Robust Multiobjective Optimization of Cutting Parameters in Face Milling

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Abstract: In this paper, a new multiobjective optimization approach is proposed for the selection of the optimal values for cutting conditions in the face milling of cobalt-based alloys. This approach aims to handle the possible manufacturing errors in the design stage. These errors are taken into consideration as a change in design parameter, and the design most robust to change is selected as the optimum design. Experiments on a cobalt-based superalloy were performed to investigate the effect of cutting speed, feed rate and cutting depth on the cutting forces under dry conditions. Material removal rate values were also obtained. Minimizing cutting forces and maximizing the material removal were considered as objectives. It is believed that the used method provides a robust way of looking at the optimum parameter selection problems.

Keywords: face milling; robust optimization; cobalt-based superalloy; sensitivity; multiobjective optimization; optimum cutting parameters

1 Introduction

Cobalt-based superalloys are used extensively in applications that require good wear, corrosion and heat resistance [1, 2]. Such features make them preferable in the nuclear and aerospace industries [3-5]. Among the cobalt-based superalloys, the most common ones are stellite alloys, especially the well-known stellite 6. The use of this alloy in industry has been increasing recently. Application areas include pulp and paper processing, oil and gas processing, pharmaceuticals, chemical processing and medical applications. It is also employed in applications where corrosion resistance is an important factor.

As the use of cobalt-based stellite alloys has extended into various industrial sectors, the need for improving corrosion resistance of stellite alloys has increased as well. It has been observed that processing changes most probably affect the corrosion performance due to its effect on the microstructure of stellite alloy [6].

Cobalt-based superalloys are primarily based on carbides in Co matrix form. Their strength at grain boundaries, distribution, size and shape of carbides depend on processing conditions. Solid solution strength of Co-base alloys is normally provided by tantalum, tungsten, molybdenum, chromium and columbium [7-9]. Today, these alloys exist in a variety of more than 20 commercially available products, being used extensively in high temperature applications requiring superior wear, corrosion and heat resistance [10-11].

There are two main problems in machining cobalt-based superalloys. The first one is short tool life due to the working hardening and attrition properties of the superalloys. The second is the severe hardening of the surface of machined work pieces due to heat generation and plastic deformation. In order to achieve adequate tool life and the surface integrity of the machined surface, it is crucial to select reasonable machining conditions and parameters [4].

It is difficult to machine superalloys. The machinability of superalloys has not been improved enough, although there are new improvements in cutting tools. Machinability can be improved by minimizing tool-chip connection area, providing a sharp cutting edge and minimizing cutting depth. Machinability can be also improved further by providing minimum heat extraction, which results in a slow cutting speed and feed rate [4].

Metal machining not only requires knowledge of related areas of science and technology, but also plays an important role in manufacturing [12]. Because of its significance and complication, much attention has been paid to the cutting process, and many approaches have been attempted to get a better understanding of metal cutting principles. So far these methods have been mainly confined to either theoretical or experimental works. It is well-known that experimental studies are reliable and practical, but they are usually time-, labor- and material-consuming. Regarding theoretical analyses, there is experience in establishing and handling mathematical models, but much less experience and even avoidance of in experimental studies. The optimization method used in this paper utilizes few experimental results; therefore, it avoids lengthy operations. In addition, it uses a simple mathematical model of the cutting forces. Thus, it avoids complicated mathematical models. The combination of both approaches achieves a robust and reliable estimation.

There are several studies on surface milling [13-15]. These studies show that cutting forces also increase when feed rate and cutting depth increase. As cutting speed is a parameter directly affecting tool life, cutting forces are not directly related to the cutting speed. Since tool life is longer in asymmetric milling than in symmetric milling [4, 14], asymmetric face milling was preferred in this study. Additionally, inclined cutting theory is used in which cutting the tool grasps the work piece well and chip is removed as soon as possible.

This paper mainly focuses on finding the optimum parameters considering the cutting forces and material removal rate for milling of cobalt-based alloys. The cutting tests were carried out under dry conditions using PVD coated inserts. The machining parameters are optimized by using a new approach based on robustness. The practical cutting parameters can be different from what the manufacturers predict due to the uncertainties in material properties and the variations of the parameters in manufacturing. The used method takes care of these uncertainties by giving small deviations to parameters. From this perspective, this study is unique as an application to machining of cobalt-based alloys. Furthermore, suitability of the method is also analyzed by finding the optimum parameters.

The commonly used quantitative methods consider a single objective, such as minimization of cost or maximization of profit, for the optimization of the machining operations. For the process of the single objective optimization, several different techniques were proposed such as differential calculus [16], geometric and stochastic programming [17], regression analysis [18, 19], linear programming [20], genetic algorithm [21], and computer simulation [22]. In addition, there are also other local search methods, such as tabu search, ant colony optimization, pattern search, scatter search and fuzzy possibilistic programming [23].

In this study, optimization of the machining operation is considered as a multiobjective optimization problem. The new approach, considering robustness that does not require gradient calculations, useful with discrete variables, has shown its effectiveness and usability [24].

2 Optimization Methodology

Generally, uncertainty can be classified into two types: reducible and irreducible [25, 26, 27, 28]. Reducible uncertainty, often referred to as epistemic uncertainty, is used to represent incomplete information about an event such as a simulation or model of an engineering problem. In contrast, irreducible uncertainty, often referred to as aleatory uncertainty [25, 26], arises due to the inherent uncertainty associated with an engineering system under consideration. Irreducible uncertainty refers to the uncertainty or a part of uncertainty that cannot be reduced at any expense due to its inherent nature such as the likelihood of the fractional components in raw crude oil. Thus, it is treated as irreducible. Research streams have been extensively developed to understand and deal with uncertainty in design problems along two inter-related, but different directions: robust optimization [29] and sensitivity analysis [30]. Li [31] proposed an integrated approach that incorporates two existing approaches into one optimization procedure: a robust optimization approach used to design around irreducible uncertainty [32] and a global sensitivity analysis to deal with reducible uncertainty [33, 34]. Despite the fact that this study employs the same approach, it focuses on implementation problems having a discrete solution set and on the investigation of the effect of certain change in parameters, instead of performing sensitivity analysis. The implementation of the proposed approach to find the optimum cutting conditions in machining a superalloy does exist in literature, although it has already implemented in two different problems [24, 35].

This approach has two main steps: obtaining Pareto optimum points and selecting the robust optimum point. In this study, the design space is formed by the obtained data from the experiments. The Pareto points are obtained by using weighting function methodology and the optimum point is selected among them according to the new approach considering robustness. A comprehensive survey on robust optimization can be found in [36]. According to this analogy, this study can be described as a tolerance design treating uncertainty at deterministic parameters. This approach has proved that it is quite useful in dealing with discrete variables defined on a population of cutting condition values obtained from experiments.

2.1 Obtaining Pareto Optimum Set

Over the past few decades, multiobjective optimization has been acknowledged as an advanced design technique in optimization. The reason is that the most real-world problems are multidisciplinary and complex, since it is common to have more than one important objective in each problem. To accommodate many conflicting design goals, one needs to formulate the optimization problem with multiple objectives.

A multiobjective optimization problem can be formulated as follow:

Min $[f_1(x), f_2(x),..., f_n(x)]$

subject to

$$g_j(x) \geq 0 \quad j = 1,2,...,m \tag{1}$$

$$h_j(x) = 0 \quad j = 1,2,...,p<n$$

where x is a n-dimensional design variable vector, $f_i(x)$ is the objective function, $g_j(x)$ and $h_j(x)$ are inequality and equality constraints.

A variety of techniques and applications of multiobjective optimization have been developed over the past decade. The progress in the field of multiobjective optimization was summarized by Marler and Arora [37] and later by Chinchuluun and Pardalos [38]. It is inferred from these surveys that if one has decided that an optimal design is to be based on the consideration of several objectives, then the multiobjective theory (Pareto theory) provides the necessary framework. If the minimization or maximization is the objective for each criterion, then an optimal solution should be a member of the corresponding Pareto set. In addition, further improvements in one criterion require a clear tradeoff with at least one another criterion.

Radfors, et al [39] in their study has explored the role of Pareto optimization in computer-aided design. They used the weighting method, the noninferior set estimation (NISE) method, and the constraint method for generating the Pareto optimal. Marler and Arora [40] have investigated the fundamental significance of the weights in terms of preferences, the Pareto optimal set, and objective-function values. Kim and de Weck [41] presented an adaptive weighted sum (AWS) method for multiobjective optimization problems. In the first phase, the usual weighted sum method is performed to approximate the Pareto surface quickly, and a mesh of Pareto front patches is identified. Each Pareto front patch is then refined by imposing additional equality constraints that connect the pseudonadir point and the expected Pareto optimal solutions on a piecewise planar hypersurface in the m-dimensional objective space. In this study, the weighted sum method was used and a brief explanation of the method is given at the following paragraphs.

Pareto serves optimality as the basic multiobjective optimization concept in virtually all of the previous literature [42]. The Pareto optimal is stated in simple words as follows: A vector X* is Pareto optimal if there exists no feasible vector X which would decrease some objective function without causing a simultaneous increase in at least one objective function. This definition can be explained graphically. An arbitrary collection of feasible solutions for a two-objective minimization problem is shown in Figure 1. The area inside of the shape and its boundaries are feasible. The axes of the graph are the objectives: F' and Q'. It can be seen from the graph that the noninferior solutions are found in the portion of the boundary between points A and B. Thus, here arises the decision-making problem from which a partial or complete ordering of the set of nondominated objectives is accomplished by considering the preferences of the decision maker. Most of the multiobjective optimization techniques are based on how to elicit the preferences and determine the best compromise solution. From this perspective, the used approach differs from other techniques. This approach chooses the optimum point by considering the change in parameters and the effect of change to objectives.

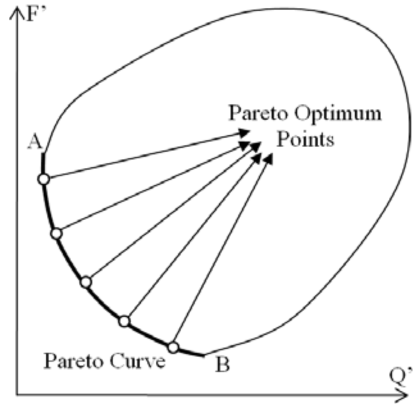

Figure 1
Graphical interpretation of Pareto optimum

The weighted sum method is based on the preference techniques of the weights' prior assessment for each objective function. It transforms the multiobjective function to a single criterion function through a parameterization of the relative weighting of the objectives. With the variation of the weights, the entire Pareto set can be generated. This means that we change the multiobjective optimization problem to a single optimization problem by creating one function of the form.

$$f(x) = \sum_{i=1}^{k} w_i f_i(x) \quad (2)$$

where $w_i \geq 0$ are the weighting coefficients representing the relative importance of the objective.

The best results are usually obtained if objective functions are normalized. In this case, the vector function is normalized to the following form

$$\tilde{f}(x) = \left[\tilde{f}_1(x), \tilde{f}_2(x), ..., \tilde{f}_k(x)\right]^T \quad (3)$$

where $$\tilde{f}_i(x) = \frac{f_i(x)}{f_i^o} \quad i=1,2,...,k \quad (4)$$

Here, f_i° is generally the maximum value of i^{th} objective function (A condition $f_i^\circ \neq 0$ is assumed).

In this study, the total force and cutting flow of material are considered as objectives. The total force value is the resultant force of the obtained forces in experiments, and the cutting flow value is obtained by using Equation 5.

$$Q = \frac{a_p . a_e . f}{1000} \quad (m^3 / \min) \tag{5}$$

where a_p, a_e and f represents cutting depth, cutting width (constant) and feed, respectively. The cutting flow of material, Q, should be maximized, and total force F should be minimized to minimize the tool wear and used power. Thus, to maximize the composite weighted function, inverse of the force is taken as objective and the objective function (J) is set as

$$J = \frac{1}{F} + w.Q \tag{6}$$

where w is a weighting co-efficient varied to obtain Pareto optimum points. In order to bring the values in the same range, Q and (1/F) are normalized with their maximum values where the relation in Equation 7 is used to obtain Pareto optimum values;

$$J = F' + w.Q' = \frac{F_{\max}}{F} + w.\frac{Q}{Q_{\max}} \tag{7}$$

The design space is related with the allowed maximal dimension of the controlled variable vectors used during the machining operation. The design variables are the cutting speed (V_c), the feed (f) and the cutting depth (a_p). The design space is a typical discrete and non-convex domain.

2.2 Selecting the Robust Optimum Point

At the second step, according to the Pareto optimum points, the optimum point is selected based on changes in the objective function when small variations are permitted in design variables. In this study, equal contributions of each variable are considered. Based on positive/negative variations in design variables, and average changes in the objective function values are calculated at every Pareto optimum point. Figure 2 shows the change in parameter and objective values for two parameter case.

The optimum point is selected as the one having the minimum changes on

$$\Delta V_j = \frac{1}{n} \sum_{i=1}^{n} \left\{ \left[F'(z_i) - F'(z_o)\right]^2 + \left[Q'(z_i) - Q'(z_o)\right]^2 \right\} \tag{8}$$

where n is the number of design variable change around every Pareto optimum point, $F'(z_o)$, $Q'(z_o)$ are the objective function values at the Pareto optimum point, $F'(z_i)$, $Q'(z_i)$ are the objective function values when a certain change is applied to a design parameter, and j is the index of the Pareto optimum point [24]. While calculating the change in objectives, the objective values that are not in the feasible region are not taken into account. For example, the changes in objective values at point 1, 5 and 6 in Figure 2 are not considered because they are not in the feasible region.

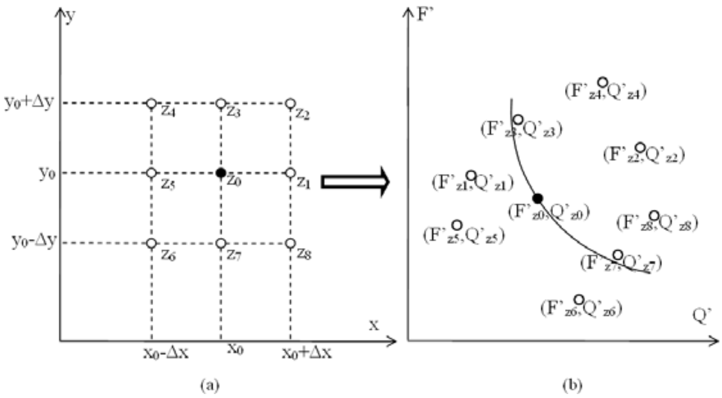

Figure 2
Change in design parameters (a) and objectives (b)

3 Experimental Setup

The experiments to investigate the cutting forces for asymmetric face milling were carried out on a CNC milling machine. The influence of the other machining conditions (feed rate, axial depth of cut and feed rate per tooth) on the cutting forces in dry cutting were also considered. A 9 kW Johnford WMC-850 series of CNC milling machine was used. The cutting forces were measured by using a Kistler 9265B series dynamometer.

Surface machining was done with the parameters selected by considering the recommended values of ISO for superalloys [43]. The experiments are given parameter values as shown in Table 1.

Table 1
Cutting conditions for face milling

Cutting speeds	V_s	m/min	30,35,40
Feed rates	f	mm/min	60,70,80,90,100
Depths of cut	a_p	mm	0.25, 0.5, 0.75
Widths of cut	a_e	mm	50
Feed rates per	F_z	mm/tooth	0.1
Coolant	--	--	Dry

To avoid thermal effects, lower cutting speeds were chosen. In addition, higher cutting speeds result in severe tool wear and the higher feeds cause a large deformation rate. Ranges for process parameters and the obtained results are shown in Table 2.

The stellite 6 workpiece used in the machining test is made from cast material. The chemical composition of the workpiece material is given in Table 3. The hardness of the workpiece is 44 HRC. The tool material ISO P30 (SECO grade H40, quality insert) was coated using PVD (Physical Vapor Deposition) [44].

4 Results and Discussion

The approach described above was applied to the experimental data given in Section 3. In this study, three parameters (the cutting speed, the feed and the cutting depth) were considered. The experiments in Table 3 were used in the calculation. The change in cutting depth was assumed as 0.25 mm, the change in feed was assumed as 10 mm/min. and the change in cutting speed was assumed as 5 m/min. The objective functions were evaluated under these assumptions. Then, the Pareto points were evaluated using weighting function. A sample calculation is given in Table 4 for the first data of Table 2 and w=0.1.

For every point, objective function values were calculated. Even though the weighting coefficient of the objective function is firstly changed from 10^{-6} to 10^{6}, it has been seen that it is enough to change from 10^{-1} to 10 to get the Pareto optimum points (Table 5).

Table 2
The experimental values obtained in machining

Data	a_p (mm)	f (mm/min)	V_c (m/min)	F_z(N)	F_y(N)	F_x(N)
1	0.25	60	30	140	50	40
2	0.25	70	30	150	70	70
3	0.25	80	30	170	90	90
4	0.25	90	30	210	130	140
5	0.25	100	30	300	140	200
6	0.25	60	35	220	125	180
7	0.25	70	35	240	140	175
8	0.25	80	35	360	175	240
9	0.25	90	35	380	150	250
10	0.25	100	35	400	180	265
11	0.25	60	40	250	160	140

12	0.25	70	40	280	165	150
13	0.25	80	40	300	170	170
14	0.25	90	40	320	180	175
15	0.25	100	40	360	200	180
16	0.50	60	30	240	120	160
17	0.50	70	30	280	120	170
18	0.50	80	30	310	150	175
19	0.50	90	30	340	280	180
20	0.50	100	30	380	300	200
21	0.50	60	35	150	200	160
22	0.50	70	35	190	210	200
23	0.50	80	35	200	200	200
24	0.50	90	35	250	210	250
25	0.50	100	35	350	220	300
26	0.50	60	40	280	130	150
27	0.50	70	40	300	210	200
28	0.50	80	40	320	200	210
29	0.50	90	40	330	210	230
30	0.50	100	40	500	310	300
31	0.75	60	30	325	160	300
32	0.75	70	30	350	170	320
33	0.75	80	30	365	185	325
34	0.75	90	30	400	225	335
35	0.75	100	30	450	250	360
36	0.75	60	35	250	180	180
37	0.75	70	35	280	200	220
38	0.75	80	35	300	220	250
39	0.75	90	35	310	250	250
40	0.75	100	35	410	310	380
41	0.75	60	40	330	300	310
42	0.75	70	40	380	320	325
43	0.75	80	40	425	280	355
44	0.75	90	40	500	330	360
45	0.75	100	40	530	375	375

Table 3

Composition of the experimental material Stellite 6

Element	C	Si	Mn	Cr	Ni	Mo	W	Ti	Fe	Ta	Co
Weight (%)	1.09	1.07	0.49	28.17	1.92	0.96	5.17	0.01	2.88	0.04	Balanced

Table 4

Calculation of an objective function value (F_{max}=153.948 and Q_{max}=3.75 for the case)

Data	a_p (mm)	f (mm/min)	V_c (m/min)	Q	Q/Q_{max}	F_z(N)	F_y(N)	F_x(N)	F_r	F_{max}/F_r	J
1	0.25	60	30	0.75	0.2	140	50	40	153.948	1	1.02

Table 5

Pareto optimum points

Data	a_p (mm)	f (mm/min)	V_c (m/min)	Weighting Coefficients
1	0.25	60	30	0.1, 0.5
2	0.75	100	30	1, 5, 10

Change is given to the design parameters of obtained Pareto optimum points and deviation in objectives is calculated (Table 6). Only feasible points are given in this table.

Table 6

Change in parameter and objective for Pareto optimum points

Change in Pareto Point 1	Obj. Func. F_{max}/F	Obj. Func. Q/Q_{max}	Deviation in F_{max}/F	Deviation in Q/Q_{max}
0.25;60; 30	1	0.2	0	0
0.25;60; 35	0.495769	0.2	0.504231	0
0.25;70; 30	0.85659	0.233333	0.14341	0.033333
0.25;70; 35	0.468829	0.233333	0.31171	0.033333
0.5; 60; 30	0.492776	0.4	0.507224	0.2
0.5; 60; 35	0.518664	0.4	0.481336	0.2
0.5; 70; 30	0.441295	0.466667	0.558705	0.266667
0.5; 70; 35	0.44404	0.466667	0.55596	0.266667
Change in Pareto Point 2	Obj. Func. F_{max}/F	Obj. Func. Q/Q_{max}	Deviation in F_{max}/F	Deviation in Q/Q_{max}
0.75;100;30	0.245073	1	0	0
0.75; 90; 30	0.27094	0.9	0.025867	0.1
0.75;100;35	0.240838	1	-0.00424	0
0.75; 90; 35	0.327401	0.9	0.082328	0.1
0.5; 100; 30	0.293888	0.666667	0.048815	0.333333
0.5; 90; 30	0.323546	0.6	0.078473	0.4
0.5; 100; 35	0.301396	0.666667	0.056323	0.333333
0.5; 90; 35	0.374371	0.6	0.129298	0.4

As a last step, the squares of total deviations and their mean were calculated by using Equation 8. It is seen that the first Pareto point has a total average deviation of 0.236451 and the second Pareto point has a total average deviation of 0.074765. the second Pareto point is the optimum point, having the minimum deviation. The optimum cutting condition found is at a_p=0.75 mm; f=100 mm/min; V_c=30 m/min.

Conclusions

Since cutting conditions regulate the machining process through the developed cutting forces, the optimization of machining parameters is important. Uncontrollable variations are unavoidable in machining due to the quality of manufacturing tools, measurement tools, operators' mistakes, imperfections during the manufacturing processes, etc. The method used was to evaluate average deviations from the Pareto optimum points because of uncontrollable variations. The selection of the optimum design point with the minimum deviation is the criterion to find the robust optimum point.

Although there are several methods in literature for the multiobjective optimization of machining processes, a new approach is used in this work. The main advantage of this approach is to get the robust optimum point. In addition, there is no need to calculate complex modeling formulations or simulations of the process, which requires a lot of time and hardware. Instead, simple statistical calculations are enough to get acceptable results. Moreover, this approach gives much more reliable solutions because experimental data were used, and these data were the exact values to represent the process.

The used method has proved that it is very useful when dealing with discrete variables defined on a population of cutting condition values obtained from experiments. It is believed that this method provides a robust way of looking at the optimum parameter selection problem. In addition, it can easily handle those cases where each of the design variables has different uncertainty ranges.

The results of the case study have shown the benefits of the new approach. The optimum cutting conditions are determined for the machining of Cobalt-based alloy stellite 6 material as a_p = 0.75 mm; f = 100 mm/min and V_c = 30 m/min.

When the results are compared with previous study which considered surface roughness, it is seen that feed values were same, but depth of cut and cutting speed get higher values since material removal rate and resultant force are considered in the meantime.

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