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Multi-Objective Optimisation of CNC Milling Process for Al 6061 using Modified NSGA-II

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Abstract

Computer numerical controlled (CNC) growth has revolutionised the manufacturing sectors by changing the way people work. In milling process, it has contributed to the higher productivity and better quality of the products. Although a lot of researches have been done on how to improve the process, the process improvement does not stop there because of evolving materials, methods and technologies. This paper presents a multi-objective optimisation of CNC milling process in order to achieve desired surface roughness and minimise machining time for Al 6061. A full factorial experiment has been conducted to model surface roughness by controlling three variables; spindle speed, feed rate and depth of cut. Multi-objective optimisation has been performed using modified Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) with two levels crossover. The optimisation result concluded that the modified NSGA-II was able to converge to Pareto-optimal, but having difficulties to spread solutions in wider range.

1. Introduction

Computer numerically controlled (CNC) machine has been implemented since the previous decades in order to realise full automation in machining. Milling process is the most well-known metal removal process. It is generally used to mate with other parts in automotive, aerospace, die and machinery design as well as in manufacturing industries. In this process, selecting sensible milling parameters is important to fulfil necessities including machining cost, quality and safety [1].

The optimisation issue in milling process turns out to be more complex whenever it deals with more than one objective. For example, a machinist might want to boost the production rate and in the meantime to minimise the production costs. There is a number of previous research works that have considered multi-objective optimization for milling process. [2] studied multi-pass milling and considered two objectives: machining time and production cost. They proposed parallel genetic simulated annealing (PGSA) to obtain the optimal cutting parameters which is based on the concept of a Non-dominated Sorting Genetic Algorithm (NSGA).

Meanwhile, [3] studied three objectives: surface roughness, material removal rate and cutting energy by using grey analysis and RSM method. Besides that, [4] used the Pareto-based Particle Swarm Optimisation to optimise spindle power and production time. On the other hand, [5] have developed some new models for milling and optimised these models to minimise the cutting temperature in end milling process by integrating the Genetic Algorithm (GA) with the statistical approach.

Besides these works, numerous researchers have also worked with multi-objective optimization for milling such as [6 – 10]. They used various optimisation algorithms such as Genetic Algorithm, PSO and other heuristic methods. In this work, an optimisation of milling process will be conducted by using modified Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) with two levels crossover to machine a base component for an assembly jig. The optimisation objectives of this work are to achieve the desired surface roughness and also to minimise the machining time.

2. Problem Modelling

The experiment was performed by using a FANUC CNC Milling α-T14ıE. The workpiece tested was Aluminium 6061. The end-milling and four-flute high speed steel was chosen as the machining operation and cutting tool. The diameter of the tool was d_t =16 mm. 84 specimens were run in this experiment. 60 specimens were used to build a prediction model and the testing set contained 24 specimens. Spindle speed (V), feed rate (f) and depth of cut (c) were selected as considered parameters. Four levels of spindle speed; 750, 1000, 1250, and 1500 revolutions per minute (rpm), seven levels of feed rate; 152, 229, 305, 380, 457, 515, 588 millimeter per minute (mmpm), and three levels of depth of cut; 0.25, 0.76, 1.27 millimeter (mm) were determined.

After completing the experiment, all original 84 samples were randomly divided into two data sets; the training set and testing test. The training set contained 60 samples which were used to build a prediction model and the testing set contained 24 samples which were used to test the flexibility of the prediction model.

Multiple regression analysis was used to establish a mathematical model to predict the surface roughness. In this case the dependent variable was surface roughness, while the independent variables were spindle speed, depth of cut and feed rate. A mathematical model was created by using the data from the training data set. The results of multiple regression analysis are presented in Table 1. The R^2 and Adjusted R^2 values for this analysis are 0.8665 and 0.8486 respectively. These numbers indicate that the correlation coefficient between the observed value of the dependent variable and the predicted value based on the regression model was high.

	Coefficients	Standard Error	t-Stat	P-value
Intercept	0.2602	0.9138	0.5754	0.005674
x_1	-0.0001667	0.0007761	-0.2149	0.8306
x_2	0.01119	0.002457	4.5706	$3.0312\text{x}10^{-05}$
x_3	-0.2442	1.1321	-0.2157	0.8300
x_1x_2	-0.000004357	$2.0428\text{x}10^{-06}$	-2.2016	0.03215
x_1x_3	0.0006847	0.001003	0.8122	0.004203
x_2x_3	-0.002785	0.002976	-1.0131	0.03156
$x_1x_2x_3$	$3.3666\text{x}10^{-07}$	$2.5297\text{x}10^{-06}$	0.1330	0.8946

Table 1. Results of Multiple Regression Analysis

According to P-value in Table 1, not all the input variables have significant correlation with the output. For the confidence interval at 95%, only the intercept coefficient, x_2, x_1x_2, x_1x_3 and x_2x_3 have correlation since the P-value less than 5%. Meanwhile, from ANOVA test, the f-value was 84.746 and the significance of f-value was $1.55568\text{x}10^{-20}$ which is less than the critical value (α=0.05). It means that at least one of the population regression coefficients was not zero. Therefore, we can establish the mathematical model to predict surface roughness for this problem as follows:

$$R_a = 0.2602 + 0.01119f - 0.000004357Vf + 0.0006847Vc - 0.002785fc \quad (1)$$

Based on the testing on data in the testing set, the accuracy average of this model is at 9.8% when we compare with actual surface roughness value from experiment. For the machining specification, the targeted surface roughness for the workpiece is 1.5 µm. Therefore, the different between calculated roughness and target value, R_d is used as the first objective function.

$$R_d = |R_a - 1.5| \quad (2)$$

Meanwhile, the basic formula to calculate the machining time (T_m) is given as follow, where L_t is the total machining length (in mm) and feed rate, f (in mm/minute).

$$T_m = \frac{L_t}{f} \quad (3)$$

In this case, we need to identify the L_t from the machining part. The L_t can be calculated using the following formula:

$$L_t = l \times nop \times nos \tag{4}$$

l is the length of machining area, *nop* refers to the number of passes, while *nos* is the number of steps. For *h* is the cutting depth, these variables can be calculated as follows:

$$nop = \frac{w}{dt.\varepsilon} \tag{5}$$
$$nos = \frac{h}{c} \tag{6}$$

ε is the ratio of the effective cutting area which is calculated by dividing the effective cutting width (*w*) of each pass and the diameter of cutting tool. In this problem, ε = 0.8 is used. Therefore, the second objective function to measure machining time, T_m is given as follow:

$$T_m = \frac{l \cdot w \cdot d}{dt \cdot \varepsilon \cdot c \cdot f} = \frac{100 \times 100 \times 20}{16 \times 0.8 c \cdot f} \tag{7}$$
$$T_m = \frac{15625}{c \cdot f} \tag{8}$$

3. NSGA-II

Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) was introduced by [11] to overcome the computational complexity in multi-objective optimization. The NSGA-II works as follow:

Step 1: Generate initial population (P(1) and offspring Q(1))
Step 2: Combine R = P u Q
Step 3: Evaluate and non-dominated sort
Step 4: Selection using Crowding Distance
Step 5: Generate new offspring (Q(t+1)) using Crossover and Mutation
Step 6: Repeat Step 2 until termination criteria met

3.1 Initial Population

In NSGA-II, the initial population (P_1) is created, and is followed by offspring (Q_1) using crossover and mutation operators. For the initial generation, the P_1 is assumed as the selected parents in order to generate the Q_1. Next, these two populations are combined together as $R_1 = P_1 \cup Q_1$.

3.2 Non-dominated Sort

For each of the individual r in R_i, set S_r is an empty set and n_r as zero. S_r contains all the individuals that are dominated by r, while n_r is the number of individuals that dominates r. For s is also an individual in R_i, if r dominates s, s is added to the set S_r. If s dominates r, then $n_r = n_r + 1$. Since n_r counts the number of individuals that dominate the solution r, if the $n_r = 0$, then r belongs to the first front (F_1). This process is repeated for all individuals in the R.

Meanwhile, if the i^{th} front (F_i) is nonempty, set $D = Ø$, which is an empty set to store the individuals for F_i. For each individual d in F_i, modify each member from the set $S_{r,}$ then, the value of n_d decreases by one. If the value of n_d is zero, individual r will be a member of D. Current front will be formed with all members of D.

3.3 Selection

In order to establish a new population, the selection is made by inheriting all solutions F_i, i=1,2, …etc. The solutions in i^{th} front, are directly inserted to the new population as long as the total number of solutions is less than the population size. When it comes to a particular F_i, where the total number of solutions in new population is larger than the population size, selection will be made within that particular F_i to determine which solutions will be added into the new population. The selection will be made according to Crowding Distance. For the solutions in similar front, the one with larger Crowding Distance is more preferred. Once the number of selected chromosomes is equivalent to the population size, the crossover and mutation as in standard evolutionary approach is conducted to generate a new population.

The Crowding Distance is calculated as follows:

Step 1 Call the number of solution in F_i as I = $|\mathrm{R}|$. For each i in the set, first assign $d_i = 0$.

Step 2 For each objective function $m = 1, 2,…,M$, sort the set in descending order, r_m.

Step 3 For $m = 1, 2,…,M$, assign maximum (max_m) and minimum (min_m) value for each objectives m.

Step 4 Calculate d_i^m for each of objective m for solution i.

$$d_i^m = \left(\frac{I_{up^i}^m - I_{low^i}^m}{max_m - min_m}\right) \quad (9)$$

Step 5 Calculate summation of d_i^m.

$$CD_i = \sum_{m=1}^{M} d_i^m \quad (10)$$

In Eq. 9, $I_{up^i}^m$ is the nearest upper m^{th} objective value for solution i. Meanwhile, $I_{low^i}^m$ represents the nearest lower m^{th} objective value for solution i. In this case, if the objective value is located at the first or last place in the r_m, the max_m and min_m value is used to replace the nearest value respectively.

3.4 Two Levels Crossover

In standard NSGA-II, two points crossover is used in regeneration process. In this work, the crossover is conducted in two levels. In the first level, a standard two points crossover is conducted, where the parent are selected from the selection pool. Meanwhile, the second level crossover is performed by using offspring from the first level crossover and the chromosome with the best Crowding Distance from the first front. In order to conduct crossover, a single point crossover is used.

4. Optimisation Results and Discussions

Multi-objective optimization for the CNC milling process has been conducted using modified NSGA-II. In order to compare the performance of modified NSGA-II, the standard NSGA-II and two different evolutionary based algorithms were used. These algorithms are Multi-Objective Genetic Algorithm (MOGA) and Hybrid Genetic Algorithm (HGA) that adopted Local Search as additional operators. In all the algorithms, the population size was set to 20, and the algorithms run with maximum 10000 generations. The results of optimisation using MOGA, HGA, NSGA-II and modified NSGA-II are plotted as shown in Fig. 1. From this figure, it clearly shows that the solution with minimum R_d, has higher T_m and vice versa.

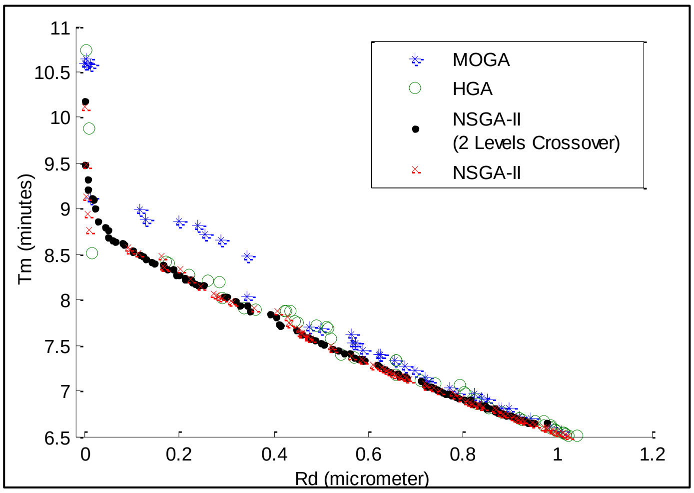

Figure 1. Multi-objective Optimisation Results

Since the real Pareto-optimal solutions are unknown in this problem, a reference Pareto-optimal set is established by combining all the non-dominated solutions from all algorithms and filtering the solutions using non-dominated sort approach. Six performance indicators were used to compare the solutions from different algorithms: (i) Number of non-dominated solution in Pareto-optimal, $\tilde{\eta}$ (ii) Hypervolume, *hv* (iii) Generational Distance, *GD* (iv) Spacing, and (v) Maximum

Spread. The performance indicators of MOGA, HGA, NSGA-II and modified NSGA-II are presented in Table 2.

Algorithm	$\tilde{\eta}$	*hv*	*GD*	*Spacing*	$Spread_{Max}$
MOGA	0	71.2046	0.106	0.08	4.16
HGA	15	73.6681	0.0378	0.1705	4.3479
NSGA-II	77	74.663	0.0032	0.0814	3.7483
Modified NSGA-II	84	81.5122	0.0143	0.06294	4.2847

Table 2: Performance indicators for optimisation algorithms

Based on Table 2, the modified NSGA-II with two levels crossover algorithm shows better performance in terms of finding the Pareto-optimal solutions. However, in term of solution accuracy, the standard NSGA-II is better than the modified algorithm. From 132 solutions found by modified algorithm, only 64% of them are in Pareto-optimal, compared with 88% in NSGA-II. Meanwhile, none of the solutions found using MOGA belongs to Pareto-optimal. On the other hand, 29% of the solutions by HGA are in Pareto-optimal. This result shows that the modified NSGA-II has better convergence towards Pareto-optimal.

Besides that, the modified NSGA-II also came out with better cumulative *hv* value from the objective space. This result means that the propose algorithm has better coverage area in the objective space. It also can be associated with better algorithm convergence in finding the Pareto-optimal. However, the GD indicator indicates that the NSGA-II has better performance compared to the proposed algorithm, MOGA and HGA. This is directly linked with the accuracy of solution that generated by NSGA-II. Even though some of the NSGA-II solutions are not in Pareto-optimal, the average distance towards the optimal solution is relatively small compared to MOGA and HGA.

In the meantime, the Spacing indicator measures the uniformity of the space between one solution with the nearest solution in a similar set. The results show that the proposed algorithm is having the best Spacing, followed by MOGA, NSGA-II and HGA. The Spacing indicator depends on the solution distribution in the objective space. The performance of the proposed algorithm in the Spacing indicator is because of the effect from the second level crossover. The second level crossover has influenced the chromosome to converge towards the less crowded space. Therefore, more solutions in the less crowded area is generated which finally improved the Spacing of solution. On the other hand, HGA has the best solution spread that is shown by Spreadmax indicator. For this indicator, the NSGA-II has the least performance compared with improved NSGA-II, HGA and MOGA. This indicator measures the distance of two extreme solutions in the objective space.

The optimisation results based on the performance indicators summarised that the modified NSGA-II with two levels crossover has better performance in converging to the Pareto-optimal solution. It was shown by the number of solutions in Pareto-optimal, hypervolume and Spacing indicators. This finding is related to the selection mechanism in NSGA-II that gives the priority to a solution with better front. From this mechanism, the solution that is generated by NSGA-II tends to yield for better front (move towards min-min direction in objective space) instead of spread in wider range. Besides that, the second level crossover also give an advantage to the proposed algorithm to have better solution uniformity in the search space.

The results of the multi-objective optimisation for milling problem give a set of choices for the machinist to select the parameter setting based on a particular requirement. For highly skilled machinist with consistent performance for example, the solution with minimum machining time and higher (but acceptable) surface roughness might be the choice. However, for the new machinist with lower skill, the solution with better surface roughness and higher machining time might be the right choice. The solution in between two extreme solutions can be selected by the new machinist in the process of mastering the machining skill.

5. Conclusions

In this study, the model of CNC milling process for Al 6061 has been developed and optimised. An experiment with 84 specimens has been conducted to measure surface roughness by manipulating three variables; spindle speed, feed rate and depth of cut for end milling process. A mathematical model has been established by using multiple regression analysis.

Based on the mathematical model, the multi-objective optimisation has been conducted with the objective to minimise the targeted surface roughness and at the same time to minimise the machining time. The optimisation is conducted using modified Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) with two levels crossover and compared with original NSGA-II, Multi-Objective Genetic Algorithm (MOGA) and Hybrid Genetic Algorithm (HGA).

The optimisation results indicate that the modified NSGA-II with two levels crossover has better performance in finding the Pareto-optimal solution and also solution uniformity compared with original NSGA-II. However, this algorithm has drawbacks in terms of generating wider spread solution. The multi-objective optimisation results give greater choices for machinist to select the appropriate solution based on a particular preference at that time.

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