MODELING OF MILLING PROCESS TO PREDICT SURFACE ROUGHNESS USING ARTIFICIAL INTELLIGENT METHOD

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Thesis submitted in fulfillment of the requirements
for the award of the degree of
Bachelor of Mechanical Engineering with Manufacturing Engineering

Faculty of Mechanical Engineering
UNIVERSITI MALAYSIA PAHANG

NOVEMBER 2009

SUPERVISOR'S DECLARATION

I hereby declare that I have checked this project and in my opinion, this project is adequate in terms of scope and quality for the award of the degree of Bachelor of Mechanical Engineering with Manufacturing Engineering.

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STUDENT’S DECLARATION

I hereby declare that the work in this project is my own except for quotations and summaries which have been duly acknowledged. The project has not been accepted for any degree and is not concurrently submitted for award of other degree.

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Dedicated to my little sister

ACKNOWLEDGEMENTS

I am grateful and would like to express my sincere gratitude to my supervisor Mr Mohd Fadzil Faisae Ab Rashid for his invaluable guidance, continuous encouragement and constant support in making this research possible. I really appreciate his guidance from the initial to the final level that enabled me to develop an understanding of this research thoroughly. Without his advice and assistance it would be a lot tougher to completion. I also sincerely thanks for the time spent proofreading and correcting my mistakes.

I also would like to express very special thanks to Dr. Kumaran Kadirgama for his suggestions and co-operation especially in artificial intelligent study. A special appreciation should be given to Dr. Ahmed N. Abdella from Electrical Engineering Faculty whom which gave me a brand new perception about artificial intelligent study.

My sincere thanks go to all lecturers and members of the staff of the Mechanical Engineering Department, UMP, who helped me in many ways and made my education journey at UMP pleasant and unforgettable. Many thanks go to M04 member group for their excellent co-operation, inspirations and supports during this study. This four year experience with all you guys will be remembered as important memory for me to face the new chapter of life as an engineer.

I acknowledge my sincere indebtedness and gratitude to my parents for their love, dream and sacrifice throughout my life. I am really thankful for their sacrifice, patience, and understanding that were inevitable to make this work possible. Their sacrifice had inspired me from the day I learned how to read and write until what I have become now. I cannot find the appropriate words that could properly describe my appreciation for their devotion, support and faith in my ability to achieve my dreams.

Lastly I would like to thanks any person which contributes to my final year project directly on indirectly. I would like to acknowledge their comments and suggestions, which was crucial for the successful completion of this study.

ABSTRACT

This thesis presents the milling process modeling to predict surface roughness. Proper setting of cutting parameter is important to obtain better surface roughness. Unfortunately, conventional try and error method is time consuming as well as high cost. The purpose for this research is to develop mathematical model using multiple regression and artificial neural network model for artificial intelligent method. Spindle speed, feed rate, and depth of cut have been chosen as predictors in order to predict surface roughness. 27 samples were run by using FANUC CNC Milling α-T14E. The experiment is executed by using full-factorial design. Analysis of variances shows that the most significant parameter is feed rate followed by spindle speed and lastly depth of cut. After the predicted surface roughness has been obtained by using both methods, average percentage error is calculated. The mathematical model developed by using multiple regression method shows the accuracy of 86.7% which is reliable to be used in surface roughness prediction. On the other hand, artificial neural network technique shows the accuracy of 93.58% which is feasible and applicable in prediction of surface roughness. The result from this research is useful to be implemented in industry to reduce time and cost in surface roughness prediction.

ABSTRAK

Thesis ini membentangkan pembentukan persamaan dalam proses penggilingan untuk meramalkan kekasaran permukaan. Parameter untuk pemotongan yang sesuai adalah sangat penting untuk mendapatkan kekasaran permukaan yang lebih baik. Namun yang demikian, teknik konvensional cuba jaya adalah memakan masa dan kosnya adalah tinggi. Kajian ini dijalankan adalah untuk menerbitkan persamaan matematik menggunakan kaedah regresi berganda dan rangkaian saraf buatan. Kelajuan pemusing, kadar pemotongan dan kedalaman pemotongan telah dipilih untuk digunakan sebagai peramal kekasaran permukaan. 27 sampel telah diuji menggunakan mesin FANUC CNC Milling α-T14E. Kesemua eksperimen telah dijalankan menggunakan rekabentuk faktor penuh. Analisis varians menunjukkan kadar pemotongan adalah parameter yang paling mempengaruhi kekasaran permukaan diikuti dengan kelajuan pemusing dan akhir sekali adalah kedalaman pemotongan. Selepas semua nilai ramalan kekasaran permukaan bagi kedua-dua teknik telah didapatkan, purata peratusan ketidaktepatan telah dikira. Persamaan matematik yang dibangunkan menggunakan teknik regresi berganda menunjukkan ketepatan sebanyak 86.7 %. Ini menunjukkan bahawa teknik ini boleh dipercayai dalam meramalkan kekasaran permukaan. Selain daripada itu, teknik rangkaian saraf buatan menunjukkan ketepatan sebanyak 93.58% iaitu sangat baik dan boleh diguna pakai dalam meramalkan kekasaran permukaan. Keputusan dalan kajian ini sangat berguna untuk diimplimentasikan di dalam industri untuk mengurangkan masa dan kos dalam meramalkan kekasaran permukaan.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

β	Coefficient of regression
Σ	Sum
i	Number of output nodes
m	Number of input nodes/Number of samples
n	Number of hidden nodes
θ	Threshold
Ø	Percentage error
Ra	Surface roughness
u	Input node values
v	Hidden node values
ω	Synaptic/Weight
Y	Actual surface roughness
$\hat{Y}$	Predicted surface roughness

LIST OF ABBREVIATIONS

Adj SS	Adjusted Sum of Squares
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
ANSE	Association of National Organisations for Supervision in Europe
ASME	American Society of Mechanical Engineers
CCDS	Cylindrical Capacitive Displacement Sensor
d.f	Degree of Freedom
FUFE	Full-Factorial
GA	Genetic Algorithm
GEP	Gene Expression Programming
GPA	Grade Point Average
M-ISRR	Multilevel In-process Surface Roughness Recognition
MRA	Multiple Regression Analysis
MS	Mean Square Error
PSO	Particle Swarm Optimization
R	Coefficient of Determination
SS	Sum of Squares

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

This chapter is discussed about the project background, the problem of the project, the objectives of the project and project scope.

1.2 PROJECT BACKGROUND

The challenge of modern machining industries is mainly focused on the achievement of high quality, in term of work piece dimensional accuracy, surface finish, high production rate, less wear on the cutting tools, economy of machining in terms of cost saving and increase of the performance of the product with reduced environmental impact. End milling is a very commonly used machining process in industry. The ability to control the process for better quality of the final product is paramount importance.

Surface texture is concerned with the geometric irregularities of the surface of a solid material which is defined in terms of surface roughness, waviness, lay and flaws. Surface roughness consists of the fine irregularities of the surface texture, including feed marks generated by the machining process. The quality of a surface is significantly important factor in evaluating the productivity of machine tool and machined parts.

The surface roughness of machined parts is a significant design specification that is known to have considerable influence on properties such as wear resistance and fatigue strength. It is one of the most important measures in finishing cutting operations. Consequently, it is important to achieve a consistent tolerance and surface finish (Godfrey C. Onwubolu., 2005).

The case study for this project is focused on modeling milling process to predict surface roughness by using AI method.

1.3 PROBLEM STATEMENT

In manufacturing industries, manufacturers focused on the quality and productivity of the product. To increase the productivity of the product, computer numerically machine tools have been implemented during the past decades. Surface roughness is one of the most important parameters to determine the quality of product. The mechanism behind the formation of surface roughness is very dynamic, complicated, and process dependent. Several factors will influence the final surface roughness in a CNC milling operations such as controllable factors (spindle speed, feed rate and depth of cut) and uncontrollable factors (tool geometry and material properties of both tool and workiepce). Some of the machine operator using 'trial and error' method to set-up milling machine cutting conditions (Julie Z.Zhang et al., 2006). This method is not effective and efficient and the achievement of a desirable value is a repetitive and empirical process that can be very time consuming.

Thus, a mathematical model using statistical method provides a better solution. Multiple regression analysis is suitable to find the best combination of independent variables which is spindle speed, feed rate, and the depth of cut in order to achieve desired surface roughness. Unfortunately, multiple regression model is obtained from a statistical analysis which is have to collect large sample of data. Realizing that matter, Artificial Neural Network is state of the art artificial intelligent method that has possibility to enhance the prediction of surface roughness.

1.4 OBJECTIVES

The objectives of this project are:

i. To develop mathematical model to predict surface roughness in milling process.
ii. To predict surface roughness using Artificial Neural Network.
iii. To compare the accuracy from both approaches.

1.5 PROJECT SCOPES

To achieve the project objectives, multiple regression analysis is used for statistical method and Artificial Neural Network is used as artificial intelligent method. The workpiece tested is 6061 Aluminum 400mmx100mmx50mm. The end-milling and fourflute high speed steel is chooses as the machining operation and cutting tool. The diameter of the tool is D=10mm. Three levels for each variable are used. For spindle speed 1000, 1250 and 1500 rpm, for feed rate 152, 380 and 588 mm/min, and for depth of cut 0.25, 0.76 and 1.27 mm.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter will provide the review from previous research that is related to this final year project. There are previous researches on surface roughness in end milling using different materials, cutting tools, experiment design and other method to obtain the surface roughness model. Other than that, milling process, full factorial experiments (FUFE), modeling surface roughness using multiple regression and Artificial Neural Network are discussed in this chapter.

2.2 MILLING PROCESS

Milling is the most common form of machining, a material removal process, which can create a variety of features on a part by cutting away the unwanted material. The milling process requires a milling machine, fixture, workpiece and cutter. The workpiece is a piece of pre-shaped material that is secured to the fixture, which itself is attached to a platform inside the milling machine.

The cutter is a cutting tool with sharp teeth that is also secured in the milling machine and rotates at high speeds. By feeding the workpiece into the rotating cutter, material is cut away the workpiece in the form of chips to create the desired shape.

Milling is typically used to produce parts that are not axially symmetric and have many features, such as holes, slots, pockets, and even three dimensional surface contours. Parts that are fabricated completely through milling often include components that are used in limited quantities, perhaps for prototypes, such as custom designed fasteners or brackets. Another application of milling is the fabrication of tooling for other processes. For example, three-dimensional molds are typically milled. Milling is also commonly used ass a secondary process to add or refine features on parts that were manufactured using a different process. Due to the high tolerances and surface finishes that milling can offer, it is ideal for adding precision features to a part whose basic shape has already been formed (Hyunh, V.M. and Fan, Y., 1992).

An end mill makes either peripheral or slot cuts, determined by the step-over distance, across the workpiece in order to machine a specified feature, such as a profile, slot, pocket, or even a complex surface contour. The depth of the feature may be machined in a single pass or may be reached by machining at a smaller axial depth of cut and making multiple passes.

2.3 SURFACE ROUGHNESS

Turning, milling, grinding and all other machining processes impose characteristic irregularities on a part's surface. Additional factors such as cutting tool selection, machine tool condition, speeds, feeds, vibration and other environmental influences further influence these irregularities.

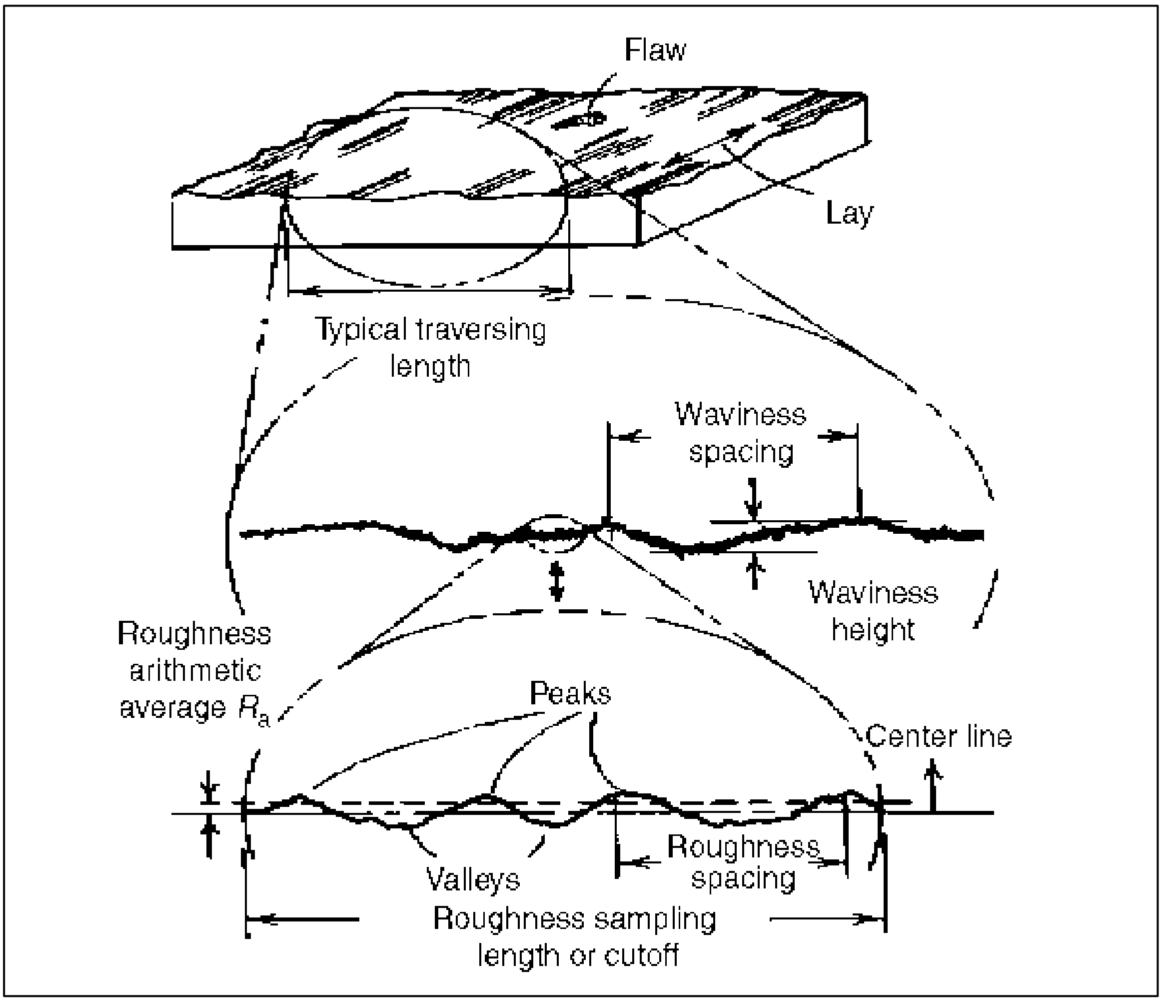

Figure 2.1: Surface texture

Source: Surface Texture [Surface Roughness, Waviness, and Lay], ANSI/ASME B 46.1, American Society of Mechanical Engineers, 1985

Roughness is essentially synonymous with tool marks. Every pass of a cutting tool leaves a groove of some width and depth. In the case of grinding, the individual abrasive granules on the wheel constitute millions of tiny cutting tools, each of which leaves a mark on the surface. Roughness plays an important role to determine how a real object interacts with its environment. Rough surfaces usually wear more quickly and have higher friction coefficients than smooth surfaces. Roughness is often a good predictor of the performance of a mechanical component, since irregularities in the surface may form nucleation sites for cracks or corrosion. Although roughness is usually undesirable, it is difficult and expensive to control in manufacturing. Decreasing the roughness of a surface will usually increase exponentially its manufacturing costs. This often results in a trade-off between the manufacturing cost of a component and its performance in application (K. Kadirgama et al., 2008).

Surface roughness is used to determine and evaluate the quality of a product, is one of the major quality attributes of an end-milled product. In order to obtain better surface roughness, the proper setting of cutting parameters is crucial before the process take place (Dr. Mike S.Lou et al., 1999). This good-quality milled surface significantly improves fatigue strength, corrosion resistance, or creep life (Huynh, V.M. and Fan, Y., 1992). Thus, it is necessary to know how to control the machining parameters to produce a fine surface quality for these parts. The control factors for the machining parameters are spindle speed, feed rate and depth of cut and the uncontrollable factors such as tool diameter, tool chip and tool wear (Julie Z.Zhang et al., 2006).

2.4 PREVIOUS RESEARCH ON MODELLING SURFACE ROUGHNESS

In order to model surface roughness, several methods had been used in previous research. K. Kadirgama et al., (2008) develop a surface roughness prediction model for 6061-T6 Aluminium Alloy machining using statistical method. The purposes of the study are to develop the predicting model of surface roughness, to investigate the most dominant variables among the cutting speed, feed rate, axial depth and radial depth and to optimize Surface Roughness Prediction Model of 6061-T6 Aluminium Alloy Machining Using Statistical Method the parameters. Response surface method (RSM) based optimization approach was used in that study. It can be seen from the first order model that the feed rate is the most significantly influencing factor for the surface roughness. Second-order model reveals that there is no interaction between the variables and response.

Sakir Tasdemir et al. (2008) studied on the effect of tool geometry on surface roughness in universal lathe. From the research The ANN approach has been applied accurately to a turning for predicting surface roughness. The biggest advantage of ANN is simplicity and speed of calculations. The present work is concerned with exploring the possibility of predicting surface finish. It is found that neural networks can be used to find out the effective estimates of surface roughness. The proposed methodology has been validated by means of experimental data on dry turning of carbide tools. The methodology is found to be quite effective and utilizes fewer training and testing data. The experimental data and the developed system analyses showed that ANN reduces disadvantages such as time, material and economical losses to a minimum.

Uroš Župerl*, Franci uš, Valentina Gecevskaa (2004) proposed that the selection of machining parameters is an important step in process planning. Therefore a new evolutionary computation technique is developed to optimize machining process. Particle Swarm Optimization (PSO) is used to efficiently optimize machining parameters simultaneously in milling processes where multiple conflicting objectives are present. First, An Artificial Neural Network (ANN) predictive model issued to predict cutting forces during machining and then PSO algorithm is used to obtain optimum cutting speed and feed rates. The goal of optimization is to determine the objective function maximum (predicted cutting force surface) by consideration of cutting constraints.

Hazim El-Mounayri, Zakir Dugla, and Haiyan Deng (2009) developed a surface roughness model in End Milling by using Swarm Intelligence. From the studies, data collected from CNC cutting experiments using Design of Experiments approach. Then the data obtained were used for calibration and validation. The inputs to the model consist of Feed, Speed and Depth of cut while the output from the model is surface roughness. The model is validated through a comparison of the experimental values with their predicted counterparts. A good agreement is found from this research. The proved technique opens the door for a new, simple and efficient approach that could he applied to the calibration of other empirical models of machining.

Mandara D. Savage et al. (2001) developed a multilevel, in-process surface roughness recognition (M-ISRR) system to evaluate surface roughness in process and in real time. Key factors related to surface roughness during the machining process were feed rate, spindle speed, depth of cut and vibration that had generated between tool and workpiece. The overall MR-M-ISRR system demonstrated 82% accuracy of prediction average, establishing a promising step to further development in-process surface recognition systems.

W. Wang et al. (2005) studied on the surface roughness of brass machined by micro-end-milling miniaturized machine tool. The cutting parameters considered were spindle speed, feed rate, depth of cut and tool diameter. They applied statistical methods, such as ANOVA and RSM to analyze the experiment data. From their experiment, they found that the value of surface roughness increase linearly with the increasing of the tool diameter and spindle speed. Feed rate played an important role when the parameters are constant.

Babur Ozcelik and Mahmut Bayramoglu (2005) developed a statistical model by response surface methodology for predicting surface roughness in high-speed flat end milling process under wet cutting conditions by using machining variables such as spindle speed, feed rate, depth of cut and step over. They observed that, the order of significance of the main variables is as total machining time, of cut, step over, spindle speed and feed rate, respectively.

Hun-Keun Chang et al. (2006) established a method to predict surface roughness in-process. In their research, roughness of machined surface was assumed to be generated by the relative motion between tool and workpiece and the geometric factors of a tool. The relative motion caused by the machining process could be measured in process using a cylindrical capacitive displacement sensor (CCDS). The CCDS was installed at the quill of a spindle and the sensing was not disturbed by the cutting. A simple linear regression model was developed to predict surface roughness using the measured signals of relative motion. Surface roughness was predicted from the displacement signal of spindle motion. The linear regression model was proposed and its effectiveness was verified from cutting tests. Prediction model had prediction accuracy of about 95%. Results showed that the developed surface roughness model could accurately predict the roughness of milled surface.

Julie Z.Zhang et al. (2006) determined optimum cutting parameters for face milling through the Taguchi parameter design method. From the experiment results showed that the effects of spindle speed and feed rate on surface roughness were larger than depth of cut for milling operations. In addition, one of the noise factors, tool wear was found to be statistically significant.

John L.Yang and Dr. Joseph C. Chen. (2001) introduced how Taguchi parameter design could be used in identifying the significant processing parameters and optimizing the surface roughness of end-milling operations. In their study, the analysis of confirmation experiment has shown that Taguchi parameter design can successfully verify the optimum cutting parameters.

Kuang-Hua Fuh and Chih-Fu Wu (1994) studied the influence exerted by the tool geometries and cutting conditions on machined surface quality and to be able to build a model predicting the surface quality for 2014 aluminium. From their research, they summarized that the surface roughness is affected mainly by the tool nose radius and the feed, and the optimum tool nose for the cutting condition can be found by using statistical model.

Oğuz çolak et al. (2005) predicted the milling surface roughness by using gene expression programming (GEP) method. They considered the cutting speed, feed and depth of cute of end-milling operations. They concluded that by using GEP algorithm, surface roughness prediction has been done using a few experiment data. GEP is coming from its ability to generate mathematical equations that can be easily programmed even into programming for use in monitoring of surface quality.

M. Brezocnik et al. (2004) proposed the genetic programming approach to predict surface roughness based on cutting parameters (spindle speed, feed rate and depth of cute) and on vibrations between cutting tool and workpiece. From their research, they conclude that the models that involve three cutting parameters and also vibrating, give the most accurate predictions of surface roughness by using genetic programming. In addition, feed rate has the greatest influence on surface roughness.

Hasan Oktem et al. (2005) used artificial neural network and genetic algorithm to determine optimum cutting g parameters leading to minimum surface roughness during end milling Aluminium 7075-T6. The parameters such as cutting speed, feed, axial radial depth of cut, and machining tolerance were selected to machine the mold surfaces. A feed forward neural network was developed to model surface roughness by exploiting experimental measurements obtained from these surfaces. Surface roughness values from experimental measurements trace a regular path in a wide of cutting conditions. It can be observed that surface roughness is considerably affected all of cutting parameters. Surface roughness becomes particularly higher for lower the value of machining tolerance.

Based on the literature review, the most parameters that widely considered when investigating the optimal surface roughness are feed rate, spindle speed and depth of cut. Most of the researches didn’t consider the uncontrolled parameters, such as tool geometry, tool wear, chip loads, and chip formations, or the material properties of both tool and workpiece. Uncontrolled parameters are hard to reach and whose interactions