UNIVERSITI PUTRA MALAYSIA

DEVELOPMENT OF MACHINABILITY DATA MODEL FOR END MILLING USING ARTIFICIAL NEURAL NETWORKS

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By

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Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Master of Science

June 2009

To:

Dad and Mom
Sisters Bee Lan, Bee Sin, Mei Yea and Brother Chang Jie

Teachers and Guides

Friends and Companions

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Master of Science

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June 2009

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Machinability data is a crucial factor affecting manufacturing cost and quality. Two artificial neural network machinability data models have been developed for the recommendation of proper cutting speed and feed rate for the peripheral end milling process. The first model is for single tool of high speeds steel with inputs of material hardness, cutter diameter and ration of radial depth of cut to cutter radius. An identical model is developed with an additional input of cutter tool type has shown to be are able give appropriate recommendation of cutting speed and feed rate. The models were trained and tested with data from the most general and widely used Machining Data Handbook by Metcut and Associates. Model A and B results in the best least MSE of 4.91×10^{-5} and 1.61×10^{-4} respectively, after being trained for 3×10^{-8} iterations. The development aspects of the models, the mapping ability of hyperbolic tangent functions in perspective of summation neurons used to develop the neural network model are discussed. The minimum number of hidden neurons needed for mapping stepped pattern using hyperbolic tangent function was analysed. Two hidden layer networks are able to represent the nonlinearity of the machinability

data to be modelled. The evaluation of the network is enhanced with the inclusion of standard deviation.

Abstrak thesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai mematuhi keperluan untuk ijazah Master Sains

PEMBANGUNAN MODEL DATA KEBOLEHMESINAN UNTUK PENGISAR HUJUNG TEPI MENGGUNAKAN RANGKAIAN NEURAL BUATAN

Oleh

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Data kebolehmesinan merupakan faktor yang penting dalam menentukan kos dan kualiti hasil buatan. Dua model data kebolehmesinan telah dibangunkan menggunakan rangkaian neural buatan untuk memberi cadangen berkenaan kelajuan pemotong dan kadar suapan pemotong semasa proses pemotongan pengisar hujung tepi. Model yang pertama dibangunkan untuk hanya satu jenis pemotong iaitu keluli kelajuan tinggi, dengan mengambil kira tiga input iaitu kekerasan bahan yang dipotong, diameter pemotong dan nisbah kedalaman jejari potongan kepada diameter pemotong. Satu lagi model serupa yang telah dibangunkan untuk mengambil kira jenis pemotong ke dalam model tersebut, juga diperhatikan dapat memberikan cadangan kelajuan pemotongan dan kadar suapan yang sesuai. Kedua-dua model telah diajar dan diuji dengan data yang diperolehi dari “Buku Panduan Data Pemotongan” oleh Metcut Research dan Associates, salah satu panduan data kebolehmesinan yang paling am dan luas dipakai. Selepas dilatih sebanyak 3×10^{-8} ulangan, Model A and B mencapai keputusan purata kuasa dua ralat yang terendah sebanyak 4.91×10^{-5} dan 1.61×10^{-4} masing-masing. Aspek pembangunan kedua-dua

model tersebut, kebolehan pemetaan fungsi tangen hiperbolik dari perspektif *neuron* pertambahan yang dipakai untuk membangunkan model tersebut telah dibincangkan. Bilangan minimum *neuron* tersembunyi yang diperlukan untuk memetakan corak tangga menggunakan fungsi tangen hiperbolik telah dianalisa. Rangkainan *neural* dengan dua lapisan tersembunyi didapati boleh mewakili ketidakselarian data kebolehmesinan yang ingin dimodelkan. Penilaian rangkaian telah dipertingatkan dengan mengambil kira kriteria sisihan piawai.

ACKNOWLEDGEMENTS

First and foremost, heartfelt gratitude to my supervisory committee chairman, Associate Professor Dr. Wong Shaw Voon, for his wisdom, patience, invaluable guidance and continuing support that sees me through the entire course of this study. The completion of the study is deeply indebted to him. My immense appreciation goes next to my supervisory committee member, Professor Dr. Megat Mohamad Hamdan Megat Ahmad for his helpful recommendations, feedbacks and encouragements that leads me to beginning and the completion of this study.

Special thanks to the helpful and friendly staffs of Institute of Advanced Technology, Faculty of Engineering, and Graduate School of Studies, Universiti Putra Malaysia who provided the necessary assistants whenever needed. Thanks to my fellow research students S.H. Tung, K.S. Tan, C.A. Chin, C.V. Yong, K.K. Chiong, B. Wang, C.L. Tan, J.Y. Tan, M. Hayasi, H.S. Kong and S.Z. Razali who extended immediate helping hand and support all along. Not to be left out, S.C. Ng. I am also grateful to all the unmentioned individuals who have, in ways directly and indirectly, assisted me during my study.

For financing my studies, due acknowledgement has to be given to Intensification of Research in Priority Area (IRPA) fund and National Science Fellowship (NSF) from Ministry of Science, Technology and Innovation (MOSTI), and my family.

Last but not least, deepest thanks to my parents, siblings, and friends for their love, support and understanding.

This thesis submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Master of Science. Members of the Supervisory Committee were as follows:

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DECLARATION

I hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Putra Malaysia or other institutions.

CHU BEE WANG

Date: 14 August 2009

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
APE	Absolute Percentage Error
BPNN	Back Propagation Neural Network
CAD	Computer-Aided Drafting
CAM	Computer-Aided Manufacturing
CAPP	Computer Aided Process Planning
CD	Cutter Diameter
CIM	Computer Integrated Manufacturing
CMDBS	Computerized Machinability Data Base System
CNC	Computer Numerical Controlled
CS	Cutting Speed
CT	Cutter Tool Type
ESMDS	Expert System Machining Data Selection
EXMACH	Expert System for Machinability Data Selection
FANN	Feedforward Artificial Neural Network
FR	Feed Rate
GRS	Generative System
GS	Generic System
HSS	High Speed Steel
MAPE	Mean Absolute Percentage Error
MDH	Machining Data Handbook
MH	Material Hardness

MLP	Multilayer Perceptrons
NC	Numerical Controlled
NMSE	Normalized Mean Square Error
NNHL	Neural Network Handling Library version 1.0
NSE	Normalized Square Error
RDOC	Radial Depth Of Cut
RFBN	Radial Basis Function Network
SE	Square Error
SRS	Storage Retrieval System

CHAPTER 1

INTRODUCTION

1.1 Machining and Machinability Data

Manufacturing is critical to the economic welfare and living standard of a country, as the living standard is determined primarily by the goods and services available to its people. Manufacturing adds value to raw materials by converting them into saleable goods. Machining is the process of removing unwanted material from a workpiece in the form of chips. If the workpiece is metal, the process is often called metal cutting or metal removal. United States industries annually spend $60 billion to perform metal removal operations because the vast majority of manufactured products require machining at some stage in their production, ranging from relatively rough or nonprecision work, such as cleanup of castings or forgings, to high-precision work involving tolerances of 0.0001 inch or less and high quality finishes. Thus machining is undoubtedly the most important of the basic manufacturing processes (Degarmo, Black & Kohser, 2003).

Machining is complex due to the interaction of multiple parameters that are involved in the process which includes (i) the machine selected to perform the process, (ii) the geometry and material of the cutting tool, (iii) the properties and parameters of the workpiece, (iv) the cutting parameters of speed, feed, depth of cut, and (v) the workpiece holding devices or fixtures or jigs. The use of proper machinability data during machining is important. The finished product quality, production efficiency and manufacturing cost are directly influenced machinability data used.

Improper machinability data causes damage to the work surface, unacceptable dimension and surface roughness tolerances, which might need rework of the surface or possible scraping of the part. Production halts for tool change when the tool wears out. Tools and down time are expensive, thus it is important to optimize the tool life. Gradual tool wear is preferred as it leads to the longest possible use of tool and the economic advantage of that longer use. Tool or tool holder break cause hazards which endanger machinist, and incurs machine repair, tool and workpiece replacement costs. Thus, proper machinability data leads to reduced industry wastes, machining time, and production cost, and increased product quality.

The task of machinability data selection has long been the task of human machinist. The main objective of machining is to satisfy the demand of part dimensions and surface finish after design requirement, workpiece material and machining process are determined. To achieve these, machinists are left with a wide range of possible speeds, feeds, depths of cut, and other machining parameters. In order to learn the proper machinability data to use, machinists can (i) attend classes at the tool and machining centre manufacturer, or, (ii) depend on their own experience and intuition. Trained manpower is important to production, and world class factories are guided by the best trained men. In high production workshops, it pays to send a lead machinist to a milling cutter school for a week, and then use them to set up each job on the milling machines. There, they learn the best inserts for different materials, feed rates and cutting speeds, rules of basic milling, and how to compute cutting speed for fast stock removal (Brown, 1998). Training manpower costs company time and money. Expertise is not always available and is lost when they leave the company.

Traditionally, the machinist usually performs machining based on decades of experience without giving much thought to optimizing conditions. Hence, product fabrication cost has been higher than it should be. In the past, the problem may not be as pronounced because the actual cutting time is so small in proportion to the time a part spent on the machine for setting up, fixing and aligning the parts on machine. The introduction of Numerical Controlled/Computer Numerical Controlled (NC/CNC) machines and Computer Aided Process Planning (CAPP) has introduced the automation of tool change, tool path, and tool alignment tasks. Thus, the time spent on actual cutting has become very significant and a competitive edge for company.

NC/CNC and CAPP has also shifted the responsibility of assigning machinability data to part programmers and process planners. These planners may not have the same experience as machinist do to accomplish this task effectively. Further, these planners perform their functions in an office, receiving little feedback from the workshop concerning the adequacy of their plans. They need a system to provide accurate machinability data efficiently. Computer Integrated Manufacturing (CIM) is an integrated system recognized as the best solution to increase productivity, and NC/CNC and CAPP are two important components of CIM. Therefore, the use of an effective computer system to provide machinability data to assist people in generating machinability data are critical, both in the industry and research institutes (Wang, 1986).

1.2 Problem Statements

The importance of the proper machinability data has lead extensive efforts to capture, document, represent, and recommend the appropriate machinability data. These result in handbooks, manuals, datasheets, tool manufacturer catalogues, database systems and expert systems, and mathematical equations.

Machinability data modelling has been difficult due to large amount and variability of machinability data. Manuals, datasheets, tool manufacturer catalogues are provided by the tool manufacturer. These machinability recommendations are generally very specific to the tool from the manufacturer. Bulky handbooks have been produced from actual data collected from workshop and laboratory experiments. The most general and widely used handbook which covers a wide range of machining processes, tools and materials is the Machining Data Handbook (MDH) from Metcut and Associates (1980).

Database systems are difficult to maintain, prone to human error in dataset record updating, and only able to give discreet outputs for datasets available in the database. Rule based expert systems are difficult to maintain when rules exceeds two hundred in number.

The numerous input and output parameters involved in machinability data selection led to the difficulties in modelling the relationship using mathematical equations. The best practices for calculations, methods and procedures have been drawn (Degarmo, Black & Kohser, 2003; Walsh, 2001; Groover, 2002; Metcut, 1980).

Mathematical equations have been developed to optimize the cutting conditions in terms of the economics of machining. The Taylor tool life equation (Equation 2.2 in Section 2.6.2) has been one of the important references in the industry to select proper machinability data. Equations for calculating the economics of machining such as the equation for maximizing production rate and minimizing production cost are based on Taylor's tool life equation. However, the equations are limited to usage on the material where the relative constant for a given material, n, and parameter whose value depends on feed, depth of cut, work material, tooling and tool life criterion used, C, variables of the Taylor tool life equation are available because the Taylor tool life equation depends on the n and C variables which differs for different materials, and therefore needs many experiments and are costly to determine. This leads to the knowledge bottleneck (Yeo, Rahman and Venkatesh, 1988) when new materials and machining processes are being introduced, while the knowledge of the proper machinability data selection are yet to be available due to costly and time consuming experiments. Additional studies and research are necessary as new tools and materials are developed. Despite extensive work for the past decades, most development in machinability data had evolved through trial-and-error methods and learnt on an empirical basis.

This study attempts to model the machinability data using artificial neural network. Artificial neural network (ANN) is an information processing paradigm inspired by the way our biological nervous system, the brain, process information. ANN model is built from interconnections of processing elements (neurons) that map the system inputs to the outputs. The key element of ANN is its ability to learn from example. After being trained, it is able to provide sensible output for the given input combination which does not exists during training. In this study, ANN act as a function approximation to map the input to the appropriate output without having to know a priori the exact relationship between the input and output parameters. This replaces the need to develop exact empirical mathematical formulas for efficient and optimized machinability data. This will also enable the machinability data representation to be computerized, eliminate the use of bulky handbooks, the ability to be trained continuously from incomplete examples sets as new materials are created without the hassle of finding the exact rules and relationship of the inputs and outputs.

1.3 Research Objectives

The objectives of this study are:

To build neural network based machinability data models for the peripheral end milling process.

To train, test and validate the machinability data recommendation from the neural network models.

1.4 Scope of research

This study concentrates on machinability data representation of the peripheral end milling process of wrought carbon steel, which is a versatile and widely used machining process as the first step towards building a generalized artificial neural network based machinability data model. The scope of parameters involved in this study is shown in Table 1.1.

Workpiece Material	Wrought Carbon Steel
Tool Material	High Speeds Steel, Carbide
Input Variables	Cutter tool type (C*T*), Material hardness (*MH*), Cutter diameter (*CD*), Radial depth of cut (*RDOC*)
Output Variables	Cutting speed (*CS*), Feed rate (*FR*)

Table 1.1 Parameters involved in neural network machinability data model.

1.5 Contribution of Study

This study contributes to the development of machinability data model for the peripheral end milling process using a method that can be trained to learn from example data to map the relationship between machinability data parameters, and the recommended the appropriate cutting speed and feed rate, which are crucial to the economics of machining, quality and productivity.

The developed models have the potential to close the gap between Computer Aided Design (CAD) and the actual cutting process in the Computer Numerical Controlled (CNC) machining centre. The specification of material hardness, tool type, cutter diameter, and the specified radial depth of cut is read from the CAD drawing in the form of G-Code. The developed neural network model will automatically recommend the appropriate cutting speed and feed rate to be written into the G-code before being sent to the CNC machining for actual machining.

1.6 Summary of Contents

Chapter 1 introduces the machining processes and machinability data selection procedures, the difficulties in identifying appropriate machinability data, the objectives and scope of research, and the contribution of the study towards machining process. Chapter 2 highlights related work that has been carried out on the subjects prior to this study. The machinability data selection methods have evolved from conventional methods to artificial intelligence-based methods. Advantages and disadvantages of the methods of study is discussed that leads to the current method selected. Chapter 3 addresses the overall research methodology, neural network machinability data model developement methodology, data analysis and data processing methodology. Chapter 4 discusses the results achieved by the developed neural network based machinability data model. The justification and implication of the methods and parameters selection on the developed model, and advantages and limitation of the developed model are deliberated. The analysis of neural network mapping characteristics based on hyperbolic tangent function and neuron concept are discussed as well. Chapter 5 concludes the finding from the study and recommends future work for the study.

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