AN ENHANCEMENT OF INTEGRATED FUZZY-TOPSIS TO IMPROVE MACHINING SURFACE ROUGHNESS

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"***This thesis is special dedicated to my lovely family and wife for their endless love, support and encouragement***"

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ABSTRACT

Machining is defined as a process to remove material in the form of chips using single or multiple wedge-shaped cutting tools to produce the desired shape. This process has successfully produced a closer dimensional accuracy and surface finish to meet the industrial demands. However, it is difficult to find the optimal machining parameter values that yield the minimum surface roughness (R_a) values to meet technical specifications for end milling and laser assisted machining (LAM). Thus, this research proposed the integration of Fuzzy Logic (FL) and Technique for Order Preference by Similarity to Ideal Situation (TOPSIS) to predict minimum R_a values and find the optimal machining parameters. In the proposed Fuzzy-TOPSIS model, initially FL is used to consider correct membership functions, linguistic terms and rules. Then, TOPSIS uses the weighted values obtained to handle instabilities in FL with advanced inference methods and rank the FL results by applying the obtained fuzzy intervals. The integration of Fuzzy-TOPSIS model has successfully reduced R_a values by 0.066µm for end milling and 0.112µm for LAM. Upon achieving the minimum values, a precise combination of optimal machining parameters can be obtained. These results reveal that the Fuzzy-TOPSIS model is capable of improving the quality of finished products during machining processes.

ABSTRAK

Pemesinan ditakrifkan sebagai satu proses untuk membuang bahan dalam bentuk cip menggunakan alat pemotong tunggal atau baji berbilang untuk menghasilkan bentuk yang dikehendaki. Proses ini telah berjaya menghasilkan ketepatan dimensi dengan lebih hampir dan kemasan permukaan bagi memenuhi permintaan industri. Walau bagaimanapun, ia adalah sukar untuk mencari nilai-nilai parameter pemesinan yang optimum bagi menghasilkan nilai-nilai minimum kekasaran permukaan (R_a) bagi memenuhi spesifikasi teknikal untuk pengisaran hujung dan pemesinan alur laser (LAM). Oleh itu, kajian ini mencadangkan integrasi antara Logik Kabur (FL) dan Teknik Keutamaan Persamaan Situasi Ideal (TOPSIS) untuk meramalkan nilai-nilai minimum R_a dan mencari parameter pemesinan yang optimum. Dalam model Fuzzy-TOPSIS yang dicadangkan ini, pada mulanya FL digunakan untuk mempertimbangkan fungsi keahlian yang betul, istilah linguistik dan peraturan. Kemudian, TOPSIS menggunakan nilai-nilai pemberat yang diperolehi untuk mengendalikan ketidakstabilan dalam FL dengan kaedah inferens maju dan menyusun keputusan FL dengan menggunakan selang kabur yang telah diperolehi. Integrasi model Fuzzy-TOPSIS telah berjaya mengurangkan nilai-nilai R_a sebanyak 0.066μm untuk pengisaran hujung dan 0.112μm untuk LAM. Setelah nilai minimum dicapai, ketepatan kombinasi parameter pemesinan yang optimum boleh diperolehi. Keputusan ini menunjukkan bahawa model Fuzzy-TOPSIS mampu meningkatkan kualiti produk siap semasa proses pemesinan.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
FL	Fuzzy Logic
TOPSIS	Technique for Order Preferences by Similarity to Ideal Situation
LAM	Laser Assisted Machining
MCDM	Multi-Criteria Decision Making
AHP	Analytical Hierarchy Process
SN_{TR}	Super Nitride Coating
TiAlN	Titanium Aluminium Nitrate

LIST OF SYMBOLS

N	Number of Sample Data
r	Correlation value
R_a	Surface Roughness
v	Cutting speed
f	Feed rate
γ	Radial rake angle

CHAPTER 1

INTRODUCTION

1.1 Background of study

In manufacturing, two main problems that engineers face in machining processes: First is to determine the machining parameters value that will produce the desired product quality and second is to maximize the capabilities of manufacturing performance using the existing resources (Benardos and Vosniakos 2003). Machining defined as a process to remove metal in the form of chips using single or multiple wedge-shaped cutting tools to produce the desired shape. There are two types of machining process namely conventional and modern machining processes. Machining process represented as a mathematical process in optimizing the process. The representation called as modeling.

Artificial Intelligence (AI) is the science and engineering of making intelligent computer programs, which related to the similar task of using computers to understand human intelligence. AI has produced a number of powerful tools, which are practical use in engineering to solve complex problems normally requiring human intelligence. AI consists of many branches, which are expert system (ES), Genetic algorithm (GA), fuzzy logic (FL), Artificial Neural Network (ANN), Simulated Annealing (SA), Ant colony optimization (ACO), Particle swarm optimization (PSO) and various hybrid systems. The prediction resulted from the AI approaches are more accurate than the non-AI ones (Tarng and Hwang 1995). In fact, nowadays AI powerful tools are extensively used to model and control of machining processes (Markos et al. 1993). A review by Abellan-Nebot and Subiron (2010) showed the details of AI techniques in the machining monitoring system. Application of AI for predicting machining performance been reported by several studies previously. AI has been widely used by previous researchers successfully in atmospheric phenomenon, engineering, economics, military, medicine and marine. FL considered for prediction, selection, monitoring, control and optimization of machining process.

Modeling has been a research issue for decades ago. In the modeling, many techniques have been applies from conventional mathematical modeling until the AI techniques. Modeling processes in predicting the optimal solutions with a minimum value of machining performance can generally classified into two methods, which are conventional and computational techniques. Conventional technique such as regression, explicit models are developed required complex physical understanding of the modeling process while computational technique such as FL is created based on the rules that is easier to be implemented.

1.2 Problem Statement

Prediction is very important in the application of the end milling and laser assisted machining process in order to produce the desired product. The desired product quality can be obtained and improved by predict the machining performance before the actual process begins. In machining process, the machining performance is an indicator to describe the quality of the manufactured product. The important factor of milling and laser assisted machining process in evaluating the quality of products is surface finish; where surface roughness (R_a) is used as indicator to determine the surface finish (Zain et al., 2010). The desired product quality might increase once the R_a value is decrease. SCHUNK is a medium-sized family company, a technology leader of choice and a global player all in one founded since 1945. Its global market leader in tool holding and work holding technology and is one of the most innovative automation providers. Based on the SCHUNK report, surface roughness problems might give the three reasons, which are:-

i. On polished, surfaces exists more contact points between the contact partners. Therefore the friction coefficient is slightly higher, the mechanical losses and the surface temperature are increased.
ii. On smooth, polished, moving surfaces, the so called "stick-slip" effect can have much more dramatic consequences. This is a change of static friction and sliding friction. It is easy to imitate this phenomenon, by trying to slide a hand over a smooth glass surface. On moving surfaces, this effect creates vibrations with high frequencies but low amplitudes.
iii. On rings which are polished and bright the graphite, one of the essential constituents of the skin, is poorly a braded from the brush or, if it is deposited on the metal at all, fails to adhere firmly. In a long-term run, this may result in ring attack.

Therefore, an effort has been taken into consideration to overcome the surface roughness problem by applying computational approach to obtain the minimum machining performance values rather than doing trial and error real experiments. Based on the previous researcher by Zain et al. (2010) it shows that the use of ANN gives a promising result in minimizing R_a in end milling compared to the experimental and regression modeling. In this study, FL model is developed in order to predict the machining performance in end milling and laser assisted machining processes. Therefore, the research question stated as:

How to predict the possible machining parameters values in compromising giving the minimum value of machining performance in end milling and laser assisted machining processes?

The discussion on FL as AI techniques to predict machining performance shows that the fuzzy components have contributed most in the prediction. Nevertheless, it must be investigated the ability and limitation of FL as discussed in

Chapter 2. Therefore, an enhancement of FL model with TOPSIS technique will be developed and compared with the real experimental results. TOPSIS technique has been chosen as one of the best grading methods of multi criteria decision making (MCDM) that is taken place in compromising subgroup of compensating models of decision making (Asgharpour 1999). Fuzzy is one of the various models of MCDM with fuzzy values (Ali et. al 2011). Due to characteristics of fuzzy numbers algebraic used such as multiple and division, scientists have tried to expand TOPSIS to Fuzzy-TOPSIS to solve the decision-making problem. Therefore, the research question stated as:

How to enhance the fuzzy logic model in order to predict the minimum value of machining performance in end milling and laser assisted machining process?

This research is dedicate to the extension of the small data sets on prediction of laser-assisted quality by employing FL and TOPSIS, which has been conducted by Chang and Kuo (2007). The integration of Fuzzy-TOPSIS has been implemented and compared with real experimental results. In end milling and laser assisted machining data sets; it contains setting of the combination numbers for producing minimum machining performance. Therefore, the integration between FL and TOPSIS proved the efficiency of the proposed integrated Fuzzy-TOPSIS model to predict the minimum machining performance with the accurate combination numbers located in datasets. Based on this statement, the research question stated as:

How efficient the performance of integrated Fuzzy-TOPSIS model to predict minimum value machining performance in end milling and laser assisted machining processes compared to real experimental results?

1.3 Objectives

The objectives of this study given as follows:

(i) To develop fuzzy logic model for predicting the minimum surface roughness values.

(ii) To develop an enhancement integrated Fuzzy-TOPSIS model for predicting the minimum surface roughness values.

(iii) To assess the capability of the proposed integration model for estimating surface roughness values of the end milling and laser assisted machining processes.

1.4 Scopes

The scopes of this research are:

(i) This study considers two machining processes; End milling and Laser Assisted Machining (LAM).

(ii) The experimental data sets based on the experiment conducted by Mohruni (2008) for End milling machining process while Chang and Kuo (2007) in the LAM process.

(iii) Surface roughness, R_a is machining performance to be minimized for End milling and LAM process.

(iv) Machining parameters of End milling process are Cutting Speed, Feed Rate, and Radial Rake Angle while Depth of Cut, Rotational speed, Feed and Pulsed Frequency are considered for LAM.

(v) The results obtained by proposed FL and Integrated Fuzzy-TOPSIS prediction models are compared with the real experimental results conducted by Mohruni (2008) and Chang and Kuo (2007).

1.5 Significance of the study

This study is to investigate the performance of FL and integrated Fuzzy-TOPSIS in modeling machining parameters for minimizing machining performance in both end milling and laser assisted machining process. To indicate the effectiveness of this computational approach, the proposed methods results compared with the real experimental results. From the literature review, there is no effort taken so far by researchers to apply integrated Fuzzy-TOPSIS for the machining prediction problems both in end milling and LAM process. So, it can be concluded that this study gives significance study in this domain area of machining.

1.6 Contributions of the study

Several process parameters such as cutting speed, feed rate, and radial rake angle considered as the case study in the end milling process since their lack of exposure by other researchers with three combinations of these process parameters in order to predict R_a values. Based on Benardos and Vosnaikos (2003), cutting speed, feed rate, and depth of cut are machining parameters that mostly affected the R_a values especially in the end milling machining process. The integrated of Fuzzy-TOPSIS has given a better prediction accuracy compared to FL model that contributed a better quality of machined-work piece. The minimum predicted machining performance in end milling and LAM shows the accurate combinations of machining parameters. This contributes to a new knowledge of prediction machining process.

The small size of datasets is not the main issue of proposed model in obtaining a good prediction. FL and integrated Fuzzy-TOPSIS are still capable in generating accurate predicted value of surface roughness using a small number of datasets; end milling 24 datasets and LAM 9 datasets. The integrated Fuzzy-TOPSIS has not discussed yet in any domain machining area especially in end milling and LAM processes, therefore, it stated as the contribution of the computational AI study.

1.7 Summary

This chapter has clearly defined related to the idea of research implementation. The background of the study, problem statements, objectives, scopes, significance and contribution of the study has been exposed. In order to solve the problems of this study, literature review is discussed in the next chapter.

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