HYBRID ARTIFICIAL FISH AND GLOWWORM SWARM OPTIMIZATION ALGORITHM FOR ELECTRICAL DISCHARGE MACHINING OF TITANIUM ALLOY

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"This thesis is special dedicated to:

My beloved husband, Ahmad Shahrulazhar Bin Che Omar

My beloved babies, Nur Damia Nabila Binti Ahmad Shahrulazhar and Nur Raisha Aqila Binti Ahmad Shahrulazhar

My beloved parents, Fatimah Binti Rahmat and Zainal Bin Miskon

My beloved families and friends

For their endless love, support, courage, understanding and du'a"

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ABSTRACT

Electrical discharge machining (EDM) is a non-traditional machining process widely used to machine geometrically complex and hard materials. In EDM, selection of optimal EDM parameters is important to have high quality products and increase productivity. However, one of the major issues is to obtain better machining performance at optimal value of these machining parameters. Modelling and optimization of EDM parameters have been considered to identify optimal EDM parameters that would lead to better EDM performance. Due to the complexity and uncertainty of the machining process, computational approaches have been implemented to solve the EDM problem. Thus, this study conducted a comprehensive investigation concerning the influence of EDM parameters on material removal rate (MRR), surface roughness (Ra) and dimensional accuracy (DA) through an experimental design. The experiment was performed based on full factorial design of experiment (DOE) with added center points of pulse on time (T_{ON}), pulse off time (T_{OFF}), peak current (I_P) and servo voltage (S_V). In the EDM optimization, glowworm swarm optimization (GSO) algorithm was implemented. However, previous works indicated that GSO algorithm has always been trapped in the local optima solution and is slow in convergence. Therefore, this study developed a new hybrid artificial fish and glowworm swarm optimization (AF-GSO) algorithm to overcome the weaknesses of GSO algorithm in order to have a better EDM performance. For the modeling process, four types of regression models, namely multiple linear regression (MLR), two factor interaction (2FI), multiple polynomial regression (MPR) and stepwise regression (SR) were developed. These regression models were implemented in the optimization process as an objective function equation. Analysis of the optimization proved that AF-GSO algorithm has successfully outperformed the standard GSO algorithm. 2FI model of AF-GSO optimization for MRR and DA gave optimal solutions of 0.0042g/min and 0.00129%, respectively. On the other hand, the SR model for Ra of AF-GSO optimization gave the optimal solution of 1.8216μs. Overall, it can be concluded that AF-GSO algorithm has successfully improved the quality and productivity of the EDM problems.

ABSTRAK

Pemesinan nyahcas elektrik (EDM) ialah pemesinan moden yang digunakan secara meluas bagi memesin bahan yang geometrinya keras dan kompleks. Pemilihan parameter optimum EDM adalah penting bagi mencapai produk berkualiti tinggi dan meningkatkan produktiviti. Namun, salah satu isu utama adalah untuk mendapatkan prestasi pemesinan lebih baik pada nilai optimum parameter tersebut. Pemodelan dan pengoptimuman parameter EDM telah dilaksanakan bagi mengenal pasti parameter EDM optimum yang akan membawa kepada prestasi EDM yang lebih baik. Disebabkan kerumitan dan ketidakpastian proses pemesinan, kaedah pengkomputeran telah digunakan untuk menyelesaikan masalah EDM. Maka, kajian ini menyelidik parameter EDM yang mempengaruhi prestasi kadar pemindahan bahan (MRR), kekasaran permukaan (Ra) dan dimensi ketepatan (DA) melalui reka bentuk eksperimen. Eksperimen EDM dikendalikan berdasarkan reka bentuk eksperimen (DOE) faktorial penuh dengan penambahan titik tengah nilai denyutan masa dibuka (T_{ON}), denyutan dari masa (T_{OFF}), arus puncak (I_P) dan voltan servo (S_V). Dalam pengoptimuman EDM, algoritma Pengoptimuman Kumpulan Cacing Bercahaya (GSO) telah dilaksanakan. Bagaimanapun, kerja-kerja terdahulu menunjukkan bahawa algoritma GSO didapati sering terperangkap dalam penyelesaian optimum setempat dan perlahan dalam penumpuan. Oleh itu, kajian ini telah menghasilkan hibrid algoritma Ikan Tiruan dan Pengoptimuman Kumpulan Cacing Bercahaya (AF-GSO) bagi mengatasi kelemahan algoritma GSO untuk mencapai prestasi EDM yang lebih baik. Bagi proses pemodelan, empat jenis model regresi, iaitu regresi linear berganda (MLR), regresi dua interaksi faktor (2FI), regresi polinomial (MPR) dan regresi majulangkah (SR) telah dibangunkan. Model regresi ini digunakan dalam proses pengoptimuman sebagai persamaan fungsi objektif. Analisis pengoptimuman menunjukkan bahawa algoritma AF-GSO telah berjaya mengatasi algoritma GSO. Model 2FI untuk pengoptimuman AF-GSO bagi MRR dan DA memberi penyelesaian optimum 0.0042g/min dan 0.00129%. Sebaliknya, model SR untuk pengoptimuman AF-GSO memberikan penyelesaian optimum 1.8216μs. Secara keseluruhan, kesimpulan daripada kajian ialah algoritma AF-GSO berjaya meningkatkan kualiti dan produktiviti masalah EDM.

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LIST OF ABBREVIATIONS

ABC	-	Artificial Colony Bee
AFSA	-	Artificial Fish Swarm Algorithm
AF-GSO	-	Hybrid Artificial Fish and Glowworm Swarm Optimization
AI	-	Artificial Intelligence
ANFIS	-	Adaptive-Network-Based Fuzzy Inference System
ANN	-	Artificial Neural Network
ANOVA	-	Analysis Of Variance
CCD	-	Central Composite Design
DA	-	Dimensional Accuracy
DOE	-	Design Of Experiment
DF	-	Degree of Freedom
EDM	-	Electrical Discharge Machining
FCM	-	Fuzzy c-means
FEA	-	Finite Element Analysis
FEM	-	Finite Element Method
FL	-	Fuzzy Logic
FA	-	Firefly Algorithm
GA	-	Genetic Algorithm
GSO	-	Glowworm Swarm Optimization
LOGMLP	-	Logistic Sigmoid Multi-Layered Perceptron
LR	-	Linear Regression
MFR	-	Multiple Factorial Regression
MLR	-	Multiple Linear Regression
MPR	-	Multiple Polynomial Regression
MRR	-	Material Removal Rate
MS	-	Mean Square

NN	-	Neural Network
NSGA-II	-	Non-Dominating Sorting Genetic Algorithm-II
PSO	-	Particle Swarm Optimization
RBFN	-	Radial Basis Function Networks
RMS	-	Root Mean Square
RSM	-	Response Surface Methodology
SA	-	Simulated Annealing
SR	-	Stepwise Regression
SS	-	Sum of Square
TA	-	Tabu Search
TANMLP	-	Tangent Sigmoid Multi-Layered Perceptron
Ti-6Al-4V	-	Titanium Alloy
WEDM	-	Wire Electrical Discharge Machine

LIST OF SYMBOLS

Adj-R^2	-	Adjusted R-squared
I_P	-	Peak current
Pred-R^2	-	Predicted R-squared
Ra	-	Surface roughness
R^2	-	R-squared
S_V	-	Servo voltage
T_{OFF}	-	Pulse off time
T_{ON}	-	Pulse on time

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CHAPTER 1

INTRODUCTION

1.1 Overview

This chapter discusses the problem background related to the machining, modeling process and optimization process. The background of study, problem statement, objectives, scopes, significance and contributions of the research are also elaborated.

In today's manufacturing environment, the main target is to increase the productivity of the products by having the desired high quality products at the minimum cost and time. Productivity is important in order to increase the profits level of the organization and generally influenced by many factors such as worker skill, motivation and effort, value of workmanship, the machines used and effectiveness of the management. Apart from productivity, quality is another important target which is related to the degree of consumers' satisfaction. Managing quality has been a key determinant in an organizations' in order to get lower total costs as well. The high quality of finish product includes of high surface finish, less tool wear and high production rate but in term of economy machining is lower cost (Nandi and Pratihar, 2004). Therefore, manufacturers have concerned with the quality of their product.

In order to achieve the productivity and quality of the products, it is required to ensure their quality level. Quality control purposely to check whether the quality lies within the desired tolerance level and under consumers expectation. It can be divided into two types which are on-line and off-line quality control. On-line quality control is defined as monitoring the quality during the manufacturing process which includes the controller and usage of the related equipment. It comprises with the raw material quality control and process control itself. The feedback is supplied by the controller to reset the process environment if they noticed that the quality of the product is out of the expectation level. Otherwise, off-line quality control is defined as the systematic method of optimizing production processes and product design (Phadke et al., 1983). It includes the process of checking the quality of end products in order to evaluate the best process environment leads to the good quality of product. This process invites an optimization problem which determine the optimal process parameters that leads to the minimum or maximum value of process performance in the manufacturing process. Rao (2011) specified that it is necessary to represent the manufacturing process in a model for optimization process. The first step for process parameter optimization basically is development of the mathematical model.

In manufacturing industries, machining process is one of the most important and widely being used compared to forming, casting and joining processes (Chandrasekaran et al., 2010). Two types of machining processes, traditional (milling, turning, grinding, drilling etc) and non-traditional (abrasive water jet, electrical discharge machining, electro-chemical machining etc). Traditional machining process consists of traditional process work piece removal in the form of chips, while non-traditional process involves the chemical items or advanced technologies in their process. In the late 1940s, EDM process has been developed in manufacturing industries as one of the standard non-traditional machining process. In the EDM process, material is removed by controlling erosion through a series of electric sparks between the tool (electrode) and the work piece to have the eroding effect on work-piece in order to form a replica of tool on work piece (Wang et al., 2003). An electric spark is used as the cutting tool to cut (erode) the work piece to produce the finished part to the desired shape (Padhee et al., 2012).

1.2 Background of Study

The most conflicting criteria that always being concern in today's machining process are improving the productivity and quality of the products. Recently, non-traditional machining processes have widely being used in manufacturing industries due to some advantages such as in terms of cost compared to traditional machining process. Additionally, non-traditional machining processes also enables to solve a problem of high complexity in shape, size and higher demand for product accuracy and surface finish (Rao and Kalyankar, 2013). Instead, traditional machining process has been stated more costly and inefficient because unable to machine them economically due to its tools material that is harder than the work piece material (Negendra Parashar and Mittal, 2007). The selection of optimal machining parameters is important in order to have high quality products and increasing the productivity in low cost (Rao, 2011). The success of the manufacturing process is determined by the selection of optimal process parameters (Rao, 2011). Therefore, the modeling and optimization of machining process are takings into consideration as to achieve these criteria.

Nowadays, EDM is one of the widely used machining processes due to its capability to machine hard material component and complex geometry which need precise and high accuracy (Zain et al., 2011). Moreover, EDM is an alternative method of serial or batch production of difficult-to-cut parts when it is not possible to conducted using traditional machining methods. In the EDM process, there are a few performances which always being concerns. The most important performances are the material removal rate (MRR), surface roughness (Ra) and dimensional accuracy (DA). These performances should be taken into account since they affected several functional attributed of the machining process (Wang and Chang, 2004). The performances of EDM basically rely on several factors such as types of work piece material, electrode tool and also the selection of the machining parameters. The EDM parameters are commonly selected by the expertise based on their experience or machining data handbook. However, the result does not guarantee the optimal performance of EDM process. In some cases, the selected machining parameters are conservative and far from the optimal value. At the same time, selecting optimal parameter requires higher cost and time consuming experiments. Due to the complexity and uncertainty of the machining processes, many researchers in the computer science areas have recently determined and preferred to use soft computing techniques to develop models for predicting the performances of the machining processes and optimized them (Chandrasekaran et al., 2010).

In late years, titanium has become an important material which has widely applied in the aerospace industries, medical and surgical instruments. Titanium alloys have been expanding popular in the aviation segment because of the expanded effectiveness and higher working temperature of air gas turbine motor (Suresh et al., 2016; Tiwary et al., 2015; Armendia et al., 2010). Also, the excellent quality weight proportion of titanium composites gives a lessening of airplane weight and, hence, a diminish in fuel utilization and emanations. Basically, titanium has a high melting temperature and low thermal conductivity where it belongs to the group of difficult-to-cut materials which is not suited for traditional machining (Chen et al., 1999). Moreover, titanium has a low modulus of elasticity which causes significant spring back after deformation under the cutting load (Kuriachen et al., 2015). Thus, according to the advantages of EDM process, it can be seen that titanium alloy can be adequately machined by EDM (Alavi and Jahan, 2017; Gu et al., 2012).

Soft computing techniques include traditional and modern techniques. The traditional optimization techniques such as dynamic programming (Bellman, 1956), integer programming (Ceria et al., 1998) and geometric programming (Ecker, 1980) always being trapped into local optima which enables to give global optimal solution and also slow convergence rate. On the other hand, modern techniques generally include the meta-heuristic algorithm such as genetic algorithm (GA) (Mitchell, 1998), particle swarm optimization (PSO) (Kennedy and Eberhart, 1995), glowworm swarm optimization (GSO) (Krishnanand and Ghose, 2005), firefly algorithm (FA) (Yang, 2009), simulated annealing (SA) (Kirpatrick, 1984), artificial bee colony (ABC) (Kaboga and Basturk, 2007) etc. The modern technique is easy to implement and has a good local search ability. However, they initially converges fast and then becomes extremely slow (Mahapatra and Chaturvedi, 2009). Based on the review, it was observed that the optimization of EDM parameters using GSO algorithm have been limitedly considered by previous researchers. Hence, this research considers the GSO algorithm for estimating the optimal solution of EDM performances.

GSO algorithm has been recently used in solving optimization problems in many areas such as robotic (Yuli et al., 2011; Krishnanand and Ghose, 2005), engineering (Wu et al., 2012; Luo et al., 2011) and remote sensing (Senthilnath et al., 2011). According to the literature, GSO algorithm has shown some weaknesses in global and high dimension search as slow convergence and low accuracy computation (Wahab et al., 2015). Although the local convergence speed of a standard GSO is quite good and the ability of exploitation the solution is very well, it might result in the premature convergence in optimizing multimodal and high dimensions problems (Wu et al., 2012). Hybrid technique has recently being proposed by previous researchers to solve such these problems in standard modern optimization. A better machining performances are expected to be acquired by the hybridization strategy. Thus, this study attempt to develop a new hybridization technique of GSO and artificial fish swarm algorithm (AFSA) to improve the weakness of the GSO algorithm to estimate the optimal parameter of EDM performances. The flow of EDM problem is simplified as in Figure 1.1.

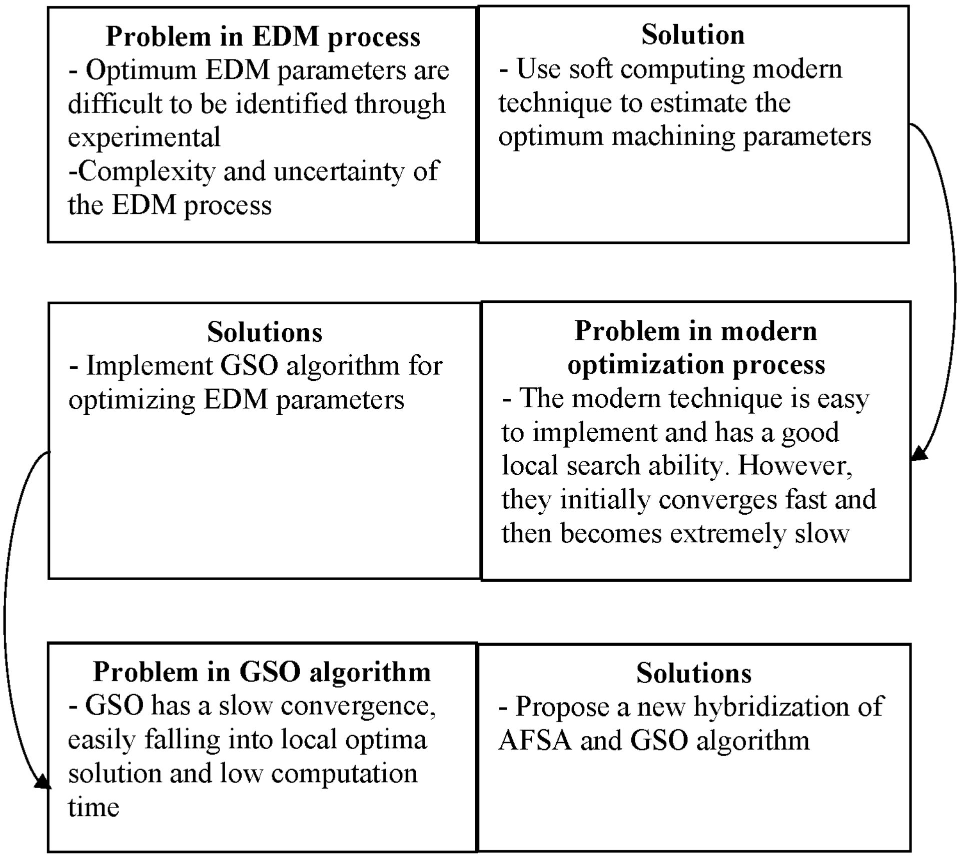

Figure 1.1 The flow of problem in EDM process

1.3 Problem Statements

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

(i) What are the significant machining parameters that influence the machining performances during the EDM experimental process?

This study investigates an optimization problem in EDM machining process with multiple machining performances. The machining performances include material removal rate (MRR), surface roughness (Ra) and dimensional accuracy (DA). MRR is an indicator for productivity while Ra and DA are measuring of quality of products (Kumar and Agarwal, 2012). The study is expected to determine the best EDM parameters which could satisfy requirements of quality and productivity, respectively. Selection of optimal EDM parameters is very crucial as it is costly process to increase the production rate by reducing the machining time. Therefore, the desired results are able to obtain optimal EDM machining parameters, pulse on time, pulse of time, peak current and servo voltage. Conducting experimental design as the comprehensive investigation enables to estimate the significant EDM parameters that lead to the better machining performances.

(ii) How to design effective mathematical models for machining performances?

In machining process, a mathematical model is developed to relate the machining performance to the machining parameters purposely for prediction and optimization (Kumar and Agarwal, 2012). Optimization requires a fitness function in order to define the problem to be optimized under a set of constraints which represent the solution space. Therefore, the second problem related to the optimization is concerned with the designing in order develop effective mathematical model as an objective function for optimization process. The mathematical model is developed based on regression analysis method that depicts the relationships between the dependent variables (machining performance) and the independent variables (machining parameters) in a simplified mathematical form.

(iii) How effective is the proposed hybrid AF-GSO algorithm in estimating optimal EDM parameters that leads to the better machining performances?

The primary objectives in solving the optimization of machining parameters are reliability, accuracy of results and efficiency of computation. Therefore, the present study proposes a hybrid artificial fish swarm algorithm (AFSA) and glowworm swarm optimization (GSO) to solve weaknesses of the standard GSO algorithm as well as improving better results of EDM performances. AFSA was reported to be a good self-adaptive ability. It enables to estimate the global optimal value regarding to the higher convergence speed (Jiang et al., 2012). In order to benefit the global search optimum and higher convergence speed of AFSA, the searching behavior of AFSA is executed in GSO algorithm. Therefore, the step of searching behavior (preying) is performed in the glowworm decision range update phase in GSO algorithm.

1.4 Objectives of the Study

The objectives of the study are:

(i) To identify the significance EDM machining parameters that affecting the EDM machining performances by conducting the EDM experiment.
(ii) To develop the mathematical models for EDM machining performances.
(iii) To develop the hybrid artificial fish and glowworm swarm optimization (AF-GSO) algorithm for determining optimal machining parameters of EDM machining performances.

1.5 Scopes of the Study

The scopes of this study are:

(i) Machining process considered is die-sinking EDM machine, one of non-traditional machining processes.
(ii) Machining performances measured are material removal rate (MRR), surface roughness (Ra) and dimensional accuracy (DA).
(iii) Machining parameters considered are pulse on time (T_{ON}), pulse off time (T_{OFF}), peak current (I_P) and servo voltage (S_V).

(iv) Performances measurement used are optimal solution, computation (CPU) time and convergence rate.

1.6 Research Significance

This study consists of three modules, conducting the machining experimental, modeling process and optimization process. The machining experimental was conducted to investigate the significant EDM machining parameters. Regression modeling technique is used to model the experimental data. Furthermore, a new hybrid AF-GSO algorithm is proposed to improve EDM machining performances simultaneously to avoid from being trapped into local optima and slow convergence problems. This study significantly helps manufacturer in producing a good quality of product.

1.7 Contributions of the Study

This study conducts an EDM machining experimental and develops various machining mathematical models for machining performances. A new hybrid AF-GSO is proposed in order to estimate the optimal EDM machining parameter. A main contribution of the proposed hybrid AF-GSO is to solve the local optima and slow convergence problem in GSO algorithm for giving improved EDM machining performances. The hybrid AF-GSO gives a new contribution to machinist since there is no attempted made by researcher previously.

1.8 Thesis Organization

This thesis consists of eight chapters. Chapter 1 describes the overview, background of the study, problem statement, objective, scope of the study, research significance and contributions of the study. Chapter 2 presents the literature review of the study includes the experimental, modeling and optimization processes. Chapter 3 discussed about the research methodology that applied in this study. Chapter 4 discussed the EDM experimental design for identifying the significance of the EDM parameters. Chapter 5 discussed on the modeling process of the experimental data using regression analysis method and their analysis. Chapter 6 discussed on the development process of hybrid AF-GSO algorithm while Chapter 7 discussed on the implementation of GSO optimization and AF-GSO optimization includes their analysis of the results. Finally, Chapter 8 discussed the conclusion and recommendation for the future work of the research.

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