

ARTIFICIAL BEE COLONY IN OPTIMIZING PROCESS PARAMETERS OF
SURFACE ROUGHNESS IN END MILLING AND ABRASIVE WATERJET
MACHINING

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ABSTRACT

The machining operation can be generally classified into two types which are traditional machine and non-traditional (modern) machine. There are two types of machining employed in this research, end milling (traditional machining) and abrasive waterjet machining (non-traditional machining). Optimizing the process parameters is essential in order to provide a better quality and economics machining. This research develops an optimization algorithm using artificial bee colony (ABC) algorithm to optimize the process parameters that will lead to minimum surface roughness (R_a) value for both end milling and abrasive waterjet machining. In end milling, three process parameters that need to be optimized are the cutting speed, feed rate and radial rake angle. For abrasive waterjet, five process parameters that need to be optimized are the traverse speed, waterjet pressure, standoff distance, abrasive grit size and abrasive flow rate. These machining process parameters significantly impact on the cost, productivity and quality of machining parts. The ABC simulations are developed to achieve the minimum R_a value in both end milling and abrasive waterjet machining. The results obtained from the simulation are compared with experimental, regression modelling, Genetic Algorithm (GA) and Simulated Annealing (SA). In end milling, ABC reduced the R_a by 10% and 8% compared to experimental and regression. In abrasive waterjet, the performance was much better where the R_a value decreased by 28%, 42%, 2% and 0.9% compared to experimental, regression, GA and SA respectively.

ABSTRAK

Secara umumnya, operasi pemesinan boleh dikelaskan kepada dua jenis iaitu mesin tradisional dan mesin bukan tradisional (mesin moden). Terdapat dua jenis pemesinan yang digunakan dalam penyelidikan ini, mesin pengisaran hujung (pemesinan tradisional) dan mesin pelelas jet air (pemesinan bukan tradisional). Mengoptimumkan proses parameter adalah penting untuk menyediakan kualiti yang lebih baik dan ekonomi pemesinan. Penyelidikan ini membangunkan algoritma pengoptimuman menggunakan algoritma koloni lebah buatan (ABC) bagi kedua-dua mesin pengisaran hujung dan mesin pelelas jet air. Terdapat tiga parameter mesin pengisaran hujung yang perlu dioptimumkan iaitu kelajuan memotong, kadar suapan dan sudut meraih jejarian. Bagi mesin pelelas jet air terdapat lima parameter yang perlu dioptimumkan iaitu kelajuan traverse, tekanan jet air, jarak standoff, saiz kersik melelas dan kadar aliran yang melelas. Parameter pemesinan memberi kesan yang ketara ke atas kos, produktiviti dan kualiti bahagian-bahagian pemesinan. Simulasi ABC dibangunkan untuk mencapai nilai minimum R_a dalam kedua-dua mesin pengisaran hujung dan mesin pelelas jet air. Keputusan yang diperolehi daripada penyelidikan dibandingkan dengan eksperimen, pemodelan regresi, Algoritma Genetik (GA) dan simulasi penyepuhlindungan (SA). Dalam mesin pengisaran hujung, ABC mengurangkan R_a sebanyak 10% dan 8% berbanding dengan eksperimen dan regresi. Di mesin pelelas jet air, prestasi adalah lebih baik dimana nilai R_a menurun sebanyak 28%, 42%, 2% dan 0.9% berbanding dengan eksperimen, regresi, GA dan SA.

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LIST OF ABBREVIATIONS

| | | |
|------------------|---|------------------------------|
| ABC | - | Artificial Bee Colony |
| AI | - | Artificial Intelligence |
| ANN | - | Artificial Neural Network |
| AWJ | - | Abrasive Waterjet |
| BP | - | Backpropagation |
| DE | - | Differential Evolution |
| EA | - | Evolutionary Algorithm |
| GA | - | Genetic Algorithm |
| NFL | - | No Free Lunch |
| NN | - | Neural Network |
| PSO | - | Particle Swarm Optimization |
| RSM | - | Response Surface Methodology |
| SA | - | Simulated Annealing |
| SN _{TR} | - | Supernitride |
| TiAlN | - | Titanium Aluminum Nitrate |

LIST OF SYMBOLS

| | | |
|----------|---|--------------------|
| γ | - | Radial rake angle |
| d | - | Abrasive grit size |
| f | - | Feed rate |
| h | - | Standoff distance |
| m | - | Abrasive flow rate |
| P | - | Waterjet pressure |
| R_a | - | Surface Roughness |
| v | - | Cutting speed |
| V | - | Traverse speed |

CHAPTER 1

INTRODUCTION

1.1 Introduction

In highly competitive manufacturing industries nowadays, the manufacturer ultimate goals are to produce a high quality product with less cost and time constraints. Thus, the flexible manufacturing system (FMS) has been introduced since 1960 to achieve this goals by introducing the fully automation of computer numerically controlled (CNC) machine tools. The idea of FMS is to provide a fully automated machine that required a minimum supervision in 24 hours per day. In the traditional FMS, it consists of a huge number of CNC which handled by complex software and it is undeniable very costly. Nowadays, a smaller version of FMS is being used which is commonly refer as Flexible Manufacturing Cell (FMC) where it consists two or more CNC machines only. According to Mike *et al.* (1998), CNC machine tools require less operator input, provide greater improvements in productivity, and increase the quality of the machined part. Generally, the machining operations can be classified into two types which are traditional and non-traditional (modern). The traditional machining operations include turning, milling, boring, and grinding while non-traditional or modern machining operations include abrasive water jet machining, electron beam machining and photochemical machining.

According to Rao and Pawar (2009), the selection of machining process parameters is a very crucial part in order for the machine operations to be success. To choose the process parameters, it is usually based on the human (or manufacturing engineers) judgement and experience. However, the chosen of process parameters usually did not give an optimal result. This is due to in the machining processing; a number of factors also could interrupt thus preventing in achieving high process performance and quality (Bernados and Vosniakos, 2002). Figure 1.1 below showed the machining parameters that affect surface roughness, R_a . To improve this quality, one of the indications is by referring to the machining performances measures, R_a (Zain et al, 2010a). In manufacturing, the quality of the product focused on the surface texture particularly the R_a because it affects the product end results such as the appearance, function and reliability. There are many factors to produce a specific roughness such as in end milling where it depends on the cutting speed, feed rate, velocity of the traverse, cooling fluids and the mechanical properties of the piece being machined. Any small changes in one of these factors could affect the results of the surface produced.

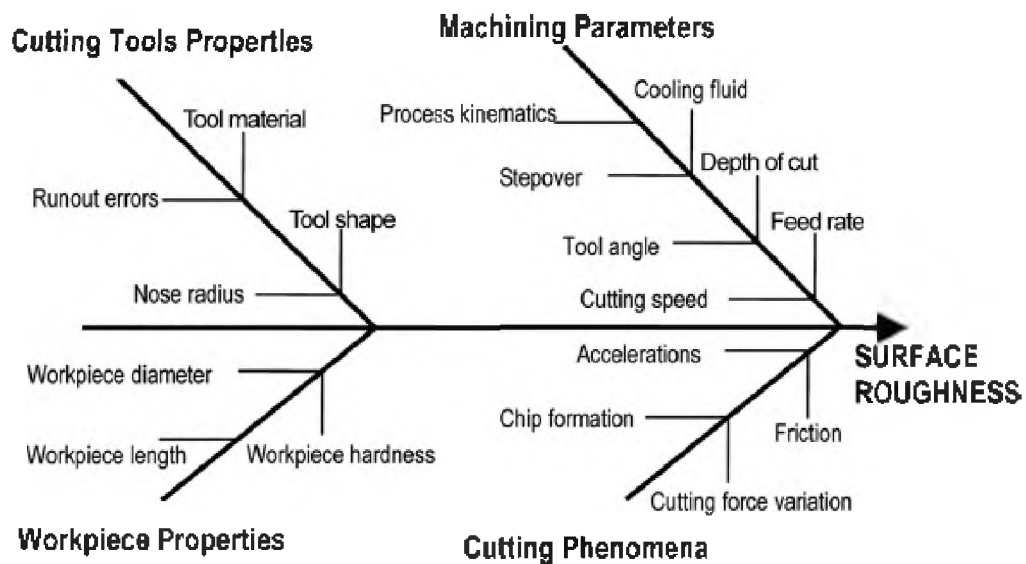


Figure 1.1 Parameters that affect R_a (Benardos and Vosnaikos, 2003)

Various techniques have been considered by a number of researchers to model and optimize machining problems. This technique includes statistical regression, conventional optimization technique such as Taguchi method, response

surface methodology (RSM) and iterative mathematical search technique. Other techniques such as Artificial neural network (ANN) and Fuzzy set-theory based modelling also have been applied. Apart from that, a number of researches also have been done using the concept of non conventional optimization technique such as genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), tabu search (TS) and ant colony optimization (ACO).

The study of insect and animal behaviour has attracted many researchers attention to better understand their colony and behaviour so that it could be modelled to solve complex problems in real world. Ant colony optimization (ACO) for example is one of the swarm intelligence techniques that were introduced by Dorigo et al. (1996) which were inspired by the foraging behaviour of ants. Similar to the concept of ACO, recently a new algorithm known as artificial bee colony (ABC) algorithm was introduced by Karboga in 2005. This algorithm mimics the intelligent behaviour of the honey bees swarm in foraging foods. ABC algorithm has been applied in many applications particularly in job scheduling, optimization and data clustering. A comparative study by Karaboga and Akay (2009) shows that standard ABC gives an excellent performance for optimizing a large set of numerical test unimodal function such as Sphere and Rosenbrock. It was found that ABC gave a better result in terms of local and global optimization due to the selection schemes employed and neighbouring production mechanism used. The results are then compared with other swarm optimization algorithms such PSO, differential evolution algorithm and evolution strategies. From the literature review, there is no research has been carried out so far to apply ABC optimization techniques for optimization of process parameters in end milling and abrasive waterjet (AWJ) machining. Recently, a research was carried out by Rao and Pawar (2009) to optimize the process parameter such as number of passes, depth of cut for each pass, speed and feed in a multi-pass milling machining operations using non-traditional optimization algorithms such as PSO, SA and ABC. The results showed that ABC and PSO produced a better solution compared to SA where the convergence rate is higher and the number of iterations is lowered.

1.2 Statement of problems

Based on the previous research by Zain et al. (2010a, 2010b, 2010c), it shows that the use of GA and SA give a promising result in minimizing R_a both in end milling and AWJ machining compared to the experimental and regression modelling. In Zain et al. (2010a, 2010b), GA and SA techniques were used to optimize the process parameters in end milling machining operation.

The results showed that GA and SA have given a much lower R_a value when compared to the experimental, regression model and response surface methodology (RSM) technique by 27%, 26% and 50%, respectively. In Zain et al. (2010c) the same optimization technique was used to optimize the process parameters in AWJ machining operations. The results show both techniques produced a minimum surface roughness value compared to experimental data and regression modelling. In this study ABC algorithm is considered in minimizing R_a for both end milling and AWJ machining. Consequently, the R_a of ABC is compared to R_a produced by experimental, regression modelling, GA optimization and SA optimization.

The research question can be stated as:

How efficient is the performance of ABC optimization to optimize process parameters for minimizing surface roughness in end milling and AWJ machining operations compared to experimental, regression modelling, GA optimization and SA optimization.

1.3 Objectives of the study

Based on the problem statements mentioned above, the objectives of the study are:

- i. To develop ABC based algorithm in optimizing surface roughness of machining process.
- ii. To estimate the optimal set of process parameters in end milling and AWJ for giving a minimum value of R_a .
- iii. To validate the proposed method with the existing techniques such as, experimental, regression modelling, GA optimization and SA optimization.

1.4 Scope of the study

The scopes of this study are:

- i. The experimental data sets are based on the experiment conducted by Mohrni (2008) for end milling machining operations and Caydas and Hascalik (2008) for AWJ machining operations.
- ii. The optimization approach method used is ABC algorithm.
- iii. The performance and results are compared with experimental, regression modelling, GA optimization and SA optimization.

1.5 Significance of the study

This study is to investigate the performance of ABC algorithm in optimizing process parameters for minimizing R_a in both end milling and AWJ machining operations. To indicate the effectiveness of this computational approach, the end results which are the R_a values will be compared with experimental, regression modelling, GA optimization and SA optimization. From the literature review, there is no effort taken so far by researchers to apply ABC algorithm for the machining optimization problems both in end milling and AWJ machining operation. So, it can be concluded that this study gives a new contribution in the area of machining.

1.6 Organization of the thesis

This thesis consists of six chapters. Chapter 1 describes the introduction to the research, problem background, problem statement, objective and scope of the study. Chapter 2 presents the literature review of the study. Chapter 3 discussed about the research methodology that applied in this study. Chapter 4 discussed the implementation of ABC optimization while Chapter 5 discussed the analysis of the results of ABC optimization. Finally, Chapter 6 discussed the conclusion and recommended the future work of the research.