HYBRIDIZATION OF CUCKOO SEARCH AND BAT ALGORITHM FOR OPTIMIZING MACHINING PERFORMANCES IN DEEP HOLE DRILLING

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DEDICATION

This thesis is dedicated to my dearly loved husband, Mohamad Faizal bin Abdullah and my beloved sons Muhammad Rayyan Mikail bin Mohamad Faizal and Muhammad Rayyan Mirza bin Mohamad Faizal who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my lovely parents, Mohamad bin Abu Bakar and Karimah bt Awang , my beloved siblings Zanariah binti Mohamad and Liza binti Mohamad, families members and friends who taught me that even the largest task can be accomplished if it is done one step at a time.

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ABSTRACT

Deep Hole Drilling (DHD) is a machining process employed to produce holes with a length exceeding ten times of its diameter. The machine is utilized to assemble high-precision workpieces. The significant issue in DHD is in producing the best results of machining performances at the optimal value through the selection of machining parameters. In machining, achieving the optimum value of machining parameters is related to the performance and quality of products. Hence, the modelling and optimisation approaches are suitable for identifying the optimal DHD parameters to improve DHD performance. In this study, the real DHD experimentation based on an experiment (DOE) of full factorial with added centre points is conduct to investigate the influence of DHD machining parameters: feed rate (f), spindle speed (s), depth of hole (d) and Minimum Quantity Lubricant, MQL (m) on surface roughness (Ra), roundness (Rd), and cylindricity (Cy). The modelling process employed in the regression analysis consists of four types of mathematical models-multiple linear regression (MLR), two-factor interaction (2FI), multiple polynomial regression (MPR), and stepwise regression (SR)-were developed based on experimental data and used as an objective function for optimisation process. In the optimisation, Cuckoo Search (CS) was implemented in order to optimize the DHD machining performances. However, previous research indicates that CS has some weaknesses: trapping in local optima and slow convergence rate. Thus, a new hybridization between Cuckoo Search and Bat Algorithm (CS-BA) was developed to improve the DHD performance. Analysis of the results indicates that, CS-BA produced the minimum values and outperformed the standard CS algorithm and established computational techniques: ABC, GR-SVM, Integrated GA-SA-Type1, and Integrated GA-SA-Type2. Overall, it can be concluded that CS-BA hybridization has enhanced the quality and productivity of DHD problems significantly.

ABSTRAK

Kaedah penggerudian lubang dalam (DHD) digunakan untuk menghasilkan lubang dengan kedalaman melebihi sepuluh kali garis pusatnya. Ia digunakan untuk memesin bahan kerja yang berketepatan tinggi. Isu utama dalam DHD adalah untuk mendapatkan keputusan nilai prestasi pemesinan yang lebih tepat pada titik optimum melalui pemilihan parameter pemesinan. Dalam pemesinan, pencapaian titik optimum bagi parameter pemesinan saling berkait dengan prestasi dan kualiti sesuatu produk. Oleh itu, pendekatan kaedah pemodelan dan pengoptimuman adalah bersesuaian bagi mengenal pasti parameter optimum bagi DHD yang akan menambahbaikkan prestatsi DHD. Dalam kajian ini, satu eksperimen sebenar DHD berdasarkan reka bentuk eksperimen (DOE) faktoran penuh dengan penambahan titik tengah telah dikendalikan untuk menyiasat pengaruh parameter pemesinan DHD terhadap perkara berikut: kadar suapan (f), kelajuan bindu (s), kedalaman lubang (d) dan Minyak Pelumas Minimum, MQL (m) pada kekasaran permukaan (Ra), kebulatan (Rd), dan kesilinderan (Cy). Proses pemodelan menggunakan analisis regresi terdiri daripada empat jenis model matematik-regresi linear berganda (MLR), regresi interaksi dua faktor (2FI), regresi polinomial (MPR), dan regresi majulangkah (SR)-telah dibangunkan berdasarkan data eksperimen dan digunakan sebagai fungsi objektif untuk proses pengoptimuman. Dalam pengoptimuman, algoritma Carian Cuckoo (CS) telah dilaksanakan untuk mengoptimumkan proses prestasi pemesinan DHD. Walau bagaimanapun, kajian lepas menyatakan CS telah menimbulkan beberapa kelemahan iaitu sering terperangkap dalam penyelesaian optima setempat dan kadar penumpuan yang perlahan. Oleh itu, satu hibrid baru antara CS dan Algoritma Kelawar (CS-BA) telah dibangunkan untuk meningkatkan prestasi DHD. Hasil kajian mendapati CS-BA memberikan nilai lebih rendah dan telah mengatasi algoritma CS, ABC, GR-SVM, Integrated GA-SA-Type1, dan Integrated GA-SA-Type2. Justeru, dapat disimpulkan bahawa strategi hibrid CS-BA ini dapat meningkatkan kualiti dan produktiviti masalah DHD.

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LIST OF ABBREVIATIONS

2F1	-	Two Factor Interaction
ACO	-	Ant Colony Optimisation
ANN	-	Artificial Neural Network
ANOVA	-	Analysis of Variance
AWJ	-	Abrasive Water Jet
BA	-	Bat Algorithm
BTA	-	Boring and Trepanning Association
CHM	-	Chemical Machining
CMM	-	Coordinate Measuring Machine
CS	-	Cuckoo Search
CS-BA	-	Hybrid Cuckoo Search and Bat Algorithm
DF	-	Degrees of Freedom
DHD	-	Deep Hole Drilling
DoE	-	Design of Experiment
ECM	-	Electrochemical Machining
FA	-	Firefly Algorithm
FL	-	Fuzzy Logic
F-test	-	Fisher‘s Statistical Test
GA	-	Genetic Algorithm
GSO	-	Glowworm swarm optimisation
HS	-	Harmony Search
HSS	-	High Speed Steel
LSC	-	Least Squares Circle
LSCY	-	Least Square Cylindricity
MFO	-	Moth-Flame Optimisation
MLR	-	Multiple Linear Regression
MRR	-	Material Removal Rate
MS	-	Mean Square
PCM	-	Photochemical Machining

PI	-	Percentage of Improvement
PSO	-	Particle Swarm Optimisation
R^2	-	Square Correlation Coefficient
RSM	-	Response Surface Methodology
SLR	-	Simple Linear Regression
SR	-	Stepwise Regression
SS	-	Sum of Square
USM	-	Ultrasonic Machining

LIST OF SYMBOLS

C_y	-	Cylindricity
d	-	Depth of hole
$d1$	-	Drill diameter
f	-	Feed rate
H	-	Profile Height
l	-	Length
L	-	Sampling Length
$L1$	-	Overall Length
$L2$	-	Flute Length
Lb	-	Lower Bound
m	-	Minimum Quantity Lubrication, MQL
n	-	Population Size
pa	-	Discovering Rate of Alien Egg
$Qmax$	-	Frequency Maximum
$Qmin$	-	Frequency Minimum
R_a	-	Surface Roughness
R_d	-	Roundness
$rand$	-	A Random Number Generator
s	-	Spindle Speed
Ub	-	Upper Bound
x	-	Profile Direction
y	-	Profile Curve
α	-	Step Size

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CHAPTER 1

INTRODUCTION

1.1 Overview

This chapter discusses the problem background related to machining, modelling and optimisation. The background of the study, problem statement, objectives, scopes, significance and contributions of the study are also explained. Nowadays, manufacturing industries have traditionally played a key role in developing economic growth. Productivity in the manufacturing industries is related to the increase in manufacturing. With the current competition in the global market, the manufacturing function is primarily concern with producing high-quality final products with reduced cost and production time. Product quality has always been one of the main elements in manufacturing industries. Given the present global economy and competition, continuous quality improvement has become a significant priority, particularly for major corporations in industrialized countries. Machining is one of the primary processes and is widely used in manufacturing industries. Machining is a metal removal process in the form of chips utilizing single or multiple wedge-shaped cutting tools (Chandrasekaran et al., 2010). Machining is used in the manufactures of almost all metal products. The primary objective of a machining process is to produce a final products with low cost and high quality (Lee et al., 2010). Generally, the machining process can be classified into two types, which are traditional and non-traditional (modern). Traditional machining involves removing unwanted segment of the metal workpiece in the form of chips such as turning, drilling and milling. Modern machining or non-traditional machining uses technology such as abrasive water jet (AWJ), ultrasonic machining (USM), chemical machining (CHM) and electrochemical machining (ECM).

1.2 Background of the Study

Machining has been the core in manufacturing industry. The greatest challenge that an engineer face when machining is determining the optimum value for various machining parameter so as to achieve high productivity and quality of the final product (Benardos and Vosniakos, 2003). In machining, the high quality of a product refers to the lower-cost manufacture. The suitable selection of machining parameters plays a significant role in determining the high quality of the final product with minimum manufacturing cost and high productivity(Rao and Pawar, 2010; Giasin et al., 2019). Generally, the selection of machining parameters is determined by human (or manufacturing engineers) judgement based on hand book and experiences (Kamaruzaman et al., 2019; Vijayanand, 2020). Moreover, in machining, the process was done continuously to get the target value despite the material cut is being used only once. Thus, this process will increase the cost manufacturing. To overcome these problems, the proper use of Design of Experiment (DoE), modelling and process optimisation are considered. DoE approach helps plan experiments and helps analyse the data obtained from the experimentation process. According to Zain et al., (2011), modelling in machining refers to estimating the potential minimum or maximum values of machining performance while optimisation refers to estimating the optimal solution of cutting condition that lead to the minimum or maximum machining values of machining performances. DoE, modelling and optimisation have been widely applied in industry because of their effectiveness in reducing cost and time. (Sangwan et al.,2015). Full factorial has been used as DoE tool in this study because of its efficient methodology for optimizing the process parameter (Rafidah et al., 2014).

Drilling is one of the most common processes used for hole-making. The drilling of holes with a large, length to diameter ratio, that is, exceeding ten, is called deep hole drilling-DHD (Den and Chin, 2005). The successful development of applications requiring deep holes such as the manufacture of hydraulic cylinders used in automotive industries, medical and biomedical products, aircraft structures, as well as other applications in the electronic, aerospace, wind energy and nuclear industries (Jurko and Panda, 2012; Fang, 2005; Thil et al., 2013) require technique or mechanism of producing such holes. In each of these industries, high hole qualities are necessary for the high performance of the products. DHD is the best mechanism to produce accurate holes and becoming increasingly more prominent and beneficial in many applications.However, producing a quality, deep hole via drilling can be a challenge

Generally in DHD, surface roughness, roundness and cylindricity provide the concept of hole quality related to the machining parameters such as feed rate (f),spindle speed (s), depth of hole (d) and Minimum Quantity Lubrication, MQL, (m) (Al-Wedyan et al., 2007). The basic principle in DHD is determined by an asymmetrical tool that needs a controlling tool during the initial work piece penetration. The cutting and passive forces are transferred as normal forces by the guide pads to the borehole wall (Biermann et al., 2014). Then the coolant pressure and flow rate is necessary to transport the chips out from the borehole (Weinert and Löbbe 2002).

It is a big challenge to select the correct machining parameters that requires higher cost and time to consume the experiments (Aggarwal and Singh, 2005; Moreira et al., 2019). In practice, those parameters are generally selected based on machinist experience and machining data book catalogue, which are high costly. The results do not achieve the optimal value in DHD process, hence loss of productivity and accuracy.

From that situation, various soft computing techniques have been considered by researchers to model and improve the machining performances, including traditional and modern techniques. Earlier the traditional techniques such as programming (Ecker, 1980), dynamic programming (Bellman, 1956) and integer programming (Ceria et al., 1998) had some weaknesses, which is being trapped in local minima or slow convergence rate that will contribute to not enough effective results (Ghose, 2002). Then, modern techniques such as Genetic Algorithm - GA (Holland 1992), Particle Swarm Optimisation - PSO (Kennedy and Eberhart, 1995), Ant Colony Optimisation - ACO (Dorigo et al., 1997), Cuckoo Search -CS (Yang and Deb ,2009) Bat Algorithm - BA (Yang, 2010) etc. are develop to overcome those weaknesses of traditional techniques. In recent times, the usage of those techniques in searching near-optimum solutions in machining has attracted many researchers and also become a research trend. In addition, those techniques also more optimal than the handbook recommendations, which can only be considered as rough and initial values (Sönmez et al., 1999). This situation will reduce the cost of manufacture.

CS algorithm has been applied in different kinds of optimisation problems across various categories. In this study, Cuckoo Search (CS) was introduced to optimise the DHD process since there are limited research regarding the optimisation of DHD parameters using CS algorithm. Based on the previous research, CS is capable of solving the problems of various fields such as Engineering (Yang and Deb, 2010; Yang and Deb, 2011), Pattern Recognition (Vazques, 2011; Rani and Malek, 2011) and Job Scheduling (Burnwal and Deb, 2012; Prakash et al., 2012). The success recorded by the CS algorithm is the fewer number of parameters required that contribute to the easy execution (Chiroma et al., 2017).

Despite its efficiency and wide use, according to the literature, CS also has some disadvantages such as slow convergence and easy of getting stuck in local optima, hence unable in giving the best possible optimal solution (Li et al., 2020; Joshi et al., 2013). Nowadays, some researchers propose a hybridization approach to solve such problems in standard algorithms and enhance performance. Hybridization approaches are popular due to the ability to solve real - world problems involving complexity, noisy environment, imprecision, uncertainty, and vagueness (Grosan and Abraham, 2007). Thus a new hybrid is proposed in this study, called Hybrid Cuckoo Search- Bat Algorithm, (CS-BA). The solution's faster convergence speed, and accuracy are the important criteria in solving optimisation problems (Yildiz 2009b). BA enables to give a faster speed of convergence rate, and this an advantage in solving optimisation problems compared to others algorithm such as particle swarm optimisation (PSO), genetic algorithm (GA), Harmony Search (HS) and Firefly Algorithm (FA) (Perez et al., 2015; Gandomi et al., 2013). BA is a simple algorithm to understand because it has only few parameters to adjust and is easy to implement (Chellamuthu et al., 2017). According to Yang 2010, BA has extra advantages of frequency tuning and dynamic control of exploration and exploitation, which is the key point in metaheuristic by varying pulse emission rates and loudness during iterations. It is considered as a balanced combination of the standard particle swarm optimisation and the intensive local search controlled by the loudness and pulse rate. Furthermore, BA is also used in solving multi-objectives optimisation problems and has been effectively used in many areas of optimisation (Yang, 2012). Considering the capability of the BA technique in some aspects stated above, thus, this study considers by hybridizing the original CS with BA to improve the weakness of the CS algorithm, thus give the optimal solution for DHD process and reducing the cost. The flow of DHD problem is simplified as in Figure 1.1.

Problem in DHD process

- Optimal machining parameters are difficult to be identified that requires higher cost and time to consume
- Complexity and uncertainty of the DHD process

Solution

- Use soft computing technique to estimate the optimal machining parameters that can reduce the cost

Problem in modern optimisation process

- Easy to implement but not efficient due to trapping in local minima and became slow convergence rate.

Solutions

- Implement CS algorithm for optimizing DHD machining parameters
- The optimisation approach can reduce the cost

Problem in CS algorithm

- Slow convergence as easily gets stuck in local optima and low accuracy computation (Li et al., 2020; Joshi et al., 2013).

Solutions
- Propose a new hybridization of CS and BA algorithm - Hybridization approach can reduce the cost

Figure 1.1 The flow of problem in DHD process

1.3 Problem Statement

Based on the Figure 1.1, three research questions to be answered in this study are stated as:

(a) What significant machining parameters affect the minimum value of machining performances during the DHD real experimentation?

The success of machining process depends on the proper selection of specifics machining parameters based on cost and quality factors (Jung 2002). Hence, the machining parameters should be appropriately selected to improve the quality of the products and enhance the productivity (Singh et al., 2019).The machinist should have deep knowledge about DHD machining parameters in order to get high efficiency during machining process. The experimental design can control the cost and quality factors which are particularly useful when performing the actual testing experiment. (Charness et al.,2018). The main focus of study is on hole qualities, including $R_{a,}$ R_d and C_y relative to the machining parameters such as feed rate (f), spindle speed (s), depth of hole (*d*) and Minimum Quantity Lubrication - MQL, (*m*). Hence, the experiment design is a best tool to determine the significant machining parameters effects, which are essential in optimizing the machining performances to obtain better results (Nahak and Gupta 2019).

(b) How to obtain the optimal machining parameters through a modern optimisation process?

Identifying the optimal machining parameters by conducting actual experiments and collecting the experimental data for analysis are difficult task, and it typically performed through a trial and error process (Manjunath et al., 2020). The trial and error process requires many workpieces to be tested with different machining parameters value, thus need more time and costly (Vishni et al., 2018). Due to these problems, the modern strategy through computational technique is recommended for estimating the optimal machining parameters. Hence, the machinist is encouraged to utilise the computational technique to determine the optimal machining parameters due to their flexible structure and easy application, thus enabling cost reduction (Chen et al., 2020). CS is one of the new computational techniques reported by several researchers that will allow the optimal machining parameters to be obtained (Mohamad et al., 2019; Saravanan et al., 2020).

(c) Could the hybridization of CS-BA effectively optimize the machining parameters that lead to obtaining the best machining performances?

The vital purpose of machining parameters optimisation is to obtain better results, reduce cost, and reduce computation time. This study proposed the use of hybrid CS-BA to solve the standard CS weaknesses, hence improving the result of DHD machining performances and reducing the cost manufacture. BA was identified to give a balanced combination of exploration and exploitation to search for the global optimal value (Gandomi et al., 2013 ;Yang et al., 2014) and is very efficient with a typically quick start hence giving the higher convergence speed (Wulandhari et al., 2018; Luo et al., 2020). Thus, based on those advantages, the prey hunting behaviour of BA is performed to generate the new solution/eggs by Levy flights in the CS algorithm.

1.4 Objective of the Study

The objectives of the study are:

(a) To establish the significant DHD machining parameters that affects the quality of machining performances (R_a, R_d and C_y) through actual machining experimentation.

(b) To estimate the optimal machining parameters based on CS algorithm for minimization of DHD machining performances hence reducing the cost

(c) To estimate the optimal machining parameters based on new hybrid CS-BA algorithm for minimization of DHD machining performances hence reducing the cost

1.5 Scopes of the Study

The scopes of the study are:

(a) The machining process is focused on DHD using twist drill bit, classified as one of the non- traditional machining processes.

(b) Hole quality investigated is in terms of surface roughness (R_a), roundness (R_d) and cylindricity (C_y).

(c) Four machining parameters that are investigated are feed rate ($65 \leq f \leq 85$), spindle speed ($900 \leq s \leq 1100$) (s), depth of hole ($50 \leq d \leq 60$), and Minimum Quantity Lubricant, MQL ($20 \leq m \leq 40$) were considered.

1.6 Research Significant

This study consists of three parts: conducting the actual experimental work, modelling and optimisation. This study came out with actual experimental work to analyze the significant machining parameters in DHD related to the machining performances measured. The regression analysis is used to develop the mathematical model for the modelling process. Then, a new hybridization CS-BA is proposed to optimize the machining performances in DHD and, at the same time to, avoid being trapped into local optima and slow convergence problems of CS algorithm. Thus, this study significantly contributes to the manufacturing industries by giving the end best results to the machinist as the reference value, thus producing high- quality final products, reducing the cost, and fulfilling customer requirements.

1.7 Thesis Outline

This thesis comprises of seven chapters. Chapter 1 describes the overview, background of the study, problem statement, objective, scope of the study and research significance. Chapter 2 presents the study's literature review on the actual experimentation, modelling, and optimisation processes. Chapter 3 discusses about the research methodology that is used in this study. Chapter 4 – MACHINING EXPERIMENTAL discusses the detail of real experimentation of DHD process in order to determine the significant machining parameters influencing the machining performances. Chapter 5 – CS OPTIMISATION discusses on the development of CS in DHD and the modelling process based on experimental data using regression analysis. Chapter 6 – HYBRID CS-BA OPTIMISATION discusses on the development of proposed hybrid CS-BA in DHD, including the analysis of the results. Finally, Chapter 7 discusses the conclusion and recommendation for the future work of the research.

1.8 Summary

This chapter has discussed the main flow problems in DHD process. Firstly, the data are collected from the actual machining experimentation process. Then the regression analysis as a modelling tool while proposed hybridization CS-BA as an optimisation technique are introduce for overcome those problems investigated.

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