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Research paper

Tool Path of Air Time Motion in Pocket Milling by Biogeography-Based Optimization (BBO)

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Abstract

The milling process is one of the most commonly metal-cutting processes in the industry because of its ability to remove material faster with desirable surface quality. Thus, it is applicable in a variety of manufacturing industries such as automotive and aerospace, where the production time is an important factor in yield parts. This paper presents a new method of biogeography-based optimization (BBO) to determine the optimal airtime motion in computer numerical control (CNC) milling process. The optimization of airtime motion is formulated as a Traveling Salesman problem (TSP). Furthermore, the result of the simulation using our developed BBO is compared with the random machining process. Consequently, the BBO averagely determined 55.62 percent optimum airtime motion rather than random machining process. The optimal tool path obtained is later tested in pocket milling process in CNC milling machine. It can be ascertained that the developed optimization model for airtime motion can be utilized for the specified product area.

Keywords: *Airtime motion; Biogeography-based optimization; Genetic algorithm; Milling;*

1. Introduction

In metal-cutting processes, cutting parameters is the dominant factors in the machining process [1]. Quality and time machining are two important but incompatible criteria in any machining processes [2]. An improvement in quality can increase the machining time thereby, reducing productivity. Thus, it is applicable in many manufacturing industries such as automotive and aerospace, where the production time is an important factor in varieties of product parts. Because of these reasons, the optimization of machining time is the key component in manufacturing industries.

In the machining process, the total machining time for a part consists of two components, which are the machining time when the tool is removing the material from the workpiece as production time and repositioning of the cutting tool in each machining cycle known as non-productive time or airtime [3]. In minimization of machining time, much research often utilized the optimization of cutting parameters, tool's sequence and variety of the tool path [4]. However, the non-productive machining time has been given less attention in minimizing the machining time. Furthermore, most researchers studied on reducing airtime motion in drilling and hole-making process because of the definition of each hole at a point the easiest way to generate airtime motion models [5]-[6]. The minimization of non-productive machining time stands an important role in a mass production with the high-speed machining process [7]. Likewise, the machining of complicated pocket shapes by various tool's diameters consist of 15 to 30% of non-productive machining time in total machining time [7]-[8].

Minimization of airtime motion is to determine the minimum length of the tool travel path. The tool path problem can be defined as a travelling salesman problem (TSP) which belongs to the non-deterministic polynomial (NP) hard combinatorial optimization problem [2]. In TSP, a salesman has to visit all the cities only once and return to the first city to complete a tour with minimum cost [9]. In their study, each tool path contour or start vertex of each tool path is defined as a coordinate of the city to be visited.

A brief review of the literature on non-productive machining time in the milling process is presented here. In the minimization of non-productive time for the milling process, Castelino et al. [8] proposed an algorithm for optimally connecting different tool path segments. The efficiency of the heuristic algorithm and the quantity of enhancement obtained in various problem sizes was presented. Oysu and Bingul [10] employed Genetic Algorithm(GA) for optimizing the tool path problem. The GA minimized the total airtime travel and the number of retraction points.

Furthermore, Oysu and Bingul [2] proposed a hybrid algorithm combining GA and simulated annealing (SA) (HGASA) in the tool path optimization problem by minimizing airtime motion during the machining process. Consequently, the HGASA produc-

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es optimal path solution than standard GA and SA. Gupta et al. [11] utilized a hybrid GA to optimize the non-productive tool path during machining a 2.5D milling process. Another study by Koenig and Jouaneh [12] tried to optimize the cutting and welding path by using the Lin-Kernighan algorithm. Their problem was defined as 100 points and be able to determine an optimized tool path in 15 seconds.
Therefore, it can be seen that many of the researchers focused only on minimizing airtime motion in drilling or hole making process, and less attention has been given to the milling process. In the paper, we present a novel approach in generating an optimal or near optimal airtime motion by adopting a new evolutionary algorithm (EA) in the milling process. The main contribution of this study is by solving the tool path problem in airtime motion during the pocket milling process by using the biogeography-based optimization(BBO) method. The performance of our proposed BBO method is compared with the random machining process and GA. In our BBO, the initial populations were utilized to generate optimum solution until the end of the optimization process. As another distinction, our BBO method utilized the fitness function to determine the immigration and emigration rates, and it is not used directly to modify the population. The BBO has been implemented in a simulation of the milling process and can be utilized to other machining processes.

2.1. The paper should have the following structure

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2. Problem Definition

There are two kinds of tool path generation techniques that are widely utilized in material removal during the milling process which are contour and zigzag [13]. In the contour tool path, the machining tool movement is designed with consecutive offsets. On the other hand, in the zigzag tool path, the machining tool takes place along parallel lines to a specified reference path in steps among neighbouring paths. The tool path milling technique includes a number of retraction movements between sub-regions. Therefore, in the tool path movement problem, each tool path contour can be defined as city coordination similar to TSP problem. Each node is defined by x-y Cartesian coordinates systems in order to determine the distance between two nodes or cities.
The total tool travelling distance L_{np} can be defined by the following equation[2].

$$L_{np} = \sum_{i=1}^{n-1} \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2} \quad (1)$$

In TSP, a salesman has to visit all cities only once and return back to the first city to complete a tour with minimum cost. The TSP approach is to let k_{ij} be 1 if visited instantaneously city j after i, and be 0 if otherwise. The distance from city i to j is defined as c_{ij} . The formulation of TSP can be defined by the following equation [2].

$$\min(L_{np}) = \min \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} x_{ij} \quad (2)$$

where,

$$\sum_{i=1,\ i\neq j}^{n} x_{ij} = 1 \ ; \qquad \forall j \quad (3)$$

$$\sum_{j=1,\ j\neq i}^{n} x_{ij} = 1 \ ; \qquad \forall i \quad (4)$$

The non-looping constraint is defined as follows.

K_{ij} = 1 or 0 (5)

The two constraints in Equation (3) and (4) are denoted to certify that each city is visited only once. The non-looping constraint avoids creating an individual looping between cities in this problem. The TSP is categorized in two forms of symmetrical and asymmetrical tool path optimization. In the symmetrical TSP, the distance between point A and B is equal to the distance between point B and A and only one way between two points. In the asymmetrical TSP, it is possible to define more than one way between point A and B. This TSP defined as asymmetric style and used to govern the shortest distance between all points. In this study, our BBO method utilized the TSP in order to determine the optimal or near optimal airtime motion.

3. Methodology

3.1. Biogeography-Based Optimization

Holding a set of attitudes, engineers believe that nature can inspire them to learn something new in the world. Based on this mindset, many natural phenomena and events seen in the environment around us were the origins of different kinds of created mathematical models in the early 1960s. GA is considered a natural rule which has been utilized as an optimization tool in which genetics laws are changed into mathematical models. As a matter of facts, the behaviours seen in these kinds of the social creature's way of living are the origins of the emergence of the aforementioned optimizations and algorithm. To give another example of creating a mathematical model from natural phenomena, the BBO algorithm can be mentioned. The complicated optimization issues and problems are considered and investigated by taking into account the mathematics of biological distributions of various categories of animals and creatures. In fact, these algorithms help to solve the problems related to the optimization issues. Among these similar algorithms of BBO and GA, the Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) can also be applied as biology-based optimization methods [14].

Some facts such as the growth of some kinds of species, their migration from one place (island) to another one, and the reasons of some special kinds of species extinction are the fundamental ideas that form the cornerstones of the BBO algorithm. BBO used a term habitat, which is defined as isolated specific pieces of lands or locations delimited geographically. Among the characteristics of these geographical locations, habitat suitability index (HSI) and suitability index variables (SIV) are distinguished and salient. The feature of HSI is considered for each geographical area, which has been defined as a habitat in the BBO algorithm. The feature of habitat with an HSI as analogous to one element of the optimization algorithm, including fitness function. High and low HSI can be utilized to understand the solution better. For instance, the high HSI is regarded as a good solution and low HSI as a poor solution. An appropriate habitat for resistance can be characterized by the HSI criteria to determine whether the habitat is suitable for resistance or not. Some other effective factors such as temperature, the amount of rainfall, land area, diversity of topographic features and vegetation are considered as fundamental characteristics of

HSI. Independent variables SIV and dependent variables HSI are defined as distinguishing the feature habitability [15].

Many species live in the habitats with a high HSI. It means that these kinds of species emigrate from these places that hosted them formerly to the new habitats. But low immigration happens in these high HSI habitats. The low rate of immigration caused by high HSI habitats have been totally saturated with an enormous number of species. Therefore, the habitats with high HSI with a low rate of immigration will have a high rate of emigration. The high rate of emigration for high-HSI habitats is due to many opportunities in these locations to immigrate to the nearby habitats. The number of species living in the habitats with low HSI is thinly distributed, and the high static status due to the sparse population of species in these areas causes the high rate of immigration. On the other hand, when immigration of species to the habitats with low HSI increased, the HSI of the habitats increase consequently. This sudden increment is due to the biological variety and equivalent to the habitat suitability which is the main reason for HSI rise in low HSI habitats [16].

In BBO, the individuals participating in this algorithm enjoy both emigration (μ) and immigration (λ) rates that are dependent on the number of species living in the intended habitats. The probability solution selection of the H_i and H_j is related to its immigration rate λ_i and emigration rate μ_j, respectively. The migration role can be defined by the following equation 6 [15].

$$H_i(SIV) \leftarrow H_j(SIV) \tag{6}$$

The immigration and emigration rates are defined as solution fitness. The solution fitness of immigration rate and emigration rate can be determined as following equations 7 and 8, respectively[15].

$$\lambda_i = I(I - \frac{k_i}{n}) \tag{7}$$

$$\mu_i = E(\frac{k_i}{n}) \tag{8}$$

where E represents the emigration rate in both equation, I is maximum possible immigration and; k_i is the rank of habitat i after sorting all habitats according to their HSI, and n is the number of solutions in the population. The highest level of possibility happens when the availability of zero species in the habitat in proved.

The highest rate of immigration to a particular habitat is defined as I in the immigration curve as shown in Figure 1 [17]. The highest level of possibility happens when the availability of zero species in the habitat in proved. With the increase and expansion of the species number, fewer species can keep successfully immigration to the habitat due to growing population and create crowded conditions of the habitat [18]. Due to these conditions, the immigration rate is successively reduced. The immigration rate returns zero at S_{max} which exhibits the maximum number of the species supported in a habitat. On the other hand, the rate of emigration becomes zero when no species is supported in the habitat [15].

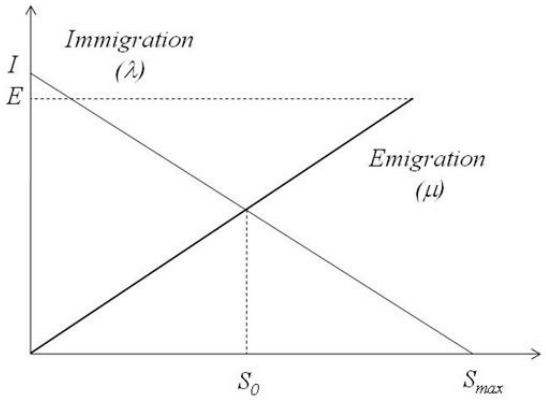


Fig 1: The species model of a single habitat [17].

In BBO, the mutation rate is determined by the following equation.

$$m_i = m_{\max} \times (1 - \frac{P_i}{P_{\max}}) \tag{9}$$

Where, m_{max} is a maximum probability; $P_{max} = argmax\ P_i$; i = 1, 2, ..., n (n is population size), and P_i is the solution probability [19]. The mutation operator can be implemented with insertion, reversion and swap with equal probability at each iteration.

4. Result and Discussion

In this paper, three types of different pocket shapes have been considered as a workpiece as shown in Figure 2. The simulations were carried out to determine the optimum airtime motion. The examples were performed by BBO algorithm coded by using MATLAB on Intel® Core™ 2 Duo CPU 2.4 GHz with Windows 7.

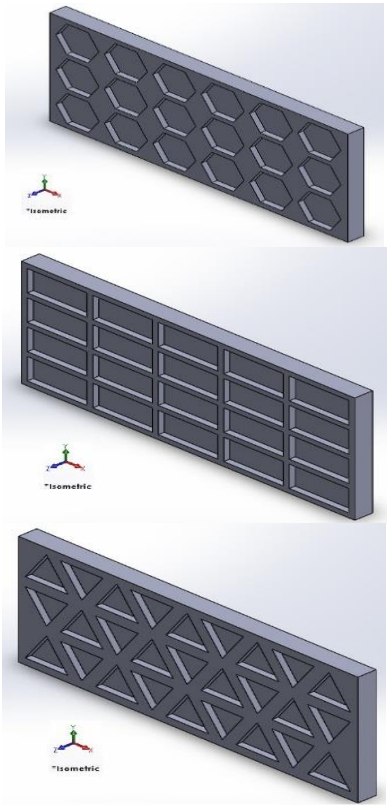


Fig 2: The three different shapes of pocket with 5 mm depth.

The offset milling process involved various retraction points. In the first step, the milling process of all workpiece with 90, 100 and

135 retraction points designed to perform by heuristics approaches. These workpieces are named as TP 1, TP 2 and TP 3, respectively. The airtime motions for three problems with the random machining process are illustrated in Figure 3.

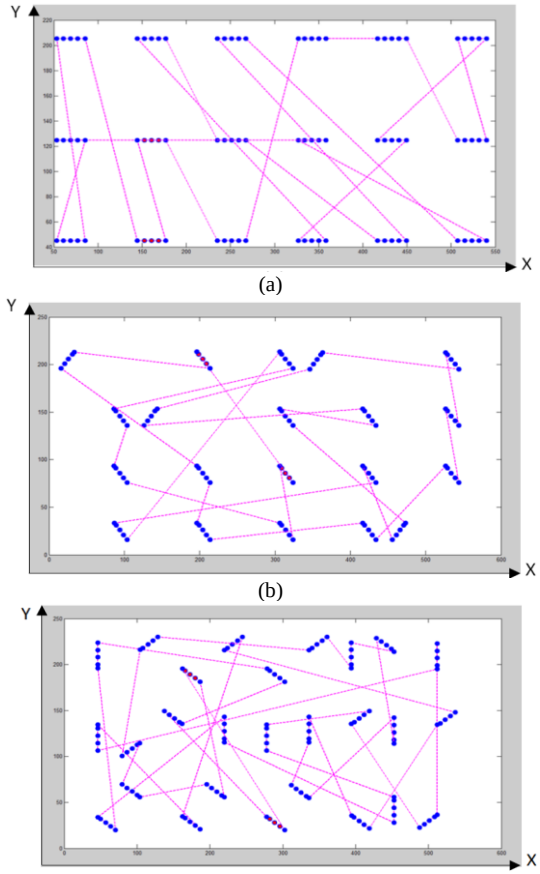


Fig 3: Random machining process for (a) problem 1 with 90 nodes (b) problem 2 with 100 nodes (c) problem 3 with 135 nodes.

The BBO is defined as 3000 iterations with habitat size 50 and maximum mutation rate 0.3 for all problems. Moreover, to eliminate uncertainties of the solutions obtained, each of the optimization methods is run five times separately for each problem and the minimum runs are treated as the ultimate responses. In TP 1 solution, the BBO has better airtime motion 2107.97 mm when compared by a random milling machining process, as shown in Table 1.

As shown in Table 1, the results show that the proposed BBO produced about 51.53 % the better minimum path solution than the random milling machining process respectively in TP 1. In TP 2, the BBO determines the better airtime motion 2115.67 mm when compared by a random milling machining process. The proposed BBO improves the optimum solution of the random milling machining process by 56.49% as illustrated in Table 1. In TP 3, the optimum airtime motion determines by proposed BBO is 2609.36 mm. The proposed BBO improved the optimum airtime motion problem of the random milling machining process by 58.83% as shown in Table 1. It can be ascertained that our proposed BBO algorithm determined the optimum airtime motion in various types of the pocket milling process.

Figure 4 demonstrates the optimum solution determined by BBO for each problems TP1, TP2 and TP3, respectively. In the comparison between Figure 3 and Figure 4, it can be concluded that the proposed BBO can determine the optimum air time motion rather than the random machining process. The various pocket's shapes defined as a problem, end of the machining process embossed script is obtained other than the script contours.

Table 1: The computation time in three problems for two proposed algorithm

	TP 1		TP 2		TP 3	
	Distance	Reduction of machining time	Distance	Reduction of machining time	Distance	Reduction of machining time
Random machining process	4349.57	0%	4862.53	0 %	6338.63	0 %
BBO	2107.97	51.53%	2115.67	56.49%	2609.36	58.83%

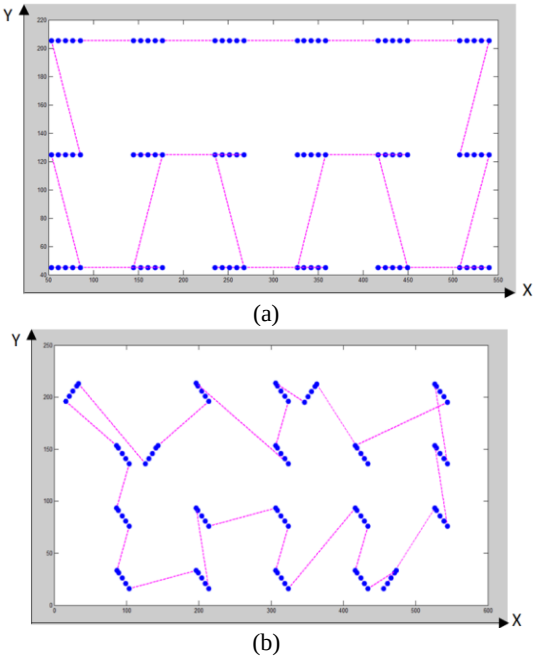


Fig 4: BBO solution for (a) TP 1 with 90 nodes (b) TP 2 with 100 nodes (c) TP 3 with 135 nodes.

In the overall, results of proposed BBO algorithm revealed an improvement in airtime motion problem. This improvement is due to the ability of the BBO algorithms to explore the larger searching space by two main operators, migration and mutation. These selection strategies, migration and mutation are the main difference of the proposed BBO algorithm with other evolutionary algorithms. The optimum tool path from the BBO algorithm is applied to produce the three various pocket shapes as illustrated in Figure 5.

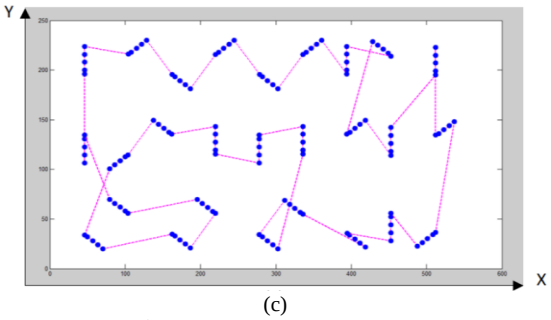


Fig 4: BBO solution for (a) TP 1 with 90 nodes (b) TP 2 with 100 nodes (c) TP 3 with 135 nodes.

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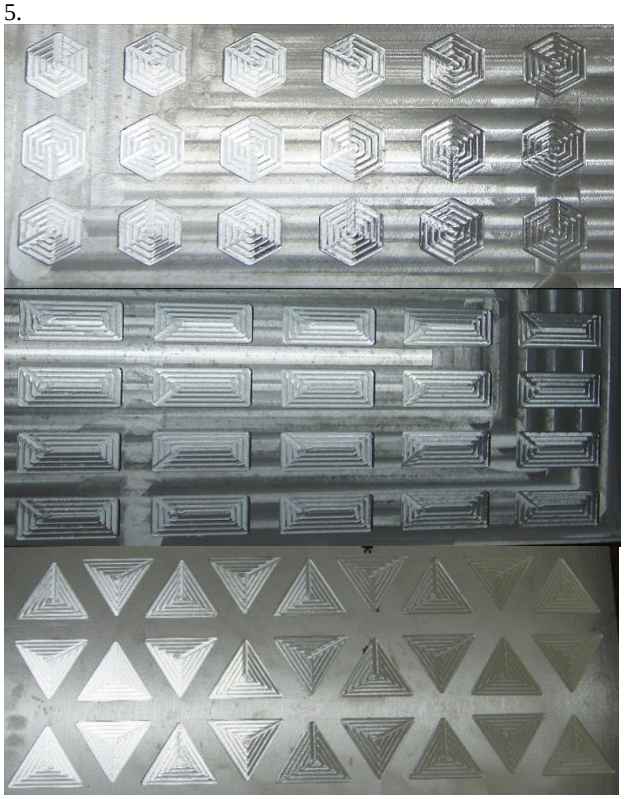


Fig 5: Manufactured three various pocket shapes determined by BBO algorithm.

5. Conclusion

A BBO method has been employed to generate an optimum tool path for various machining on a sheet of raw material. The developed algorithms have been utilized to reduce airtime motion. In conclusion, it can reduce the cost of machining considerably, and indirectly reduce the electricity consumption, labour, tool life and machining life. In this study, the performance of the BBO is compared with the random machining process. The optimal tool path is later tested during the pocket milling process on a CNC milling machine. According to the result, it can be ascertained that our proposed BBO gave better performance and able to determine an optimal tool path solution. In addition, the developed BBO algorithms can also be utilized for various kinds of the machining process.

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