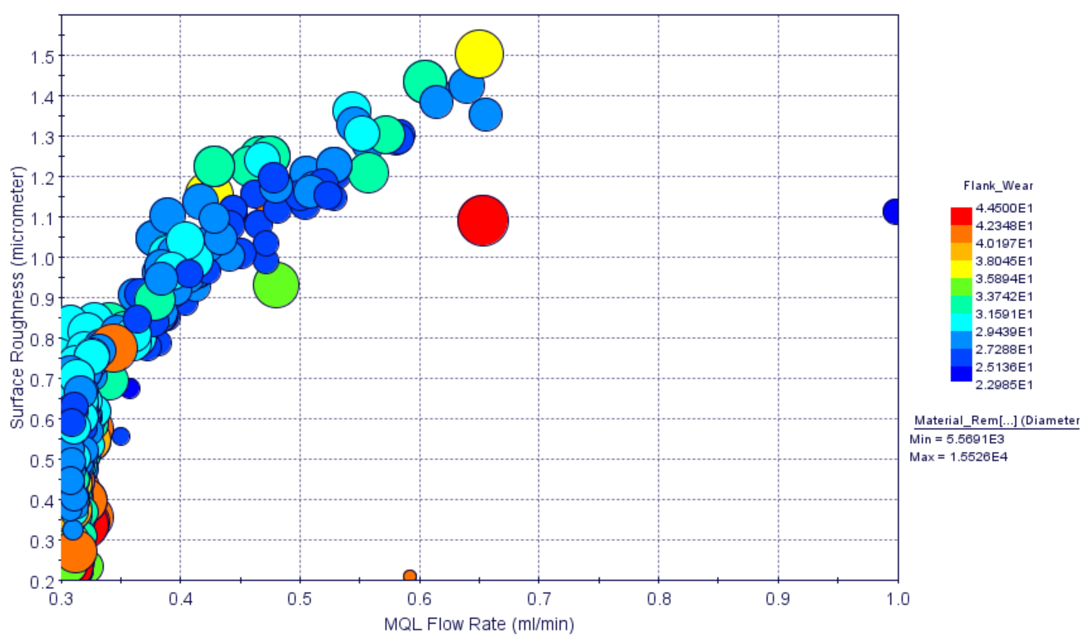


Figure 6. Pareto designs distribution with MQL flow rate.

The final result of a multi-objective optimization is a set of 1156 different designs belonging to the Pareto frontier that is the set of non-dominated optimal solutions. The distribution of Pareto designs against the design variables is shown by 4-dimensional bubble charts in Figures 4 – 8. In the 4-dimensional bubble chart the *x*-axis represents the design variable, while on the *y*-axis the one response variable, i.e., surface roughness in this case, is plotted, while the bubble diameter and bubble colour indicate respectively the material removal rate and the flank wear. Figure 4 shows the distribution of Pareto optimal designs with the increase in depth of cut. Most of the Pareto designs lie in a range of depth of cut from 2.0 mm to 3.5 mm. For the feed rate, the distribution of Pareto designs shows that most of the designs are obtained between 300 mm/min and 440 mm/min. The speed range for the most compromised designs is 5380 rpm to 5480 rpm. The most feasible Pareto designs are obtained between the MQL flow rates of 0.3 ml/min and 0.6 ml/min. The range of volume fraction of nanofluid which gives the best compromised designs is 1.1% to 2.6%.

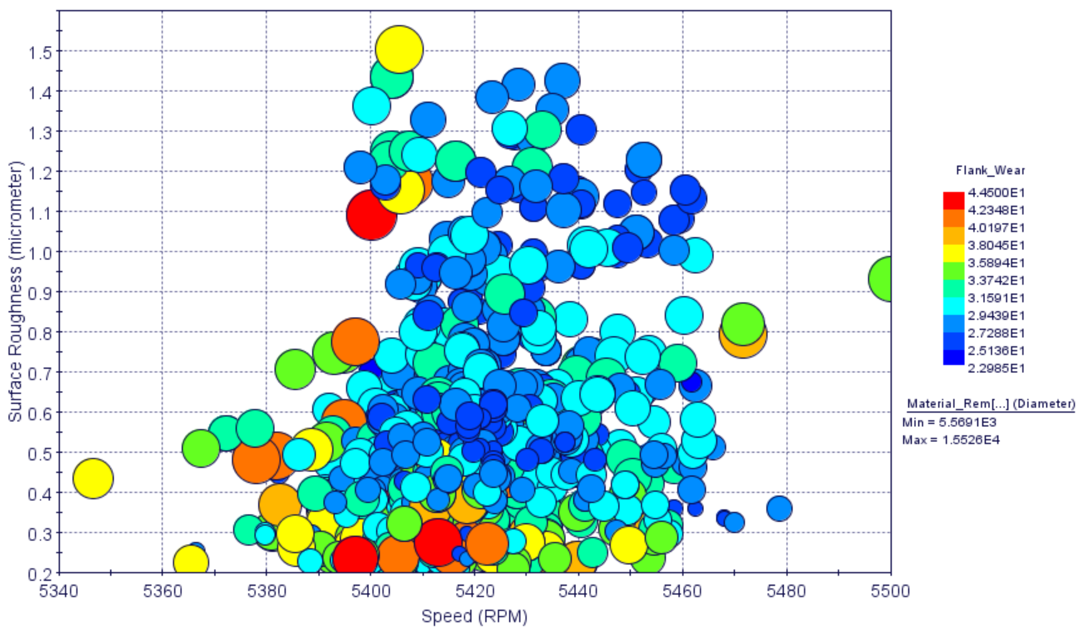


Figure 7. Pareto designs distribution with cutting speed.

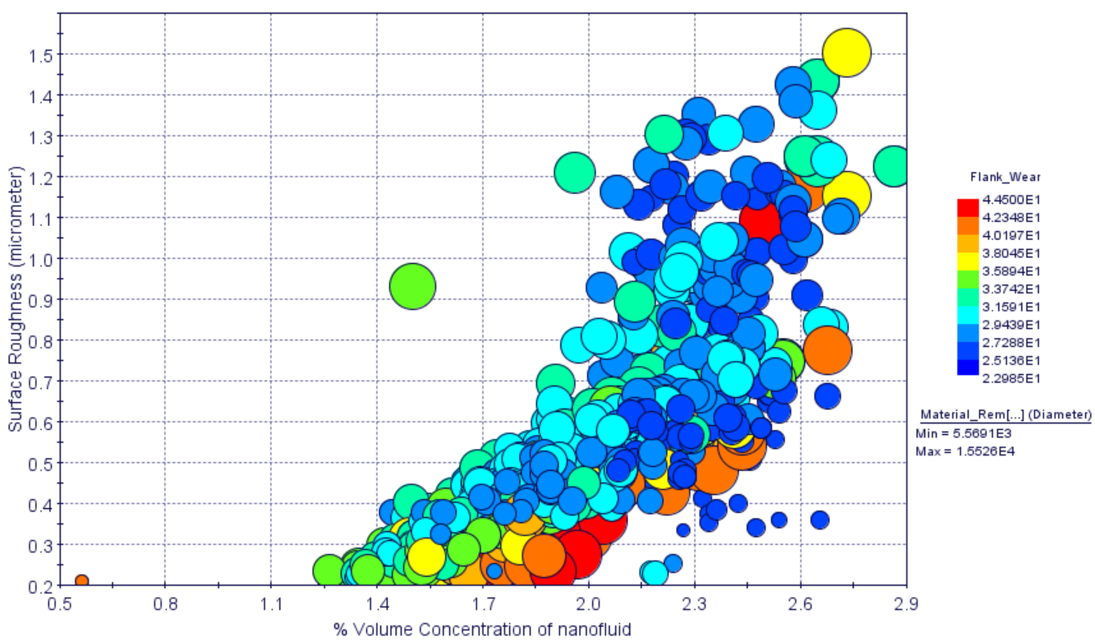


Figure 8. Pareto designs distribution with volume concentration of nanofluid.

Selection of the Best Compromised Design

The result of multi-objective optimization is a set of Pareto optimal solutions which present the trade-offs among the three objectives. At the end of the optimization, there are too many solutions to choose from. In this case, 1156 Pareto designs are obtained. In order to decide which design is the most optimal or most compromised among all the solutions from a list of optimal Pareto designs, a multi-criteria decision making approach is used. Alternative Pareto designs are ranked according to their fitness to the applied evaluation criteria. The MCDM approach is based on a genetic algorithm which is iteratively run for all the sets of Pareto designs as the initial population until the ranking of designs is obtained. The results converge to a list of designs arranged in descending order of their fitness evaluation. Preference weightage is assigned to the objectives according to process requirements. Assignment of these weights depends highly on the decision maker. Table 2 shows the most optimal design parameters as obtained after MCDM iterations. These designs are based on equal weightage assigned to each response variable, while the best compromised design is also obtained for the conditions where surface roughness is given higher weightage, i.e., the quality of the production process is twice as important as the flank wear and material removal rate.

Table 2. Best compromised design parameters obtained after MCDM.

Speed (RPM)	Feed rate (mm/min)	Depth of cut (mm)	MQL flow rate (ml/min)	% volume concentration of nanofluid	R_a (µm)	MRR (mm^3/min)	Tool Wear (µm)	Preference weightage
5428.5	433.00	2.8	0.31	2.10	0.6580	1.3271x10^4	33.20	R_a = 2 MRR =1 TW = 1
5427.4	342.55	2.9	0.31	1.43	0.2084	1.0992 x10^4	33.96	R_a = 1 MRR =1 TW = 1

CONCLUSIONS

A multi-objective optimization approach is applied to the end milling process of aluminium alloy 6061 T6 with minimum quantity lubrication using water-based TiO_2 nanofluid as the cutting medium. Minimization of surface roughness, maximization of the material removal rate and minimization of tool flank wear are taken as objective functions optimized simultaneously in terms of the cutting parameters. Design and functional constraints are applied to the optimization problem in addition to the process goals in order to filter the undesired or unfeasible designs. The result of the optimization is the Pareto solutions, i.e., non-dominated solutions selected from the sets of feasible designs. Selection of the best solution from a large number of Pareto designs is carried out by a Pareto-rankings approach using a genetic algorithm based multi-criteria decision making application. The results show that a configuration of input parameters with cutting speed = 5427.4 rpm, feed rate = 342.55 mm/min, depth of cut = 2.8950 mm, MQL flow rate = 0.31 ml/min and volume concentration of nanofluid = 1.43% can be considered as the best alternative parametric configuration for achieving the desired objectives and process goals provided all the three objectives are given equal weightage. The design parameters for an optimization problem with higher weightage assigned to the surface quality of the product are cutting speed = 5428.5 rpm, feed rate = 433.0 mm/min, depth of cut = 2.79 mm, MQL flow rate = 0.31 ml/min and volume concentration of nanofluid = 2.1%.

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