MODELLING AND SIMULATION OF SURFACE ROUGHNESS OBTAIN FROM MICRO MILLING BY USING ARTIFICIAL NEURAL NETWORK

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For my beloved mother, father, brothers and sisters

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ABSTRACT

Surface roughness is one of the most important properties in any machining process and in micro milling it is really critical as the product needs to be of a very high surface quality. Therefore the present research is aimed at finding the optimal process parameters for end milling process and optimum surface roughness. In this study by using regression model and Artificial Neural Networks (ANN) which are widely used for both modeling and optimizing the performance of the manufacturing technologies. Optimum machining parameters are of great concern in manufacturing environments, where economy of machining operation plays a key role in competitiveness in the market. The End milling process is a widely used machining process in aerospace industries and many other industries ranging from large manufacturers to a small tool and die shops, because of its versatility and efficiency. The present work involves the estimation of optimal values of the process variables like, speed, feed and depth of cut, whereas the surface roughness was taken as the output. The obtained results proved the ability of ANN method for End milling process modeling and optimization. The final measurement experiment and predicting the error of surface roughness in neural network have been performed to verify the surface roughness optimum error percentage 1.71μm. For this study, the accuracy of artificial neural network and regression model 98.2% and 96.3 respectively.

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LIST OF SYMBOLS AND ABBREVIATIONS

ANN	-	Artificial neural network
BP	-	Back propagation
DOE	-	Design of experiments
GA	-	Genetic algorithm
MAPE	-	Mean absolute percentage error
MSE	-	Mean squared error
AI	-	Artificial Intelligence
Adj	-	Adjusted
CNC	-	Computer Numerical Control
Vc	-	Cutting Speed
DOC	-	Depth of Cut
Ra	-	Average Surface Roughness
Exp	-	Exponential
RPM	-	Revolution per Minute
RSM	-	Response Surface Methodology
g_{air}	-	Thermal Conductivity
SS	-	Sum of Square
TiAlN	-	Titanium Aluminum Nitrate
Vs	-	Versus
B1	-	Biases of the hidden neurons
B2	-	Bias of the output neuron
N	-	Number of data
oi	-	i-th ANN predicted value of average surface roughness, μm

R	-	Correlation coefficient
µm	-	Micro meter
ti	-	ith target (experimental) value of average surface roughness, µ m
X		Input vector to ANN
W1	-	Weights between input and hidden layer
W2	-	Weights between hidden layer and output layer
IPM	-	feed rate, in inches per minute
F	-	feed per tooth
N	-	number of teeth in the cutter being used
%	-	eij is the percentage error
Mij	-	measured value
Pij	-	predicted values
i	-	represents the ith validation Experiments
j	-	represents the jth output

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CHAPTER 1

INTRODUCTION

1.1 Research background

In recent years the modern machines have the challenges in the industries which is mainly focused on the achievement of high quality, in term of work piece dimensional accuracy, high production rate, surface finish, less wear on the cutting tools, economy of machining in terms of cost saving and increase in 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.

The key change drivers in the case of cutting technology include diminishing component size, enhanced surface quality, closer tolerances and manufacturing accuracies, reduced prices, diminished component weight, and reduced batch sizes (Byrne., 2003). The surface character of the machined parts is one of the most significant product quality characteristics and one of the most frequent customer requirements. Surface quality is often expressed by the measurement of surface roughness.

According to (Parveen et al., 2013), CNC (Computer Numerical Control) milling machine is one of the common machine tools in machine industry. The face milling is an operation for producing plane or flat surfaces using a face milling cutter. It is applied for finishing of machine components. In face milling, the cutter is mounted on a spindle having an axis of rotation perpendicular to the work pieces surface and removes material in the manner. Face milling process is gaining popularity in industries in recent years due to the capability in improving machining performance, reducing cost while achieving reduced lead times, and higher productivity. However, the demand for high quality focuses attention on the surface condition and the quality of the product, especially the roughness of the machined surface because of its effect on product appearance, function, and reliability.

In addition, a good quality machined surface significantly improves fatigue strength, corrosion resistance, and creep life. Surface roughness are defined as a group of irregular waves in the surface, measured in micrometers (μm). With the more precise demand of modern engineering products, the control of surface texture has become more important. The surface roughness data obtained by measurement can be manipulated to determine the roughness parameter (Parveen et al., 2013).

(Thanongsak et al., 2012), Micro-end milling is the most flexible process among all mechanical micromachining processes. Its capabilities provide many advantages for manufacturing of complex features, especially those in medical devices and implants. However, scaling the conventional milling process down to a micro scale result in encountering several problems.

Aluminum alloys are extensively used as a main engineering material in various industries such as automotive industries, the mold and die components manufacture and the industry in which weight is the most important factor. Surface roughness is an important measure of product quality since it greatly influences the performance of mechanical parts as well as production cost. These materials help machining and possess superior machine ability index. Milling is one of the most commonly used machining processes in aluminum alloys shaping. It has considerable economic importance because it is usually among the finishing steps in the fabrication of industrial mechanical parts. Their effect on products is important because they may cause some critical problems such as the deterioration of surface quality, thus reducing the product durability and precision.

Surface roughness is one of the most important properties in any machining process and in micro milling it is really critical as the product needs to be of a very high surface quality. Many researchers have focused on the surface roughness obtained in the micro milling process, (Rawangwong et al., 2012).

As mentioned above, surface roughness is an important measure of product quality. Surface roughness have an impact on the mechanical properties like fatigue behavior, corrosion resistance, creep life, etc. Sometimes, various catastrophic failures causing high costs have been attributed to the surface finish of the components in question. As a result, there have been many great research developments in modeling surface roughness and optimization of the controlling parameters to obtain a surface finish of desired level since the only proper selection of cutting parameters can produce a better surface finish.

Nevertheless, such studies are far from completion since it is very difficult to consider all the parameters that control the surface roughness for a particular manufacturing process. The parameters that affect surface roughness include machining parameters, cutting tool properties and work pieces properties etc. In the manufacturing industries, various machining processes are adopted to remove the material from a work piece for the better product. Likewise, end milling process is one of the most critical and common metal cutting operations used for machining parts because of its ability to get rid of materials faster with a reasonably good surface quality. In recent times, numerical controlled machine tools have been implemented to realize full automation in milling since they provide greater improvements in productivity increase the quality of the machined parts and require fewer operators input recognized by (Rawangwong et al., 2012).

Although micro milling emerges as a newly developing method, it is in nature originally and directly scaled down from the conventional milling. The two cutting processes have the similar kinematics, and the cutting process can be characterized by mechanical interaction of a sharp tool with the work material, causing breakage inside, the material along defined paths, and eventually leading to removal of the useless part of the work piece in the form of chips (Alting et al., 2003).

Micro milling plays an increasingly significant part in bridging the crack between the traditional precision macro and the emerging micro machining for making functional parts. However, a number of vital issues, arise on transition of mature macro-domain knowledge into the micro stage, which influence the underlying mechanisms of the process, resulting in alterations in the chip-formation process, reducing forces, vibrations and process stability, and the genesis and subsequent character of the resulting machined surface (Liu et al., 2004a).

These constraints, for example, unpredictable tool life and premature tool failures, significant downsized tool-work interactions, are mainly resulting from the miniaturization of machined components, cutting tools and processes, making the manufacturing technique considerably challenging in achieving favorable cutting performance. In the work, tooling performance is referred as the cutting operation of micro tools, and it is universally weighted by a combination of characterization methods, such as the cutting forces, chip formation, tool wear and life, dimensional accuracy and surface polish. Research on this aspect has the potential to improve the tool design and optimize the cutting process. At present, scientific knowledge on the genes governing the tooling performance has not been systematically examined yet and the present capability of the manufacturing technique needs to be continually prepared to fill current and future production needs. It would consequently be of outstanding significance to address a comprehensive insight so as for further drawing out its industrial applications.

1.2 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.

Although surface roughness have an important property in any machining process and in micro milling it is really critical as the product needs to be of a very high surface quality. As presented the events that occurred in manufacturing industries by looking along the surface roughness for the quality of the products that can effect to the market income. In this research can predict the events that appeared by using the intelligent neural network.

Furthermore, minimizing the error of surface roughness in the micro milling machine which consider the effectiveness of increasing and decreasing the feed rate and tool edge radius. Although, by using artificial neural network prediction is depending on other parameters which are depth of cut, cutting speed and feed rate. Besides that surface roughness value were optimized in milling using statically regression methods.

1.3 Objectives

1. To develop predictive model of surface roughness in milling process.
2. To apply Artificial Neural Network in the machining.
3. Optimization of machining processes by regression method and used to assist in the controller training.

1.4 Scope of study

To obtain a better understanding regarding machining parameter and surface roughness which focusing on neural net organization. Traditionally, the selection of cutting conditions for metal cutting is left to the machine operator. In such events, the experience of the operator plays a major function, but even for a skilled operator it is very difficult to achieve the optimum values each time. Machining parameters in metal milling are cutting speed, feed rate and depth of cut. The setting of these parameters determines the quality characteristics of milling parts.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this current research for obtaining the optimum of surface roughness by using micro milling process. Therefore, three milling parameters have been selected, spindle speed, feed rate and depth of cut. Adequate settings of cutting parameters are most important to obtain better surface roughness. By using intelligence method of neural network system that will predict the accurate surface roughness with playing rules of hidden layers and weighted of input parameters. Beside that study the effect of feed rate, cutting speed and depth of cut on surface roughness by developing artificial neural networks (ANN) models.

2.2 Previous Study

(Abbasi et al., 2012), focused on the Response surface methodology (RSM) prospects with Gradient method and discussed the problem of getting insignificant results, the possibility of getting trapped in local minima or maxima for a given objective function. In this context, the application of ANN is suggested for improving the estimation with lesser calculations.

(Ramesh et al., 2012), studied the effect of depth of cut, cutting speed and feed rate on the surface roughness of Ti-6Al-4V (Titanium alloy) in the turning operation. The base of selection for experimentation was L27 orthogonal array (Taguchi's principle) under dry condition. The development of surface plots and the response surface model were suggested the feed rate as the most influential parameter followed by depth of cut and cutting speed.

(Nataraja et al., 2011), the surface roughness, an indicator of surface quality is one of the most specified customer requirements in a machining process. In this review paper the importance to find a better optimization method, which can suggest to induce an optimum value of editing parameters for minimizing the surface roughness.

(Khorasan et al., 2011), Indicated that the importance of parameter in the milling operation in the manufacturing process is tool life. There are three main parameters, i.e. cutting speed, feed rate and depth of cut were suggested by using artificial neural network and Taguchi design of experiment for tool life prediction in the milling operation.

(Sehgal et al., 2013) focused in Two methods, artificial neural network (ANN) and response surface methodology (RSM) is used for optimized prediction of surface roughness. Therefore investigated that the artificial neural network (ANN) model predicts with higher accuracy compared with response surface methodology (RSM).

(Pontes et al., 2009), reported that the construction of good ANN models is a complex and demanding task when compared to other modeling techniques. This is the trade-off for the superior computing capability of an artificial neural network. Although this analysis was suggested that great improvement could be made on works produced on the subject, if basic requirements in Neuro-computing were observed, and possibilities offered by the technique were better explored. It shows that in many works, inadequate treatment is given to model validation. Consequently, confidence in the use of ANN models could be substantially improved where data and information required to reproduce results and networks are supplied.

(Sivasakthive et al., 2010) reported that the effects of helix angle, spindle speed, feed rate, axial depth of cut and radial depth of cut were experimentally investigated. The investigation presented a central composite rotatable second order response surface methodology to develop a mathematical model to predict tool wear in terms of helix angle, spindle speed, feed rate, axial and radial depth of cut.

(Singh et al., 2012), neural network and the fuzzy inference system called Adaptive Neuro-Fuzzy Inference System (ANFIS) for prediction modeling of surface roughness during machining of GFRP composites. The data had been obtained in experiments by taking machining parameters like spindle speed, feed rate and depth of cut as input; and surface roughness of the machined composite product has been treated as output. Experimental data have been utilized for prediction modeling of the surface roughness with an accuracy of 91%.

(Vivek et al., 2013), reported that the high speed micro-milling is gaining popularity due to its high material removal rate and good surface finish. The author focused on the characterization of the burr formation in high speed micro-milling. Also the Influence of various process parameters, that are spindle speed, feed rate, depth of cut, tool diameter and number of flutes of the micro-milling tool has been analyzed on the burr size and on the quality of the machined surface via measuring the surface roughness.

(Kuttolamadom et al., 2010), that examined the achievability of surface roughness specifications within efforts to reduce automotive component manufacture cycle time, particularly by changing cutting feeds. Therefore, controlled milling experiments show the relationship between feed rate and surface quality for 6061 aluminum, and the results are used to recommend machining practices for cycle time reduction while maintaining quality requirements.

(Aburashid et al., 2009), reported that predicting surface roughness by using multiple regression prediction models was investigated. Therefore Three milling parameters have been selected, spindle speed, feed rate and depth of cut. This showed that the statistical model could predict the surface roughness with about 90.2% accuracy of the testing data set and 90.3% accuracy of the training data set.

(Routara et al., 2009) surface roughness models as well as the significance of the machining parameters have been validated with analysis of variance. Thus it was found that the response surface models for different roughness parameters are specific to work piece materials. An effort has also been created to obtain optimum cutting conditions with respect to each of the five roughness parameters considered in the present study with the help of response optimization technique.

(Mounayr et al., 2008), has studied an innovative Artificial Neural Network (ANN) model that predicts both cutting force and surface roughness in end milling were developed and validated. Moreover A set of five input variables were selected to represent the machining conditions while twelve quantities representing two key process parameters, namely, cutting force and surface roughness, form the variables of the network output.

(El-rahman et al., 2013) in this paper the Multi-Layer back propagation (BP) network is a supervised, continuous valued, multi-input and single-output feed forward multi-layer network that follows a gradient descent method interfaced with the virtual environment to predict surface roughness in the end milling process. Therefore ANN based model is produced by using the optimized network for this exceptional case (100 networks are tested) that the most accurate model will be suggested for in process part surface roughness prediction.

2.3 The Interface of Artificial Neuro-intelligence

Generally, the interface of Neuro-Intelligence is optimized to solve forecasting, classification and function approximation problems. Neuro-Intelligence is neural network software designed to assist experts in solving real world problems. Aimed at solution of technology problems, Neuro-Intelligence features only proven algorithms and techniques, is fast and easy-to-use. Neuro-Intelligence supports all stages of neural network application. It is used in this work to:

- Analyze and preprocess the pre measured test results,
- Find the best neural network architecture that represents the end milling process trend accurately.
- Test and optimize the selected network.

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