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Optimization of Machining Time in Milling Process using Genetic Algorithm Method

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Abstract: The machining time in the milling process is one of the most important factors that affect the performance of machining in the milling process. In this study, the genetic algorithm (GA) is being applied to optimize the parameters such as depth of cut, feed per tooth, and cutting speed. In addition, this study also investigates the effect of the population sizes, selection method, and reproduction options in Genetic Algorithm Toolbox (GAT) on machining times in milling processes using the GA method. In this study, the workpiece of pocket milling develop by Solidwork software, and the fitness function develop using Matlab software. The population sizes are used to observe the effect on the parameters, and the most significant is the machining time. Based on the result obtained, the optimized machining time is 8.66007 minutes. The optimized value for depth of cut, feed per tooth, and cutting speed is 1mm, 0.127mm/tooth, and 30m/min, respectively, were achieved together with the optimized machining time. In conclusion, Genetic Algorithm is capable of minimizing the machining time by determining the optimum machining parameters.

Keywords: Optimization, Machining Time, Miling, Genetic Algorithm

1. Introduction

Milling is the most frequent machining type, a material removal technique that removes unwanted material from a product. A milling machine, workpiece, fixture, and cutter are all required in the milling process. The usage of CNC milling machines to manufacture design elements such as grooves, slots, notches, holes, and pockets is expected since it is typically used as a secondary or finishing step for machined components. Cutting and tool geometry parameters must be improved to reduce energy consumption and machining time. Most of the time, the selection of machining parameters is based on the machinist's previous expertise; nevertheless, using a process simulation tool can assist in optimizing the process parameters.

In this work, an end mill that is regularly used in actual production is used as the topic for the parameters of tool geometry design. A large proportion of effort in the field of Artificial Intelligence applications has been done for turning and flat-end or face milling operations. A Neural Network (NN)

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[1, 2, 3, 4] and an Adaptive Neuro-Fuzzy Inference System (ANFIS) [2] are used in this study to construct a predictor. An observation has been made on how a large proportion of effort in the field of Artificial Intelligence application has been done for turning and flat end or face milling operations [5]. One of the natural selection methods that may be used to determine the optimal parameter value for a given area is the Genetic Algorithm (GA) [6].

Cutting speed, feed per tooth, and depth of cut are the critical machining parameters that influence machining time. Poor machining parameter selection causes quick wear and breakdown of cutting tools. Machining time is vital in the milling process for planning, scheduling, and manufacturing. This study aims to investigate the effect of parameters in Genetic Algorithm (GA) on machining time and to optimize the machining time in the milling process using Genetic Algorithm (GA) method.

2. Methodology

In this study, the workpiece of pocket milling is developed by Solidwork software, and the fitness function is generated by MATLAB software. For the fitness function, three parameters will be optimized: cutting speed, feed rate, and depth of cut. The thesis will investigate the effect of GA parameters on the machining time.

2.1 Development of Workpiece

A simple square bar with dimensions of 130 x 130 x 30 mm is utilized as the model for a pocket in the Apple Watch. All the dimensions must be defined to construct the fitness function in the following process stage.

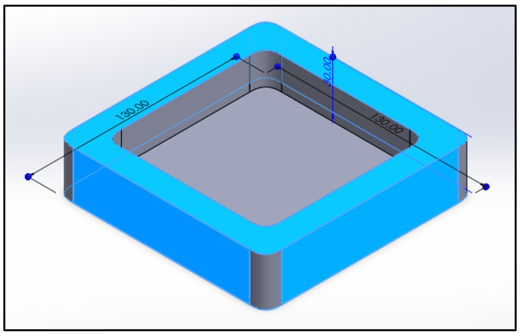

Figure 1: Dimension of the workpiece

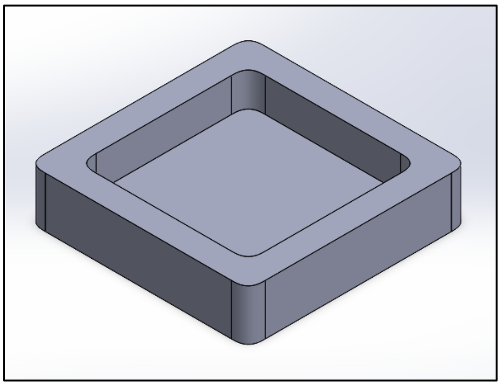

Figure 2: The pocket workpiece isometric view

2.2 Development of fitness function

The machining time of the milling process is the fitness function in this study. The fitness function is the function that will be executed by Genetic Algorithm Toolbox (GAT) each of the variables that are being optimized will be included in the function.

$$T_m = \sum_{i=1}^{N} \left(\frac{\pi D_i L_i}{1000 v_i f_i Z_i} + \frac{\pi {D_i}^{1-w_T} L_i {W_i}^{\delta_T} {Z_i}^{\lambda_T - 1}}{1000 E_T} \, {v_i}^{\alpha_T - 1} {f_i}^{\beta_T - 1} {d_i}^{\gamma_T} \right) \qquad Eq.\ 1$$

Table 1: The parameter upper and lower bound [7]

Parameter	Lower bound	Upper bound
Depth of cut, d_i (mm)	1	4
Feed rate, f_i (mm/tooth)	0.063	0.127
Cutting speed, v_i (m/min)	9	30

As given the equation 1, π have a value of 3.142. As for the other variables data, they are obtained from a journal [7] where given as the tool with a diameter, D_i = 16mm, the total tool path length, L_i = 1312mm, the number of tool teeth, Z_i = 2mm, radial depth of cut, W_i = 9.6mm, w_T = 1.36, δ_T = 0.3, λ_T = 0.3, E_T = 148880, α_T = 3.03, β_T = 1.51, and finally γ_T = 1.51. All the data stated are being replaced in the fitness function and then, it is being calculated until only the depth of cut (d_i), feed rate (f_i) and cutting speed (v_i) are left to be unknown.

2.3 Genetic Algorithm Toolbox (GAT) in Matlab Software

GA maintains a population of persons, each representing a potential answer to a certain issue. Every person is represented by a finite-length vector of components or variables. Variables are expressed in terms of some alphabet, typically the binary alphabet 0 and 1 [8]. An initial population is created by randomly generating many individual solutions. The number of potential solutions varies on the nature of the issue. On rare occasions, answers may be "seeded" in regions where ideal solutions are more likely to be discovered. Some methods of selection evaluate each solution's fitness and give preference to the best ones. Roulette wheel selection and tournament selection are two common and well-researched selection techniques. This study applies two types of selection methods which are the Roulette and Tournament method. How the GA produces the subsequent generation is controlled by the Options Reproduction panel. Here, you define the degree of elitism and the percentage of the population that is produced by mating (the rest is generated by mutation). The percentage of people in the next generation who were produced by crossover, excluding elite children, is known as the crossover fraction.

3. Results and Discussion

The study searched the lowest value from the three parameters based on the lower and upper bounds ranges for the best optimizing machining time. Besides, three configurations need to be applied from the genetic algorithm toolbox (GAT) to observe whether it would affect the three primary parameters.

3.1 Effect of population sizes

One of the goals of this study is to look at the impact of population size (number of chromosomes) on the algorithm's performance. Various population sizes (ranging from 5 to 200 chromosomes in the population) are regularly employed in the identification techniques [9]. Table 2 shows the results obtained to find the optimize value for the three parameters in reducing machining time.

Table 2: The effect of population sizes to the parameters.

Populations	Selection Method	Reproduction (Crossover Fraction)	Parameters	
			Best Machining Time, T_m (min)	Mean Machining Time, T_m (min)
5	Roulette	0.6	8.69088	8.70007
10			8.66046	8.68140
20			8.66007	8.66341
40			8.66007	8.66899
60			8.66008	8.69267
80			8.66008	8.66678
100			8.66007	8.66336
110			8.66006	8.66053
150			8.66012	8.66689
200			8.66007	8.66275

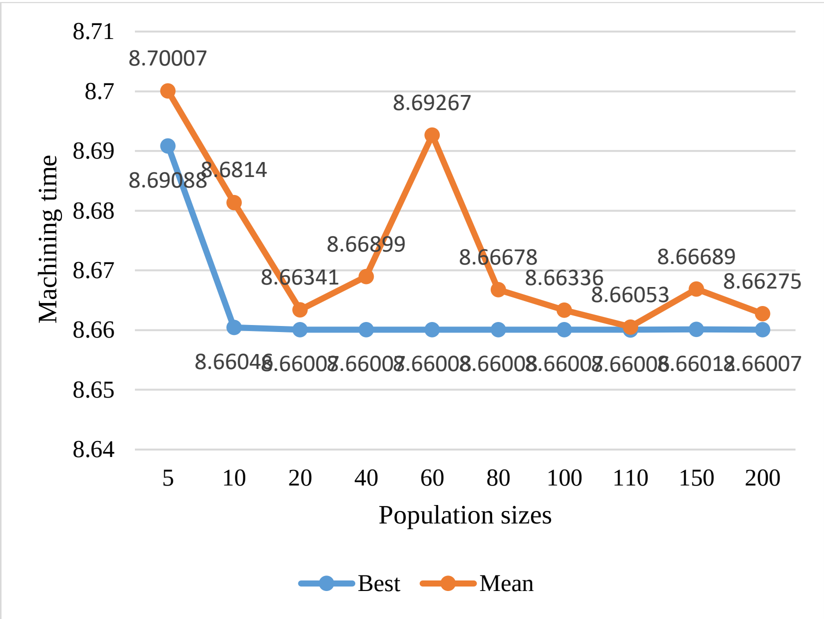

Figure 3: Graph for the effect of population sizes

The simulation is being run with the changes of population size from the range of 5 to 200. Population sizes of 110 was being chosen as the most suitable population size range. The best and mean machining time obtained were 8.66006 minutes and 8.66053 minutes, respectively. As being discussed in Chapter 2, the researcher of [10] did used a population size of 20 and gained high performance and efficient result. As reflected from the statement, the same population size is implemented in this study. Even though the result of best population size gained from this thesis and the study from [10] is different, the population size in GAT did affecting the machining time.

3.2 Effect of selection method

The term selection operator refers to the process of selecting individuals at random or according to their fitness [11]. The roulette-wheel approach is the first selection operator that is applied [12]. Besides, tournament selection use computations on the value of fitness to find the optimal person to go to another population [13]. Individuals with high fitness scores are more likely to win the match and be passed on to the next population.

Table 3: The effect of roulette and tournament in selection method.

Populations	Selection Method		Reproduction (Crossover Fraction)	Parameters: Best Machining Time, T_m (min)	Parameters: Mean Machining Time, T_m (min)
110	Tournament	2	0.6	8.66018	8.71698
		4		8.66008	8.66365
		6		8.66006	8.66491
		8		8.66006	8.66048
		10		8.66007	8.66067
	Roulette	-		8.66007	8.66609

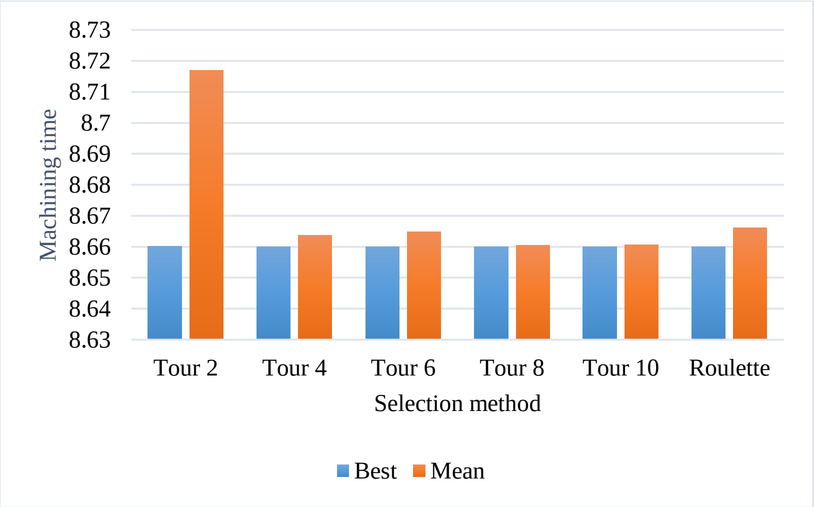

Figure 4: Graph for the selection method

Two types of selection methods are being chosen to be used: Tournament and Roulette. Population sizes and reproduction (crossover fraction) are set at a default value of 110 and 0.6, respectively. It is appeared to be the tour size of 8 has the most optimized machining time with a mean machining time is 8.66048 minutes. Using tournament selection, roulette wheel selection, and rank-based roulette wheel selection, [14] conducted a study to examine the effectiveness of genetic algorithms in solving TSP issues. According to the findings, binary tournament selection is better at reaching the best solution quality while requiring less computational effort. Due to the previous statement, tournament method is the most suitable method to be apply in GAT.

3.3 Effect of reproduction

Reproduction (also known as selection) increases the number of copies of superior strings [15]. In a population, reproduction chooses good strings and creates a mating pool. The reproduction of people in the existing population is required to maintain the development of a new population.

Table 4: The effect of reproduction towards the parameters.

Populations	Selection Method (Tournament)	Reproduction (Crossover Fraction)	Parameters	
			Best Machining Time, T_m (min)	Mean Machining Time, T_m (min)
110	8	0.6	8.66007	8.66297
		0.7	8.66006	8.66094
		0.8	8.66010	8.66381
		0.9	8.66008	8.66040
		1.0	8.79531	8.79531

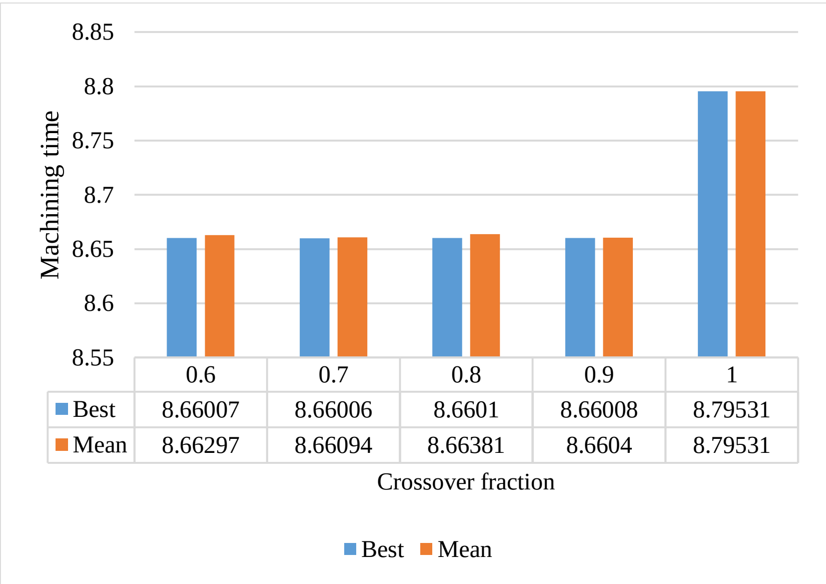

Figure 5: Graph for the reproduction (crossover fraction)

The simulation is being run to observe the reproduction effect (crossover fraction) on the machining time. The crossover fraction of 0.7 is being determined to be the most suitable one as it has the shortest best and mean machining times where the value is 8.66006 minutes and 8.66094 minutes, respectively. Through crossover, the algorithm can separate the best genes from several individuals and recombine them to create possibly superior offspring. It is more likely for the algorithm to produce individuals with higher fitness values when there is more diversity in a population because of mutation [16]. After considering the previous statement, the crossover is ideal for executing the fitness function.

3.4 The optimization of the machining time in the milling process using Genetic Algorithm (GA)

In achieving the optimize machining time for milling process, this thesis is applying the GA as the tool for finding the optimization of the three main parameters. The population sizes, selection method, and reproduction configurations has been used in observing the effect towards the parameters and the most significantly is the machining time.

Table 5: Best and mean machining time obtained using the best population sizes, selection method and crossover fraction.

Populations	Selection Method (Tournament)	Reproduction (Crossover Fraction)	Parameters	
			Best Machining Time, T_m (min)	Mean Machining Time, T_m (min)
110	8	0.7	8.66007	8.66236

Table 6: The most optimize parameter values for minimizing the machining time.

Parameters		
Cutting speed, x(1) (m/min)	Feed rate, x(2) (mm/tooth)	Depth of cut, x(3) (mm)
30	0.127	1

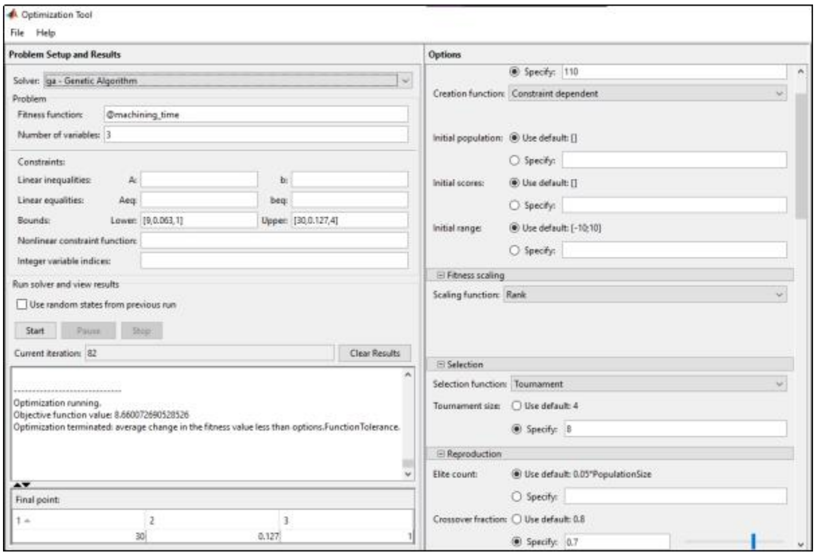

Figure 6: Simulation run with the chosen population sizes, selection method, and reproduction

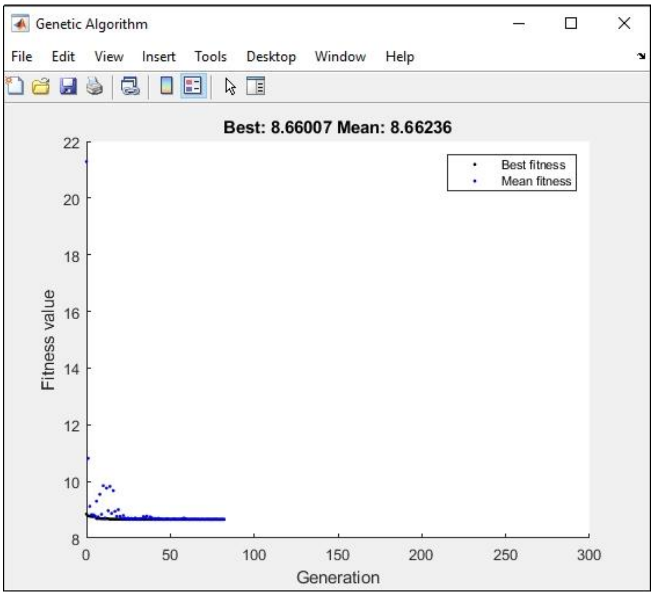

Figure 7: Result of best and mean machining time.

The result obtained in order to find the most optimized machining time and the three parameters which included the depth of cut, feed rate, and cutting speed are being tabulated according to the Table 4.4 and Table 4.5. Besides, Figure 4.4 and Figure 4.5 are the simulation run by GAT with applying the population sizes of 110, selection method with tournament size of 8 and reproduction with crossover fraction of 0.7 that being determined from the simulation run in section 4.1. Based on the result obtained, the most optimized machining time is 8.66007 minutes. And as for the most optimized depth of cut, feed rate, and cutting speed values, the result obtained are 1 mm, 0.127 mm/tooth, and 30 m/min, respectively.

4. Conclusion

Milling is one of the most extensively utilized procedures in the manufacturing industry. By employing manual mathematical modeling, it takes time to optimize a parameter. As a result, an artificial intelligence method called GA is used to carry out the optimization process. The objectives are exploring the effect of parameters such as depth of cut, feed rate, and cutting speed. According to the 110 population sizes, tournament size of 8, and crossover fraction of 0.7, the minimized machining time can be determined throughout the simulation which the value obtained is 8.66007 minutes. At once, the depth of cut, feed rate, and cutting speed are also being verified along with the same simulation, and the values achieved are 1 mm, 0.127 mm/tooth, and 30 m/min, respectively. They are running a validation simulation after determining the depth of cut, feed rate and cutting speed from the most optimized machining time and adding the stepover or being known as an offset to be one of the parameters together with the depth of cut, feed rate and cutting speed. This could lead to improved machining performance.

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