



UNIVERSITI PUTRA MALAYSIA

**DEVELOPMENT OF A NEURAL-FUZZY MODEL FOR MACHINABILITY
DATA SELECTION IN TURNING PROCESS**

KONG HONG SHIM

ITMA 2008 5



**DEVELOPMENT OF A NEURAL-FUZZY MODEL FOR MACHINABILITY
DATA SELECTION IN TURNING PROCESS**

By

KONG HONG SHIM

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

October 2008



Especially Dedicated To

My beloved family, my teachers and my friends



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirements for the degree of Master of Science

DEVELOPMENT OF A NEURAL-FUZZY MODEL FOR MACHINABILITY DATA SELECTION IN TURNING PROCESS

By

KONG HONG SHIM

October 2008

Chairman : Wong Shaw Voon, PhD

Faculty : Institute of Advanced Technology (ITMA) / Engineering

A neural-fuzzy model has been developed to represent machinability data selection in turning process. Turning process is a branch of machining process, which is used to produce cylindrical parts. Considerable efforts have been done to automate such machining process in order to increase the efficiency and precision of manufacturing. One of the issues is machinability data selection, which is always referred as the proper selection of cutting tools and machining parameters. This task is a complex process; and usually depends on the experience and skill of a machinist. Although sources like machining data handbooks and tool catalogues are available for reference, the process is still very much depending on a skilled machinist.

Previously, mathematical and empirical approaches have been attempted to reduce the dependency. However, the complexity of machining makes it difficult to formulate a proper model. Applications of fuzzy logic and neural network have been considered too to solve the machining problem; and have shown good potential. But, some issues remain unaddressed. In fuzzy logic, among the issues are tedious process of rules identification and inability to self-adapt to changing machining conditions. On the other hand, neural network has the issues of black box problem and difficulty



in optimal topology determination. In order to overcome these difficulties, a neural-fuzzy model is proposed to model machinist in selecting machinability data for turning process. The neural-fuzzy model combines the self-adapting and learning abilities of neural network with the human-like knowledge representation and explanation abilities of fuzzy logic into one integrated system. The characteristics of fuzzy logic would solve the shortcomings in neural network; and vice versa.

Generally, the developed neural-fuzzy model is designed to have five layers; input and output layers, and three hidden layers. Each of the layers has different classes of nodes; in which are input nodes, input term nodes, rule nodes, output term nodes and output nodes. The model is developed using Microsoft Visual C++ .NET (MSVC++ .NET). Object oriented approach is applied as the development process to enhance reusability.

The results from the model have been validated and compared against machining data of Machining Data Handbook from Metcut Research Associate. Good correlations have been shown, indicating the feasibility of representing machining data selection with neural-fuzzy model. The mean absolute percentage error for four different types of tools is below 3%, and averaging at 2.4%. Apart from that, the extracted fuzzy rules are compared with the general rules of thumbs in turning process as well as rules from other paradigm; and found to be consistent. This would simplify the task of obtaining fuzzy rules from machining data. Beside that, the model is compared with other artificial intelligence approaches, such as fuzzy logic, neural network and genetic algorithm. The neural-fuzzy model has shown good result among them. In addition, the characteristics of the model are studied and

analyzed as well; in which include membership functions, shouldered membership functions and randomness.

This research has shown promising results in employing neural-fuzzy model to solve problems; in this case, machinability data selection in turning process. The developed neural-fuzzy model should be further considered in a wider range of real-world machining processes for learning and prescribing knowledge.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

**PEMBANGUNAN MODEL NEURAL-FUZZY UNTUK PEMILIHAN DATA
KEBOLEHMESINAN DALAM PROSES MELARIK**

Oleh

KONG HONG SHIM

Oktober 2008

Pengerusi : Wong Shaw Voon, PhD

Fakulti : Institut Teknologi Maju (ITMA) / Kejuruteraan

Sebuah model neural-fuzzy telah dibangunkan untuk mewakili pemilihan data kebolehmesanan dalam proses melarik. Proses melarik adalah satu daripada cabang proses pemesinan, yang digunakan untuk menghasilkan bahagian berbentuk silinder. Banyak usaha telah dijalankan untuk menjadikan proses pemesinan begini automatik, bagi meningkatkan kecekapan dan ketepatan pembuatan. Salah satu daripada isunya ialah pemilihan data kebolehmesanan, yang selalu dirujuk sebagai pemilihan wajar peralatan pemotongan dan parameter pemesinan. Tugas ini adalah satu proses yang kompleks, dan selalu bergantung kepada pengalaman dan kemahiran seseorang jurummesin. Walaupun terdapat sumber seperti buku panduan data pemesinan dan katalog peralatan untuk rujukan, proses ini masih lagi bergantung kepada seseorang jurummesin yang berkemahiran.

Sebelum ini, pendekatan matematik dan empirik pernah dicuba untuk mengurangkan kebergantungan ini. Namun demikian, kompleksiti pemesinan menjadikannya sukar untuk merumus satu model yang wajar. Aplikasi logik fuzzy dan rangkaian neural juga telah dipertimbangkan untuk menyelesaikan masalah pemesinan ini; dan telah menunjukkan potensi yang baik. Tetapi, terdapat isu-isu yang masih belum

diselesaikan. Dalam sistem logik fuzzy, di antara isu-isunya ialah proses pengenalpastian peraturan yang meletihkan dan ketidakdapatannya menyesuaikan diri kepada keadaan pemesinan yang berlainan. Sebaliknya, rangkaian neural pula mempunyai isu-isu dalam masalah kotak hitam dan kesukaran dalam penentuan topologi yang optimum. Untuk mengatasi masalah ini, satu model neural-fuzzy dicadangkan untuk memodelkan jurumessin dalam pemilihan data kebolehmessinan dalam proses melarik. Model neural-fuzzy menggabungkan kebolehan penyesuaian diri dan pembelajaran rangkaian neural dengan kebolehan perwakilan pengetahuan manusia dan penerangan logik fuzzy dalam satu sistem berintegrasi. Ciri-ciri logik fuzzy akan menyelesaikan kelemahan dalam rangkaian neural, dan begitu juga sebaliknya.

Secara amnya, model neural-fuzzy yang dibangunkan ini direka mempunyai lima lapisan; iaitu lapisan input dan output, dan tiga lapisan tersembunyi. Setiap lapisan ini mempunyai kelas-kelas nod yang berlainan; yang mana adalah nod input, nod input sebutan, nod peraturan, nod output sebutan dan nod output. Model ini dibangunkan dengan menggunakan Microsoft Visual C++ .NET (MSVC++ .NET). Pendekatan berorientasikan objek digunakan sebagai proses pembangunan untuk mencapai kebolehgunaan semula.

Keputusan yang diperolehi daripada model ini telah disahkan dan dibandingkan dengan data pemesinan yang diperolehi daripada Buku Panduan Data Pemesinan oleh Metcut Research Associate. Korelasi yang baik telah dipaparkan dalam kajian ini; menunjukkan kebolehlaksanaan mewakili pemilihan data pemesinan dengan model neural-fuzzy. Min peratusan ralat mutlak untuk empat jenis peralatan adalah

dibawah 3% dan puratanya adalah 2.4%. Selain itu, peraturan fuzzy yang diekstrak telah dibandingkan dengan petua am dalam proses melarik dan peraturan daripada paradigma lain, dan didapati konsisten. Ini akan memudahkan tugas mendapatkan peraturan fuzzy daripada data pemesinan. Model tersebut juga dibandingkan dengan pendekatan kecerdasan buatan lain, seperti logik fuzzy, rangkaian neural dan algoritma genetik. Model neural-fuzzy telah menunjukkan keputusan yang baik di antara pendekatan tersebut. Tambahan pula, ciri-ciri model neural-fuzzy juga dikaji dan dianalisa; yang mana melibatkan fungsi keahlian, bahu fungsi keahlian dan kerawakan.

Penyelidikan ini menunjukkan keputusan yang menggalakkan dalam menggunakan model neural-fuzzy untuk menyelesaikan masalah; dalam kes ini, pemilihan data kebolehmesinan dalam proses melarik. Model neural-fuzzy yang dibangunkan ini seharusnya dipertimbangkan lebih lanjut lagi dalam proses pemesinan dunia sebenar yang lebih luas untuk pembelajaran dan preskripsi pengetahuan.

ACKNOWLEDGMENTS

This study could not have been accomplished without the help of many fine individuals. It gives me great pleasure to acknowledge the valuable assistance and contribution of the following people.

First of all, I wish to express my sincere gratitude and appreciation to my Supervisory Committee chairman, Associate Professor Dr. Wong Shaw Voon, Department of Mechanical and Manufacturing Engineering, Universiti Putra Malaysia (UPM), for his patience and continuous supervision, valuable advice, and guidance throughout the course of the research.

I would also like to express my appreciation to another Supervisory Committee member, Associate Professor Datin Dr. Napsiah Ismail, Head of Department, Department of Mechanical and Manufacturing Engineering, Universiti Putra Malaysia for her constructive suggestion, proper guidance and encouragement throughout the duration of my study.

The appreciation is also extended to my colleagues, friends and all other individuals who have directly or indirectly delivered their generous assistance in completing the study.

Last but not the least, the deepest appreciation goes to my family, whose patience and understanding make it possible for me to complete this research.



I certify that a Thesis Examination Committee has met on 23rd October 2008 to conduct the final examination of Kong Hong Shim on his thesis entitled “Development of a Neural-fuzzy Model for Machinability Data Selection in Turning Process” in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Master of Science.

Members of the Thesis Examination Committee were as follows:

Abdul Rahman Ramli, PhD

Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Yusof Ismail, PhD

Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Internal Examiner)

Faizal Mustapha, PhD

Senior Lecturer
Faculty of Engineering
Universiti Putra Malaysia
(Internal Examiner)

Mohd. Hamdi Abd. Shukor, PhD

Associate Professor
Faculty of Engineering
Universiti Malaya
(External Examiner)

HASANAH MOHD. GHAZALI, PhD

Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 29 January 2009



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

Wong Shaw Voon, PhD

Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Napsiah Ismail, PhD

Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Member)

HASANAH MOHD. GHAZALI, PhD

Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 12 February 2009



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 UPM or other institutions.

KONG HONG SHIM

Date: 3 December 2008

TABLE OF CONTENTS

	Page
DEDICATION	ii
ABSTRACT	iii
ABSTRAK	vi
ACKNOWLEDGEMENTS	ix
APPROVAL SHEETS	x
DECLARATION	xii
LIST OF TABLES	xvi
LIST OF FIGURES	xviii
LIST OF ABBREVIATIONS/NOTATIONS/GLOSSARY OF TERMS	xxi

CHAPTER

1 INTRODUCTION	1
1.1 Problem Statements	4
1.2 Objectives	6
1.3 Scope of Research	7
1.4 Layout of Thesis	8
2 LITERATURE REVIEW	9
2.1 Turning Process	9
2.2 Machinability Data Selection	11
2.2.1 Speed	17
2.2.2 Feed	18
2.2.3 Depth of Cut	18
2.3 Tool Material	19
2.3.1 High Speed Steels	20
2.3.2 Carbides	20
2.4 Workpiece Material	21
2.5 Artificial Intelligence	23
2.5.1 Fuzzy Logic	23
2.5.2 Neural Network	37
2.5.3 Neural-fuzzy	41
2.6 Machinability and Artificial Intelligence	47
2.7 Summary	54



3 METHODOLOGY, DESIGN AND DEVELOPMENT	56
3.1 Research and Development Approach	56
3.2 Neural-fuzzy Model Design	59
3.2.1 Layer 1	61
3.2.2 Layer 2	61
3.2.3 Layer 3	63
3.2.4 Layer 4	64
3.2.5 Layer 5	65
3.3 Linguistic Variables and Linguistic Values	66
3.4 Membership Functions	68
3.4.1 Triangular Membership Function	69
3.4.2 Gaussian Membership Function	71
3.5 Shouldered Fuzzy Sets and Overlapping	72
3.6 Learning Algorithms	76
3.6.1 Rule Finding Phase	76
3.6.2 Backward Propagation	80
3.7 Training Procedures	88
3.8 Data Collection and Preparation	90
3.9 Implementation	92
3.9.1 Programming Language Visual C++ .NET	93
3.9.2 Multithreading and Multitasking	94
3.9.3 Object-oriented Programming	99
3.9.4 Classes	101
3.10 Testing and Validation	103
4 RESULTS AND DISCUSSIONS	106
4.1 Performance of Neural-fuzzy Algorithm	106
4.2 Membership Functions	112
4.2.1 Symmetrical Triangular Membership Function	113
4.2.2 Asymmetrical Triangular Membership Function	116
4.2.3 Gaussian Membership Function	119
4.3 Shouldered Membership Functions	120
4.4 Sequential/ Non-sequential Training	124
4.5 Rules Extraction	129
4.6 Comparison between Neural-fuzzy Model and Other Approaches	139
4.7 Summary	142

5 CONCLUSIONS AND RECOMMENDATION	146
5.1 Conclusions	146
5.2 Recommendation	149
5.3 Limitations	149
REFERENCES	151
APPENDICES	161
Appendix A	161
Appendix B	162
Appendix B1	163
Appendix B2	170
Appendix B3	173
Appendix C	178
Appendix D	183
Appendix E	185
Appendix F	187
Appendix G	189
BIODATA OF THE STUDENT	196
LIST OF PUBLICATIONS	197



List of Tables

Table	Page
2.1 Comparative results for different modeling approaches	45
2.2 Features and applications of mathematical/ empirical methods	48
3.1 Linguistic values for input material hardness	67
3.2 Linguistic values for input depth of cut	67
3.3 Linguistic values for output cutting speed	67
3.4 Ranges of cutting speed	68
4.1 Results summary of different tool type	112
4.2 Linguistic values for input material hardness for rules extraction	131
4.3 Linguistic values for input depth of cut for rules extraction	132
4.4 Linguistic values for output cutting speed for rules extraction	132
4.5 Rules extracted from neural-fuzzy model	133
4.6 Rules extracted from genetic algorithm optimization, with constraints	136
4.7 Rules extracted from genetic algorithm optimization, without constraints	138
4.8 Results summary of different approaches	141
4.9 Summary of studies and results	143
A.1 Recommended cutting speed for carbon steel (Extracted from Machining Data Handbook, 3 rd edition [21])	161
C.1 Validation of neural-fuzzy model results of high speed steel	178
C.2 Validation of neural-fuzzy model results of brazed uncoated carbide	179
C.3 Validation of neural-fuzzy model results of indexable uncoated carbide	180
C.4 Validation of neural-fuzzy model results of coated carbide	181
D.1 Validation of results for neural-fuzzy model with shouldered membership functions of high speed steel	183
E.1 Validation of results for neural-fuzzy model with non-sequential training of high speed steel	185

F.1	Recommended cutting speed from Machining Data Handbook and interpolated cutting speed of high speed steel	187
G.1	Validation of fuzzy model results of high speed steel for comparison	189
G.2	Validation of non-linear neural network results of high speed steel for comparison	190
G.3	Validation of genetic algorithm optimization with constraints results of high speed steel for comparison	191
G.4	Validation of genetic algorithm optimization without constraints results of high speed steel for comparison	193
G.5	Validation of neural-fuzzy model results of high speed steel for comparison	194

List of Figures

Figure	Page
2.1 Turning process	10
2.2 Cutting speed, feed, and depth of cut for a turning process	14
2.3 Fuzzy inference system using max-min method	31
2.4 Fuzzy inference system using max-product method	32
2.5 The Sugeno fuzzy inference technique	35
2.6 Architecture of a typical artificial neural network	38
3.1 Research and development approach	58
3.2 Architecture of implemented neural-fuzzy model	60
3.3 Triangular membership function	70
3.4 Gaussian membership function	72
3.5 Shouldered regions and overlapping of neighboring regions	73
3.6 Completely disjoint neighboring fuzzy regions	75
3.7 Excessive overlap in neighboring fuzzy regions	75
3.8 Divisions of inputs and output universe into fuzzy regions: (a) material hardness, (b) depth of cut and (c) cutting speed	78
3.9 The convergence of steepest descent method	82
3.10 Effect of learning rate size (a) small learning rate, slow convergence; and (b) large learning rate, divergence	84
3.11 Local and global minima	85
3.12 Training procedures of the model	89

4.1	Initial membership functions of input material hardness for high speed steel tool	107
4.2	Initial membership functions of input depth of cut for high speed steel tool	107
4.3	Initial membership functions of output cutting speed for high speed steel tool	108
4.4	Mean squared errors in training history for high speed steel tool	110
4.5	Cutting speed prediction with neural-fuzzy model for high speed steel tool	111
4.6	Symmetrical triangular membership functions training	115
4.7	Type of triangle shapes	117
4.8	Mean squared errors of high speed steel	118
4.9	Mean squared errors in training history for shouldered membership functions	122
4.10	Membership functions of input depth of cut for high speed steel tool at epoch 248000	123
4.11	Mean squared errors in training history for non-sequential training	127
4.12	Mean squared errors in training history for sequential training	128
4.13	Initial membership functions of input material hardness for rule extraction	130
4.14	Initial membership functions of input depth of cut for rule extraction	131
4.15	Initial membership functions of output cutting speed for rule extraction	131
4.16	Contour chart of fuzzy rules extracted from neural-fuzzy model learning	134
4.17	Contour chart of fuzzy rules extracted from genetic algorithm optimization, with constraints	137
4.18	Contour chart of fuzzy rules extracted from genetic algorithm optimization, without constraints	138

4.19	Non-linear neural network of machinability data for turning process	140
B1.1	A typical trapezoid	164

List of Abbreviations

MDH	Machining Data Handbook
CNC	Computer Numerically Controlled
DNC	Direct Numerically Controlled
COG	Centre of gravity
GARIC	Generalized Approximate Reasoning-based Intelligent Control
FBFN	Fuzzified Basis Function Networks
RA	Regression analysis
RSM	Response surface methodology
FN-ASRC	Fuzzy-nets-based In-process Adaptive Surface Roughness Control
FAN	Fuzzy Adaptive Network
FNN	Fuzzy Neural Network
MIMO	Multi-input-multi-output
NFL	Neural-fuzzy library
MFC	Microsoft Foundation Classes
MSE	Mean squared error
MAPE	Mean absolute percentage error
CAM	Computer Aided Manufacturing
CIM	Computer Integrated Manufacturing



CHAPTER 1

INTRODUCTION

One of the most important processes in manufacturing industry is machining. Generally, machining is a group of processes that consist of removal of the material and modification of the surfaces of a workpiece after it has been produced by various manufacturing methods such as casting and forging. The other processes provide the general shape of the starting workpiece, while machining creates the final dimension, geometry and finish. As variety of work materials, variety of part geometric features, dimensional accuracy and good surface finishes are involved, machining is commercially and technologically important. With today's demanding productivity and profitability in manufacturing industry, machining has increasingly needed to be performed optimally.

As substantial amount of material is removed from the raw material in order to achieve required shape, machining is an expensive process. Furthermore, a lot of energy is expended in this process. Machining may be more economical provided that the number of parts required is relatively small; or the material and part shape allows them to be machined at high rates and quantities with high dimensional accuracy. It is important to view machining processes as a system, consisting of the workpiece, cutting tool, machine tool and production personnel. Machining cannot be carried out efficiently or economically without a through knowledge of the interactions among these four elements [1].

Turning process is one of the machining processes, which produces cylindrical parts using a single-edged cutting tool to remove material from a rotating workpiece. Three parameters can be used to describe turning process; in which are speed, depth of cut and feed. In the process, the cutting tool is set at a certain depth of cut (mm) and travels with a certain speed (m/ min) towards a direction parallel to the axis of the workpiece rotation. The feed is the distance the tool travels horizontally per unit revolution of the workpiece (mm/ rev). Turning process is widely used in core manufacturing processes and in a wide range of products. It has been investigated by various disciplines; which include not only mechanics and control theory, but economy too.

Machinability data selection is a complex process due to the number of possible variables and variations. Thus, this process cannot be easily formulated to meet design specification by any empirical or mathematical model. This includes the proper selection of machining cutting tools [2] and machining variables; in which among others are speed, depth of cut, feed, tool material and work material. Other variables such as the cutting fluid and temperature [3] are important as well. These machining data selection variables have major impacts on a machine performance in terms of productivity, reliability and product quality [4, 5]. In practice, optimized machinability data is obtained from a skilled machinist's experience and intuition [6, 7] in order to satisfy the required accuracy. Efforts have been made to capture this optimal machinability data into machining data handbooks and other media to serve as references when performing machining processes. However, there are still some problems with this practice. Therefore, models incorporating artificial intelligence technologies such as fuzzy logic and neural network are employed.

Fuzzy logic is a mathematical theory of imprecise reasoning that allows us to model the reasoning process of human in linguistic terms [8]. Fuzzy logic has been deployed to replace the role of mathematical model with another that is built from a number of rules with fuzzy variables such as output temperature and fuzzy terms such as relatively high and reasonably low [9-12]. While fuzzy logic allows the use of linguistic terms to represent data sets in the reasoning process, neural network is able to discover connections between data sets simply by having simple data represented to its input and output layers. Neural network are artificial and simplified models of the neurons that exist in the human brain [13]. It has the ability to learn the relationship among input and output data sets through a training process. The network can be regarded as processing device, and usually has some sort of ‘training’ rule whereby the weights of connections are adjusted on the basis of presented patterns.

Although applications of fuzzy logic and neural network in machining processes bring significant improvement to the processes, they are not without issues; in which are inherent to each of the paradigms. Most of the issues in fuzzy logic applications are in the formation of the fuzzy rules [14, 15], whereas the issues lie with the neural network application are mostly in its topology [16].

In order to overcome these shortcomings, this research proposes an integrated neural-fuzzy model for machinability data selection in turning process as they are complementing each other. The main feature of the neural-fuzzy model is that it takes advantage of the capacity that fuzzy logic stores human expertise knowledge