HYBRID GREY RELATIONAL ANALYSIS-SUPPORT VECTOR MACHINE (GR-SVM) IN PREDICTING MACHINING SURFACE ROUGHNESS

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"This thesis is special dedicated to my dear parents and lovely siblings for their endless love, support and courage

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ABSTRACT

Machining process is defined as a process of material removal from a work piece in the form of chips. This process has improved significantly over the years to meet the field requirements. However, a major issue in the process is how to obtain accurate results of the machining performance measurement value at optimal point of cutting conditions. Machining performance for surface roughness has been widely discussed by researchers but determining the optimal solution for surface roughness remains as one of the most challenging problem due to the complexity of the modeling process. Thus, this research proposed a hybrid model combining Grey Relational Analysis (GRA) and Support Vector Machine (SVM) to predict surface roughness values for end milling and abrasive water jet (AWJ) machining processes. In the proposed hybrid Grey Relational-Support Vector Machine (GR-SVM) prediction model, GRA acts as a feature selection method in pre-processing process to eliminate irrelevant factors and SVM solves the regression functions in machining problems to determine the surface roughness value. Efficiency of the proposed prediction model was demonstrated by comparing the results of the hybrid model with the experimental data and results of conventional SVM prediction model based on correlation and Root Mean Square Error (RMSE) values. The results showed that the hybrid GR-SVM prediction model presented the most accurate results due to its ability to remove redundant features and irrelevant elements from the experimental datasets. These results have shown that the optimal solution of machining performance can be achieved by using the proposed hybrid GR-SVM prediction model.

ABSTRAK

Process pemesinan ditakrifkan sebagai satu proses pembuangan bahan daripada bahan kerja dalam bentuk cip. Proses ini telah berkembang dengan pesat sejak beberapa tahun untuk memenuhi bidang keperluan. Walau bagaimanapun isu utama dalam proses ini ialah kaedah untuk mendapatkan keputusan yang tepat bagi nilai pengukuran prestasi pemesinan pada titik optimum syarat pemotongan. Prestasi pemesinan untuk kekasaran permukaan telah dibincangkan dengan meluas oleh para penyelidik tetapi menentukan penyelesaian optimum untuk kekasaran permukaan kekal sebagai salah satu masalah yang paling mencabar kerana kerumitan proses model. Oleh itu kajian ini mencadangkan satu model hibrid yang menggabungkan Analisis Hubungan Grey (GRA) dengan Sokongan Mesin Vektor (SVM) untuk meramalkan nilai kekasaran permukaan bagi proses pemesinan pengisaran hujung dan pelelas jet air (AWJ). Dalam model ramalan hibrid Hubungan Grey-Sokongan Mesin Vektor (GR-SVM), GRA bertindak sebagai kaedah pemilihan ciri dalam proses pra-pemprosesan untuk menghapuskan faktor-faktor tidak relevan sementara SVM pula menyelesaikan fungsi regresi dalam masalah pemesinan untuk menentukan nilai kekasaran permukaan. Kecekapan model ramalan yang dicadangkan ditunjukkan dengan membandingkan keputusan model hibrid dengan data eksperimen dan keputusan model ramalan SVM konvensional berdasarkan nilai-nilai korelasi dan punca kuasa ralat kuasa dua (RMSE). Hasil kajian menunjukkan bahawa model ramalan hibrid GR-SVM memberikan keputusan yang paling tepat kerana kemampuannya untuk menghapuskan ciri-ciri berlebihan dan unsur-unsur yang tidak relevan daripada set data eksperimen. Keputusan ini menunjukkan bahawa penyelesaian prestasi pemesinan yang optimum dapat dicapai dengan menggunakan cadangan model ramalan hibrid GR-SVM.

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LIST OF ABBREVIATIONS

AIS	Artificial Immune System
ANFIS	Adaptive-Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
AWJ	Abrasive Water Jet
EBM	Electric Beam Machining
ECM	Electrochemical Machining
FL	Fuzzy Logic
GRA	Grey Relational Analysis
GR-SVM	Grey Relational- Support Vector Machine
LSE	Least Square Error
PCM	Photochemical Machining
RBF	Radial Basis Function
SN_{TR}	Super Nitride Coating
SRM	Structural Risk Minimization
SVM	Support Vector Machine
TiAlN	Coated Carbide Tools

LIST OF SYMBOLS

N	Number of Sample Data
r	Correlation value
R_a	Surface Roughness
Al	Aluminum
Cu	Copper
Mg	Magnesium
Cr	Chromium
Zn	Zink
Mn	Manganese

CHAPTER 1

INTRODUCTION

This chapter discusses the brief overview about the research conducted in this study. The topic includes background of the study, problem statement, objectives and scopes of the study. Research significant and contributions of the study are also discussed in this chapter.

1.1 Background of the study

As the demands of consumer economy grows rapidly, machining recently be the most important and widely used in manufacturing process instead of forming, molding, and casting processes. Generally, machining can be defined as a process of material removal from a workpiece in the form of chips. In the recent years, machining technology has been improved significantly to meet the requirements in different fields. Basically, there are two types of machining process, namely conventional machining and modern machining (Zain et al., 2011a). Conventional machining consists of traditional process work piece removal in the form of chips such as turning, milling, grinding and boring while modern machining comes in terms of chemical items or advanced technologies such as abrasive water jet (AWJ), electrochemical machining (ECM), electric beam machining (EBM) and photochemical machining (PCM).

The need of modern machining or unconventional machining was firstly emphasized by Merchant in 1960 for the development of newer concepts in machining process (Panday and Shan, 1980). Due to the new advent technologies that thrive nowadays, the machining process continuously evolve from time to time as researcher have found and developed many new techniques and modern tool of machining. There are two fields that have been interest for researches in machining, which are modeling and optimization. According to Zain et al. (2011a), modeling in machining refers to the process of estimating the potential minimum or maximum value of machining performance while optimization refers to the process of estimating optimal solution of cutting condition that leads to the minimum or maximum machining value of machining performances. Various techniques were considered and carried out to model and optimize the machining performances. This study only focuses on modeling of machining performance. The primary purpose of the machining modeling is to estimate the minimum values (such as surface roughness, operation time, operation cost etc.) or maximum values (such as material removal rate, tool wear etc.) of machining performance measurements.

It has been recognized that cutting force, power, torque, surface roughness, tool-wear, chip form, chip breakability, tool-life, surface integrity and part accuracy are the most common machining performances that evaluated by major measure (Jawahir et al., 2003). According to Yusup et al. (2012), surface roughness is the most machining performance that has been considered by the researchers for the past five years (2007-2011), due to the facts that surface roughness affects several functional attributes of the machining process (Wang, 2009). Practically, surface roughness plays an important role in wear resistance, tensile, ductility, and fatigue strength for machine parts (Wang and Chang, 2004). According to Caydas and Hascalik (2008), surface roughness is a technological quality measurement of a product and a factor that considerably affects the manufacturing cost. Consequently, modeling of surface roughness, which is the process of predicting the minimum value of surface roughness, is a crucial part in machining process in order to meet the field requirements.

Due to the uncertainty and complexity in modeling of surface roughness in machining process, computational approaches are being preferred apply by the researchers (Jawahir et al., 2003). Computational approaches have become a most potential research area and received a great deal of attention to the researchers to develop a model for giving an improved value of surface roughness measurement. It became exaggerate from time to time since it gave a best result to the researchers. According to Zain et al., (2011a), single-based computational approaches were managed to estimate the optimal process parameters, leading to the minimum value of surface roughness. Computational approaches include fuzzy logic (FL), artificial neural network (ANN), genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), simulated annealing (SA), Artificial Intelligent System (AIS), Grey Relational Analysis (GRA), and support vector machine (SVM). Moreover, the evolutionary of modern technology has lead to the new approaches in modeling of machining performances.

The evolutionary of computational approach has become an important problem solving methodology among researchers to improve the machining performances (Grosan and Abraham, 2007). This approach includes the hybridization process of single-based computational approach in order to get better performance in machining modeling. This study considers the hybridization of SVM and GRA, in estimating a better result for prediction of surface roughness value. Based on the literature, an attempt of hybridization of SVM and GRA has been made in predicting consumption of spare parts (Huang et al., 2010) and also agriculture field (Shi, 2012). For the predicting of spare parts consumption, the influencing factors were selected by grey relational analysis and SVM regression was used as the prediction model of the spare parts consumption for the military aircrafts and for agriculture field, the production of China grain was predicted using the hybridization of SVM and GRA. Both prediction results show that the hybrid SVM and GRA gave high prediction performance with a small number of prediction errors.

However, there is still no attempt of hybridization SVM and GRA in machining area. Thus, this study, which is modeling of surface roughness, is considered as a new contribution to the machining field.

1.2 Problem Statement

The success of machining process depends on the proper selection of cutting condition based on cost and quality factors. The major issue in machining process is how to obtain accurate result of machining performances, such as surface roughness values using various machining factors of cutting operations. Furthermore, the need for estimating the best machining performances with the most suitable cutting tools has been felt over the last few decades. These machining performances should be selected to optimize the economics of machining operations. For instance, selection of cutting condition of surface roughness in machining process still remains as one of the most challenging problems due to the complexity of the process. Traditionally, the selection of cutting condition in machining process is left to the machine operator. However, this process mostly depends on the machinist expertise and also gives a high cost. Moreover, in machining process, the cutting process was done continuously in order to get the target value despite the material can be used only once. So, this process will give highly cost with a lot of the wasted material used. In such cases, machinist experience plays a major rule but sometimes it is difficult to maintain the optimum values for each experiment (Aggawal and Singh, 2005).

With the help of computational approaches in predicting machining performances, there is no machinist expertise will be used and the machining cost can be reduced. Hence, this study promotes the use of SVM computational approach in estimating surface roughness value of machining process. SVM becomes a new trend in recent research especially in modeling of machining performances, which is a relatively new computational learning method constructed based on the statistical learning theory classifier (Chiu and Guao, 2008). SVM has widely been used in modeling of various fields such as financial (Tay and Coa, 2001; Pai and Lin, 2005;

Min et al., 2006), health (Furey et al., 2000; Cai et al., 2001; Akay, 2009), and agriculture. Based on the structural risk minimization (SRM) principal, SVM can get decision-making rules and achieve small error for independent tests set and hence can solve the learning problems efficiently (Samantha et al., 2003).

However, in some cases, the data in machining model may contain irrelevance and redundant feature that is used as input features in development of SVM model. This kind of data not only increased the training time, but it may lead to the overfitting problem that reduces the prediction performance. This irrelevance and redundant data also need to be eliminated from the input features in order to get a better prediction model. Conventional SVM approach does not have the ability to recognize this irrelevant element. So, there is a need of the model that is able to remove the unwanted data in order to improve the model performance. As a result, this research promotes the hybridization approach, hybrid GR-SVM, to estimate the minimum values of surface roughness so that the machining target can be achieved. GR-SVM is a hybridization model of SVM computational approach and also GRA approach. GRA is basically an analysis technique that has been proposed in Grey System Theory by Professor Deng Julong (Xuerui and Yuguang, 2004). GRA acts as feature selection approach which is able to selects a subset of relevant features, and also removes redundant and irrelevant features from the data to build robust learning models.

In relation to the machining problem discussed above, three research question of this study are:

i. How to predict potential values of the machining performances for giving a possible value of minimum surface roughness?
ii. How to modify the existing single-based computational approach model in order to give better results of surface roughness?
iii. How to identify the effectiveness of proposed hybridization model?

1.3 Aim of the research

The aim of the research is to identify the minimum value of surface roughness in end milling and AWJ machining processes using the proposed hybrid GR-SVM model.

1.4 Objectives of the research

The objectives of this study are:

i. To develop conventional SVM model in predicting the minimum value of surface roughness.
ii. To develop a new hybridization GR-SVM model for predicting minimum surface roughness value.
iii. To evaluate and validate the performance of the proposed hybrid model in predicting minimum surface roughness value.

1.5 Scope of the research

The scopes of the study are:

i. Two machining process, end-milling (conventional machining) and AWJ (modern machining) are considered.
ii. The machining performance considered for both end-milling and AWJ is surface roughness (R_a).
iii. Process parameters of end-milling are cutting speed (v), feed rate (f), and radial rake angle (γ).

iv. Process parameters of AWJ are traverse speed (*V*), waterjet pressure (*P*), standoff distance (*h*), abrasive grit size (*d*), and abrasive flow rate (*m*).
v. Experimental data of end-milling conducted by Mohruni (2008).
vi. Experimental data of AWJ conducted by Caydas and Hascalik (2008).

1.6 Research significant

This study is to develop and analyze the performance of proposed GR-SVM model, which is a hybridization of SVM and GRA approach in prediction of machining surface roughness value. In order to indicate the effectiveness of the proposed model, the final results are compared with the conventional SVM prediction model. With the development of proposed hybrid GR-SVM model, there is no expertise or machinist will be used in order to find the minimum surface roughness value hence the cost of the machining process can be reduced.

1.7 Contributions of the study

The contributions of this study can be divided into two parts, they are:

i. Improvement of conventional SVM model. The proposed hybrid GR-SVM model has potential to estimate the influential factors of process parameters to the surface roughness value. The influential factors of process parameters are ranked based on Grey Relational Grade (GRG) value obtained. Process parameter with the high GRG value is considered to give a high effect to surface roughness value.
ii. Better quality of machined-work piece. The proposed hybrid model is expected to improve the prediction accuracy that leads to much minimum value of surface roughness.

1.8 Summary

This chapter discussed several topics related to the idea of research implementation. Research background, problem statements, aims, objectives and scopes were precisely mentioned in this chapter. The contributions of the study also were highlighted.

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