MODELING AND OPTIMIZATION OF MULTI-HOLES DRILLING PATH USING PARTICLE SWARM OPTIMIZATION

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ABSTRACT

In today's competitive environment, optimization is considered as an important element for maintaining and improving both aspect of manufacturing such as quality and productivity. In multi-holes drilling process, 70% of the machining time involved the tool movement and tool switching. Various researches had been conducted to reduce the tool movement and switching time. This research aim to reduce the machining time by minimizing the tool path using metaheuristics algorithms. The problem is modelled using travelling salesman problem (TSP) concept. Later the problem is optimized using Particle Swarm Optimization (PSO) and compared with other algorithms including the new metaheuristics algorithms. Then a machining experiment has been conducted to validate the optimization results. The optimization results clearly indicated that the PSO algorithm outperformed all comparison algorithms for the drilling tool path problem. The machining experiment results confirmed that the PSO algorithm provide faster tool path compared with commercial CAD CAM software, with average 5%.

ABSTRAK

Di dalam persekitaran yang kompetitif hari ini, pengoptimaan merupakan element yang penting untuk mengekalkan serta meningkatkan aspek dalam pembuatan seperti kualiti dan produktiviti. Di dalam proses penggerudian berbilang lubang, 70% daripada masa pemesinan ialah melibatkan pergeraran dan pertukaran mata alat. Pelbagai kajian telah dibuat untuk mengurangkan pergerakan dan masa pertukaran mata alat. Kajian ini bertujuan untuk mengurangkan masa pemesinan dengan mengurangkan masa pemesinan dengan mengurangkan jarak laluan mata alat menggunakan kaedah metaheuristik. Masalah ini dimodelkan menggunakan konsep *'travelling salesman problem'*. Kemudian, is di optimumkan menggunakan *Particle Swarm Optimization (PSO)* dan dibandingkan dengan algorithma lain termasuk algorithma yang baharu dicipta. Kemudian eksperimen pemesinan dilakukan untuk mevalidasi keputusan pengoptimaan. Keputusan pengoptimaan menunjukkan algorithma PSO mempunyai prestasi yang lebih baik untuk masalah laluan mata alat penggerudian ini. Eksperimen pemesinan pula mengesahkan bahawa PSO mampu menjana laluan mata alat yang lebih singkat berbanding perisian komersil dengan peningkatan purata 5%.

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CHAPTER 1

INTRODUCTION

1.1 Background of the Project

Computer numerically controlled (CNC) machine has been implemented since the previous decades in order to realize full automation in machining. CNC machine tools require less manpower, give more noteworthy improvements in productivity, and improve the quality of the final product (Setiawan, Tambunan, & Yuliana, 2013). 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. One of the popular machining modes for CNC milling is for drilling multi-holes on the workpiece (Narooei et al., 2014).

Drilling is widely used in machining processes for various purposes (R. V. Rao, 2011). Drilling is defined as cutting process that used a drill bit to cut a circular cross-section hole in metallic and nonmetallic materials [4–6]. This process is very important in the industries like automotive, aircraft and aerospace, dies or mold, home appliances, medical and electrical equipment (Mundhekar & Jadhav, 2015). Normally, holes produced by drilling are larger than the drill diameter and depending on its applications so that the drilled holes will subjected to other operations such as reaming or honing to better surface finish and accuracy of dimensional (Kalpajian, Kalpakjian, & Schmid, 2003).

Additionally, the type of drill is selected according to the job upon several factors, (G. Y. Zhu & Chen, 2011) considered the type of machine tools, workpiece materials, setup, diameter of the hole and also the composition and hardness of workpiece. Moreover, there are six steps are taken in CNC drilling operation as discussed in (Borkar, Puri, Kuthe, & Deshpande, 2014). Roughly at first, the workpiece is designed in Computer Aided Design and Computer Aided Manufacturing (CAD/CAM) software. Then, the machining tools and parameters are determined in CAD/CAM software. Next, the process plan and machining code is generated using CAD/CAM software. After that, the machining code is transferred to CNC machine and the workpiece is setting up on the CNC machine. Lastly, the machining process is started and the regular inspection is conducted (Borkar et al., 2014).

Hole-making operation process requires most of the machining time for manufactured part (Narooei et al., 2014). Based on previous research, on average, 70% of the machining time in multi-holes drilling process is due to the tool movement and tool switching time. Based on this fact, the optimization of drilling path could improve the productivity of the machining process by reducing the total machining time [11]. Previously, a number of researches had been done to study and optimize the hole making path. One of the research works is conducted by (Ghaiebi & Solimanpur, 2007). They modeled the problem as a 0–1 non-linear problem, and optimize the problem using Ant Colony Optimization (ACO) algorithm. The optimization results indicated that the ACO method is capable to achieve targeted optimum solution. However, the ACO performance was mainly reduced by premature convergence that causes the solution trapped in local optimum (Ghaiebi & Solimanpur, 2007).

Lim et al. (2014) on the other hand proposed a hybrid cuckoo-genetic algorithm to optimize similar problem (Lim, Kanagaraj, & Ponnambalam, 2014). However, the proposed algorithm has only been tested with uniform holes arrangement that can be simply solved even by using non-population based techniques. Besides the presented works, many other researchers have studies the drilling path optimization such as [13–15]. However, these works are limited to the regular shape of holes arrangement.

Furthermore, Particle Swarm Optimization (PSO) is rapidly gaining popularity as a biologically inspired computational search and optimization method developed in 1995 by [16–21] based on the social behaviors of birds flocking or fish schooling. PSO becomes a meta-heuristic algorithm, which is based on swarm intelligence with many researchers exploring the concepts, issues, and applications of the algorithm [17, 22, 23]. Thus, PSO has undergone many changes since its introduction for continuous optimization problem [24–26].

Application of optimization techniques is very useful for maintaining and improving both aspect of manufacturing such as quality and productivity in today's competitive environment (Tufail, 2016). The tool travel and tool switch scheduling are the major issues in the optimization of hole-making operations. As an example the industrial products such as molds, dies, engine block that consists of a large number of holes with different diameters, depths and surface finish (A. M. Dalavi, Pawar, Singh, Warke, & Paliwal, 2016).

Besides that, the similar model in tool path planning also can be applied in different applications such as in milling, laser cutting and turret punch. It also benefits to other application of tool path research such as printed circuit board (PCB) drilling [14, 29–33]. Therefore, it is important to study the factors or techniques that facilitate the optimization of drilling process towards achieving the organizational excellence. In pursuit of this, the optimization principles have to be adopted in the industrial environment especially for manufacturing system.

1.2 Research Objective

The objectives of the research are:

1. To model irregular hole making sequence using Travelling Salesman Problem approach
2. To develop an algorithm based on Particle Swarm Optimization to optimize the hole making sequence
3. To validate the algorithm through experiment

1.3 Project Scope

The scopes of this project are as follow:

i. Problem modelling will concentrated on the travelling salesman problem (TSP) concept.
ii. Optimization algorithm considered are within the metaheuristics group.
iii. Optimization algorithm screening is conducted by applying the algorithms to different discrete combinatorial problem, i.e. assembly sequence planning.
iv. Drilling process considered is within a 300 mm x 300 mm size aluminium 6061 grade.

v. In machining process, only machining time is recorded, while the other parameters are constant.
vi. In validation stage, the optimized tool path by the best algorithm is compared with tool path from commercial CAD CAM software. Machining experiment involving other algorithm is not conducted because of time and resources constraints.

1.4 Problem Statement

Previously, a number of research had been done to study and optimize the hole making path. One of the research works is conducted by Ghaiebi and Solimanpur (2007). They modeled the problem as a 0–1 non-linear problem, and optimize the problem using Ant Colony Optimization (ACO) algorithm. The experimental results indicated that the ACO method is capable to achieve targeted optimum solution. However the ACO performance was mainly reduced by premature convergence that causes the solution trapped in local optimum (Ghaiebi & Solimanpur, 2007).

Lim et al. (2014) on the other hand proposed a hybrid cuckoo-genetic algorithm to optimize similar problem (Lim et al., 2014). However, the proposed algorithm only been tested with uniform arrangement holes, that can be simply solve even by using non-population based techniques. Besides the presented works, many other researchers have studies the drilling path optimization such as (M. M. Ismail et al., 2012; Tsai et al., 2012; Yang et al., 2012). However, these works are limited to regular shape of holes arrangement.

Previously, Particle Swarm Optimization (PSO) has been successfully applied in many research and application areas. PSO is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by social behaviour of bird flocking or fish schooling. It has shown to be an efficient, robust and simple optimization algorithm. Most of the PSO studies are empirical, with only a few theoretical analyses that concentrate on understanding particle trajectories (Kao et. al, 2009).

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter review the existing research in drilling toolpath optimization. In the following section, optimization of drilling process in the manufacturing system is discussed. In section 3, application area is discussed and presented. Section 4 later present the modeling approach in drilling path optimization. Then, section 5 and 6 discuss the algorithms and optimization objectives used to optimize multi-holes drilling path. Finally, the summary and conclusion of the review are presented.

2.2 Overview of published papers

The aim of this chapter is to review available literatures on optimization of drilling path. Therefore, we only concentrate on the research that considers the holes making process and optimization of drilling operations. For screening purpose, we review the titles, keywords and abstracts. In addition, a systematic search for the specific keywords such as (optim⁄ and drill-ing⁄ and algo-rithm⁄) and (drill-ing/ and optim⁄) was conducted. This paper reviews almost all of the research publications on drilling path optimization based on the main academic databases (i.e. Science Direct, Scopus and Google Scholar).

A comprehensive research has been conducted on all of the documents that have been collected. There are 61 papers were selected after removing duplications [2, 5, 11–16, 21, 23–25, 27, 29, 31–77]. In order to group the published paper and highlighted the main trends in optimization, each paper was analyzed to determine the relevant features such as application areas, problem modeling, optimization of algorithms and optimization objective in drilling paths.

All the papers were published in the year 2000 and above with the exception of three journal papers published in 1995, 1996 and 1999 [18, 30, 42]. However, search in conferences papers was considered to the last ten years. Overall, Figure 1 presents an increasing trend in publications of the research work in this area. The result indicated that the optimization in drilling paths have potential and importance in manufacturing industries for future. In earlier studies, many researchers trying to find the more efficient way to optimize paths in term of machining time, distance and cost by improving the productivity for drilling operations based on their necessity situations.

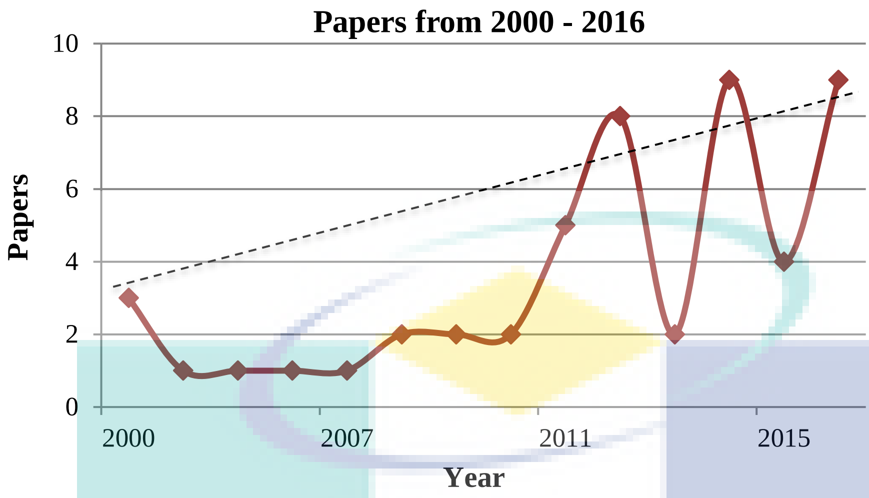

Figure 1: Papers publication over the year (2000 – 2016)

Figure 2 shows the origin country of the published research in drilling path optimization according to the main author. The main contributors to the research in this area are Egypt, Malaysia, China and India. This trend is related to the industrial nature these countries. In Egypt, this kind of research is to produce mold and die to support automotive industry. Meanwhile, the countries like Malaysia, China and India are known for producing the printed circuit board (PCB) for electronics application.

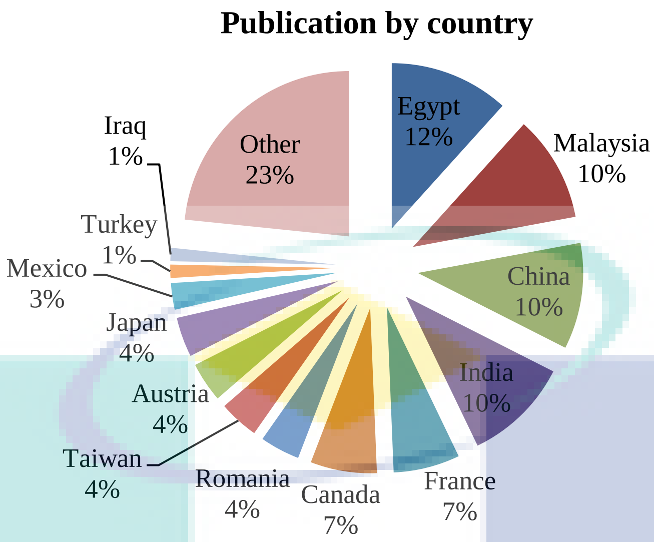

Figure 2: Publications by country

2.3 Application Areas

Based on the review that has been conducted, the drilling path optimization has been implemented in different areas. Figure 3 show the application of drilling process such as general drilling, PCB drilling, CNC drilling, EDM-drilling, injection mold and combination of drilling like CNC PCB drilling machine as discussed in [40, 71].

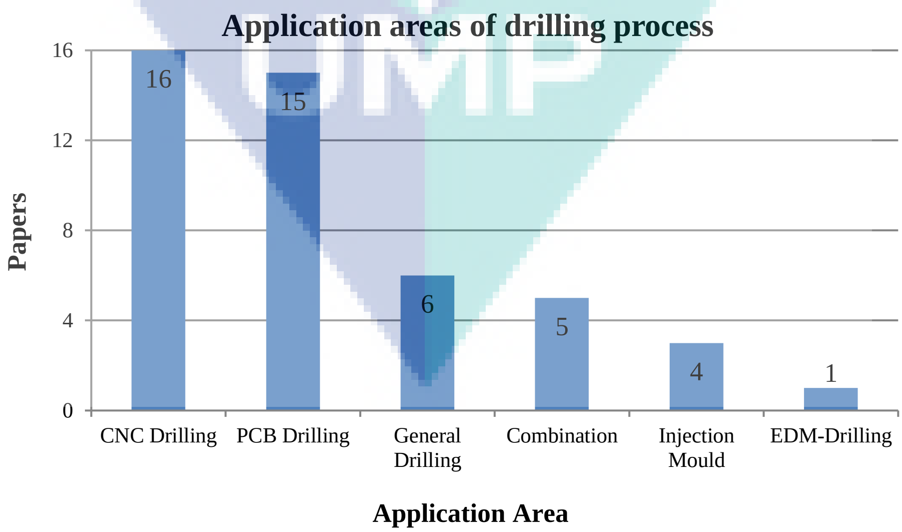

Figure 3: Paper frequency vs. application area

Figure 3 shows bar chart for the application of drilling process based on cited papers. CNC drilling process is the highest application area about 40% paper frequencies are used. Meanwhile, 37.5% paper frequencies show that PCB drilling are used as application area of the drilling process. Besides, about 15% researchers used general drilling process and then followed by combination drilling process, injection mold [28, 34, 43] and energetic descent method (EDM) drilling (EL-Midany et al., 2007) for application of the drilling path optimization.

Most studies implemented CNC machine in the application of drilling path to achieve full automation in the machining process. This trend is because CNC machine tools require less manpower and give improvements quality of final products (Setiawan et al., 2013). CNC Milling machine is one of the popular modes by CNC for multi-holes drilling path optimization (Narooei et al., 2014). Besides, electronic manufacturing industries mostly used CNC machines for drilling holes on PCB [33, 37].

Meanwhile, PCB drilling is also a popular application for the researchers to conduct tool path optimization in the drilling process. The PCB drilling is one of a critical process because it used a third of the total PCB production time (Yang et al., 2012). PCB drilling is rarely made in small quantities. Usually, the batch size is from several hundreds to thousands of pieces. Currently, the PCB is widely used in the simple electronic products, compared to a few decades ago (Ancău, 2008). The PCB holes are typically drilled with small-diameter drill bits made by solid coated tungsten carbide (Srivastava, 2015).

Furthermore, a few researchers implemented general drilling as observed in [39, 46, 58] for machining process besides CNC and PCB drilling. It is also generally used in automotive, aircraft, industries, home appliances and electrical equipment’s (Mundhekar & Jadhav, 2015). The low number of published papers on application areas likes combination drilling, injection mold and EDM-drilling due to the potentially for the special case of holes drilling. For instance, small-hole EDM drilling is potentially suitable for micro-fabrication due to its high precision and the good surface quality (EL-Midany et al., 2007). A typical plastic injection mold could have over 100 holes of different diameters, surface finish, and different depths and a large number of tool switches [28, 43]. These facts show the importance to optimize the drilling path to ensure minimum total processing cost of hole-making operations (A. M. Dalavi et al., 2016).

2.4 Problem Modeling

Figure 4 present the modeling approach in the drilling path optimization. Most of the researchers implement TSP concept, precedence sequence and TCP concept to optimize the drilling path based on studies conducted.

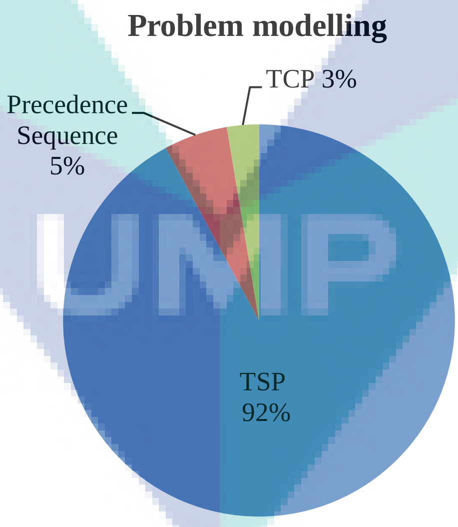

Figure 4: Summary of problem modeling in optimization

Based on Figure 4, TSP concept is the most widely used in modeling problem about 92% researchers used this concept for drilling path optimization. Then, 5% for precedence sequence and 3% of traveling cutting tool problem (TCP) based on papers summary from the pie chart above.

For instance, CNC drilling process for tool path optimization is modeled as a traveling salesman problem (TSP) can be formulated as a linear integer programming [54, 64] as follows:

Minimize

$$F(x) = \sum_{i}^{n} \sum_{j}^{n} X_{ij} D_{ij} \tag{1}$$

Subject to

$$\sum_{i=1}^{n} X_{ij} = 1, j = 1, \dots, n \tag{2}$$

$$\sum_{j=1}^{n} X_{ij} = 1, i = 1, \dots, n \tag{3}$$

Where *n* is the total number of holes to be drilled, D_{ij} is the travel distance from point *i* to point *j* and X_{ij} is designed as the variables ∈ {0, 1} to define the tool path. Xij = 1 is the travel distance from point *i* to point *j* as part of the path that through on all the holes in the matrix. Otherwise, X_{ij} = 0 is the path does not travel from point *i* to point *j* as part of the tool path.

In addition, the special case of TSP problem can be modeled for CNC machine tools by using CAD/CAM systems for automated Numerical Control (NC) program automatically to improve their productivity. In this problem, the TSP and Parallel ACO have been combined to find the shortest cutting tool travel path (CTTP) with automatic

G-code generation for the drilling operation. The TSP model and meta-heuristics algorithm are implemented to solve the problem of high computational time and avoid human errors. There is no necessity to perform any modification since it can be easily implemented for free distribution or commercial CAD/CAM software (Medina-Rodriguez & Montiel-Ross, 2012).

In the meantime, the precedence sequence model in holes making operations can minimize the summation of non-productive traveling distance and tool changing cost especially in mold drilling. The TSP model finds difficulty when the number of holes increased. Therefore, basic TSP model cannot be used in mold drilling as involved drilling and tapping operation which tapping process must be performed after the drilling (Khalkar, Yadav, & Singh, 2015). The precedence sequence is modeled to reduce the production cost can be formulated as:

$$\text{Cost (Z)} = \text{Cost (y)} + \text{Penalty value (P)} * \text{Number of constraint violation} \qquad (4)$$

However, the penalty value is selected as the number of constraints violation should not be appear in optimum sequence. The example for a particular problem as penalty value is calculated by 750 and the following table of objective function value also the number of constraints violation for initial ten sequences as shown in (Khalkar et al., 2015). The operation precedence constraint has got importance because most of the times of hole making process are followed by subsequent operations. So, the optimization of hole-making operations drilling that followed by reaming with sequence precedence should be required (Khalkar et al., 2015).

Moreover, traveling cutting tool problem (TCP) is similar to the TSP problem which is used to evaluate the drilling path (Qudeiri et al., 2013). This evaluation of TCP is considered an NP-hard problem. Meanwhile, the classical TCP problems that proposed by (Wei CLimhen Esmonde, Kanagaraj, & Ponnambalam, 2014) were used for validating the performance of the proposed algorithm. The model of TCP optimization have been studied and conducted by several researchers. In the TCP, the paths no need return to the first point. The only objective is to determine the shortest path. But by solving the TSP, the final path must be returned to the initial city.

2.5 Optimization algorithm

Various algorithms were implemented to optimize the drilling path in order to find the shortest route for the drilling problem. Based on the literature survey that was conducted, there are 16 types of algorithms as shown in Figure 5.

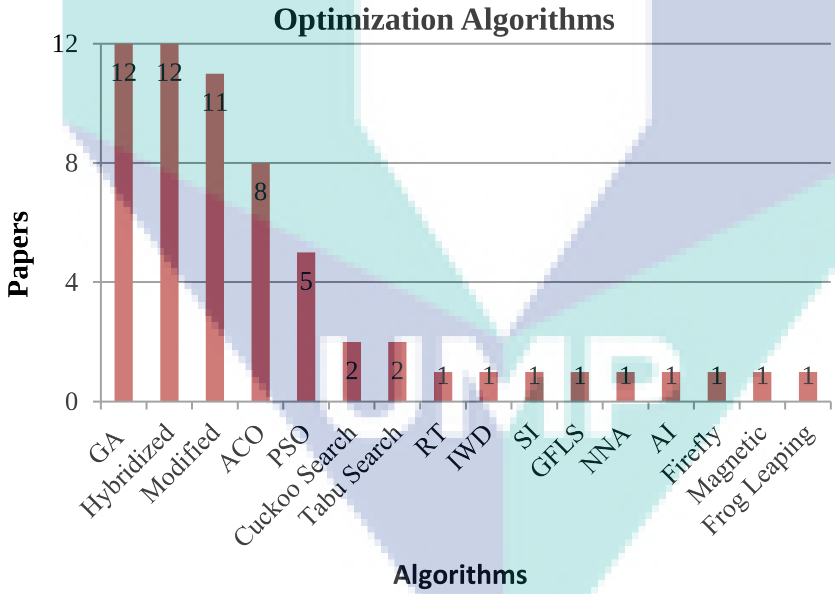

Figure 5: Summary of optimization algorithms

Based on Figure 5, GA and hybridized algorithms are the most frequently used about 20 % from papers review. Meanwhile, 18% of research papers were used modified algorithms to optimize drilling path. Besides, about 13 % of researchers applied ACO algorithms to find the shortest possible route based on previous studies. This percentage is followed by PSO algorithms (i.e. 8%). Tabu search algorithm and combinatorial cuckoo search algorithm have been applied in holes making operations by 3%. Then, the remaining algorithms are record-to-record travel (RT), intelligent water drop (IWD), swarm intelligent (SI), guided fast local search (GFLS), novel natural approach (NNA), artificial intelligence (AI), firefly, magnetic optimization and frog leaping algorithms have been applied by several researchers to solve the TSP problems. Table 1 presents the optimization algorithm, type of problem and objective function for cited publications in drilling path optimization.

Table 1: Algorithms and objective type based on citations

Algorithm	**Reference**	**SO**	**MO**	**Optimization objectives**					
				1	**2**	**3**	**4**	**5**	**6**
GA	[14]	X		X					
	[27]	X						x	
	[54]	X			X				
	[55]	X		X			X	x	
	[56]		X		X	X	X		
	[57]	X		X					
	[58]		X	X	X				x
	[59]		X	X	X		X		x
	[60]	X					X		
	[61]	X				X	X		
	[62]		X			X	X		
	[63]	X				X	X		
HA	[11]	X			X				
	[64]	X			X			x	
	[65]		X				X	x	
	[66]		X				X	x	
	[67]		X				X	x	
	[68]		X				X	x	
	[69]		X				X	x	
	[70]	X					X	x	

Algorithm	Reference	SO	MO	Optimization objectives					
				1	2	3	4	5	6
	[71]	X	X					x	
	[72]	X		X					
	[73]	X							
	[74]	X							
MA	[5]	X		X	X			x	
	[12]	X						x	
	[15]	X		X					
	[16]	X		X					
	[21]	X					X		
	[24]		X	X	X				
	[29]	X					X		
	[31]	X					X		
	[45]	X		X					
	[53]	X		X					
	[76]	X		X					
ACO	[2]		X	X	X				
	[32]	X		X					
	[49]	X		X					
	[50]		X	X	X				
	[51]	X		X					
	[52]	X			X			x	
	[53]	X		X					
	[77]	X							
PSO	[23]	X		X					
	[25]	X		X					
	[46]	X		X					
	[47]	X				X			
	[48]	X		X					
CS	[43]		X		X	X	X		
	[44]		X	X	X				
TS	[41]	X						x	
	[42]		X		X	X			
RT	(Kentli & Alkaya, 2009)	X						x	
IWD	(Srivastava, 2015)	X		X					

Algorithm	Reference	SO	MO	Optimization objectives					
				1	2	3	4	5	6
SI	(G. Y. Zhu, 2006)		X	X	X				
GFLS	(EL-Midany et al., 2007)	X							x
NNA	(Abu et al., 2010)	X			X				
AI	(Abdullah et al., 2015)	X		X					
FF	(M. M. Ismail et al., 2012)	X		X					
MOA	(Mohd Muzafar Ismail et al., 2013)	X		X					
FL	(Amol M Dalavi, 2016)	X				X			

GA genetic algorithm, HA hybridized algorithm, MA modified algorithm, ACO ant colony optimization, PSO particle swarm optimization, CS combinatorial cuckoo search, TS tabu search, RT record-to-record travel, IWD intelligent water drop, SI swarm intelligent, GFLS guided fast local search, NNA novel natural approach, AI artificial intelligence, FF firefly, MOA magnetic optimization algorithm, FL frog leaping, SO single objective, MO multi-objective, 1optimize travel distance, 2 reduce machining time, 3 reduce total cost, 4 improve efficiency, 5 increase productivity, 6 size of holes

2.5.1 Genetic Algorithm

Genetic algorithm is a global search algorithm widely used in solving the TSP problem. GA is also similar to artificial algorithms that have already been used successfully in solving the complex combinatorial problems in terms of quality and convergence speed solution (Abdullah Make, Ab. Rashid, & Razali, 2016). GA is proven to be able to reduced total time and distance of tool travel for multi-holes drilling path.

Additionally, the basic mechanism of GAs is designed to mimic processes in natural evolution system (Kumar & Pachauri, 2012). GA is frequently applied in holes drilling problem because of its capabilities and robustness. There are four steps to be taken in GA method include uncertainties in initialization, selection, reproduction and termination based on (Abdullah et al., 2015). Thus, (Chen & Guo, 2012) employed Grefenstette coding rule to make use of these uncertainties of GA. In the GA method, the fitness function can be formulated as:

$$f = 1 / \sum d_i \tag{5}$$

where:

f is the fitness function;

d_i is the length of the i^{th} path section.

A machining program using genetic algorithm and traveling salesman problem to shorten the machining time for drilling sequence was built (T. Abbas et al., 2014). At the same time, the machining program improves the efficiency of CNC machines without degrading motion accuracy. The effectiveness of the genetic algorithm showed around 50% in some case to reduce the machining time and cost of drilling operations. While (Liu & Liu, 2011) applied genetic algorithms in the optimization of the drilling path on PCB to improve the efficiency and find the shortest optimal path selection of PCB drilling process. Genetic algorithm which has been used in the different points for practice was proven has good parallelism, generalization, overall and robustness.

2.5.2 Hybridized algorithm

The hybridized algorithm meaning is the mixture of two or more algorithms. A hybrid algorithm is considered as meta-heuristics primarily refer to the process of combining algorithms to form a new algorithm that is predicted to beat its general benchmark problems. For example, (Kanagaraj et al., 2014) proposed a hybrid algorithm cuckoo search with genetic algorithm (hybrid-CSGA) to solve the path optimization problem for PCB holes drilling operations. The result showed that hybrid-CSGA reaches the near-optimal solution much earlier than the CS and GA approach for small and large size problem instances in PCB holes drilling path optimization.

Besides, a hybrid Taguchi genetic algorithm (HTGA) to optimize the CNC-PCB drilling path was applied by (Al-Janan & Liu, 2014). The optimization was performed and the number of feasible solutions is exponentially related to the number of holes positions. Then, (T. Abbas et al., 2014) used hybrid ACO approach for CNC machines involving multi-holes drilling that are mostly arranged in concentric circular patterns. The proposed algorithm is applied to the drilling path planning of 2000 holes for food-industry separator plate. Moreover, a hybrid evolutionary approach is applied to CNC drill route optimization by (Sigl & Mayer, 2005). In hybrid version Route Optimizer RO3 based on an evolutionary algorithm (EA), they achieved machine time savings about 10% compared to visual optimization by a human expert. Therefore, hybridized algorithm was implemented for solving TSP is more efficient to find the shortest route in drilling path.

2.5.3 Modified algorithm

Modified algorithms refer to the improvement of existing algorithms to achieve better performance. For example, (Abbas et al., 2011) proposed ACO algorithm to optimize drilling path planning for a rectangular matrix of holes for CNC drilling machines. Then, to improve the algorithm, two modifications to the basic ACO algorithm are proposed. Both modifications were described by adjusting the initial pheromone matrix as ACO-2. In ACO-2, the initial pheromone was modified in the row, column and diagonal directions. Meanwhile, the initialization of the pheromone matrix ACO-3 was modified in row and column directions only. So that, the result of case studies showed the discovered path via the modified ACO algorithms lead significant reduction in machining time and distance compared to the basic ACO algorithm.

Furthermore, (Zhang, 2012) modified the genetic algorithm to improve the efficiency and quality of the machining of porous parts. Genetic algorithm is complexity insufficient and difficult to fall into local optimization. Therefore, the algorithm was modified to prevent premature phenomenon by introducing dual drill at the same time processing. With the intention to improve the machining efficiency of the CNC laser drilling, (Guo et al., 2014) applied improved ant colony algorithm of the k-means clustering approach. The optimization results based on experimental studies have shown that the proposed method is better performance, and the machining efficiency is greatly improved.

2.5.4 Ant colony optimization algorithm

Besides genetic algorithm, the ant colony optimization is another standalone algorithm that frequently used to optimize drilling toolpath. The basic ACO algorithm was inspired by natural strategy and capability of ants driven to find the shortest paths from their nest to the food location. The ACO was inspired from the following steps [54, 64]:

- Different ants will try another path that is not the same route with other ants.
- Ants deposit a chemical compound called pheromone along the travel path.
- Then, different ants have ability to sense the pheromone level on the path. They can make the decision on which path should be taken.
- An ant always chose the one path with more pheromone deposit (random decisions)
- Deposited pheromone will evaporates over time. Finally, the best path will be the one most traveled is the richest in pheromone.

Previously, a number of researches had been done to study and optimize the hole making path. One of the research works is conducted by (Ghaiebi & Solimanpur, 2007). They modeled the problem as a 0–1 non-linear problem, and optimize the problem using ACO algorithm. The experimental results indicated that the ACO method is capable to achieve targeted optimum solution. However the ACO performance was mainly reduced by premature convergence that causes the solution trapped in local optimum (Ghaiebi & Solimanpur, 2007).

In advance, a new algorithm is similar to ant colony optimization (ACO) algorithm is applied for the process parameter optimization of selected advanced machining processes (R. V Rao & Kalyankar, 2011). This algorithm is called artificial bee colony (ABC) algorithm. It is inspired by the teaching-learning process in the bee colony system. The researchers implement this technique for drilling parameter optimization using electrochemical machining (ECM) process and electrochemical discharge machining (ECDM) processes.

2.6 Objective Function

Based on cited papers, the objective function for drilling path includes aspects of minimizing the travel distance, reduce the time taken for drilling operations, cutting cost of the project, efficiency of machining or drilling process, productivity and size of holes. Figure 6 below presented six objective functions that been used in the optimization of drilling paths.

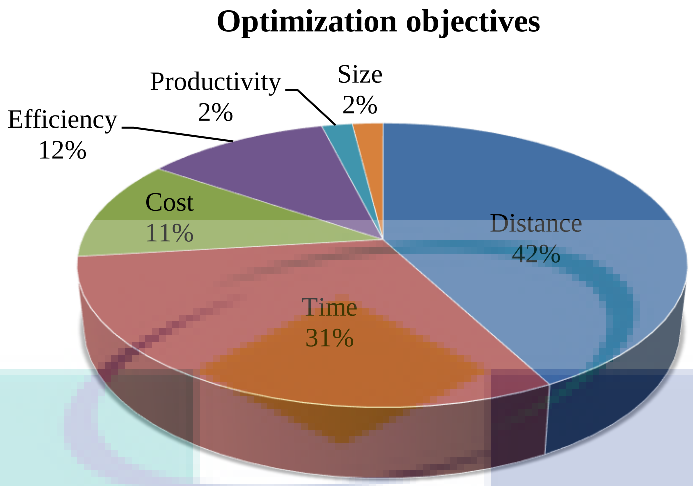

Figure 6: Summary of optimization objectives of drilling operations

The most frequently used optimization objective is minimizing the distances. 42% of the published papers were reported used this objective function in drilling path optimization. Then, about 31% of the papers focus to reducing the time taken of holes to be drilled based on the literature. On the other hand, 12% of the researchers considered the efficiency of machining or drilling. In the meantime, 11% of the researchers aimed to reduce the cost of the machining. However, only 2% of the published research papers focus on the productivity and accuracy of holes sizing.

The objective function to minimize the travel distance in tool path optimization is described in simple summation for the path that visits all the holes in the matrix. Therefore, the distance matrix D_{ij} can be formulated as in-plane distance [36, 54, 64] between node centers as follows:

$$D_{ij} = Dji = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (5)$$

Where, x and y are absolute coordinates, x_i is the coordinate location of point i along the x-axis, x_j is the coordinate location of point j along the x –axis, y_i is the coordinate location of point i along the y-axis and y_j is the coordinate location of point j along the y-axis.

On the other hand, drilling operations require most of the machining time for manufactured part (Narooei et al., 2014). In other words, the shorter machining path become, the faster machining time will be. The optimization of the drilling path has got a significant importance to reduce the machining time which directly leads to improves productivity in manufacturing systems (Ghaiebi & Solimanpur, 2007). The selection of total operation time for different drilling paths is proposed by (G.-Y. Zhu & Zhang, 2008). Therefore, the operation time is selected as the evaluation function in their work as follow:

$$t = t_{\text{move}} + n \times t_{\text{drill}} \tag{6}$$

where:

n is the number of holes needed to be machined;

t_{drill} is the time used for the drilling operation determined by the parameters in NC program and has nothing to do with the selected paths;

t_{move} is the time used when the worktable is moving and affected by the selected drilling path.

In contrast, (Farhad Kolahan & Liang, 2000) minimize the overall cost of processing hole-drilling operations, instead of the operation time. Other researchers, such as (Narooei et al., 2014) used a cost function for multi-hole drilling involving a simple workpiece. This cost function can be mathematically written as:

$$f(x, y, z) = \sum_{i=1}^{n-1} \sum_{j=2}^{n} \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} + \sum_{k=1}^{n} |z_k| \tag{7}$$

Where, the tool routing path is calculated by the incremental positioning i or j related to the coordinates point (x, y) of the previous point during the drilling operations and the position *k* along the *z*-axis which is 0.5 cm distance between the tool tip and the workpiece surface. Thus, depth of the drilling is 1 cm, as shown in Equation (7).

Besides, (Chen & Guo, 2012) employed genetic algorithm to improve the efficiency of holes drilling by optimizing the air travel of holes drilling. To improve the machining efficiency of the CNC laser drilling, (Guo et al., 2014) presented the path optimization method based on an improved ACO with k-means clustering approach. Meanwhile, (Noorfarooque et al., 2015) designed and implemented an Arduino controlled PCB drilling machine. In this work, the drill holes are automatically detected from an image of circuit. Therefore, this approach eliminating need to enter the drill hole locations manually. Further, the efficiency of drilling machine uses path planning method is used to make the system more stable and accurate.

Moreover, [73, 74, 79] demonstrated the optimization of printed circuit board (PCB) manufacturing by improving drilling process productivity. In [72, 73], the productivity is defined from the total processing time, which involved setup time, cutting time, tool exchange and drill movement time. Then, (Kanagaraj et al., 2014) applied a hybrid algorithm cuckoo search with genetic algorithm (hybrid-CSGA) to tackle the problem of small and large size for path optimization PCB holes drilling process due to complexity and exponential growth of solution space.

2.7 Critical Discussions

Based on the number of publication over the years, the research in this area is still growing and attracting the researchers. Based on Figure 1, the number of the publication was growth excessively since 2010. This trend is related to the growth of the computational field as well as the awareness of optimization algorithms for the researchers with a non-computer science background. The research on the drilling path optimization can be classified as a marriage between manufacturing and computer science fields.

Optimization of drilling path can lead to reduce machining time which directly improves the productivity of manufacturing part (Ghaiebi & Solimanpur, 2007). Based on studies conducted, CNC machine and PCB drilling are widely used by researchers in application areas for drilling path optimization. CNC machine tools require less manpower, give improvements in productivity and quality of the final product (Setiawan et al., 2013) especially for CNC milling process (Iberahim et al., 2014). Thus, electronic manufacturing industries mostly used CNC machines for drilling holes on PCB [33, 37]. However, PCB is used in the simplest electronic product (Ancău, 2008) and typically drilled with small-diameter drill bits made by solid coated tungsten carbide (Srivastava, 2015). Therefore, both of them play an important role to improve the process of productivity in drilling paths.

Based on the papers reviewed, TSP is more efficient way to model the possible routes in drilling operations. TSP can be directly implemented since the multi-holes drilling exactly same with TSP formulation. However, TSP problem is a complex combinatorial problem. The search space for the problem is excessively increased when the number of holes increased. Sometimes, the basic TSP model cannot be used when the drilling process involved precedence sequence (Sigl & Mayer, 2005). For example, in mold drilling that involved drilling and reaming in tool path optimization. The reaming process must be performed after the drilling (Khalkar et al., 2015). Therefore, the basic TSP model cannot be used in that situation.

Thus, various optimization algorithms have been applied to optimize drilling path problem. Most of the researchers applied meta-heuristic algorithms like genetic algorithm, hybridized algorithm, modified algorithm and particle swarm optimization. It is because the existing algorithms have a high computational time which takes a long time to run the optimization. Besides that, the existing algorithms are also having the premature convergence problem. In order to reduce premature convergence issue, researchers were modified and hybridized algorithm (Zhang, 2012). Furthermore, majority of the existing algorithm were designed to optimize continuous problem. Therefore, these algorithms need to be modified to suit with TSP model. In most of the cases, researchers define the continuous chromosome/particle/solution as a weight to determine the sequence of the path [9, 49]. Besides that, researchers also developed a discrete representation of the TSP model such as discrete GA, discrete PSO, and discrete ACO (G. Y. Zhu, 2006).

Although there are quite a number of existing researches in drilling path optimization, there are still many opportunities to contribute in this area. For example, the existing researches mainly focus on the regular or uniform arrangement of the holes. At the moment, not many research works study the irregular holes arrangement. This type of problem is expected to be more complicated due to unpredicted optimum path (Khalkar et al., 2015). Besides that, the existing research mainly adopted the well-established optimization algorithm like genetic algorithm, ant colony optimization and particle swarm optimization algorithms. These algorithms were proven to produce good solution in various research areas. The current trend shows that researchers tend to hybridize the algorithm. Based on Figure 5, hybrid algorithm is the most frequently used by the researchers about 20% to optimize drilling path. This approach is to enhance the performance of the original algorithm, by taking the advantages of mechanisms from different algorithms.

However, there is a lack of application of new optimization algorithms that were introduced around last five years. The new optimization algorithms like dragonfly algorithm, ant lion optimizer, whale optimization and multi-objective grey wolf optimizer [65–69] have good potential to be implemented in drilling path optimization. However, these algorithms need to be modified to suit with the TSP model for multi-holes drilling since these algorithms were proposed to optimize continuous problem.

Overall, the popular objective functions in drilling path optimization are to minimize the travel distance, reduce machining time and reduce cost of operations in tool path optimization. These objective functions had fulfilled the purpose of previous drilling path optimization. Beside these objective functions, the energy consumption and environmental consideration also can be included in the future research work. It is important since the industry now moves towards the sustainable manufacturing.

In the next few years, the research in drilling path optimization is predicted spread widely among researchers and industrial practitioners. Many researchers only focus on regular holes arrangement compared to irregular holes arrangement. This phenomenon is because irregular holes arrangement requires high computational time to search for real optimum solution. But meta-heuristic algorithm is proven to produce good solution in various research areas. Moreover, the new meta-heuristic algorithms also considered for enhancement as the potential research study. More application can be conducted on real life cases together with sustainable manufacturing.

CHAPTER 3

METHODOLOGY

3.1 Introduction

In this chapter the methodology of the research will be clarified. This research is divided into three main phase. In the first phase, the problem will be modelled using Travelling Salesman Problem model. Besides that, the evaluation procedure to measure tool path length also will be established.

In the second phase, an optimization algorithm will be developed. Before proceed with the optimization algorithm, a screening is made to select suitable optimization algorithms. This is conducted by testing algorithm for different problem within similar discrete combinatorial problem. In this case, an assembly sequence planning problem is selected. Next, a general approach to solve the hole path sequence from the developed model will be formed, followed by draft a Particle Swarm Optimization (PSO) flow to match with hole making sequence. The PSO for the problem is coded into computer program using MATLAB. The algorithm testing made using problem from literature.

The final stage is about to validate the optimization results. The drilling process will be conducted using standard CNC programme. The machining time will be collected. Then, drilling process for similar design using path generated from the PSO algorithm. The methodology of this research is summarize in Figure 7.

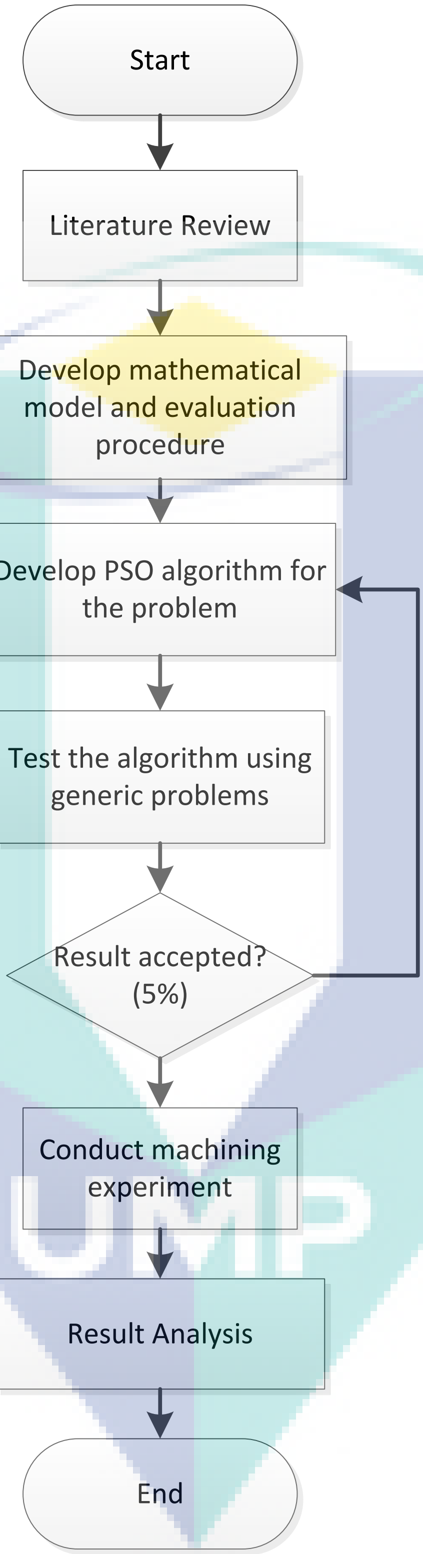

Figure 7: Flow Chart of the Project

3.2 Problem Modelling of Multi-holes Drilling Path

The problem of multi-holes drilling path is modelled as a travelling salesman problem (TSP). TSP is implemented to find the shortest route of drilling paths. To solve the problem, the final path must be returned to the initial path. For example in Figure 8, the salesman begins their journey from point A to B, C, D, E and return to A. So the total distance is 79 km. For the same starting point, if the salesman moves to point A, D, C, B, E and return to A, the total distance is 87 km. In this case, the shortcut path is better in term of the journey distance.

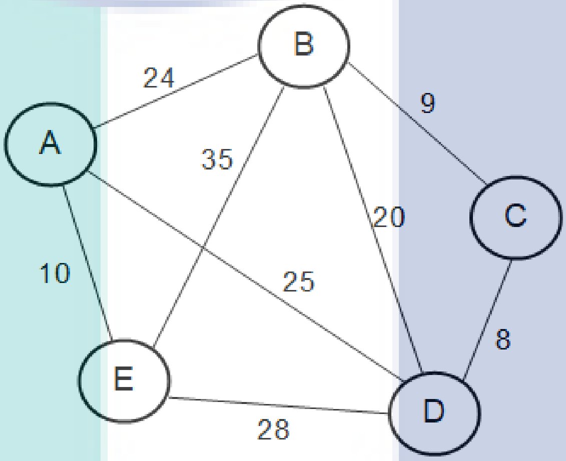

Figure 8: Example of TSP problem

To model the problem, the following objective function is used.

$$F(x) = \sum_i^n \sum_j^n X_{ij} D_{ij} \quad (1)$$

$$\sum_{i=1}^n X_{ij} = 1, j = 1, \dots, n \quad (2)$$

$$\sum_{j=1}^n X_{ij} = 1, i = 1, \dots, n \quad (3)$$

$$D_{ij} = Dji = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (4)$$

Where;

n, number of holes;

D_{ij}, distance from point i to j;

X_{ij}, $\in \{0, 1\}$;

$X_{ij} = 1$, travel distance from point i to point j as part of the path that through on all the holes in the matrix;

$X_{ij} = 0$, the path does not travel from point i to point j as part of the tool path.

x and y are the Cartesian coordinates;

x_i, coordinate location of point i along the x-axis;

x_j, coordinate location of point j along the x –axis;

y_i, coordinate location of point i along the y-axis;

y_j, coordinate location of point j along the y-axis.

Equation (1) is the summation for all distances, between holes and chosen travel tool path. Equation (2) shows the set of constraints ensure that each hole j is only visited once in the path defined by X_{ij}. While Equation (3), ensure the path coming out of every hole i move to one other hole, j. Equation (4) described the distance matrix as in-plane distance between node centres.

3.3 Particle Swarm Optimization Development

Particle Swarm Optimisation (PSO) is a meta-heuristic searching method that is inspired from the swarming behaviour of flocking birds. This mechanism is particularly in respect to migrating birds population and its flying directions. Every single migrating bird is considered a particle which usually adjusts their searching or flying direction according to the previous flying experience. Each particle represents the potential solution with a certain position (current solution), velocity (magnitude and direction towards the optimal solution) and fitness value (performance measure of the specific problem). Compared to another evolutionary approach, such as ACO and GA method, PSO is respectively known to have a faster convergence towards the optimal solution (Adnan & Razzaque, 2013).

In the beginning, the initial parameters are determined. The initial parameters are the particle number (n_p) and the maximum iteration ($iter_{max}$). Then, the initial position (X) consist of random number within 0 and 10 is created. At the same time, the random velocity (V) is also generated. As an example, Table 2 shows one of the particles from origin population is, x_1= [4.24 2.15 9.29 3.44 4.52 6.51] and v_1= [2.00 7.10 2.30 0.50 4.08 8.40].

Table 2: Position value of cities

Cities	1	2	3	4	5	6
x_1	4.24	2.15	9.29	3.44	4.52	6.51
v_1	2.00	7.10	2.30	0.50	4.08	8.40

The sequence of holes is sorted according to the x_1 value in descending order. For example, the largest x_1 value is belong to hole 3. Then it is followed by 6, 5, 1, 4 and 2.

In the end, the tool path will return to the starting hole position. For this example, the path that being decoded from this approach is [3 6 5 1 4 2 3].

The function of predefined objective is to evaluate the feasible route. Then, the total summation of travelling time is defined as t_{36}, t_{65}, t_{51}, t_{14}, t_{42} and t_{23} for fr_1 = [3 6 5 1 4 2 3]. The last one is to update the swarm position and velocity. The function is to establish new swarm set which is followed by the current best personal particle solution, P_{best} and best solution among all particles, G_{best} that appear in every iteration.

Next, the particle best solution (Pbest) and global best (Gbest) are updated. Pbest refers to the current best solution for a particular particle, while the Gbest is the overall best solution. The Pbest and Gbest solutions are used to update the velocity and position of the solution. The following formula is used to update velocity (22) and position (23):

$$V_i^{t+1} = wV_i^t + c_1 r_1 (Pbest_i^t - X_i^t) + c_2 r_2 (Gbest^t - X_i^t) \tag{22}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{23}$$

In equation (22), t denotes the iteration number, while w is the inertia weight for regulating the previous effect of historical velocities. On the other hand, c_1 and c_2 are the acceleration coefficients, while r_1 and r_2 are the random number between [0, 1]. The Pbest, Gbest and particle position are updated until the specific iteration number is reached.

Previously, a lot of studies proposed different approaches to reducing premature convergence in PSO. Premature convergence in soft computing occurs because of lack of the diversity in the solution during the iteration process. In PSO, this phenomenon is directly related to velocity and position-updating procedure. The solution position is influenced by the Pbest and Gbest with some randomness by r_1 and r_2. The Pbest, however, only influences a specific particle, compared with Gbest that affects all of the particles to move towards it. In the case where Gbest is not updated (no better solution found) in a few consecutive iterations, there is a possibility for the majority of the particles to reach the Gbest. This situation will reduce the solution diversity.

To overcome this problem, this work proposed to consider the top three best solutions instead of the only single solution in Gbest. For this purpose, the single solution in Gbest is replaced with the average of the three best solutions.

$$Gbest^t = (g_1^t + g_2^t + g_3^t)/3 \tag{24}$$

In equation (24) g_1^t, g_2^t and g_3^t refer to the solution particle in the first, second and third ranks respectively for the t^{th} iteration. In the modified PSO, the Gbest is replaced with the new Gbest in equation (24). The reason to consider the three top solutions for Gbest is to improve the solution diversity. In the proposed mechanism, the particle position will follow the average position from the three best solutions. Furthermore, the possibility for all three solutions not being updated is small compared with single Gbest solution in the original PSO. This mechanism makes the search direction become more diverse, and the chance to trap in local optima can be reduced.

To prove this concept, a simple test using Rastrigin function is conducted. For this function, the optimum point is (0, 0). In this test, only six particles are used. The first particle is set as (0, 0) while the remaining five particles are randomly generated using the same pseudorandom for both PSO and MPSO. The purpose of setting the first particle as the optimum point is to observe the particle movement over the iteration. For this purpose, the iteration is only set to 10. The particle position for the first, fifth and tenth iteration are captured. All other parameters for PSO and MPSO are the same.The procedure of MPSO is presented as follows:

Procedure of Modified PSO

Initialise MPSO parameters: Population size (*npop*), coefficients (w, c_1, c_2), iteration counter ($iter$ = 0) and maximum iteration ($iter_{max}$)

Initialise random velocity, V_i and position, X_i for i = 1,2,…, *npop*

While $iter \leq iter_{max}$

$iter = iter + 1$

Decode the X_i into feasible assembly sequence, F_i

Evaluate the fitness function for i^{th} solution, f_i

Update personal solution, $Pbest_i$

Update *Gbest*

Update velocity

$$V_i^{t+1} = wV_i^t + c_1 r_1 (Pbest_i^t - X_i^t) + c_2 r_2 (Gbest^t - X_i^t)$$

Update position

$$X_i^{t+1} = X_i^t + V_i^{t+1}$$

End

3.4 Computational Experiments

A computational experiment was conducted to measure the performance of PSO to optimize making sequence. From our review, the range number of holes for drilling path is 50 to 150 approximately. Thus, the problems were classed into small (*n*= *1-50*), medium (*n*= *51-100*) and large (*n* =101-150). The population size for all algorithms is set to 20 with maximum iteration is 300. Then, the optimization is repeat for 15 times with different pseudo-random seeds. The output data being recorded from optimization are the minimum, average and standard deviation of fitness value.

The multi-holes drilling is modeled and optimized using the PSO algorithm in the MATLAB software. The performance of PSO algorithm has been tested. The computational results of PSO algorithm is compared to other meta-heuristic algorithms as Genetic Algorithm (GA) and Ant Colony Optimization (ACO) algorithm. For other algorithms include Whale Optimization Algorithm (WOA), Ant Lion Optimizer (ALO), Dragonfly Algorithm (DA), Grasshopper Optimization Algorithm (GOA), Moth-flame Optimization (MFO) and Sine Cosine Algorithm (SCA).

3.5 Validation via Machining Experiment

An experiment has been conducted to validate the results from multi-holes drilling optimization. The experiments has been conducted to compare the machining time for top three algorithms, and also the tool path that automatically generated using CADCAM software. The sample of the tool path are shown in Figure 9 – 12. For this purpose, the material use is aluminum plate 300x300 mm and the thicness is 3 mm. For the drilling process, a CNC milling machine, Haas VF-6 model is used with the speed rate 100, spindle speed 1500 rpm as in Figure 13 and 14.

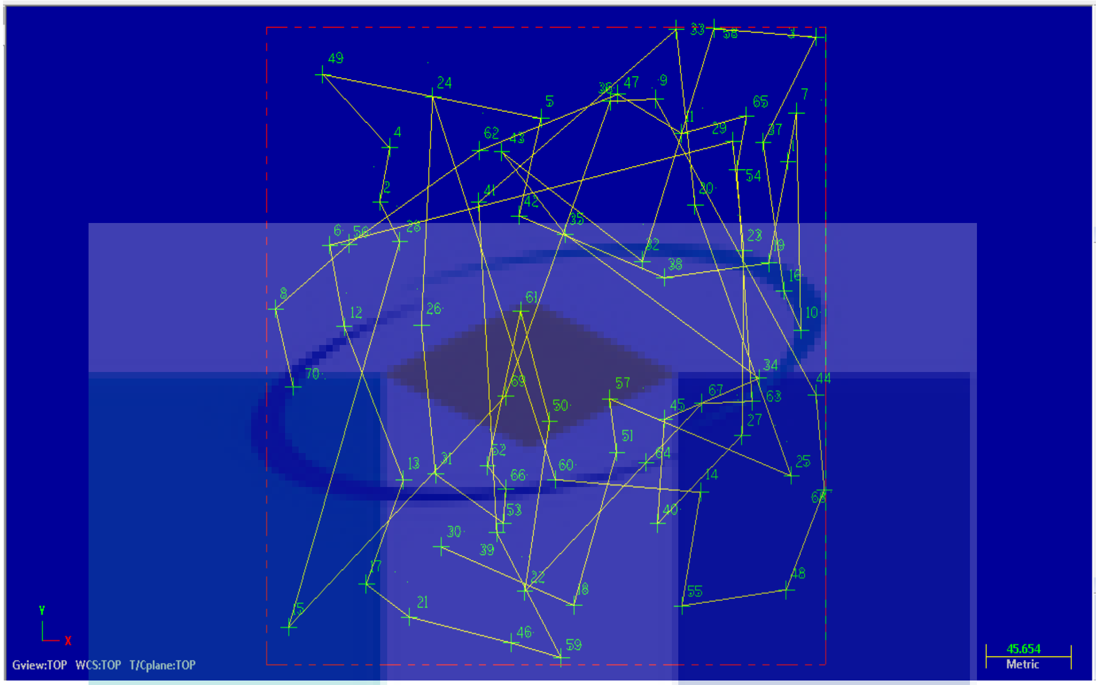

Figure 9: Sample of 70 holes test problem

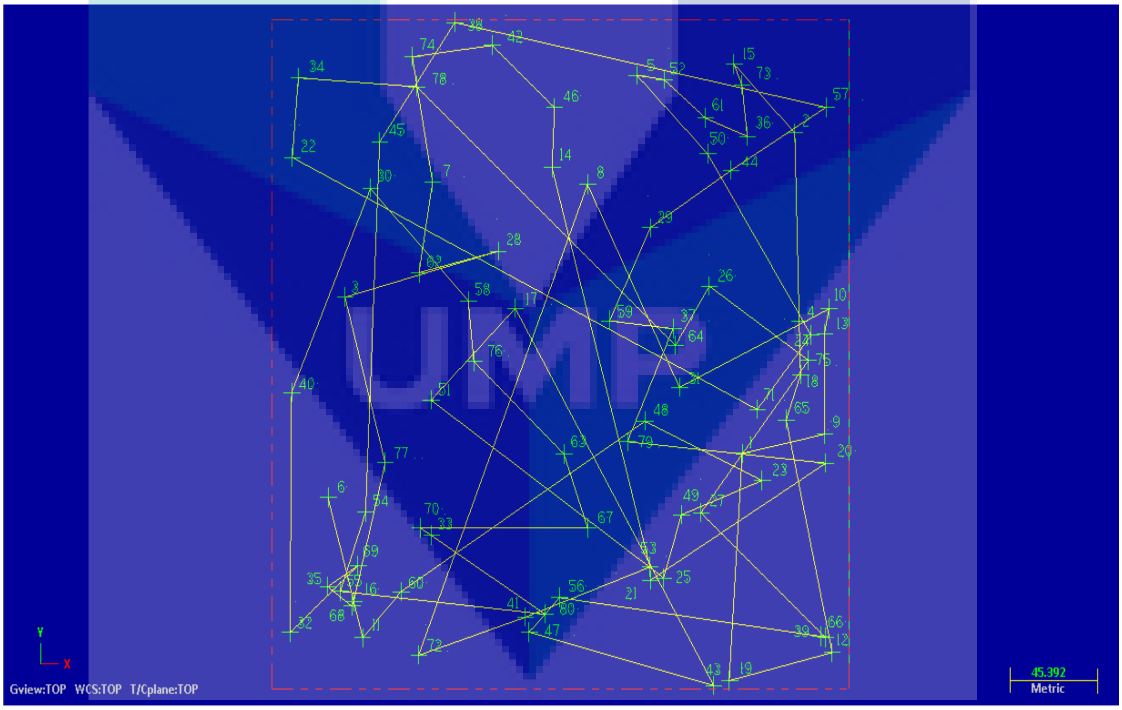

Figure 10: Sample of 80 holes test problem

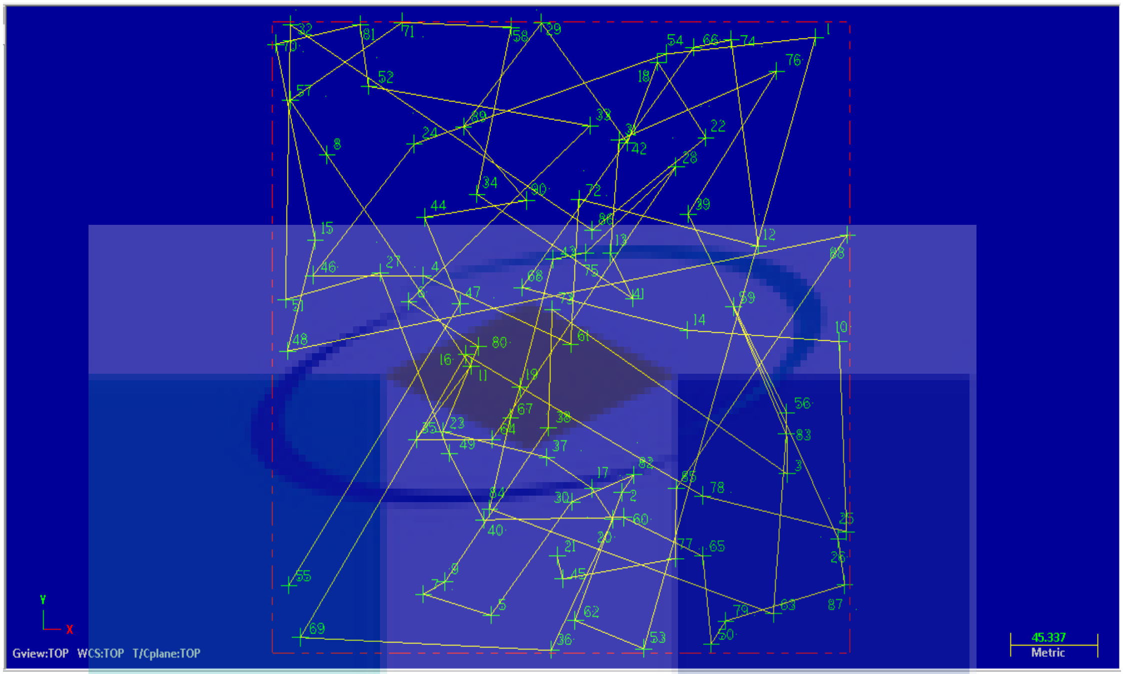

Figure 11: Sample of 90 holes test problem

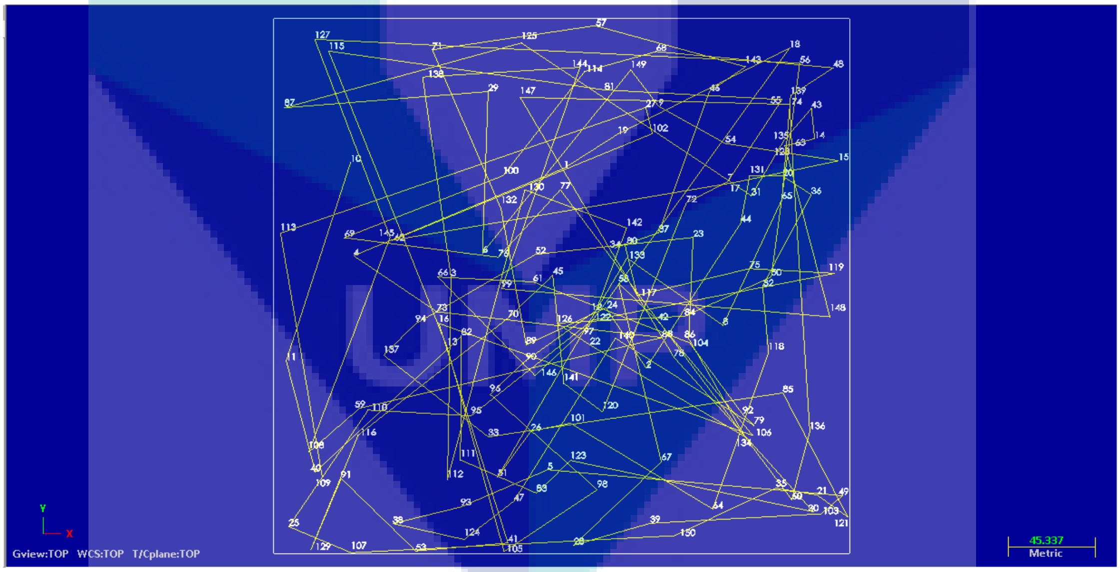

Figure 12: Sample of 150 holes test problem

Figure 13: CNC Milling Machine (Haas VF6)

Figure 14: Drilling process using CNC milling

CHAPTER 4

RESULTS DISCUSSIONS AND ANALYSIS

This chapter present the results and finding from this research. This chapter is divided into two main section. The first section present and discuss the results of computational experiment. Then the second section discuss about the machining experiment.

4.1 Computational Experiments Result

Table 3, 4 and 5 presents the minimum, average and standard deviation of the optimization results obtained from 15 runs. The number in bold shows the best value for minimum and average fitness for a particular problem. Based on the observation from Table 3, the ACO algorithm performed better in small size problem. But when the size of problem increased to medium, the PSO algorithm have shown better performance in four out of five problems in term of average fitness as in Table 4. The best PSO performance is observed in the large size problem (Table 5), with the best minimum and average fitness in all problems. Overall, the proposed PSO came out with the majority of the best minimum and average fitness. This is followed by the ACO, GA and MFO algorithms.

Table 3: Optimization Results for Small Size Problem

Problem Size		GA	PSO	ACO	WOA	ALO	DA	MFO	SCA
10	**Min**	1081	**1047**	**1047**	1113	1085	1208	**1047**	**1047**
	Average	1277	1214	**1047**	1196	1248	1332	1128	1146
	SD	144	117	0	60	92	82	70	60
20	**Min**	139	136	**124**	163	148	188	137	176
	Average	189	180	**131**	188	192	227	173	211
	SD	27	20	6	26	20	18	20	14
30	**Min**	2011	2350	**1708**	2423	2249	2802	1968	3095
	Average	2772	2720	**2007**	3096	3110	3449	2516	3516
	SD	553	235	202	323	366	321	252	168
40	**Min**	2438	2801	**2630**	3396	3079	4172	2457	4516
	Average	3683	3510	**3063**	3908	3928	4642	3412	4840
	SD	811	387	253	341	341	317	339	179
50	**Min**	**2997**	**3280**	4075	4030	4511	4823	3858	6000
	Average	**4280**	**4244**	4815	4948	4978	5861	4306	6146
	SD	981	515	756	554	396	549	325	114

Table 4: Optimization Results for Medium Size Problem

Problem Size		GA	PSO	ACO	WOA	ALO	DA	MFO	SCA
	Min	2810	**4387**	5132	5482	5238	6355	4530	6923
60	**Average**	5683	**4990**	6101	6069	6001	7148	5374	7364
	SD	1654	341	444	496	327	525	496	206
	Min	6055	**5315**	6286	6325	6558	7634	5850	8508
70	**Average**	7097	**6038**	6773	6888	7028	8202	6211	8641
	SD	503	470	340	367	385	450	336	112
	Min	8975	**5857**	7810	7461	7963	9403	7018	9969
80	**Average**	10198	**6755**	8242	8249	8489	9765	7387	10395
	SD	727	562	362	759	488	272	293	283
	Min	**4866**	7041	9507	8342	9537	10598	8396	11336
90	**Average**	**7737**	7797	10353	8872	10221	11123	8971	11767
	SD	2803	766	668	345	493	427	529	245
	Min	10398	8199	10908	9962	10061	11769	9384	12867
100	**Average**	12330	**8681**	11563	10423	10820	12329	9890	13118
	SD	1144	**412**	439	533	499	369	430	157

Table 5: Optimization Results for Large Size Problem

Problem Size		GA	PSO	ACO	WOA	ALO	DA	MFO	SCA
110	**Min**	8621	**6412**	13341	10847	11377	13261	10204	14200
	Average	11762	**9324**	14082	11634	11967	13670	10782	14505
	SD	2682	1833	477	707	391	321	459	192
120	**Min**	11586	**10582**	14690	11524	13423	14104	11521	15179
	Average	12064	**11290**	15223	12387	14021	14771	11820	15369
	SD	4059	607	651	658	604	617	281	206
130	**Min**	11787	**10565**	14369	11229	12753	15614	12953	16628
	Average	15266	**11368**	15602	12952	14436	16310	13258	16932
	SD	2346	563	1170	1010	958	493	316	226
140	**Min**	14114	**13150**	17646	13122	15366	16957	14107	18777
	Average	17998	**13954**	18474	14143	16296	18170	14910	19007
	SD	2180	709	571	916	632	714	507	214
150	**Min**	15965	**12050**	17317	14012	15542	17643	14739	18968
	Average	18841	**13393**	18365	14843	16436	18225	15079	19352
	SD	1612	1477	942	656	790	504	308	249

A standard competition rank method (SCR) was used for better view of optimization result. In this method, rank 1 assigned the best algorithm based on average fitness. Meanwhile, the rank 8 is the worst algorithm. For the same result of different algorithms, they shared the same rank. Then, the following result left empty. Table 6 presents summary frequency of standard competition rank for different algorithms.

Table 6: Standard competition rank for average fitness

	GA	PSO	ACO	WOA	ALO	DA	MFO	SCA
Rank 1	1	10	4	0	0	0	0	0
Rank 2	1	1	0	3	0	0	10	0
Rank 3	2	3	2	3	0	0	4	1
Rank 4	3	0	1	5	5	0	1	0
Rank 5	3	1	1	4	5	1	0	0
Rank 6	1	0	4	0	5	5	0	0
Rank 7	1	0	3	0	0	7	0	1
Rank 8	4	0	0	0	0	2	0	13
Average	5.4	1.7	4.2	3.6	5	6.6	2.4	7.6

Based on the data, PSO was ranked as 1 about 10 times. So, the proposed PSO come out with the best mean in majority. Then, this is followed by ACO, GA, MFO, WOA, ALO, DA and SCA algorithms. Overall result, the PSO algorithm performed a good performance for optimization. This finding is related to the simple mechanism in PSO that make this algorithm converge faster towards the optimal solution. Besides, the divergence of the search direction in PSO also contributed to the promising performance. Later, a machining experiment will be conducted to validate the optimization results. As suggestion, continuous effort to explore more new meta-heuristics algorithms to improve their efficiencies. Besides, researchers also need to consider environmental issues and energy consumption for sustainable manufacturing.

4.2 Validation Results

The machining time for Particle Swarm Optimization (PSO) toolpath is presented in Table 7. It is divided into 3 problems that is small problem, medium problem and large problem. The independent variable for small problem is 10, 30 and 40, while for medium problem the independent variable is 70, 80, and 90 and the independent variable for large problem is 130, 140, and 150. On the table, it’s shown that the machining time after the drilling process is increase from small problem until the large problem.

Besides, the machining time for Auto Generated Path is presented in Table 8. It also divided into 3 problems that is small problem, medium problem and large problem. The independent variable for small problem is 10, 30 and 40, while for medium problem the independent variable is 70, 80, and 90 and the independent variable for large problem is 130, 140, and 150. On the table for Auto generated path also shown that the machining time after the drilling process is increase from small problem until the large problem.

Table 7: Time of Drilling Process (PSO Generated path)

Problem	Number of Holes	Machining time (Second)
Small	10	56.6
	30	164.1
	40	219.1
Medium	70	382.5
	80	435.6
	90	489.2
Large	130	699.2
	140	751.8
	150	806.2

Table 8: Time of Drilling Process (CADCAM Generated Path)

Problem	Number of Holes	Machining Time (Second)
Small	10	57.0
	30	168.4
	40	222.7
Medium	70	384.9
	80	496.3
	90	559.8
Large	130	739.8
	140	792.0
	150	842.1

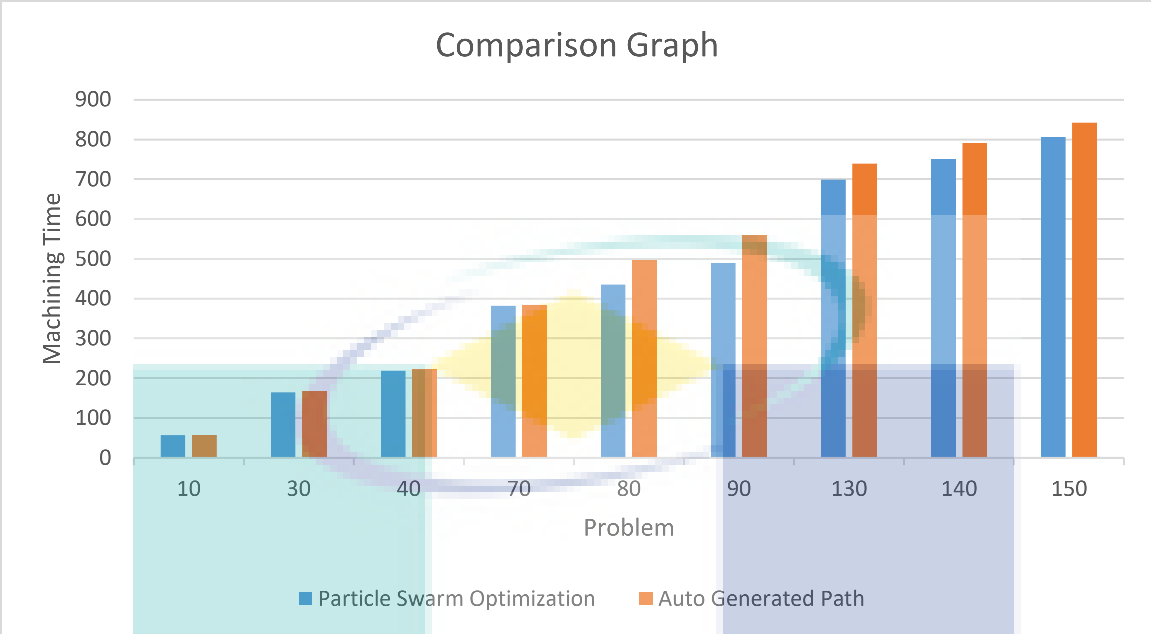

Figure 15: Comparison between PSO and CADCAM Generated Path.

Based on Figure 15, the machining time for both Particle Swarm Optimization (PSO) generated path and CADCAM generated path is increased from small to large problem drilling process. Also, the machining time for Particle Swarm Optimization (PSO) generated path is lower than Auto Generated Path. This is because the PSO generated path is shorter than Auto Generated Path. Besides, from the graph the machining time different is not much for small problem drilling hole but when the problem is increased (from 80 and above) the different of machining time between PSO and Auto generated path is more obvious. In other word this result means that the PSO able to search for better drilling path compared with Auto Generated Path.

4.3.1 Mathematical Model

Mathematical model is an equation that was generate from some problem. Using the mathematical model user can predict the machining time only using the equation from the mathematical model without run the experiment to take the machining time. User just need to substitute the value of X with the number of holes and from the calculation user can get the machining time. From the machining time, the mathematical model for Particle Swarm Optimization (PSO) and Auto Generated Path was established and presented in Figure 16 and Figure 17. The mathematical model for Particle Swarm Optimization (PSO) is y = 5.3454x + 5.4114 and the mathematical model for Auto generated path is y = 5.6766x + 6.9255.

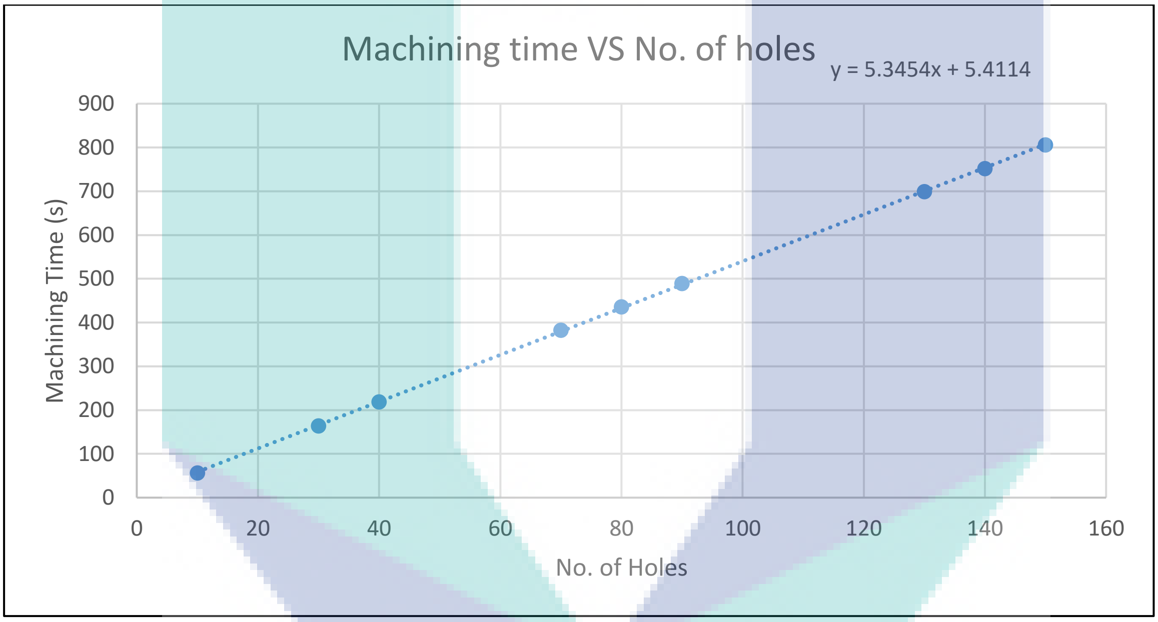

Figure 16: Machining time for PSO generated toolpath

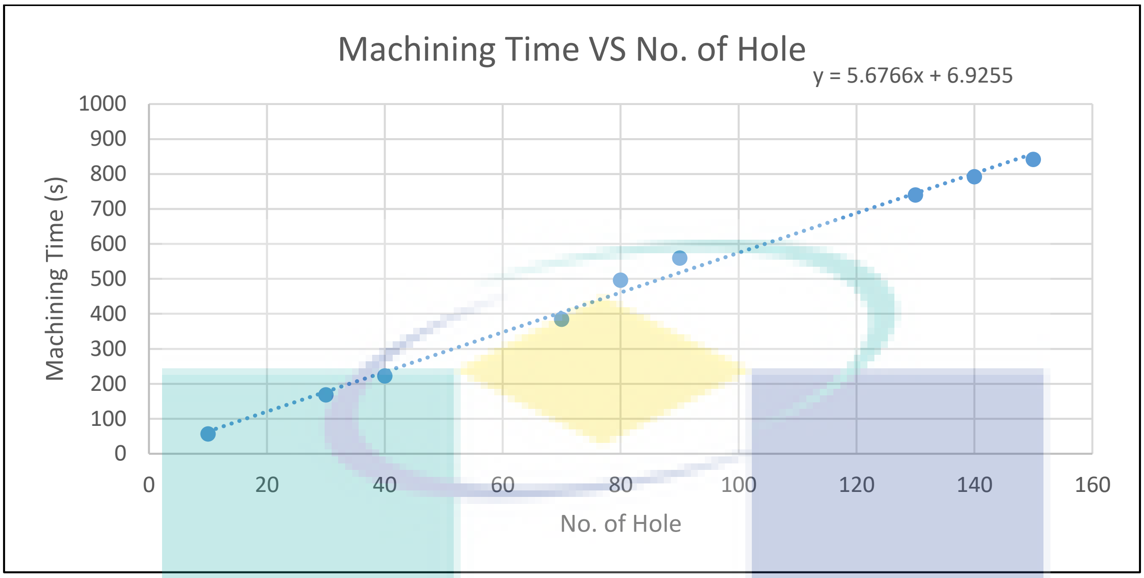

Figure 17: Machining time for CAD CAM generated path

The percentage of difference between Particle Swarm Optimization (PSO) and auto generated path was presented in Table 9.

Table 9: Percentage of improvement achieved by PSO toolpath

Machining Time of CADCAM Generated Path	Machining Time of PSO Generated Path	Percentage of Improvement (%)
57.0	56.6	0.702
168.4	164.1	2.553
222.7	219.1	1.617
384.9	382.5	0.624
496.3	435.6	12.231
559.8	489.2	12.612
739.8	699.2	5.488
792.0	751.8	5.076
842.1	806.2	4.263
		5.018

PSO method was adapted to reduce tool travel path, reduction cost and minimizing machining time. In recent years researchers focused on improving four parameters, minimizing machining time, reduction of cost and tool travel path and increase surface quality on CNC machining for increasing the machining efficiency. Machining time is gaining wide attention on its application on drilling process because the shortest time of machining process, so, the reduction cost will be much lower.

The results show that the difference of machining time between PSO generated and Auto generated path is not much for small problem while when the problem increase and become more large problem, the difference of machining time between PSO generated path and Auto generated path much more obvious. From that we can say that the larger the problem holes that we get, the much higher different of machining time between PSO generated path and Auto generated path.

While on the percentage difference of machining time, Particle Swarm Optimization (PSO) was much reliable compared to Auto Generated Path, which can prove by its average accuracy of 5.018% and respectively. This could be explained, based on the result means the percentage that the Particle Swarm Optimization (PSO) generated path is faster than Auto Generated Path is 5.018. This is because the machining time of Particle Swarm Optimization (PSO) generated path is shorter than Auto Generated Path. This proves that the problem can be solved by using a Particle Swarm Optimization (PSO) approach.

Using the PSO approach, global and local solutions could be simultaneously found for better machining time of the drilling process. To compare the PSO method with other global minimizing strategies, we looked for an approach that has been accepted as one of the best in the literature, where the source code is readily available. It can be seen that PSO generated path from AI method performs well compared with Auto generated path from CAD-CAM software.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

In this final chapter, computational experiment results and machining validation result will be concluded. Besides that, a few recommendations for future works are suggested.

5.2 Conclusions

In this research, an efficient algorithm to optimize multi-holes drilling path has been studied. The research begins with literature review to identify the trend and research gap. Then the problem has been modelled using travelling salesman problem (TSP) concept. Next, optimization algorithms have been developed for the problem. Before optimizing the tool path drilling problem, these algorithm has been implemented to optimize another discrete combinatorial problem, assembly sequence planning (ASP). Later, the optimization for multi-holes drilling path problem is conducted using metaheuristics algorithms. Finally, a validation experiment has been made to confirm the results from optimization.

The finding of the problem modelling indicated that the most dominant approach that used to model multi-holes drilling is by using TSP concept. Beside a simple representation, this concept also widely implemented for other applications. Meanwhile, the results from ASP optimization indicated that the hybrid metaheuristics algorithm did not suitable to be used for TSP model because of extensive constraints. Therefore, the hybrid algorithm was not preceded for drilling path optimization.

Computational experiment of multi-holes drilling tool path indicated that the Particle Swarm Optimization (PSO) performed better, although it was compared with new optimization algorithms such as Whale Optimization Algorithm (WOA), Ant Lion Optimizer (ALO), Dragonfly Algorithm (DA), Grasshopper Optimization Algorithm (GOA), Moth-flame Optimization (MFO) and Sine Cosine Algorithm (SCA). This finding is related to the simple mechanism in PSO that make this algorithm converge faster towards the optimal solution. Besides, the divergence of the search direction in PSO also contributed to the promising performance.

Validation experiments proved that the PSO able to generate less machining time compared with commercial CAD-CAM software. For the test problems used, PSO able to generate faster tool path in the range of 1 to 12% better than tool path that generated by commercial CAD-CAM software. As a conclusion, this research demonstrated a potential of PSO algorithm to optimize multi-holes drilling tool path via computational and machining experiments.

5.3 Recommendations

There are a few suggestion to expand this research to the next level. The first suggestion is to embed the PSO algorithm inside CAD-CAM software. However, this suggestion requires expert in computer-aided design. Besides that, a user-friendly interface for the model and algorithm could be developed for the non-programming expert.

Meanwhile, in term of the problem application, the tool path planning for more complicated problem such as CNC milling or laser cutting process could be done. Besides considering the point-to-point movement, the algorithm also has potential to optimize the line.

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