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COMBINING FUZZY LOGIC AND NEURAL NETWORKS FOR DECISION SUPPORT IN AN INDUSTRIAL ENVIRONMENT

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présenté par: SHEN Yulan

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To my parents,Jiapeng LI and Zuyao SHEN

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Résumé

La logique floue et les réseaux neuronaux sont deux techniques attrayantes qui ont récemment reçu une attention accrue pour soutenir les décisions prises dans le monde réel des problèmes non-linéaires . Cependant, ils ont aussi bien des limites. Le plus grand problème en ce qui concerne la logique floue est de déterminer la base de données des connaissances, qui servira de support à la décision. Tandis que pour les réseaux neuronaux, c'est l'interprétation des résultats qui peut poser un problème. Il est donc nécessaire de trouver une méthode qui est capable d'alléger certains de ces problèmes.

Dans cette étude, on propose une approche qui combine la logique floue et les réseaux neuronaux. Cette approche emploie la fonction d'apprentissage des réseaux neuronaux pour acquérir le comportement du système, en se basant sur les données existantes du système, ensuite elle applique les réseaux neuronaux rappelant la fonction pour générer les bases de données floues des connaissances.

On présente ici les bases de données floues des connaissances pour la sélection de paramètres de coupe dans les opérations de fraisage développées par la méthode NeuFuz et par la méthode manuelle. Une interface d'utilisateur est

développée sur une plateforme UNIX dans le but d'intégrer le FDSS (système flou d'aide à la décision) avec un système CAO/FAO (conception assistée par ordinateur & fabrication assistée par ordinateur).

On a réalisé trois essais avec cette méthode NeuFuz pour des problèmes d'aide à la décision. La méthode NeuFuz est premièrement testée dans le domaine de la fabrication pour sélectionner les paramètres de coupe. Un deuxième essai est aussi appliqué dans le domaine de la fabrication pour prédire l'erreur existante avant la réalisation de la trajectoire de mesurage pour une machine de mesure des coordonnées. L'application de cette méthode NeuFuz dans le domaine industriel est entreprise. Une estimation de la vie des poteaux pour Hydro - Québec est faite en utilisant cette méthode NeuFuz. La méthode NeuFuz est validée en comparant les résultats estimés avec les résultats réels. Les facteurs les plus importants, qui ont une influence sur la précision, sont la complexité du problème, le nombre des exemples, le domaine couvert par les exemples et la définition des ensembles flous des prémisses.

Abstract

Fuzzy logic and neural networks are two attractive techniques that have recently received growing attention in decision support for real world nonlinear problems. However, they have limitations. The biggest problem in fuzzy logic is to determine its knowledge database whereas a major problem in neural networks is to explain its conclusions. Therefore, it is necessary to find a method which is able to alleviate some of these problems.

An approach which combines the fuzzy logic and neural networks is proposed in this study. It uses the neural networks training function to learn the system behaviour based on existing system data, then applies the neural networks recalling function to generate the fuzzy knowledge databases.

Fuzzy knowledge databases for the cutting parameters selection in milling operations developed by the NeuFuz method and the manual method are presented. A user interface is developed on a UNIX platform in order to integrate the FDSS (fuzzy decision support system) with a CAD/CAM (computer aided design & computer aided manufacturing) system.

Three tests of this NeuFuz method for decision support problems are carried out. The NeuFuz method is first tested in the manufacturing field to select the cutting parameters. The second test is also in the manufacturing field to predict the pre-travel error of a coordinate measuring machine. The application of this NeuFuz method in an industrial domain is then undertaken. An estimation of the poles life for Hydro-Quebec is done by using this NeuFuz method. The NeuFuz method is justified in comparison with the real results. The most important factors which have an influence on the accuracy are the complexity of the problem, the number of the examples, the coverage of the examples and the definition of the fuzzy premises sets.

Condensé en français

Dans le contexte de la globalisation des marchés, les entreprises de petite et moyenne tailles doivent affronter un défi énorme, celui d'améliorer leur aptitude à faire face à la concurence avec les autres entreprises. Elles doivent augmenter leur productivité, améliorer leurs produits et développer des produits nouveaux en utilisant les technologies nouvelles et les plus avancées. Beaucoup de décisions doivent être prises en se basant sur des informations imprécises, incomplètes, incertaines et/ou vagues.

La logique floue transfère une grande gamme de cette sorte d'information en un petit nombre de termes flous. Donc, il réduit le nombre d'informations avec lesquelles le décideur doit se contenter pour prendre une décision.

La logique floue et les réseaux neuronaux sont deux techniques attrayants qui ont récemment reçu une attention accrue pour soutenir les décisions prises dans le monde réel des problèmes non-linéaires . Cependant, ils ont aussi bien des limites.

Le plus grand problème en ce qui concerne la logique floue est de déterminer la base de données de connaissances, qui servira de support à ia décision. Un système performant de soutien d'aide à la décision en se basant sur la logique floue dépend de sa base de données de connaissances qui n'est pas toujours facile à établir quand le problème est complexe. Tandis que pour les réseaux neuronaux, c'est l'interprétation des résultats qui peut poser problème. Il est donc nécessaire de trouver une méthode qui est capable d'alléger certains de ces problèmes.

L'approche la plus prometteuse pour concevoir une base de données de connaissances basée sur la logique floue pour des problèmes complexes est celle qui utilise des réseaux neuronaux. La fonction d'apprentissage-rappel des réseaux neuronaux peut fournir des conclusions floues. Alors, la génération d'une base de données de connaissances en se basant sur la logique floue devient possible.

Dans cette étude, on propose une approche qui combine la logique floue et les réseaux neuronaux. Cette approche emploie la fonction d'apprentissage de réseaux neuronaux pour acquérir le comportement du système en se basant sur les données existantes du système, ensuite elle applique les réseaux neuronaux rappelant la fonction pour générer les bases de données floues des connaissances.

L'étude présentée dans ce mémoire a pour but d'automatiser le procédé de génération d'une base de données de connaissances en se basant sur la logique floue et en utilisant les réseaux neuronaux. La méthode NeuFuz qui combine la logique floue et les réseaux neuronaux est développée dans cette étude.

Le choix des paramètres de coupe optimaux est une condition préalable pour produire un produit technique qui a une bonne qualité à un prix compétitif. Plusieurs systèmes informatiques de soutien d'aide à la décision, pour la sélection de paramètres de coupe, basés sur des méthodologies expérimentales et théoriques ont déjà été développés. Ces systèmes sont habituellement développés en utilisant des programmes de système expert tel que GURU ou autres.

Balazinski, Bellerose et Czogala dans [1], montrent que ces programmes sont souvent coûteux, difficiles à employer, et nécessitent souvent des calculs et des données qui sont difficiles ou impossibles à obtenir. À cause de certaines grandes parties manquantes dans ces systèmes, ils ne sont pas capables de fournir des résultats dans des conditions incertaines et ils n'arrivent pas à faire l'interpolation pour toutes les valeurs dans un intervalle donné.

Par exemple, la version CUTDATA 2.0 développée par Metcut Research Associates inc. ne donne pas de paramètres corrects de coupe dans des situations où la dureté est autour 150 Bhn et la profondeur de coupe entre 4.5 mm et 5.2 mm. L'autre difficulté dans ces systèmes, c'est que leurs bases de données sont trop grandes et par conséquent trop lentes pendant l'utilisation.

D'autres méthodes, telles que la recherche de l'information dans Machining Data Handbook[2], ne peuvent résoudre ni l'incertitude ni les problèmes d'interpolation, aussi leur information n'est pas compacte, donc la vitesse de recherche d'information est très lente.

Les opérations de fraisage représentent un pourcentage significatif de toutes les opérations de fabrication et seront le centre de cette étude. Les bases fiables de données de connaissances utilisant la logique floue pour le choix des paramètres de coupe pour toute sorte d'opérations de fraisage sont présentées dans cette étude. On présente ici les bases de données floues de connaissances pour la sélection des paramètres de coupe dans les opérations de fraisage développées par la méthode NeuFuz et par la méthode manuelle.

L'emploi croissant de système de CAOFAO (conception assistée par ordinateur & fabrication assistée par ordinateur) force le développement de modèles de décision pour le choix de paramètres de coupe. Des interfaces graphiques pour l'utilisateur sont préparées dans un environnement CAOFAO (CATIA), ayant dans leurs structures l'inférence floue ainsi que les bases de données des connaissances basées sur la logique floue pour le choix des paramètres de coupe en fraisage. L'interface utilisateur est développée sur une plateforme UNIX dans le but d'intégrer le FDSS (système flou d'aide à la décision) avec un système CAO/FAO.

On a réalisé trois essais de cette méthode NeuFuz pour des problèmes d'aide à la décision. La méthode NeuFuz est premièrement testée dans le domaine de la fabrication pour sélectionner les paramètres de coupe. Un deuxième essai est aussi appliqué dans le domaine de la fabrication pour prédire l'erreur existante avant la réalisation de la trajectoire de mesurage pour une machine de mesure des coordonnées. L'application de cette méthode NeuFuz dans le domaine industriel est entreprise. Une estimation de la vie des poteaux pour Hydro - Québec est faite en utilisant cette méthode NeuFuz.

La méthode NeuFuz est validée en comparant les résultats estimés avec les résultats réels. Les facteurs les plus importants qui ont une influence sur la précision sont la complexité du problème, le nombre d'exemples, le domaine couvert par les exemples et la définition des ensembles flous des prémisses.

Cette étude est divisée en quatre chapitres. Le premier chapitre contient la théorie de la logique floue et des réseaux neuronaux. Le deuxième chapitre introduit le concept de génération de la base de données de connaissances basée sur la logique floue en utilisant la méthode NeuFuz et la méthode manuelle. Dans le troisième chapitre on propose trois applications industrielles de la méthode NeuFuz. Les conclusions et les recherches futures sont présentées dans le dernier chapitre.

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Symbol and abbreviation list

AI:	Artificial Intelligence
AIC:	AIXwindows Interface Composer
CAD:	Computer-Aided Design
CAM:	Computer-Aided Manufacturing
CAPP:	Computer-Aided Process Planning
CMM:	Coordinate Measuring Machine
FDSS:	Fuzzy Decision Support System
GUI:	Graphic User Interface
IGES:	Initial Graphics Exchange Specification
MOR:	Modulus Of Rupture
NC:	Numerical Control

Appendix list

Introduction

In the context of market globalisation, small and medium size businesses face a tremendous challenge to improve their ability to compete. They must increase their productivity, enhance their products and develop new ones using new and more advanced technologies. Many decisions have to be made on the basis of imprecise, incomplete, uncertain and/or vague information. Fuzzy logic transfers a large range of this kind of information into a small number of fuzzy terms. Therefore, it reduces the number of information that the decision-maker has to contend with to make a decision.

A good performance of fuzzy logic decision support system depends on its knowledge database which is not always easy to establish when the problem is complex. The most promising approach to make a fuzzy knowledge database for complex problems is using neural networks. The neural networks training-recalling function can provide the fuzzy conclusions. Then, the generation of a fuzzy knowledge database becomes possible.

The study presented in this thesis is currently working toward automating the process of generating a fuzzy knowledge database from neural networks. The NeuFuz method which combines the fuzzy logic and neural networks is developed in this study.

Proper cutting parameters are a prerequisite for producing a product which has a good quality at a competitive price. Several computer-aided decision support systems for the selection of cutting parameters based on theoretical and experimental methodologies have already been developed. These systems are usually developed using expert system shell programs such as GURU or others. As presented by Balazinski, Bellerose and Czogala in [1], these programs are often expensive, difficult to use, and sometimes require calculations and data which are difficult or impossible to get. The main shortages in these systems are not being able to provide results in uncertain conditions and a certain lack of interpolation for all values in an interval. For example, CUTDATA version 2.0 developed by Metcut Research Associates inc. can't give proper cutting parameters in situations where the hardness is around 150 Bhn and the depth of cut is between 4.5 mm and 5.2 mm. Other serious difficulties in these systems are that their databases are too large and are therefore slow to use. Other methods, such as looking for information from the Machining Data Handbook [2], cannot resolve the uncertainty and the interpolation problems as well. Also, their information is not compact, therefore the information search speed is very slow. Milling operations represent a significant percentage of all machining operations and will be the focus of this study. Reliable fuzzy knowledge databases for the choice of cutting parameters for all kind of milling operations are presented in this study.

The increasing use of CADCAM (Computer Aided Design & Computer Aided Manufacturing) systems compels the development of good cutting parameters selection tools. Therefore, user graphic interfaces, which contain fuzzy inference and fuzzy knowledge databases for the choice of cutting parameters in milling in a CADCAM (CATIA) environment are prepared.

This study is divided into four chapters. Chapter 1 contains the theory of the fuzzy logic and the neural networks. Chapter 2 introduces how to generate fuzzy knowledge database by using the NeuFuz method and by the manual method. In chapter 3 the three industrial applications of the NeuFuz method are proposed. Conclusions and future researches are presented in Chapter 4.

Chapter 1

Fuzzy logic and neural networks

1.1 Fuzzy logic

1.1.1. Problem analysis

In general, traditional decision-support systems remain an accurate and cost-efficient solution to problems involving simple, linear factors. These systems are designed to make a single decision on the basis of a few independent inputs. Because of this independence, adding further inputs to the system rapidly complicates the decision support paths and requires the recalculation of all transfer functions. Many decisions in real situations have to be made on the basis of imprecise, incomplete, uncertain and/or vague information. On decision support problems, we meet systems for which the mathematical description of the system behaviour is difficult to derive from basic physical principles because the physical processes taking place are too complex.

1.1.2. Why fuzzy logic?

In decision-support systems, the fuzzy logic approach has a distinct edge over conventional methods. As discussed by Self in [3], "preprocessing" a large range of values into a small number of fuzzy membership grades reduces the number of values that the decision-maker has to contend with to make a decision. Fewer values have to be evaluated, fewer rules are needed, therefore in many cases a fuzzy decision support system (FDSS) can solve the same problem faster.

In traditional decision-support modelling, the first step is to derive a mathematical model to describe the system. This requires a detailed understanding of all variables in the system and this is not always easy or possible if the system is very complicated.

In contrast, fuzzy modelling deals with the relationship of the output to the input, lumping many parameters together. Thus, the fuzzy decision support system is of a higher order and often provides a more accurate and stable response.

A fuzzy decision support system (FDSS) called FUZZY-FLOU (v.01) was developed at École Polytechnique de Montréal. The complete description of FDSS FUZZY-FLOU is presented in [4].

1.1.3. Introduction of fuzzy logic

Developed by Zadeh in 1965 [5], fuzzy logic has been proven very successful in solving problems in many areas where conventional model based (mathematical modelling of the system) approach is either very difficult or inefficient/costly to implement. This technique can broaden the usefulness of expert systems, allowing operation in grey areas where precise values may not be known or may not be necessary for drawing conclusions. As discussed by Balazinski, Czogala and Mascle in [6], fuzzy systems can be developed to be used alone or as parts of another software such as an expert system. They can provide a more familiar fuzzy interface to the system or allow the user to make educated guesses. Fuzzy systems allow reasoning to take place even when certain facts are not completely established.

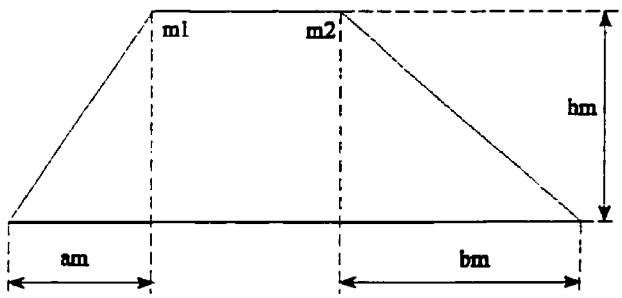
Fuzzy logic uses the knowledge of human experts in describing the system behaviour, as presented by Kaufmann in [7]. The fuzzy approach tries to mimic an aspect of human reasoning by doing approximate reasoning. In this way, fuzzy systems use less precise information than conventional systems but are more like our everyday experience as human decision makers. The system is essentially described by a set of rules using human language with linguistic variables. Such a description of the system significantly simplifies the problem. Small, large, hot, rapidly, etc. are fuzzy terms. These terms are not precise but they are meaningful, and they allow us to describe our world and reason about it, as presented by Pedrycz in [8]. Fuzzy systems allow users to give input in these imprecise terms and use them to derive precise advice. Qualitative labels, i.e. the linguistic variables, are used in expressing the system behaviour using the rules, for example, "if the input increases slightly then the output decreases moderately".

In fuzzy logic, an input is called a premise and an output is called a conclusion. The degree of membership is the "confidence" or "certainty" - expressed as a number from 0 to 1 - that a particular value belongs in a fuzzy set. The membership function is a formula used to determine the fuzzy set to which a value belongs and the degree of membership in that set, as defined by Self in [3].

In a universe of discourse U, a fuzzy set A of U is defined by a membership function u_A. A membership function $u_A(x)$ expresses the degree of membership of each element x_i in the fuzzy set A. A $u_A(x_i)$ of 0 denotes no membership, a $u_A(x_i)$ of 1 denotes full membership, and a $u_A(x_i)$ between 0 and 1 denotes partial membership.

The trapezoidal shape used in FDSS is defined as quinary (m1, m2, am, bm, hm) where:

- m1: the beginning of the membership function maximum,
- m2: the end of the membership function maximum,
- am: the left positive distance between the starting point of the fuzzy set and m1,
- bm: the right positive distance between m2 and the ending point of the fuzzy set,
- hm: the hight of the fuzzy set.



A fuzzy logic knowledge database consists of three sections which are the premises section, the conclusions section and the rules section.

1.2 Neural networks

1.2.1. Problem analysis

Although fuzzy based design has several advantages including simplicity and ease in design, it is associated with some critical problems as well. As the system complexity increases, it becomes difficult to determine the right set of rules of the fuzzy logic knowledge database to describe the system behaviour, as presented by Kosko and Isaka in [9]. A significant amount of time is needed to properly adjust the rules before a solution is obtained, as concluded by Marks in [10]. For more complex systems, it may be even impossible to come up with a set of rules.

1.2.2. Why neural networks?

Neural networks can be useful when rules are not known, either because the topic is complex or because no human expert is available. If training data can be generated, the system may be able to learn enough information to function as well as or better than an expert system, as presented by Gallant in [11]. This approach also has the benefit of ease of modification by retraining with an updated data set, thus eliminating programming changes and rule reconstruction.

The data-driven aspect of neural networks allows a system adjustment as a result of changing environments and events. Another advantage of neural networks is the speed of operation after the network is trained, which will be enhanced dramatically as neural chips become readily available, as presented by Gallant in [11]. Neural networks can be one of the best solutions for some of the problems that have proven difficult for expert system developers, and can allow them to address problems not amenable to either approach alone. Neural networks have the potential to provide some of the human characteristics of problem solving that are difficult to simulate using the logical, analytical techniques of expert system and standard software technologies. For example, neural networks can analyze large quantities of data to establish patterns and characteristics in situations where rules are not known and can, in some cases make sense of incomplete or noisy data.

1.2.3. Introduction of neural networks

The state of the art in neural computing is inspired by our current understanding of biological neural networks; however, after all the research in biology and psychology, important questions remain about how the brain and the mind work. Advances in computer technology allow the construction of interesting and useful artificial neural networks that borrow some features from the biological systems. For example, a soma in biology is called a node or a cell in neural networks. Also, the dendrite, the axon and the synapse are known as the input, the output and the connection between cells of a neural network model.

A neural network model consists of a set of computational units which are also called cells and a set of one-way data connections joining units. At certain times, a unit examines its inputs and computes a signed number called an activation as its output.

An example is shown in figure 1.1; the eight circles represent eight cells which are separated in three layers in a neural network model. Cells in layer one are connected with cells in layer two and layer two is connected with layer three. The new activation is passed along those connections leading to other units. Inputs entered from layer one, then pass through layer two and three to generate the outputs. The analogy with the biological system should not be taken too literally. Connectionist models are far too simple to serve as realistic brain models at the cell level, but they might serve as very good models for essential information processing tasks that organisms perform.

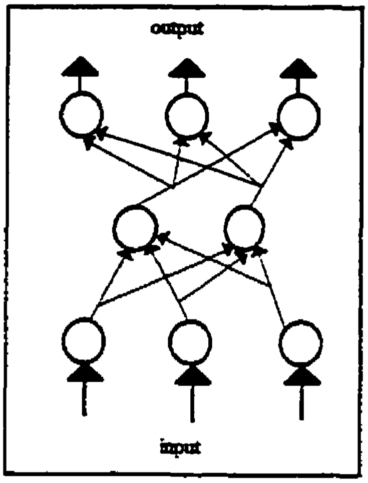


Figure 1.1. Neural network: input & output.

From a computational viewpoint, neural networks offer two primary advantages: a training function and a recalling function that are qualitatively different from standard artificial intelligence approaches, as described by Gallant in [11].

The neural network training function can be viewed as the process of establishing an input-output map from a set of examples. Neural networks, in contrast to being programmed, are trained. This means that examples are presented to the neural network model and the neural network model adjusts itself by some learning rules. Training is achieved through a learning rule which adapts or changes the connection weights of the neural network model in response to the example inputs and the desired outputs of those inputs. The inputs are presented along with desired outputs during the training phase. The neural networks recalling function can be viewed as a search in the memory of the trained model for the best match between the new inputs and their outputs. The recalling function consists in presenting new inputs to the trained model and providing results which are called the recalling-output for these new inputs.

Neural networks are currently used in industry and table 1.1 below taken from [11] shows their current use in Japan:

Table 1.1. Neural networks current use in Japan.

Matsushita Electric	air conditioner, washing machine, vacuum cleaner, rice cooker, kerosene fan heater, electric thermo pot, microwave oven, induction heating cooker
Sanyo	washing machine, cloth drier, microwave oven, desk type electric heater, electric carpet, electric fan, kerosene fan heater, rice cooker
Hitachi	rice cooker, kerosene fan heater, washing machine, vacuum cleaner
Sharp	refrigerator, washing machine, rice cooker, kerosene fan heater
Mitsubishi	kerosene fan heater, induction heating cooker
Toshiba	kerosene fan heater, washing machine
Fujitsu General	kerosene fan heater
Corona	kerosene fan heater
Toyotomi	kerosene fan heater

1.3. Why combine fuzzy logic with neural networks?

Neural networks and fuzzy logic are the two key technologies that have recently received growing attention in quickly solving real world nonlinear, complex problems. Although these technologies have had successes in solving those problems, they have limitations as well.

Even though, fuzzy logic is one of the biggest success story for expert systems in artificial intelligence, the main practical problem in using a conventional fuzzy logic system is the construction of its knowledge database. Fuzzy systems use structured knowledge representation in a symbolic manner. It can be difficult and expensive to get a human expert to express his or her knowledge in terms of If-Then rules. Once extracted, a set of rules can be incomplete and inconsistent, as described by Pedrycz in [8]. A lot of effort is therefore required to complete and ensure that the fuzzy knowledge database is consistent. For example, the consumer strongly requires more intelligent and more sensitive decision-support systems with finer capabilities. Manufacturers address this by increasing the amount of information available to the device. This increase in information leads to a higher complexity of design that causes the difficulties in generating the fuzzy knowledge databases.

Neural networks cannot directly encode structured knowledge. Unlike traditional expert systems where knowledge is made explicit in the form of rules, neural networks generate their own rules which are implicitly generated by being shown examples. This training function adapts and changes the connection weights of the neural network model to generate their input-output map which is often seen as a "Black Box". A major problem in neural networks is to understand this "Black Box". Because of this problem, neural networks have been criticized for "not being able to explain their conclusions". In contrast to the neural networks approach, knowledge representation in fuzzy logic systems is comprehensible for users. If neural networks can be explained by explicit If-Then rules as it is in fuzzy knowledge database, the neural networks performance could be better understood.

Neural networks are sometimes being introduced to speed up the development of a complex rule base system, as presented by Kosko in [12]. Also, knowledge that cannot be made explicit, can be handled by these nets, as described by Medsker and Liebowitz in [13]. Therefore it seems that a combination of fuzzy logic and neural networks can alleviate some of the problems mentioned above and be useful to solve complex engineering problems.

The combination method which is developed in this study uses a fuzzifier function to pre-process data for a neural network. The fuzzifier function converts system original input data into fuzzy degree of membership data for each fuzzy set.

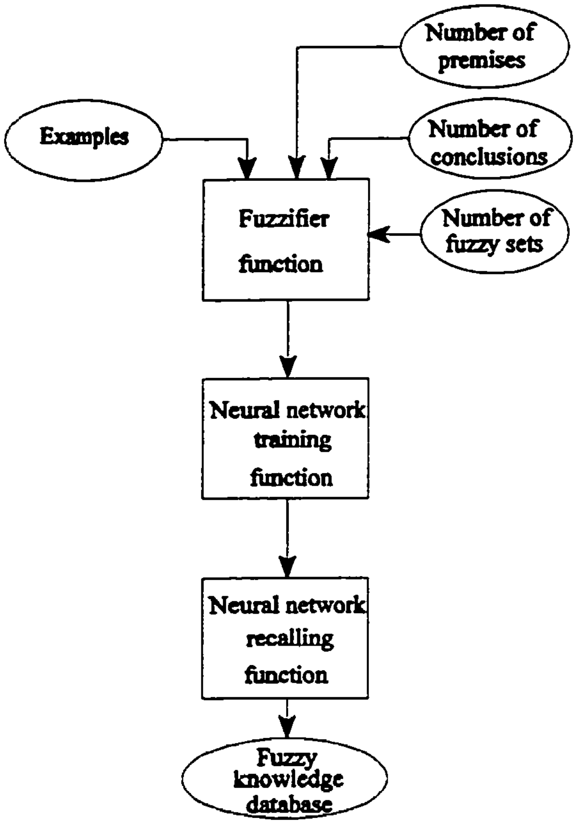


Figure 1.2 A combination method with fuzzifier function.

As shown in figure 1.2, with the information on the number of premises, conclusions and fuzzy sets, a fuzzifier function transfers the input examples into a fuzzy degree of membership data for each fuzzy set. Then these data will be used in the neural networks training and recalling function to obtain the recalling function output. At the end, the obtained recalling-outputs are used as the conclusions in a fuzzy knowledge database. Therefore, the fuzzy knowledge database rules are obtained and the fuzzy knowledge database can be generated.

The general methodology is now established in figure 1.2. The next chapter will explain in practical terms the general procedure which must be followed to generate a fuzzy knowledge database alone and with the aid of neural networks.

Chapter 2

Fuzzy knowledge database generation with and without the NeuFuz method

2.1. Fuzzy knowledge database structure analysis

In order of generate a fuzzy knowledge database, a good understanding of its structure is necessary. A fuzzy knowledge database includes a premises section, a conclusions section and a rules section which matches the premises and the conclusions. An analysis on the topics of the premise fuzzy set number, the fuzzy set shape and the rules section is carried out to properly explain the generation of the fuzzy knowledge database. This chapter also explains the generation of such a database from a neural network application.

2.1.1. Fuzzy set number analysis

The number of fuzzy sets is decided on the basis of the complexity of the problem and the precision required. Suppose there is a problem with one premise and one conclusion which describe a linear relationship. As shown in figure 2.1 (A), only two rules are needed for such a linear problem.

rule #1	*IF*	*premise is a*
	THEN	*conclusion is a'*
rule #2	*IF*	*premise is b*
	THEN	*conclusion is b'*

Rule #1 defines point A and rule #2 defines point B. Points A and B effectively describe this linear relationship with high accuracy. Therefore, the premise should have at least two fuzzy sets, one describe point A and another for B. These fuzzy sets can be put anywhere in the range of this premise. As shown in figure 2.1 (B), points M and N can also define this line.

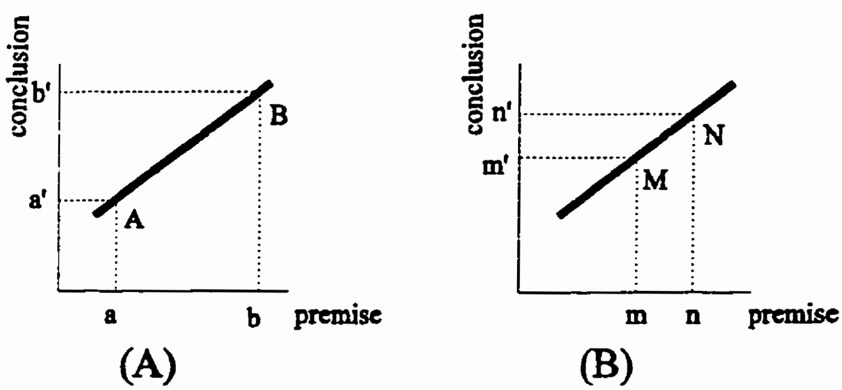


Figure 2.1. Linear problem defined by two points.

Several rules could be needed to define a nonlinear problem and a higher precision can be reached by increasing the number of rules.

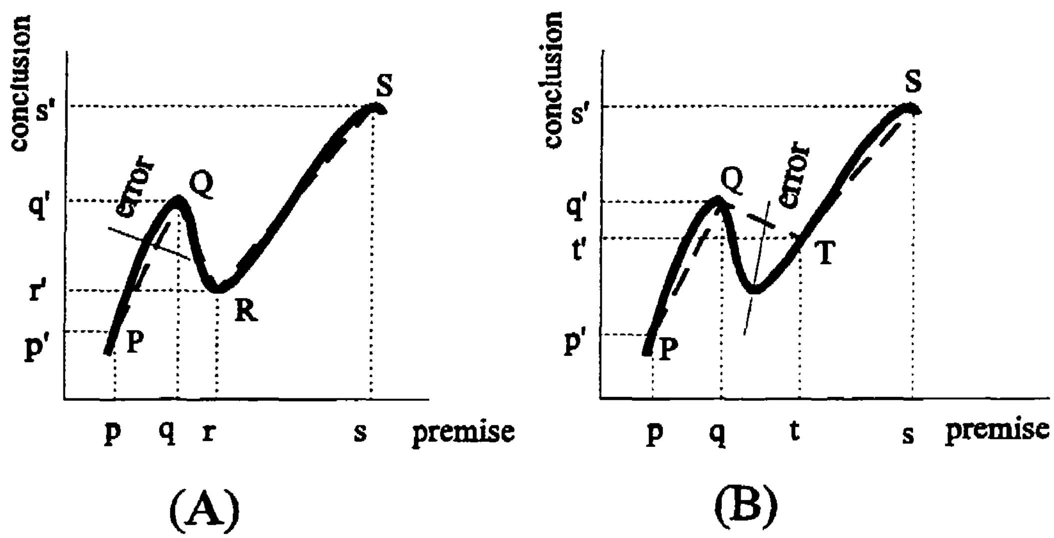


Figure 2.2. Nonlinear problem defined by several points.

As shown in figure 2.2 (A), points P, Q, R and S are decided as four critical points. This nonlinear relationship can be simulated by three lines which are line PQ, line QR and line RS. Four rules are needed to define these four points. Therefore, the premise should have four fuzzy sets and these four fuzzy sets should cover the range of values from p to s. Otherwise the model will have unacceptable error. As shown in figure 2.2 (B), with the line PQ, line QT and line TS, the nonlinear relation is badly simulated in the q to t interval where the error is much bigger than part (A). It is obvious that the determination of critical points has influences on fuzzy precision.

If this nonlinear problem is divided into a lot of small lines, better simulation could be reached. That means higher precision can be reached by increasing the number of rules. In other words, the number and location of premise fuzzy sets has an effect on the fuzzy accuracy.

2.1.2. Fuzzy set shape analysis

Several shapes have been tried for the fuzzy premise set. As shown in figure 2.3 (A), between the premise value a and b in a trapezoidal shape, the value of the degree of membership is a constant. In this case, the same conclusions are obtained when the premise value varies between a and b. It is not possible to have a gradual variation from a set to another. But, this solution could be good in certain circumstances such as when a "dead band" is required.

The triangular shape is considered as being able to provide a total gradual variation everywhere in a premise range which can ensure the proper results for each value of a premise. As shown in figure 2.3 (B) and (C), there are two kinds of triangular shape. But, In part (B), only one fuzzy rule is executed when the premise value varies between c and d which causes no fuzzy reasoning in this field. Therefore, the same conclusion is provided in the triangle part between the value c and d which brings uselessness for gradual variation. Compare the shape

(B) and (C), the triangular shape in part (C) is the only one which is adaptable for a problem which has a gradual variation.

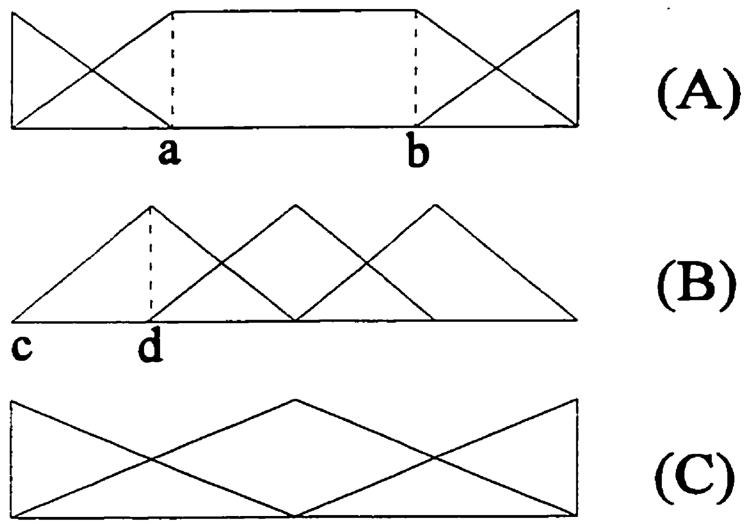


Figure 2.3. Fuzzy set shapes.

The symmetric triangular shape of a fuzzy conclusion set supports a variation which is more gradual from one partition set to another. The partition of a fuzzy conclusion set should be more regular, to better centre the gravity centre of partition functions. Equal symmetric triangles were chosen as the shape of a fuzzy conclusion set which can ensure each conclusion set has the same importance during a fuzzy inference.

2.1.3. Fuzzy rules section analysis

Rules are the most important part in a fuzzy knowledge database. The analysis of the rules section helps to reveal the variables which should be taken into account to generate fuzzy knowledge database.

Figure 2.4 is an example of a fuzzy knowledge database in ASCII format for cutting parameter selection. The database contains two premises, two conclusions and six rules. Figure 2.5 is a graphical representation of the fuzzy knowledge database shown in figure 2.4.

As shown in figure 2.4, there are two premises in the knowledge database premises section. Two fuzzy sets which are SOFT and MED are included in the first premise which is the HARDNESS. Three fuzzy sets which are FINISHING, SEMI-FINISHING and ROUGHING are included in the second premise which is the DEPTH OF CUT. There are two conclusions which are the SPEED and the FEED PER TOOTH in the conclusions section. There are also six rules in the rules section.

Tool material: High Speed Steel

Workpiece material: Free Machining Stainless Steels, Wrought

Workpiece subgrade: Austenitic

```
                        # 1 Hardness (Bhn)
1st premise             ( 135   135   0     140   1   soft )
                        ( 275   275   140   0     1   med )

                        # 1 Depth of cut (mm)
2nd premise             ( 1  1  0  3  1   finishing )
                        ( 4  4  3  4  1   semi-finishing )
                        ( 8  8  4  0  1   roughing )

                        ~ 1 Speed (m/min)
                        ( 27   27   1  1  1   a )
                        ( 30   30   1  1  1   b )
1st conclusion          ( 37   37   1  1  1   c )
                        ( 40   40   1  1  1   d )
                        ( 46   46   1  1  1   e )
                        ( 49   49   1  1  1   f )

                        ~ 1 Feed per tooth (mm)
                        ( 0.15   0.15   0.02   0.02   1   v.low )
                        ( 0.20   0.20   0.02   0.02   1   low )
2nd conclusion          ( 0.25   0.25   0.02   0.02   1   med )
                        ( 0.30   0.30   0.02   0.02   1   high )
                        ( 0.36   0.36   0.02   0.02   1   v.high )
                        ( 0.40   0.40   0.02   0.02   1   e.high )

                        *
                        ( 1   1   6   2 )
                        ( 1   2   4   4 )
fuzzy rule section      ( 1   3   2   6 )
                        ( 2   1   5   1 )
                        ( 2   2   3   3 )
                        ( 2   3   1   5 )
```

Figure 2.4. An example of a fuzzy knowledge database in ASCII format.

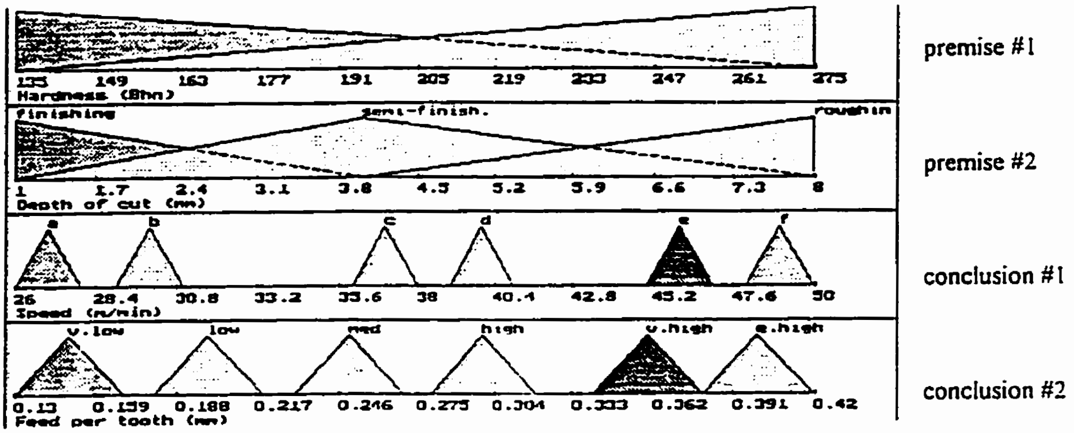


Figure 2.5. Graphical representation of the fuzzy knowledge database shown in figure 2.4.

The rules section shown in this example can be changed. For example, the third rule of this rules section is **(1 3 2 6)**. It means:

IF	*the HARDNESS is SOFT (#1 from 1st premise)*
AND	*the DEPTH OF CUT is ROUGHING (#3 from 2nd premise)*
THEN	*the SPEED is B -- 30 m/min (#2 from 1st conclusion)*
	the FEED PER TOOTH is E.HIGH -- 0.40 mm (#6 from 2nd conclusion)

In this case, 1 is the first number of the third rule (1, 3, 2, 6), means that the value of the degree of membership of the **first** set SOFT in the first premise HARDNESS is 1 and the values of the degree of membership of the other sets in the first premise are 0. Since there are only two fuzzy sets in the first premise, the values of the degree of membership of the first premise are **(1, 0)**

Similarly, **3** is the second number of the third rule (1, **3**, 2, 6), means that the value of the degree of membership of the **third** set ROUGHING in the second premise DEPTH OF CUT is 1, and the values of the degree of membership of the other sets in the second premise are 0. Since there are three fuzzy sets in the second premise, the values of the degree of membership of the second premise are **(0, 0, 1)**.

In this knowledge database file, there are two conclusions. The third and the fourth number (**2**, **6**) in the rule (1, 3, **2**, **6**) are conclusions, which are:

***2** means the **second** set in the first conclusion SPEED - 30 m/min;*

***6** means the **sixth** set in the second conclusion FEED PER TOOTH - 0.40 mm.*

Therefore, the last two numbers in each rule are the conclusions. The new format of this rule section is thus:

(1 1 6 2) ---> (1 1 Conclusions)
(1 2 4 4) ---> (1 2 Conclusions)
(1 3 2 6) ---> (1 3 Conclusions)
(2 1 5 1) ---> (2 1 Conclusions)
(2 2 3 3) ---> (2 2 Conclusions)
(2 3 1 5) ---> (2 3 Conclusions)

In a fuzzy rules section, the number of rules depends on all the possible combinations between the premise fuzzy sets. In this case, there are two sets for the first premise and three sets for the second premise. Thus there are 2x3 combinations which correspond six rules in the rules section. These combinations can be written in the vectorial formats of their fuzzy sets as shown below:

				vectorial formats					
#1 premise	*#2 premise*		—>	*#1 premise*		*#2 premise*			
1	*1*	*conclusions*	—>	*1*	*0*	*1*	*0*	*0*	*conclusions*
1	*2*	*conclusions*	—>	*1*	*0*	*0*	*1*	*0*	*conclusions*
1	*3*	*conclusions*	—>	*1*	*0*	*0*	*0*	*1*	*conclusions*
2	*1*	*conclusions*	—>	*0*	*1*	*1*	*0*	*0*	*conclusions*
2	*2*	*conclusions*	—>	*0*	*1*	*0*	*1*	*0*	*conclusions*
2	*3*	*conclusions*	—>	*0*	*1*	*0*	*0*	*1*	*conclusions*

This set of vectors shown in figure 2.6 can be used in the neural network recalling function. The output obtained from the neural network recalling function are the fuzzy knowledge database conclusions.

1	*0*	*1*	*0*	*0*
1	*0*	*0*	*1*	*0*
1	*0*	*0*	*0*	*1*
0	*1*	*1*	*0*	*0*
0	*1*	*0*	*1*	*0*
0	*1*	*0*	*0*	*1*

Figure 2.6. Neural network recalling function input.

2.2. The generation of a fuzzy knowledge database with the NeuFuz method

2.2.1. The definition and the process of the NeuFuz method

The NeuFuz method developed in this study uses the neural network training function to learn the system behaviour based on existing system data. It then uses the neural network recalling function to generate fuzzy knowledge databases based on the trained neural network model.

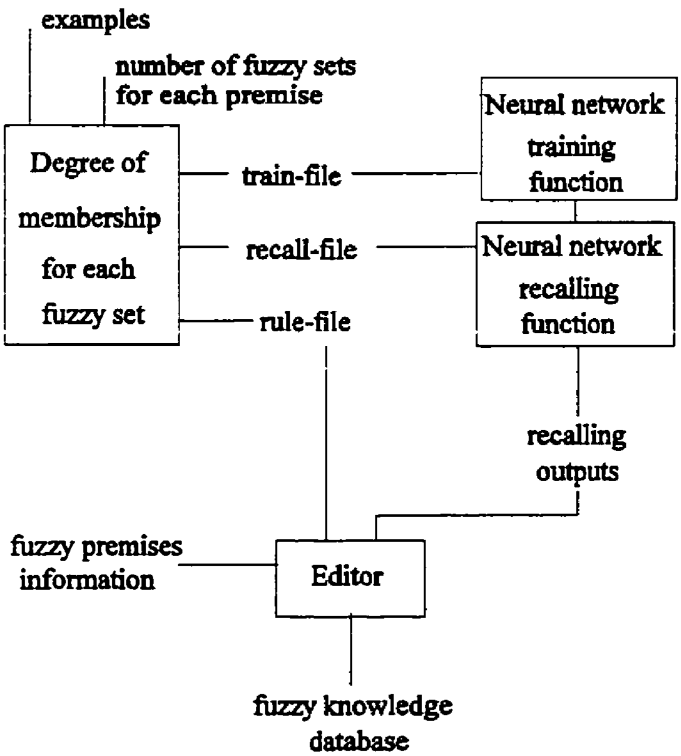


Figure 2.7. Process of the NeuFuz method.

The combined process of fuzzy logic and neural network is shown in figure 2.7. The procedure of the NeuFuz method which uses neural networks training-recalling function to generate fuzzy knowledge databases is explained below:

(1) Prepare a file which includes a set of examples.

(2) Decide the number of fuzzy sets for each premise in this file.

(3) Transform a set of examples into the values of the degree of membership by a developed program. Three files are obtained from this program. The train-file includes all the values of the degree of membership for each premise data . It also contains the associated conclusions. The recall- file includes all the vectors combinations according to the number of fuzzy premise sets. The rule-file has a fuzzy rules section format.

(4) Train neural network with the train-file. Use the recall- file as the neural network recalling function input. A file which includes the neural network recalling-output is then obtained.

(5) Put these recalling-outputs in the fuzzy knowledge conclusion section. Combining with the rule-file obtained from step (3), a fuzzy knowledge database can be generated.

To better explain the complete procedure, a simple adding is programmed by the NeuFuz method.

2.2.2. A simple adding

2.2.2.1. The original examples analysis

As shown in table 2.1, there are one hundred adding examples. Each example includes three premises and one conclusion. Values vary from 0.1 to 0.9 in the first premise A, from 1 to 99 in the second premise B and from 1 to 9 in the third premise C. The relation between them is A+B+C=D. Since this application is a simple linear case, the number of fuzzy sets has little influence on the fuzzy precision. As shown in figure 2.8, in an attempt to explore the new NeuFuz method, a trial was done with three fuzzy sets for premise A, four fuzzy sets for premise B and five fuzzy sets for premise C.

Examples: Addition $\longrightarrow A + B + C = D$
3 premises, 1 conclusion
100 examples

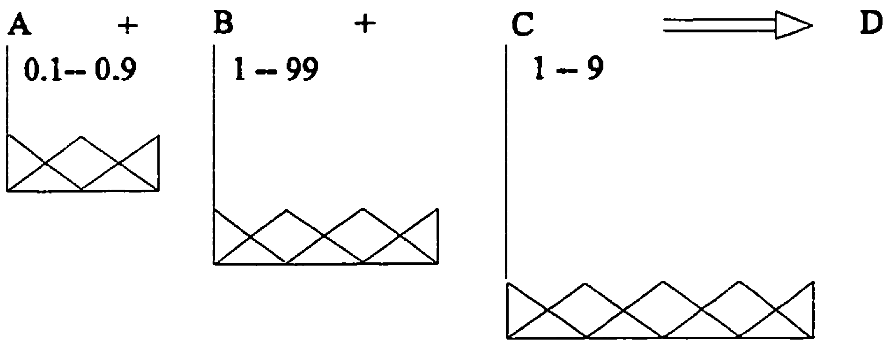


Figure 2.8. Adding example explanation.

Table 2.1. Adding data file which includes 100 examples.

	premises			conclusion		premises			conclusion		premises			conclusion
	A	B	C	D		A	B	C	D		A	B	C	D
1	0.1	23	4	27.1	35	0.7	69	3	72.7	69	0.1	76	5	81.5
2	0.7	18	6	24.7	36	0.5	44	2	46.5	70	0.4	62	1	63.4
3	0.5	16	9	25.5	37	0.6	66	6	72.6	71	0.8	46	4	50.8
4	0.2	88	7	95.2	38	0.3	56	5	61.3	72	0.6	1	3	4.6
5	0.7	26	3	29.7	39	0.1	24	1	25.1	73	0.5	92	5	97.5
6	0.5	90	2	92.5	40	0.4	33	8	41.4	74	0.7	83	6	89.7
7	0.6	33	6	39.6	41	0.8	12	6	18.8	75	0.2	27	1	28.2
8	0.3	41	5	46.3	42	0.6	29	9	38.6	76	0.4	16	7	23.4
9	0.1	56	1	57.1	43	0.5	2	5	7.5	77	0.8	39	8	47.8
10	0.4	62	8	70.4	44	0.7	79	7	86.7	78	0.3	79	6	85.3
11	0.8	76	6	82.8	45	0.2	6	3	9.2	79	0.5	63	3	66.5
12	0.6	4	9	13.6	46	0.4	75	8	83.4	80	0.9	11	4	15.9
13	0.5	82	5	87.5	47	0.8	24	4	28.8	81	0.7	36	2	38.7
14	0.7	93	7	100.7	48	0.3	33	8	41.3	82	0.8	44	9	53.8
15	0.2	77	3	80.2	49	0.5	56	6	62.5	83	0.4	31	7	38.4
16	0.4	66	8	74.4	50	0.9	91	4	95.9	84	0.7	94	6	100.7
17	0.8	29	4	33.8	51	0.7	32	8	40.7	85	0.6	97	1	98.6
18	0.3	39	8	47.3	52	0.6	72	3	75.6	86	0.8	72	9	81.8
19	0.5	73	6	79.5	53	0.4	69	4	73.4	87	0.9	51	3	54.9
20	0.9	21	4	25.9	54	0.7	24	3	27.7	88	0.4	38	4	42.4
21	0.7	16	8	24.7	55	0.6	52	1	53.6	89	0.1	52	2	54.1
22	0.8	34	3	37.8	56	0.8	41	4	45.8	90	0.5	17	4	21.5
23	0.4	21	4	25.4	57	0.9	21	6	27.9	91	0.2	22	5	27.2
24	0.7	14	3	17.7	58	0.4	16	7	23.4	92	0.3	43	9	52.3
25	0.6	17	1	18.6	59	0.1	85	9	94.1	93	0.9	8	1	9.9
26	0.8	32	4	36.8	60	0.5	13	5	18.5	94	0.5	99	9	108.5
27	0.9	41	6	47.9	61	0.1	43	6	49.1	95	0.1	56	7	63.1
28	0.4	58	7	65.4	62	0.7	38	9	47.7	96	0.7	41	3	44.7
29	0.1	62	9	71.1	63	0.5	56	7	63.5	97	0.4	21	6	27.4
30	0.5	77	5	82.5	64	0.2	28	2	30.2	98	0.3	71	4	75.3
31	0.1	67	4	71.1	65	0.7	36	4	40.7	99	0.6	68	2	70.6
32	0.7	23	6	29.7	66	0.5	70	1	71.5	100	0.5	34	4	38.5
33	0.5	46	9	55.5	67	0.6	43	8	51.6					
34	0.2	31	7	38.2	68	0.3	31	2	33.3					

2.2.2.2. Neural network training function train-file preparation

A hundred examples of the adding were presented in table 2.1 and the number of fuzzy sets was decided as shown in figure 2.8. Therefore, all information required to prepare a neural network training function train-file is available.

To follow the process of the NeuFuz method, the fourth example of the adding data file shown in table 2.1 which is (0.2, 88, 7, 95.2) is taken:

premise A	*premise B*	*premise C*	*conclusion D*
0.2	88	7	95.2

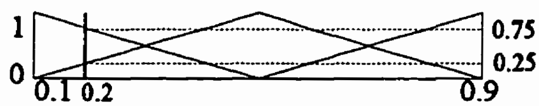
The first step of the NeuFuz method is to subdivide the premise data into the values of the degree of membership of its fuzzy sets. There are three fuzzy sets for premise A, four sets for premise B and five sets for premise C.

As shown in figure 2.9, for the value 0.2 of premise A, its value of the degree of membership in the first set is 0.75, in the second set it is 0.25 and it has a zero degree of membership in the third set. So the original value 0.2 in the premise A is transformed to the values of the degree of membership which are (0.75, 0.25, 0).

For the value 88 of premise B, its values of the degree of membership in the first two sets are 0 and 0, in the last two sets are 0.3367 and 0.6633. So the original value 88 in the premise B is transformed to the values of the degree of membership which are (0, 0, 0.3367, 0.6633).

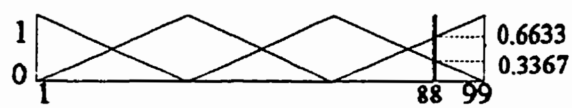
For the value 7 of premise C, it denotes a full degree of membership in the fourth set. So the values of the degree of membership of the original value 7 in premise C are (0, 0, 0, 1, 0).

premise A: 0.2 —>



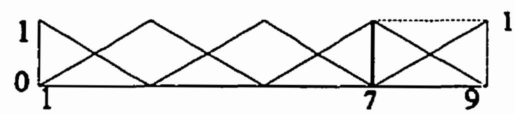
values of the degree of membership —> (0.75 0.25 0)

premise B: 88 —>



values of the degree of membership —> (0 0 0.3367 0.6633)

premise C: 7 —>



values of the degree of membership —> (0 0 0 1 0)

Figure 2.9. From original value to the fuzzy degrees of membership.

So the neural network training function inputs which are derived from the premises (0.2, 88, 7) of the adding data file are:

premise A	*premise B*	*premise C*
0.75 0.25 0	*0 0 0.3367 0.6633*	*0 0 0 1 0*

Thus, the final neural network training function input-output of this adding example (0.2, 88, 7, 95.2) are:

premise A	*premise B*	*premise C*	*conclusion D*
0.75 0.25 0	*0 0 0.3367 0.6633*	*0 0 0 1 0*	*95.2*

A train-file which includes one hundred lines in the above format is prepared for the neural network training function. It is listed in Appendix A.

2.2.2.3. Neural network model built for adding

The neural network model below has been trained by the neural network training function train-file. Figure 2.10 is the neural network model graphical representation which is devised for this application. As presented by Brault in [14], usually the number of cells in a neural network hidden layer is the cell number in neural network input layer multiplied or divided by two. As shown in figure 2.10, there are twelve input in the input layer, one output in the output layer. Twenty four neurons are used in the hidden layer. For the example in the previous section, the values (0.75, 0.25, 0, 0, 0, 0.3367, 0.6633, 0, 0, 0, 1, 0) are served as twelve inputs in the input layer and the value 95.2 is served as the output in the output layer for the neural network training function. One hundred similar examples are used for the neural network training.

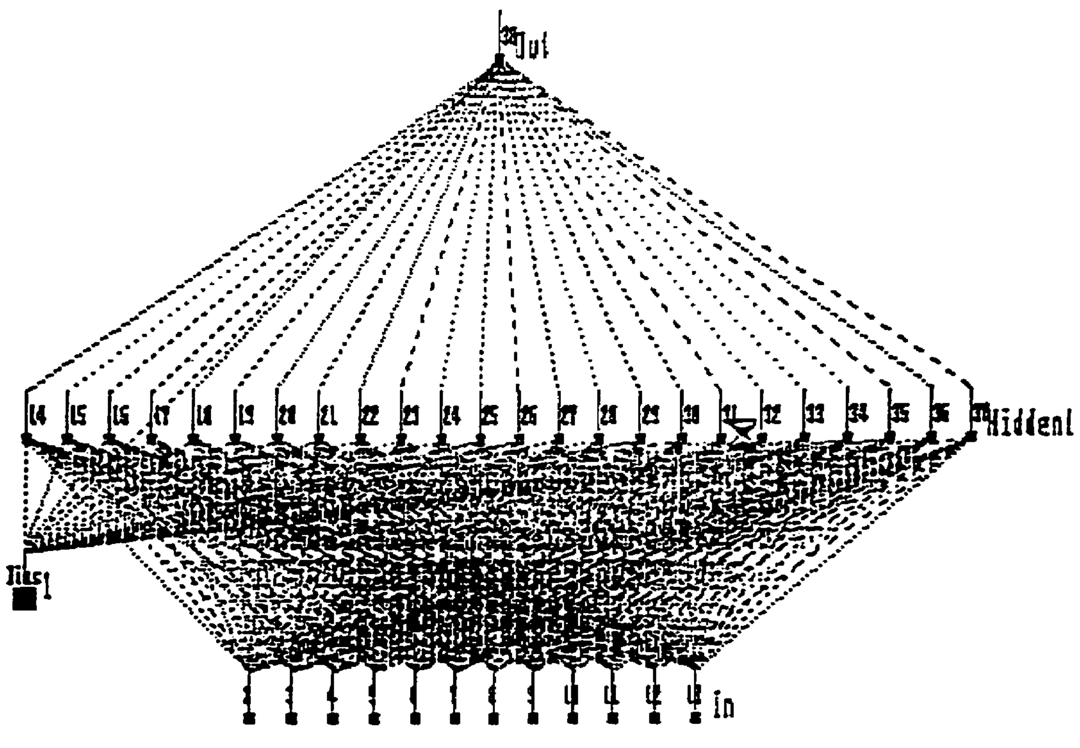


Figure 2.10. Neural network model graphical representation for adding.

2.2.2.4. Neural network recalling function recall-file preparation

In this application, there are three fuzzy sets for premise A, four fuzzy sets for premise B and five fuzzy sets for premise C. Therefore, there are 3x4x5 combinations between the premise fuzzy sets which means that sixty fuzzy rules must exist in this application. Table 2.2 shows all these sixty combinations of these fuzzy sets and their vectorial formats which are called as the rule-file and the recall-file in figure 2.7. The combinations of these vectorial formats are used as the recall-file for the neural network recalling function. The format of the neural network recalling function recall- file is shown below:

```
1 0 0    1 0 0 0    1 0 0 0 0
1 0 0    1 0 0 0    0 1 0 0 0
1 0 0    1 0 0 0    0 0 1 0 0
1 0 0    1 0 0 0    0 0 0 1 0
1 0 0    1 0 0 0    0 0 0 0 1
1 0 0    0 1 0 0    1 0 0 0 0
1 0 0    0 1 0 0    0 1 0 0 0
1 0 0    0 1 0 0    0 0 1 0 0
...      ...        ...
...      ...        ...
0 0 1    0 0 0 1    0 0 0 1 0
0 0 1    0 0 0 1    0 0 0 0 1
```

The recalling function recall-file includes a total of sixty lines in the above format. The neural network model in figure 2.10 was trained by the training function train-file. Then, the recalling function asks this trained model to provide a set of recalling-outputs for the prepared recall-file. Table 2.3 shows the sixty neural network recalling-outputs.

Table 2.2. Recalling function recall-file and rule-file for adding.

combination of fuzzy sets			vectorial format			combination of fuzzy sets			vectorial format		
prem.A	prem.B	prem.C	prem.A	prem.B	prem.C	prem.A	prem.B	prem.C	prem.A	prem.B	prem.C
1	1	1	100	1000	10000	2	3	1	010	0010	10000
1	*1*	*2*	*100*	*1000*	*01000*	2	3	2	010	0010	01000
1	1	3	100	1000	00100	2	3	3	010	0010	00100
1	1	4	100	1000	00010	2	3	4	010	0010	00010
1	1	5	100	1000	00001	2	3	5	010	0010	00001
1	2	1	100	0100	10000	2	4	1	010	0001	10000
1	2	2	100	0100	01000	2	4	2	010	0001	01000
1	2	3	100	0100	00100	2	4	3	010	0001	00100
1	2	4	100	0100	00010	2	4	4	010	0001	00010
1	2	5	100	0100	00001	2	4	5	010	0001	00001
1	3	1	100	0010	10000	3	1	1	001	1000	10000
1	3	2	100	0010	01000	3	1	2	001	1000	01000
1	3	3	100	0010	00100	3	1	3	001	1000	00100
1	3	4	100	0010	00010	3	1	4	001	1000	00010
1	3	5	100	0010	00001	3	1	5	001	1000	00001
1	4	1	100	0001	10000	3	2	1	001	0100	10000
1	4	2	100	0001	01000	3	2	2	001	0100	01000
1	4	3	100	0001	00100	3	2	3	001	0100	00100
1	4	4	100	0001	00010	3	2	4	001	0100	00010
1	4	5	100	0001	00001	3	2	5	001	0100	00001
2	1	1	010	1000	10000	3	3	1	001	0010	10000
2	1	2	010	1000	01000	3	3	2	001	0010	01000
2	1	3	010	1000	00100	3	3	3	001	0010	00100
2	1	4	010	1000	00010	3	3	4	001	0010	00010
2	1	5	010	1000	00001	3	3	5	001	0010	00001
2	2	1	010	0100	10000	3	4	1	001	0001	10000
2	2	2	010	0100	01000	3	4	2	001	0001	01000
2	2	3	010	0100	00100	3	4	3	001	0001	00100
2	2	4	010	0100	00010	3	4	4	001	0001	00010
2	2	5	010	0100	00001	3	4	5	001	0001	00001

Table 2.3. Recalling-output from recalling function.

	recalling-output		recalling-output
1	2.14	31	67.84
2	4.04	32	69.75
3	6.06	33	71.75
4	8.04	34	73.73
5	10.01	35	75.71
6	34.88	36	100.65
7	36.78	37	102.55
8	38.79	38	104.57
9	40.77	39	106.55
10	42.75	40	108.52
11	67.45	41	2.9
12	69.35	42	4.8
13	71.36	43	6.81
14	73.34	44	8.8
15	75.31	45	10.77
16	100.26	46	35.63
17	102.16	47	37.53
18	104.18	48	39.54
19	106.16	49	41.53
20	108.13	50	43.5
21	2.53	51	68.2
22	4.43	52	70.1
23	6.45	53	72.11
24	8.43	54	74.1
25	10.4	55	76.07
26	35.27	56	101.02
27	37.17	57	102.92
28	39.18	58	104.93
29	41.16	59	106.91
30	43.14	60	108.89

2.2.2.5. The generation of a knowledge database with the recalling-outputs

From this part, the following steps are required to generate the fuzzy knowledge database.

(1) Take the second line of the recall-file from table 2.2.

premise A	*premise B*	*premise C*
1 0 0	*1 0 0 0*	*0 1 0 0 0*

(2) Take the second recalling-output from table 2.3.

recalling-output
4.04

(3) Combine the recall-file and recalling-output.

premise A	*premise B*	*premise C*	*recalling-output*
1 0 0	*1 0 0 0*	*0 1 0 0 0*	*4.04*

(4) Change their format to the combination of the premise fuzzy sets:

premise A	*premise B*	*premise C*	*conclusion D*
1	*1*	*2*	*4.04*

(5) Write the recalling-output 4.04 into the fuzzy knowledge database conclusions section. As shown in figure 2.12, it has the **second** position

in the conclusions section. Therefore, the format of this rule is changed to:

premise A	*premise B*	*premise C*	*position number*
1	*1*	*2*	*2*

This is the second rule needed in the fuzzy knowledge database file.

As shown in figure 2.11, the first premise varies from 0.1 to 0.9 and the tips of the three sets are 0.1, 0.5 and 0.9. The tips of the four sets for the second premise are 1, 33.66, 66.33 and 99. The tips of the five sets for the third premise are 1, 3, 5, 7 and 9. The values in the neural network recalling-output file are the tip of the triangles in the conclusions section. The obtained fuzzy knowledge database by using the NeuFuz method is shown in figure 2.12.

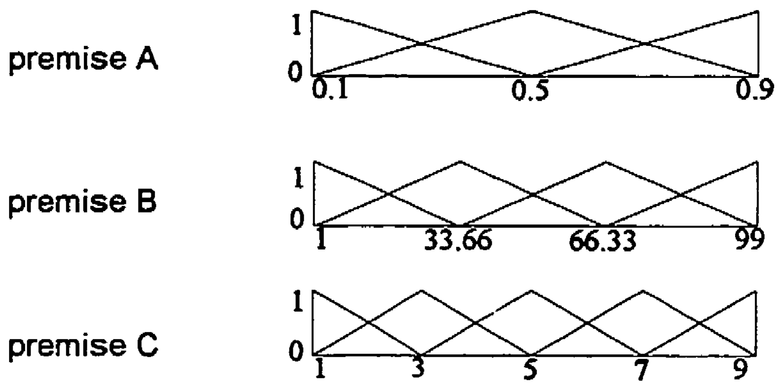


Figure 2.11. The graphical representation of premise A, B and C.

```
# 1 premise A
(0.1 0.1 0   0.4 1)
(0.5 0.5 0.4 0.4 1)
(0.9 0.9 0.4 0   1)

# 1 premise B
(1     1     0     32.67 1)
(33.66 33.66 32.67 32.67 1)
(66.33 66.33 32.67 32.67 1)
(99    99    32.67 0     1)

# 1 premise C
(1 1 0 2 1)
(3 3 2 2 1)
(5 5 2 2 1)
(7 7 2 2 1)
(9 9 2 0 1)

~ 1 conclusion D
(2.14   2.14   0.5 0.5 1)
(4.04   4.04   0.5 0.5 1)
(6.06   6.06   0.5 0.5 1)
(8.04   8.04   0.5 0.5 1)
(10.01  10.01  0.5 0.5 1)
(34.88  34.88  0.5 0.5 1)
(36.78  36.78  0.5 0.5 1)
(38.79  38.79  0.5 0.5 1)
(40.77  40.77  0.5 0.5 1)
(42.75  42.75  0.5 0.5 1)
(67.42  67.42  0.5 0.5 1)
(69.35  69.35  0.5 0.5 1)
(71.36  71.36  0.5 0.5 1)
(73.34  73.34  0.5 0.5 1)
(75.31  75.31  0.5 0.5 1)
(100.26 100.26 0.5 0.5 1)
(102.16 102.16 0.5 0.5 1)
(104.18 104.18 0.5 0.5 1)
(106.16 106.16 0.5 0.5 1)
(108.13 108.13 0.5 0.5 1)
(2.53   2.53   0.5 0.5 1)
(4.43   4.43   0.5 0.5 1)
(6.45   6.45   0.5 0.5 1)
(8.43   8.43   0.5 0.5 1)
(10.4   10.4   0.5 0.5 1)
(35.27  35.27  0.5 0.5 1)
(37.17  37.17  0.5 0.5 1)
(39.18  39.18  0.5 0.5 1)
(41.16  41.16  0.5 0.5 1)
(43.14  43.14  0.5 0.5 1)
(67.84  67.84  0.5 0.5 1)
(69.75  69.75  0.5 0.5 1)
(71.75  71.75  0.5 0.5 1)
(73.73  73.73  0.5 0.5 1)
(75.71  75.71  0.5 0.5 1)
(100.65 100.65 0.5 0.5 1)
(102.55 102.55 0.5 0.5 1)
(104.57 104.57 0.5 0.5 1)
(106.55 106.55 0.5 0.5 1)
(108.52 108.52 0.5 0.5 1)
(2.9    2.9    0.5 0.5 1)
(4.8    4.8    0.5 0.5 1)
(6.81   6.81   0.5 0.5 1)
(8.8    8.8    0.5 0.5 1)
(10.77  10.77  0.5 0.5 1)
(35.63  35.63  0.5 0.5 1)
(37.53  37.53  0.5 0.5 1)
(39.54  39.54  0.5 0.5 1)
(41.53  41.53  0.5 0.5 1)
(43.5   43.5   0.5 0.5 1)
(68.2   68.2   0.5 0.5 1)
(70.1   70.1   0.5 0.5 1)
(72.11  72.11  0.5 0.5 1)
(74.1   74.1   0.5 0.5 1)
(76.07  76.07  0.5 0.5 1)
(101.02 101.02 0.5 0.5 1)
(102.92 102.92 0.5 0.5 1)
(104.93 104.93 0.5 0.5 1)
(106.91 106.91 0.5 0.5 1)
(108.89 108.89 0.5 0.5 1)

*
(1 1 1 1)
(1 1 2 2)
(1 1 3 3)
(1 1 4 4)
(1 1 5 5)
(1 2 1 6)
(1 2 2 7)
(1 2 3 8)
(1 2 4 9)
(1 2 5 10)
(1 3 1 11)
(1 3 2 12)
(1 3 3 13)
(1 3 4 14)
(1 3 5 15)
(1 4 1 16)
(1 4 2 17)
(1 4 3 18)
(1 4 4 19)
(1 4 5 20)
(2 1 1 21)
(2 1 2 22)
(2 1 3 23)
(2 1 4 24)
(2 1 5 25)
(2 2 1 26)
(2 2 2 27)
(2 2 3 28)
(2 2 4 29)
(2 2 5 30)
(2 3 1 31)
(2 3 2 32)
(2 3 3 33)
(2 3 4 34)
(2 3 5 35)
(2 4 1 36)
(2 4 2 37)
(2 4 3 38)
(2 4 4 39)
(2 4 5 40)
(3 1 1 41)
(3 1 2 42)
(3 1 3 43)
(3 1 4 44)
(3 1 5 45)
(3 2 1 46)
(3 2 2 47)
(3 2 3 48)
(3 2 4 49)
(3 2 5 50)
(3 3 1 51)
(3 3 2 52)
(3 3 3 53)
(3 3 4 54)
(3 3 5 55)
(3 4 1 56)
(3 4 2 57)
(3 4 3 58)
(3 4 4 59)
(3 4 5 60)
```

Figure 2.12. Fuzzy knowledge database from the NeuFuz method.

2.2.2.6. Comparison and accuracy

A comparison is shown in table 2.4. The difference between the exact value and the value obtained from the NeuFuz method is very small. The minimum accuracy in this application is 0.45%. This is an extremely simple application which has an easy linear relationship between its premises and conclusion. Also, these one hundred examples are very well prepared since they cover the complete premises range. These are two important reasons for the high precision which is achieved in this application.

Table 2.4. Comparison and accuracy in adding simulation.

	premises			value exact	value NeuFuz	difference	accuracy
	A	B	C				
1	0.16	34	8	42.16	42.157	0.003	0.007%
2	0.20	87	6	93.20	93.212	0.012	0.013%
3	0.59	58	3	61.59	61.522	0.068	0.110%
4	0.61	12	1	13.61	13.661	0.051	0.370%
5	0.73	63	4	67.73	67.634	0.096	0.140%
6	0.88	42	5	47.88	47.836	0.044	0.092%
7	0.90	26	2	28.9	28.898	0.002	0.007%
8	0.33	72	7	79.33	79.26	0.070	0.088%
9	0.49	99	9	108.49	108.51	0.020	0.018%
10	0.50	1.5	1.5	3.50	3.5159	0.0159	0.450%
11	0.42	40.19	6.8	47.41	47.394	0.016	0.034%
12	0.16	31	8	39.16	39.14	0.020	0.051%

In more complex situations, it is much harder to construct the fuzzy knowledge database. A good example of such a complex database is given next where the technique is applied to the selection of cutting parameters.

2.3. The restructuring of the cutting parameters from the Machining Data Handbook in a knowledge database in a manual manner

2.3.1. Cutting parameters analysis

Since it is the most complete and the most used in the field, the Machining Data Handbook [2] was picked as a reference in this study. The milling statistics accumulated for many years are collected into tabular forms which are standard in industry. In milling, seven parameters are considered very important in generating the knowledge databases for the choice of cutting parameters. They are:

- *type of milling operation;*
- *workpiece material;*
- *tool material;*
- *depth of cut;*
- *cutting speed;*
- *feed per tooth;*
- *tool material grade.*

They will be explained in detail in the next paragraphs.

To determine the cutting parameters from this handbook, first of all , there are two parameters which should be chosen. They are the type of milling operation and the workpiece material in terms of its mechanical characteristics which are its hardness, chemical composition and thermal treatment. Then, the tool material and the depth of cut should be chosen. At the end, the speed, the feed per tooth and the tool material grade can be obtained. These therefore correspond to the conclusions of the proposed system.

This method does not provide a solution at intermediate points. For example, the Machining Data Handbook [2] gives the speed and the feed per tooth for the depth of cut which is 4(mm) or 8(mm). But there is no information that can be found in situations where the depth of cut is between 4(mm) and 8(mm). Therefore, it is not possible to determine the speed and the feed per tooth for one value which is in an interval of the hardness and the depth of cut by using the Machining Data Handbook [2].

Also, the information in the Machining Data Handbook [2] is not compact, therefore the information search speed is very slow. As presented by Balazinski, Bellerose and Czogala in [15], fuzzy logic helps to handle this kind of problem.

Type of milling operation

From the Machining Data Handbook [2], the principle milling operations are grouped into nine categories:

- *2.1 face milling;*
- *2.2 face milling with diamond tools;*
- *2.3 face milling with diamond impregnated cup wheel;*
- *2.4 slab milling;*
- *2.5 side and slot milling;*
- *2.6 end milling-peripheral;*
- *2.7 end milling-peripheral with diamond tools;*
- *2.8 end milling-slotting;*
- *2.9 thread milling.*

The type of milling operation is the first step in the procedure to choose the cutting parameters.

Workpiece material

The second important parameter is the workpiece material. The Machining Data Handbook [2] presents a maximum of sixty-one material classes in the section on milling. In this study, the following information on the workpiece material are important:

- *chemical composition;*
- *thermal treatment;*
- *hardness.*

These characteristics are sufficient to properly separate the workpiece material classes and to define the premises in the fuzzy knowledge database.

Tool material

The tool material is another very important factor to decide the cutting parameters in milling. Different speeds and feeds are recommended when the material of the tool is different. The tool material is divided into seven groups according to the Machining Data Handbook [2]. They are:

- *High Speed Steel;*
- *Brazed Uncoated Carbide;*
- *Indexable Uncoated Carbide;*
- *Coated Carbide;*
- *Carbide;*
- *Diamond;*
- *Impregnated Diamond.*

Depth of cut

The depth of cut is the material thickness that is removed by a tool on the surface of the workpiece. It is one of the factors which determines the method of cutting: roughing, semi-finishing or finishing.

A roughing operation can remove as much material as the physical system permits. Usually, roughing can generate a desired dimension. But, due to the surface finish and the dimensional accuracy requirements, the workpiece cannot be machined by roughing only in most cases. A finishing operation which uses a small depth of cut is therefore required to generate the proper dimensions and surfaces.

During a roughing operation, the depth of cut is usually much greater than that for a finishing operation. For a roughing operation, the cutting speed is low and the feed per tooth is large. For a finishing operation, the feed per tooth is moderate and the cutting speed is high. Semi-finishing is a kind of operation between the roughing and finishing.

Cutting speed

The cutting speed is the rate at which the cutting tool revolves measured as a tangential speed in feet or meters per minute. For each type of operation, there exists a maximum speed of cut.

An excessive cutting speed will cause the cutting tool to break down quickly resulting in higher costs and wasted time replacing or sharpening cutting tools. Too slow a cutting speed will result in the loss of valuable time, resulting in a higher cost for each part. Therefore, the cutting speed is a very important factor which affects the production rate and also the life of the cutting tool.

Feed per tooth

The feed is the amount by which a cutting tool advances into the work, which generally controls the rate of metal removed from a workpiece. The feed per revolution is defined as the distance travelled between the tool and the workpiece during a single revolution of the tool. The feed per tooth is the feed per revolution divided by the number of teeth.

Tool material grade

In many cases, removable inserts, such as ceramic, titanium, etc., are used to improve the tool performance. For several milling operations, speeds and feeds are recommended for the widely used coated carbides. From the Machining Data Handbook [2], several coated tool material grades are recommended when the speed and the feed per tooth are obtained. The recommended tool material grade is defined as a conclusion in fuzzy knowledge database. All recommendations are presented in codes, for example P50. Each tool manufacturer has a wide variety of carbide grades. In order to implement the recommendations contained in the fuzzy knowledge database, it is usually necessary to consult section 14, Tool Materials, in the Machining Data Handbook [2] from where it can be found that the code P50 means product R4 in Sandvik Inc.

2.3.2. Fuzzy knowledge database concept

In order to fully exploit the capabilities of fuzzy logic and obtain coherent results which are as close as possible to reality, a clear definition of the concepts is important. In fact, if they are not properly defined, the results can be far from the reality with unacceptable errors. The first step in the process which must be carried out, is to clearly define the system in terms of its premises and its conclusions.

2.3.2.1. Premises of fuzzy knowledge database

From the specific characteristics which are chemical composition, thermal treatment and hardness of each material, it is possible to define the premises of the fuzzy knowledge database. These are divided into two categories.

1) the common premises which are valuable for all material categories. They are:

-- the workpiece material hardness;

-- the depth of cut.

2) the specific premises which apply only for certain materials. They are:

-- the workpiece material chemical content;

-- the workpiece thermal treatment;

-- the tool material.

Machinability is the property of a material which governs the ease or difficulty with which a material can be machined using a cutting tool. Among the material chemical contents, the most important factors which have an influence on the machinability are: carbon, sulphur, lead, chrome, nickel, tungsten, aluminum, chrome, silicon and copper.

2.3.2.2. Conclusions of fuzzy knowledge database

According to the Machining Data Handbook [2], the conclusions are always the same for the fuzzy knowledge databases for most milling operations. The conclusions are:

- *the speed (m/min);*
- *the feed per tooth (mm);*
- *the first recommended coated tool material grade;*
- *the second recommended coated tool material grade.*

For the operations 2.2 face milling with diamond tools, 2.3 face milling with diamond impregnated cup wheel and 2.7 end milling-peripheral with diamond tools the conclusions are the speed and the feed per tooth.

2.3.2.3. The generation of a fuzzy knowledge database in a manual manner

A milling operation, whose tool material is high speed steel, the workpiece material is a free machining stainless steel, wrought and the subgrade of material is austenitic, is chosen as an example to present the manual manner used to generate such a fuzzy knowledge database. The ASCII and graphical format of this fuzzy knowledge database are shown in figure 2.4 and 2.5.

In the Machining Data Handbook [2], as shown in table 2.5, it is very clear that there are two premises and two conclusions for this type of milling operation.

Table 2.5. Information listed in the Machining Data Handbook.

Hardness(Bhn)	Depth of cut(mm)	Speed(m/min)	Feed per tooth(mm)
135 to 185	1 4 8	49 40 30	0.20 0.30 0.40
225 to 275	1 4 8	46 37 27	0.15 0.25 0.36

The first premise HARDNESS is presented by two tables in the Machining Data Handbook [2] which can be comprehended that there are two fuzzy sets for this premise. The Machining Data Handbook [2] gives three values 1, 4, and 8 for the second premise DEPTH OF CUT which indicates that three critical points exist in this premise. Therefore, there are three fuzzy sets for this premise. As discussed in section 2.1.2, a triangular shape (C) is selected since this is a problem with a gradual variation. As shown in figure 2.5, the premises have a triangular shape for their fuzzy sets. The shape of the HARDNESS has two triangles and the DEPTH OF CUT has three triangles.

The conclusions for this milling operation in the Machining Data Handbook [2] are the SPEED and the FEED PER TOOTH. Also, as discussed in section 2.1.2, the equal symmetric triangular shape is chosen for the conclusion fuzzy sets. As shown in figure 2.5, the conclusion SPEED and the FEED PER TOOTH have equal symmetric triangular shape. For each value of the field covered, the tip of triangles correspond to the values in the Machining Data Handbook [2]. As shown in figure 2.5, the triangle tip of each conclusion set is the value which is extracted directly from the Machining Data Handbook [2]. For example, the tips of the SPEED fuzzy sets are 27 m/min, 30 m/min, 37 m/min, 40 m/min, 46 m/min and 49 m/min in fuzzy knowledge database file. They are the six values presented in the Machining Data Handbook [2] as shown in table 2.5.

Figure 2.4 is a knowledge database in ASCII format which includes two premises starting with a # symbol, two conclusions starting with a ~ symbol and six rules which reveal the relations between the premises and the conclusions starting with a * symbol. The NeuFuz and manual methods for generating fuzzy knowledge databases are presented. In the next section, the running environment of the NeuFuz method and the fuzzy decision support system (FDSS) will be explained.

2.4. The running environment for the fuzzy decision support system (FDSS) and the NeuFuz method

The FDSS applied for the choice of cutting parameters is picked as an example to explain its running environment.

2.4.1. Codification of fuzzy knowledge databases for the selection of cutting parameters

A codification is necessary to properly organize this research work; thus files can be differentiated from each other. There are nine categories of milling operations, seven kinds of tool materials, sixty one types of workpiece materials and sixteen workpiece material subgrades in the Machining Data Handbook [2] milling section.

A knowledge database whose general operation is milling, specific operation is face milling, tool material is high speed steel, workpiece material is tool steels, wrought and workpiece subgrade is hot work is coded as m2110802.dat in this study. This file code includes eight characters and is explained below:

M 21 1 08 02

where:

1. the first character is the type of machining operation, for example: M is milling;

2. the second and the third character show the type of milling operation, for example: 21 is face milling and they vary from 21 to 29;

3. the fourth character is the tool material, for example: 1 is high speed steel and it varies from 1 to 7;

4. the fifth and the sixth character describe the workpiece material, for example 08 is for tool steels wrought and they vary from 01 to 61;

5. the last two characters are used to differentiate, if it exists, the subgrade of the workpiece material, for example 02 is for hot work and these numbers vary from 00 to 16. When there is no subgrade, these two last characters are 00.

Another example is **M2375701.dat**, where:

> ***M** is milling operation;*
>
> ***23** means the type of milling is face milling with diamond impregnated cup wheel;*
>
> ***7** means the tool material is impregnated diamond;*
>
> ***57** means the workpiece material is composites;*
>
> ***01** means the workpiece material subgrade is Kevlar 49.*

In order to obtain the cutting parameters in milling from a fuzzy decision support system (FDSS), a proper fuzzy knowledge database should be first selected. The fuzzy knowledge database selection procedure is presented below:

> *(1) general operation;*
>
> *(2) specific operation;*
>
> *(3) tool material;*
>
> *(4) workpiece material;*
>
> *(5) workpiece subgrade.*

With these above five steps, a fuzzy knowledge database code is created. Then, cutting parameters will be obtained after a FDSS calculation.

2.4.2. FDSS interfaces built in a UNIX environment

AIXwindows Interface Composer, commonly called AIC, is a comprehensive, second-generation Graphic User Interface (GUI) Builder. AIC and the computer language C++ are used to generate user interfaces which can be found in figure 2.13 and 2.14.

As shown in figure 2.13, this first user interface is used to choose proper fuzzy knowledge database. All the fuzzy knowledge databases for the cutting parameters selection are installed in a directory of a UNIX system user account. Five choice steps were explained in section 2.4.1. All these five steps are programmed in menu form which simplifies the selection processes in the first interface. From the first interface shown in figure 2.13, a fuzzy knowledge database can be chosen. Click the button "Do calculation" in the bottom of this interface, a second interface which includes several functions from the FDSS FUZZY-FLOU software will appear.

As shown in figure 2.14, this interface which has a fuzzy inference reads that fuzzy knowledge database obtained from the first interface which is m2110101.dat and will ask the values for the workpiece hardness, the depth of cut, etc. Then, it will coherently give the results for the speed, the feed per tooth and the tool material grade for user's specific cases.

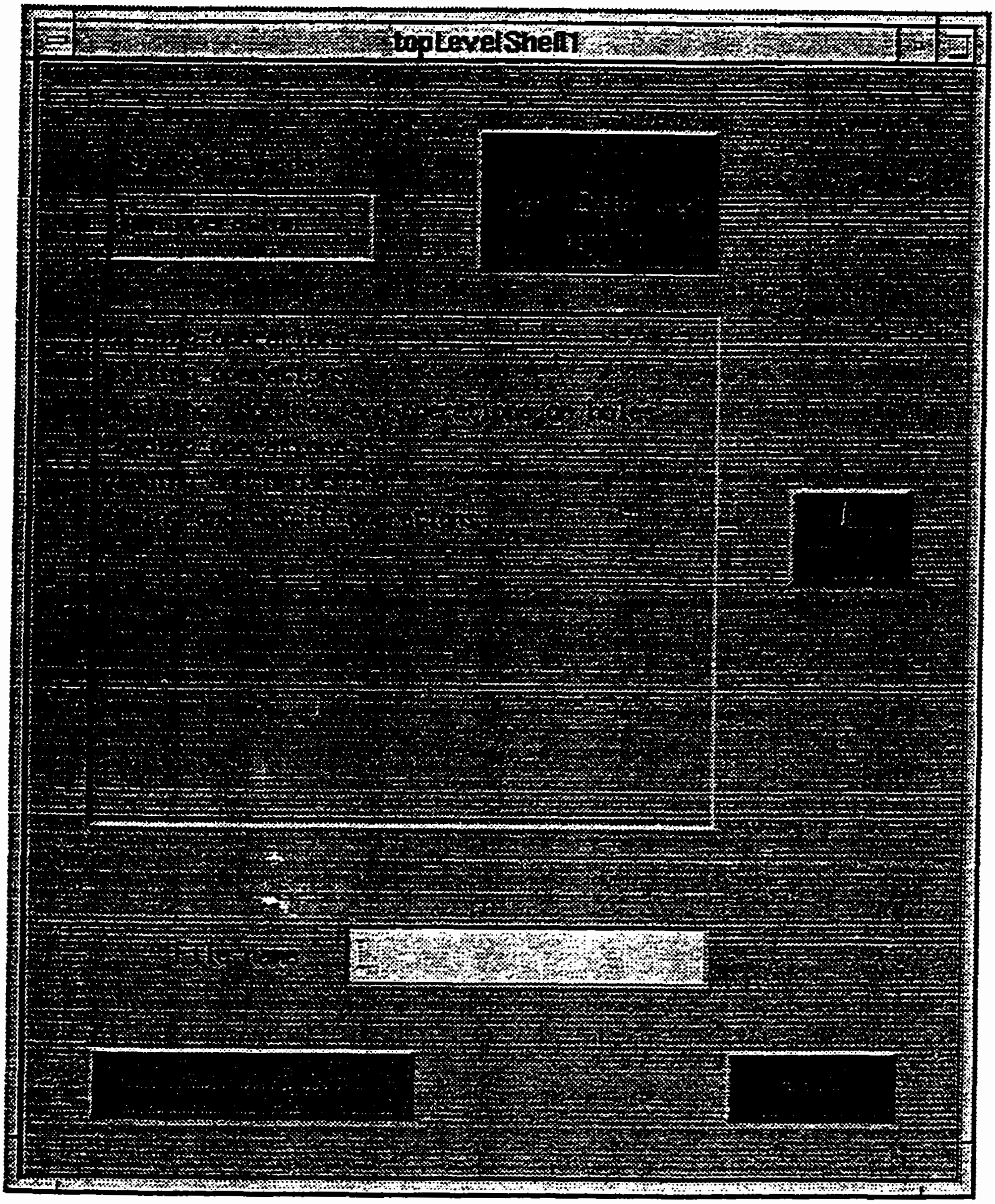


Figure 2.13. Interface for database selection.

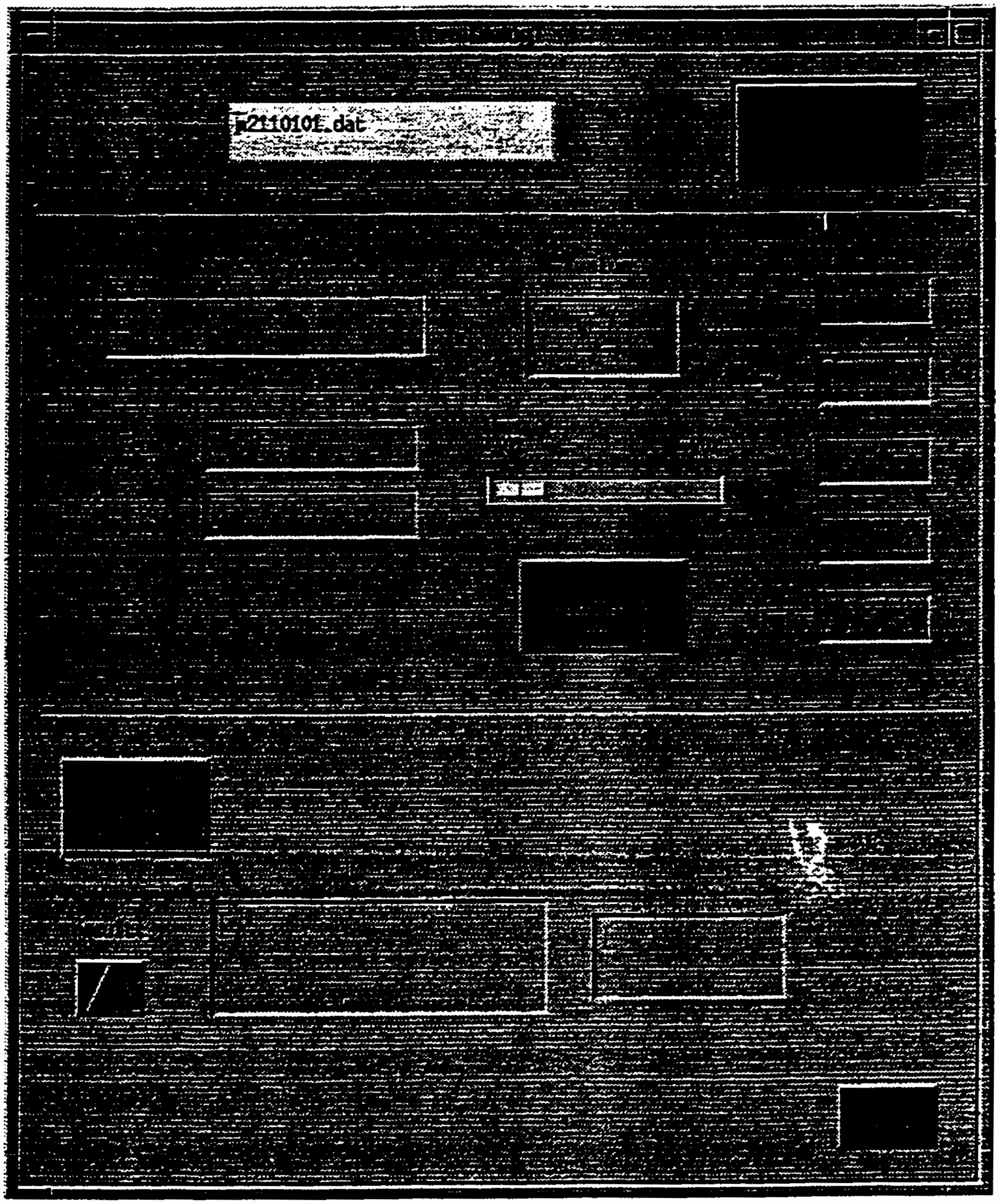


Figure 2.14. Interface for fuzzy inference.

2.4.3. FDSS interfaces integrated in a CADCAM (CATIA) environment

Despite the fact that many CAD/CAM systems provide the facility that is able to generate NC tool path directly from CAD data, this area is far from fully developed. Determining machining conditions has traditionally been the task of machine operators or machinists. They usually performed these operations based on decades of experience. However, due to the introduction of numerical control (NC) and computer-aided process planning (CAPP), the responsibility of assigning machining data has shifted to part programmers and process planners. Today's planners may not have the same experience as operators do to accomplish this task effectively. Therefore, to integrate a function which can provide the machining parameters to the part programmers or process planners in a CADCAM environment seems necessary.

CATIA is a computer-aided design and computer-aided manufacturing (CAD/CAM) graphics system marketed by IBM. It consists of a base module, which provides the basic interactive graphics functions and several application modules. The application modules include:

- *3-D design: for 3-D design;*
- *Drafting: for drafting;*
- *Advanced surfaces: for sculptured-surfaces design;*
- *Solid geometry: for solid geometry design;*

** Kinematics: for kinematics simulation;*

** Building design: for architectural design;*

** Library: for custom symbols and objects define, storage and classify;*

** Numerical control: for NC part programming;*

** Robotics: for design, simulation and programming robot cells.*

A common database is shared among all applications. Preprocessor and postprocessor are available to translate between CATIA and IGES (Initial Graphics Exchange Specification) data format.

A function named CUTPRM is added in the main menu of CATIA. The user graphic interfaces which are described in the previous section appear inside CATIA when the function CUTPRM is called. The part programmers and the process planners can then use these interfaces to obtain the cutting parameters in milling for their specific tasks when they are working on CATIA.

2.4.4. The NeuFuz method running environment

The new developed NeuFuz method can be ran on a DOS environment. The approximate time needed for running the program, step (3) in section 2.2.1, is around one minute with a 486 personal computer. Ten to twenty minutes is needed for the neural network to run its training and recalling functions which is step (4) in section 2.2.1. With a common EDITOR in DOS, the fifth step in section 2.2.1 which is to paste the neural network recalling-output and to arrange all premises information in fuzzy database format takes only five to ten minutes.

Three industrial applications of this NeuFuz method will be presented in the next chapter. Each application takes about twenty minutes to process.

Chapter 3:

The NeuFuz method applications

3.1. Introduction

The NeuFuz method which uses neural networks training recalling function to aid the generation of a fuzzy knowledge database is a new method developed in this research work. The procedure of the NeuFuz method is described in detail in section 2.2.1. Three industrial applications which are cutting parameters selection, CMM machine pre-travel error correction and pole life estimation are undertaken in this study. The first two applications are in the manufacturing domain and the third one is an application in an industrial field.

3.2. Application 1: cutting parameters selection

The construction of a fuzzy knowledge database from the Machining Data Handbook [2] is not always easy. Occasionally it took a lot of time to figure out the explicit rules for certain milling operations.

Table 3.1. Sixty cutting parameter examples.

	premises		conclusions			premises		conclusions	
	hardness	depth of cut	speed	feed per tooth		hardness	depth of cut	speed	feed per tooth
1	200	3	41.61	0.24	31	170	5	36.75	0.31
2	210	1	47.39	0.17	32	180	1.2	47.44	0.19
3	210	4	38.39	0.27	33	180	7	31.54	0.36
4	220	4	38.18	0.27	34	190	6	33.82	0.33
5	220	8	28.18	0.38	35	190	8	28.82	0.38
6	230	1	46.96	0.17	36	200	2	44.61	0.21
7	230	4	37.96	0.27	37	205	5.5	34.37	0.31
8	240	4	37.75	0.26	38	135	2.5	44.5	0.25
9	240	8	27.75	0.37	39	135	6	35	0.35
10	250	1	46.54	0.16	40	185	2.5	43.43	0.23
11	250	4	37.54	0.26	41	185	6	33.93	0.33
12	260	4	37.32	0.26	42	200	1	47.61	0.18
13	260	8	27.32	0.36	43	200	4	38.61	0.28
14	135	1	49	0.20	44	200	8	28.61	0.38
15	135	4	40	0.30	45	225	2.5	42.57	0.22
16	135	8	30	0.40	46	225	6	33.07	0.32
17	185	1	47.93	0.18	47	275	2.5	41.5	0.20
18	185	4	38.93	0.26	48	275	6	32	0.31
19	185	8	28.93	0.39	49	135	1.5	47.5	0.22
20	225	1	47.07	0.17	50	135	4.5	38.75	0.31
21	225	4	38.07	0.27	51	135	7.5	31.25	0.39
22	225	8	28.07	0.37	52	185	1.5	46.43	0.20
23	275	1	46	0.15	53	185	4.5	37.68	0.30
24	275	4	37	0.25	54	185	7.5	30.18	0.37
25	275	8	27	0.36	55	225	1.5	45.57	0.18
26	150	1.5	47.18	0.21	56	225	4.5	36.82	0.28
27	150	3	42.68	0.26	57	225	7.5	29.32	0.36
28	160	4.5	38.21	0.30	58	275	1.5	44.50	0.17
29	160	6.5	33.21	0.35	59	275	4.5	35.75	0.26
30	170	2	45.25	0.22	60	275	7.5	28.25	0.35

The fuzzy knowledge database for cutting parameter selection on page 24 figure 2.4 is generated by human intelligence based on the information in the Machining Data Handbook [2] shown on table 2.5. As shown in table 3.1, sixty examples of cutting parameter examples which are extracted from the manual fuzzy knowledge database are prepared for the application of the NeuFuz method.

To compare the manual method and the NeuFuz method, the same format of the premises and the same number of fuzzy sets for each premise are taken. As shown in page 21, there are two premises which are the hardness and the depth of cut. The first premise has two fuzzy sets and the second has three fuzzy sets. There are 2x3 combinations between these two premises which means that six rules exist. The combinations and their vectorial format are shown below.

combination of fuzzy sets			*vectorial format*				
1	*1*	—>	*1*	*0*	*1*	*0*	*0*
1	*2*	—>	*1*	*0*	*0*	*1*	*0*
1	*3*	—>	*1*	*0*	*0*	*0*	*1*
2	*1*	—>	*0*	*1*	*1*	*0*	*0*
2	*2*	—>	*0*	*1*	*0*	*1*	*0*
2	*3*	—>	*0*	*1*	*0*	*0*	*1*

A set of recalling-outputs is obtained when the above vectors are used as the recall-file in neural network recalling function. These recalling-outputs which are shown below are served as the conclusions in the fuzzy knowledge database.

recalling-output 1 (speed)	*recalling-output 2 (feed per tooth)*
48.365520	*0.199071*
39.757656	*0.296895*
30.084604	*0.392995*
46.003777	*0.157189*
37.131165	*0.251897*
27.370123	*0.360121*

The fuzzy knowledge database which is generated by the NeuFuz method is shown in figure 3.1.

```
# 1 Hardness (Bhn)                                          *
(135    135    0      140    1      soft)                   (1 1 1 1)
(275    275    140    0      1      med)                    (1 2 2 2)
                                                            (1 3 3 3)
# 1 Depth of cut (mm)                                       (2 1 4 4)
(1      1      0      3      1      finishing)              (2 2 5 5)
(4      4      3      4      1      semi-finish.)           (2 3 6 6)
(8      8      4      0      1      roughing)

~ 1 Speed (m/min)
(48.37  48.37         1      1      1      a)
(39.76  39.76         1      1      1      b)
(30.08  30.08         1      1      1      c)
(46.00  46.00         1      1      1      d)
(37.13  37.13         1      1      1      e)
(27.37  27.37         1      1      1      f)

~ 1 Feed per tooth (mm)
(0.1991        0.1991 0.02   0.02   1      v.low)
(0.2969        0.2969 0.02   0.02   1      low)
(0.3930        0.3930 0.02   0.02   1      med)
(0.1572        0.1572 0.02   0.02   1      high)
(0.2519        0.2519 0.02   0.02   1      v.high)
(0.3601        0.3601 0.02   0.02   1      e.high)
```

Figure 3.1. Fuzzy knowledge database from the NeuFuz method

A comparison between the knowledge database generated by human intelligence and the one obtained by the NeuFuz method is based on ten cases. The maximum difference is 3.3%. Sixty cases were fed into the system and it took only twenty minutes to process the complete set. A second and third tests were carried out with only forty and twenty cases. Their maximum errors were 6.4% and 8.6%. It is clear that better results can be achieved by increasing the neural network training information. The relationship of these two premises and two conclusions is linear in this application, the number of fuzzy sets and the critical points are well defined which ensure the high accuracy.

Table 3.2. Comparison and accuracy in cutting parameters selection

	premises		fuzzy speed	NeuFuz speed	diff.	fuzzy feed	NeuFuz feed	diff.
	hardness	depth of cut						
1	140	3.5	41.39	41.10	0.7%	0.28	0.28	0
2	155	1.4	47.37	46.87	1.1%	0.21	0.21	0
3	165	7.6	30.36	30.47	0.4%	0.38	0.38	0
4	175	6.7	32.39	32.46	0.2%	0.36	0.35	2.8%
5	195	8	28.72	28.93	0.7%	0.38	0.38	0
6	215	4.9	36.03	36.07	0.1%	0.30	0.29	3.3%
7	235	5.4	34.36	34.48	0.3%	0.30	0.30	0
8	245	2.2	43.04	42.97	0.2%	0.20	0.20	0
9	255	2.9	40.73	40.73	0	0.22	0.22	0
10	265	4.2	36.71	36.83	0.3%	0.26	0.26	0

3.3. Application 2: pre-travel error correction

Coordinate measuring machines (CMM) are a key tool for the verification and improvement of the dimensional quality of manufactured parts and products. Usually, a CMM uses a kinematic touch trigger probe to register its axes position when the probe tip contacts the object surface.

There is always a spatial delay, called pre-travel, between the position where contact first occurred and where the ruby appears to be when triggering occurs, as presented by Balazinski, Czogala, Mayer and Shen in [16]. Being able to predict the pre-travel error has become more and more important to correct the measurements taken.

The following factors are broadly recognized as being relevant to the value of the pre-travel, as presented by Balazinski, Czogala, Mayer and Shen in [16]:

1. The horizontal and vertical angles, α and β, between the probe axis and the touched surface normal vector. Under normal operation conditions, this also corresponds to the approach direction.

2. The tilt of the probe axis relative to gravity, a.

Table 3.3. CMM data file.

a	β	α	error	a	β	α	error	a	β	α	error	a	β	α	error
0	0	10	-0.014	0	20	10	-0.008	30	0	10	-0.013	30	20	10	-0.010
0	0	20	-0.012	0	20	20	-0.006	30	0	20	-0.012	30	20	20	-0.011
0	0	30	-0.009	0	20	30	-0.005	30	0	30	-0.015	30	20	30	-0.013
0	0	40	-0.009	0	20	40	-0.004	30	0	40	-0.011	30	20	40	-0.012
0	0	50	-0.010	0	20	50	-0.006	30	0	50	-0.009	30	20	50	-0.012
0	0	60	-0.006	0	20	60	-0.005	30	0	60	-0.010	30	20	60	-0.009
0	0	70	-0.006	0	20	70	-0.005	30	0	70	-0.007	30	20	70	-0.007
0	0	80	-0.006	0	20	80	-0.006	30	0	80	-0.008	30	20	80	-0.005
0	0	90	-0.005	0	20	90	-0.005	30	0	90	-0.005	30	20	90	-0.004
0	0	100	-0.004	0	20	100	-0.005	30	0	100	-0.004	30	20	100	-0.001
0	0	110	-0.004	0	20	110	-0.007	30	0	110	-0.003	30	20	110	0.001
0	0	120	-0.005	0	20	120	-0.006	30	0	120	-0.002	30	20	120	-0.003
0	0	130	-0.006	0	20	130	-0.005	30	0	130	-0.004	30	20	130	-0.002
0	0	140	-0.004	0	20	140	-0.004	30	0	140	-0.005	30	20	140	-0.003
0	0	150	-0.001	0	20	150	-0.002	30	0	150	-0.008	30	20	150	-0.004
0	0	160	-0.001	0	20	160	-0.001	30	0	160	-0.008	30	20	160	-0.005
0	0	170	-0.001	0	20	170	-0.004	30	0	170	-0.007	30	20	170	-0.005
0	0	180	-0.004	0	20	180	-0.001	30	0	180	-0.007	30	20	180	-0.006
0	0	190	-0.001	0	20	190	-0.005	30	0	190	-0.006	30	20	190	-0.005
0	0	200	-0.004	0	20	200	-0.003	30	0	200	-0.006	30	20	200	-0.005
0	0	210	-0.004	0	20	210	-0.005	30	0	210	-0.006	30	20	210	-0.005
0	0	220	-0.006	0	20	220	-0.006	30	0	220	-0.008	30	20	220	-0.005
0	0	230	-0.008	0	20	230	-0.008	30	0	230	-0.007	30	20	230	-0.003
0	0	240	-0.010	0	20	240	-0.011	30	0	240	-0.006	30	20	240	-0.005
0	0	250	-0.011	0	20	250	-0.011	30	0	250	-0.006	30	20	250	-0.006
0	0	260	-0.010	0	20	260	-0.010	30	0	260	-0.007	30	20	260	-0.006
0	0	270	-0.009	0	20	270	-0.010	30	0	270	-0.010	30	20	270	-0.009
0	0	280	-0.007	0	20	280	-0.006	30	0	280	-0.010	30	20	280	-0.010
0	0	290	-0.007	0	20	290	-0.006	30	0	290	-0.007	30	20	290	-0.007
0	0	300	-0.006	0	20	300	-0.007	30	0	300	-0.006	30	20	300	-0.007
0	0	310	-0.008	0	20	310	-0.006	30	0	310	-0.005	30	20	310	-0.007
0	0	320	-0.008	0	20	320	-0.006	30	0	320	-0.006	30	20	320	-0.007
0	0	330	-0.008	0	20	330	-0.008	30	0	330	-0.005	30	20	330	-0.008
0	0	340	-0.008	0	20	340	-0.007	30	0	340	-0.004	30	20	340	-0.007
0	0	350	-0.010	0	20	350	-0.005	30	0	350	-0.005	30	20	350	-0.007
0	0	360	-0.007	0	20	360	-0.009	30	0	360	-0.009	30	20	360	-0.008

As shown in table 3.3, the example data file in this application includes three premises which are 'A' varies from 0 to 30, 'β' varies from 0 to 20, 'α' varies from 0 to 360 and one conclusion pre-travel error which is taken from the measurements on a ring gauge. The fuzzy knowledge database generated by the NeuFuz method is listed in Appendix B.

The following figure shows the difference between the real circle shape (line ——) based on the CMM measurement and the shape from the fuzzy knowledge database which is obtained by the NeuFuz method (line ·······).

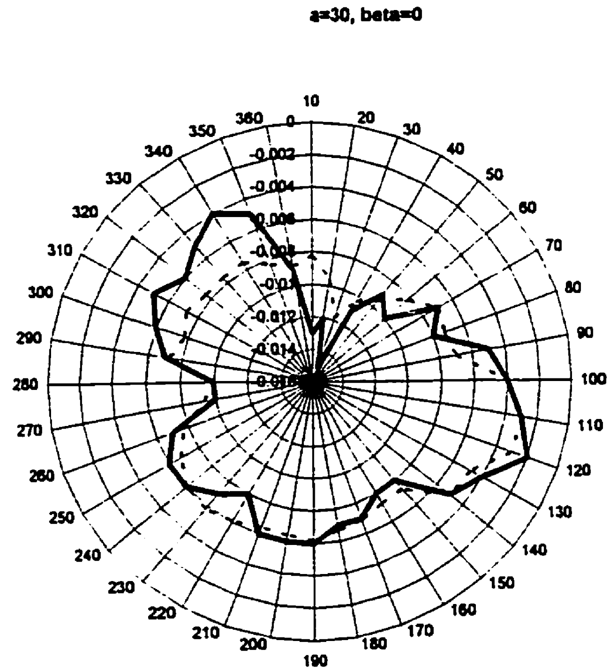


Figure 3.2. Comparison in a=30, β=0.

Since these two patterns are similar, the difference between the real shape and the NeuFuz shape is minor. An approximate prediction of the pre-travel error which is useful in the correction of the CMM machine measurement can be achieved by using this fuzzy knowledge database.

It is very difficult to generate a fuzzy knowledge database for this nonlinear problem by human intelligence. The NeuFuz method appears to be very useful in solving the above problem. With sufficient training data, the fuzzy knowledge database for a nonlinear problem can be easily and quickly obtained from the NeuFuz method.

As discussed in section 2.1.1, the determination of the critical points has an influence on the nonlinear problem simulation. In this application, it is difficult to predict the critical points since no precise experience is available. Another solution which increases the number of fuzzy sets in each premise is always available for the improvement of the accuracy. In this application, one hundred and forty four rules are used. Due to the limitation of the program which can execute only two hundred rules, another test with more fuzzy rules could not be carried out.

3.4. Application 3: pole life estimation

Hydro-Quebec has hundreds of thousands of poles installed in the field. For maintenance purpose, knowing their modulus of rupture is very important. The method used to obtain the modulus of rupture (MOR) is to bring some poles to the laboratory and to test them on a rupture test instrument. From the experience of Hydro-Quebec, the age of the poles, the number of damage per inch in the pole and the humidity are the three most important factors affecting the modulus of rupture. Since the relation between these three factors and the modulus of rupture is not linear, the difficulty to obtain the modulus of rupture is obvious.

To solve this problem, the NeuFuz method was applied. In the laboratory of Hydro-Quebec, one hundred and forty five poles were tested. A hundred and twenty examples taken from these poles were used to generate the fuzzy knowledge database. Each example includes three premises which are the age, the damage and the humidity, and one conclusion which is the modulus of rupture. Appendix C shows one hundred and twenty examples for the poles. The first premise "age" is divided into three fuzzy sets, the second premise "damage" is divided into three fuzzy sets and the third premise "humidity" is divided into four fuzzy sets according to the instructions from Hydro-Quebec. A fuzzy knowledge database which is demonstrated in figure 3.3 is obtained by the NeuFuz method.

1 Age

(2	2	0	11.5	1	young)
(13.5	13.5	11.5	11.5	1	middle)
(25	25	11.5	0	1	old)

1 Damage

(1	1	0	4	1	less)
(5	5	4	4	1	middle)
(9	9	4	0	1	many)

1 Humidity

(11	11	0	6.33	1	wet)
(17.33	17.33	6.33	6.33	1	wet-middle)
(23.66	23.66	6.33	6.33	1	dry-middle)
(30	30	6.33	0	1	dry)

~ 1 MOR •

(1.093903	1.093903	0.005	0.005	1)	(1	1	1	1)
(1.039167	1.039167	0.005	0.005	1)	(1	1	2	2)
(1.02009	1.02009	0.005	0.005	1)	(1	1	3	3)
(0.968917	0.968917	0.005	0.005	1)	(1	1	4	4)
(0.846313	0.846313	0.005	0.005	1)	(1	2	1	5)
(0.785376	0.785376	0.005	0.005	1)	(1	2	2	6)
(0.763927	0.763927	0.005	0.005	1)	(1	2	3	7)
(0.710332	0.710332	0.005	0.005	1)	(1	2	4	8)
(0.709324	0.709324	0.005	0.005	1)	(1	3	1	9)
(0.650422	0.650422	0.005	0.005	1)	(1	3	2	10)
(0.630175	0.630175	0.005	0.005	1)	(1	3	3	11)
(0.580417	0.580417	0.005	0.005	1)	(1	3	4	12)
(1.031803	1.031803	0.005	0.005	1)	(2	1	1	13)
(0.974467	0.974467	0.005	0.005	1)	(2	1	2	14)
(0.954608	0.954608	0.005	0.005	1)	(2	1	3	15)
(0.901589	0.901589	0.005	0.005	1)	(2	1	4	16)
(0.777402	0.777402	0.005	0.005	1)	(2	2	1	17)
(0.717037	0.717037	0.005	0.005	1)	(2	2	2	18)
(0.695989	0.695989	0.005	0.005	1)	(2	2	3	19)
(0.643916	0.643916	0.005	0.005	1)	(2	2	4	20)
(0.643205	0.643205	0.005	0.005	1)	(2	3	1	21)
(0.586619	0.586619	0.005	0.005	1)	(2	3	2	22)
(0.567281	0.567281	0.005	0.005	1)	(2	3	3	23)
(0.520559	0.520559	0.005	0.005	1)	(2	3	4	24)
(0.995668	0.995668	0.005	0.005	1)	(3	1	1	25)
(0.93737	0.93737	0.005	0.005	1)	(3	1	2	26)
(0.916619	0.916619	0.005	0.005	1)	(3	1	3	27)
(0.862948	0.862948	0.005	0.005	1)	(3	1	4	28)
(0.738636	0.738636	0.005	0.005	1)	(3	2	1	29)
(0.679008	0.679008	0.005	0.005	1)	(3	2	2	30)
(0.658496	0.658496	0.005	0.005	1)	(3	2	3	31)
(0.607587	0.607587	0.005	0.005	1)	(3	2	4	32)
(0.6069	0.6069	0.005	0.005	1)	(3	3	1	33)
(0.551783	0.551783	0.005	0.005	1)	(3	3	2	34)
(0.533507	0.533507	0.005	0.005	1)	(3	3	3	35)
(0.488611	0.488611	0.005	0.005	1)	(3	3	4	36)

Figure 3.3. Fuzzy knowledge database from the NeuFuz method.

The other twenty-five examples tested in Hydro-Quebec laboratory are used to verify whether the results from the NeuFuz method are acceptable. The results are assessed in table 3.4.

Table 3.4. Comparison of the real MOR to the NeuFuz MOR.

	premises			MOR exact	MOR NeuFuz	average of error
	age	damage	humidity			
1	10	5	17	0.75	0.75	0.0%
2	8	7	16	0.67	0.70	4.5%
3	12	3	24	0.93	0.83	10.7%
4	3	6	30	0.61	0.61	0.0%
5	2	2	21	0.90	0.96	6.7%
6	5	3	30	0.82	0.83	1.2%
7	19	1.5	30	0.59	0.85	44%
8	16	8	25	0.62	0.58	6.4%
9	9	7	16	0.72	0.69	4.2%
10	8	8	24	0.84	0.63	25%
11	11	4	30	0.52	0.72	38%
12	17	7	19	0.75	0.64	14%
13	17	2.5	14	1.00	0.90	10%
14	16	5.5	13	0.72	0.74	2.8%
15	16	6	17	0.65	0.68	4.6%
16	3	1.5	23	0.93	0.98	5.4%
17	10	7.5	23	0.51	0.64	25%
18	3	5	30	0.74	0.72	2.7%
19	3	2.5	28	0.83	0.88	6.0%
20	3	1.5	30	0.88	0.93	5.7%
21	6	1	25	0.93	0.97	4.3%
22	19	6.5	30	0.46	0.58	26%
23	9	2.7	24	0.82	0.87	6.0%
24	10	3.5	27	0.77	0.78	1.0%
25	11	6	30	0.52	0.63	21%

According to the table 3.4, the average error of the pole modulus of rupture obtained by the NeuFuz method is 11%. Hydro-Quebec was quite satisfied by this result. Instead of wasting the labour and the time to transport poles to their laboratory, the researchers of Hydro-Quebec can estimate the pole modulus of rupture in their office with this fuzzy knowledge database which is generated by the new developed NeuFuz method.

The results in table 3.4 indicated that the maximum errors mostly happen in some critical cases. For example, the age is very old, the damage is very small and the humidity is very high. This provides the evidence that the examples don't cover the entire ranges of premises and the fuzzy premise sets are ill defined.

A set of examples which doesn't cover the entire ranges of premises will give the neural network difficulties in providing precise recalling-outputs. For example, in table 3.4, 44% is the worst error obtained which happens in a situation where the age is 19 (pretty old), the damage is 1.5 (very small) and the humidity is 30 (very dry). Taking a glance at the examples available in appendix E, it is easy to find that the MOR information about the age is old, the damage is very small and the humidity is very dry is lacking. This can be a reason why the results in this kind of situation are not satisfactory.

Also, the ill defined fuzzy sets will cause the error to increase in the fuzzy reasoning. As explained in figure 2.2, if the determination of the critical points are not precise, then the nonlinear problem can't be well simulated. In this application, the fuzzy sets are defined according to the experiences from Hydro-Quebec. If their experiences are not precise, then the accuracy of the NeuFuz method will be reduced. For example, in the premise AGE, maybe more fuzzy sets are needed to define this nonlinear relationship or maybe the critical points which are located in 2, 13.5 and 25 are not the best positions of the critical points. It is therefore very important to use meaningful and complete data to train the neural network and to define the fuzzy sets.

3.5. Discussion

Four applications were conducted. Their results indicated that this newly developed method is useful and efficient in generating the fuzzy knowledge database for decision support process.

The speed of the NeuFuz method is distinctive. Usually it takes twenty minutes to make a fuzzy knowledge database from a set of examples.

The study shows that the precision of the NeuFuz method is strongly associated with the complexity of the problem, the number of the examples, the coverage of the examples and the definition of the fuzzy premises sets.

A trial to reveal the relation of the NeuFuz method precision and the complexity of the problem was carried out. As described by Taras in [17], the estimation of pole life is a complex application. However, the adding application is simple and linear. The accuracy obtained from the adding application is much higher than the one from the pole life estimation application. Therefore the method appears to provide a better precision for linear as opposed to more complex problems.

Attempts were undertaken to discuss the relation between the NeuFuz precision and the number of examples. In the cutting parameters selection application, sixty, forty and twenty examples were tried. Better results can be achieved by increasing the neural network training examples.

In pole life estimation application, the precision is worse than the other applications. This could be explained as the lack of information for the entire premise range, the ill determination of the critical point positions, the ill definition of the premise fuzzy set number and the high complexity in this nonlinear problem.

Chapter 4

Conclusion and future research

4.1. Conclusion

A NeuFuz method was proposed to combine the fuzzy logic and neural networks. Both manual and NeuFuz methods for the generation of the fuzzy knowledge database were presented and compared. The time required in generating a fuzzy knowledge database from the NeuFuz method was less than with the manual method.

Three tests in industrial domain were conducted to verify the applicability of this new developed method. By comparing the predicted results with known values, it was observed that the NeuFuz method can provide useful aid in generating the fuzzy knowledge database when sufficient system data is available despite the complexity of the problem. The complexity of the problem, the number of the examples, the coverage of the examples and the definition of the fuzzy premises sets has an influence on the accuracy of the NeuFuz method.

A FDSS system was integrated in a CAM/CAD (CATIA) environment. The function button CUTPRM in CATIA main menu provides a user friendly interface to select a right fuzzy knowledge database for a specific milling case. With the integrated fuzzy inference module, a set of cutting parameters can be obtained in about ten seconds which is more efficient than other methods.

4.2. Future research

Future work will attempt to fully demonstrate the factors which have an influence in neural networks performance. For example, the cell number in the neural network hidden layer.

Some important situations in which the NeuFuz method may be useful are as follows:

- *Inadequate knowledge bases;*
- *Volatile knowledge bases;*
- *Data-intensive systems.*

The fuzzy knowledge databases which were created for the selection of cutting parameters in milling provide good precision. However, it should be pointed out that the optimum performance or efficiency of any machining operation includes additional factors which have an influence on the magnitudes of speed and feed. As discussed by Balazinski, Bellerose and Czogala in [1], these factors are the part configuration and the machine tool condition, etc. Future research works have to be forced to develop a system more sophisticated to aid the fuzzy decision support system on the choice of cutting parameters by considering all the possible factors which affect this choice. The developed model in this study can serve a starting point for future developments.

The automated process planning system naturally bridges the gap between CAD and CAM. It can provide real integrated production. Artificial intelligence (AI) based techniques, such as neural networks and fuzzy decision support system should attract more and more research attention in implementing automated process planning systems.

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Appendix A:Train-file for adding

1.000000	0.000000	0.000000	0.326531	0.673469	0.000000	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	27.100000	
0.000000	0.500000	0.500000	0.479592	0.520408	0.000000	0.000000
0.000000	0.000000	0.500000	0.500000	0.000000	24.700001	
0.000000	1.000000	0.000000	0.540816	0.459184	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	1.000000	25.500000	
0.750000	0.250000	0.000000	0.000000	0.000000	0.336735	0.663265
0.000000	0.000000	0.000000	1.000000	0.000000	95.199997	
0.000000	0.500000	0.500000	0.234694	0.765306	0.000000	0.000000
0.000000	1.000000	0.000000	0.000000	0.000000	29.700001	
0.000000	1.000000	0.000000	0.000000	0.000000	0.275510	0.724490
0.500000	0.500000	0.000000	0.000000	0.000000	92.500000	
0.000000	0.750000	0.250000	0.020408	0.979592	0.000000	0.000000
0.000000	0.000000	0.500000	0.500000	0.000000	39.599998	
0.500000	0.500000	0.000000	0.000000	0.775510	0.224490	0.000000
0.000000	0.000000	1.000000	0.000000	0.000000	46.299999	
1.000000	0.000000	0.000000	0.000000	0.316327	0.683673	0.000000
1.000000	0.000000	0.000000	0.000000	0.000000	57.099998	
0.250000	0.750000	0.000000	0.000000	0.132653	0.867347	0.000000
0.000000	0.000000	0.000000	0.500000	0.500000	70.400002	
0.000000	0.250000	0.750000	0.000000	0.000000	0.704082	0.295918
0.000000	0.000000	0.500000	0.500000	0.000000	82.800003	
0.000000	0.750000	0.250000	0.908163	0.091837	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	1.000000	13.600000	
0.000000	1.000000	0.000000	0.000000	0.000000	0.520408	0.479592
0.000000	0.000000	1.000000	0.000000	0.000000	87.500000	
0.000000	0.500000	0.500000	0.000000	0.000000	0.183673	0.816327
0.000000	0.000000	0.000000	1.000000	0.000000	100.699997	
0.750000	0.250000	0.000000	0.000000	0.000000	0.673469	0.326531
0.000000	1.000000	0.000000	0.000000	0.000000	80.199997	
0.250000	0.750000	0.000000	0.000000	0.010204	0.989796	0.000000
0.000000	0.000000	0.000000	0.500000	0.500000	74.400002	
0.000000	0.250000	0.750000	0.142857	0.857143	0.000000	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	33.799999	
0.500000	0.500000	0.000000	0.000000	0.836735	0.163265	0.000000
0.000000	0.000000	0.000000	0.500000	0.500000	47.299999	
0.000000	1.000000	0.000000	0.000000	0.000000	0.795918	0.204082
0.000000	0.000000	0.500000	0.500000	0.000000	79.500000	
0.000000	0.000000	1.000000	0.387755	0.612245	0.000000	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	25.900000	
0.000000	0.500000	0.500000	0.540816	0.459184	0.000000	0.000000
0.000000	0.000000	0.000000	0.500000	0.500000	24.700001	
0.000000	0.250000	0.750000	0.000000	0.989796	0.010204	0.000000
0.000000	1.000000	0.000000	0.000000	0.000000	37.799999	

0.250000	0.750000	0.000000	0.387755	0.612245	0.000000	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	25.400000	
0.000000	0.500000	0.500000	0.602041	0.397959	0.000000	0.000000
0.000000	1.000000	0.000000	0.000000	0.000000	17.700001	
0.000000	0.750000	0.250000	0.510204	0.489796	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000	0.000000	18.600000	
0.000000	0.250000	0.750000	0.051020	0.948980	0.000000	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	36.799999	
0.000000	0.000000	1.000000	0.000000	0.775510	0.224490	0.000000
0.000000	0.000000	0.500000	0.500000	0.000000	47.900002	
0.250000	0.750000	0.000000	0.000000	0.255102	0.744898	0.000000
0.000000	0.000000	0.000000	1.000000	0.000000	65.400002	
1.000000	0.000000	0.000000	0.000000	0.132653	0.867347	0.000000
0.000000	0.000000	0.000000	0.000000	1.000000	71.099998	
0.000000	1.000000	0.000000	0.000000	0.000000	0.673469	0.326531
0.000000	0.000000	1.000000	0.000000	0.000000	82.500000	
1.000000	0.000000	0.000000	0.000000	0.000000	0.979592	0.020408
0.000000	0.500000	0.500000	0.000000	0.000000	71.099998	
0.000000	0.500000	0.500000	0.326531	0.673469	0.000000	0.000000
0.000000	0.000000	0.500000	0.500000	0.000000	29.700001	
0.000000	1.000000	0.000000	0.000000	0.622449	0.377551	0.000000
0.000000	0.000000	0.000000	0.000000	1.000000	55.500000	
0.750000	0.250000	0.000000	0.081633	0.918367	0.000000	0.000000
0.000000	0.000000	0.000000	1.000000	0.000000	38.200001	
0.000000	0.500000	0.500000	0.000000	0.000000	0.918367	0.081633
0.000000	1.000000	0.000000	0.000000	0.000000	72.699997	
0.000000	1.000000	0.000000	0.000000	0.683674	0.316327	0.000000
0.500000	0.500000	0.000000	0.000000	0.000000	46.500000	
0.000000	0.750000	0.250000	0.000000	0.010204	0.989796	0.000000
0.000000	0.000000	0.500000	0.500000	0.000000	72.599998	
0.500000	0.500000	0.000000	0.000000	0.316327	0.683673	0.000000
0.000000	0.000000	1.000000	0.000000	0.000000	61.299999	
1.000000	0.000000	0.000000	0.295918	0.704082	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000	0.000000	25.100000	
0.250000	0.750000	0.000000	0.020408	0.979592	0.000000	0.000000
0.000000	0.000000	0.000000	0.500000	0.500000	41.400002	
0.000000	0.250000	0.750000	0.663265	0.336735	0.000000	0.000000
0.000000	0.000000	0.500000	0.500000	0.000000	18.799999	
0.000000	0.750000	0.250000	0.142857	0.857143	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	1.000000	38.599998	
0.000000	1.000000	0.000000	0.969388	0.030612	0.000000	0.000000
0.000000	0.000000	1.000000	0.000000	0.000000	7.500000	
0.000000	0.500000	0.500000	0.000000	0.000000	0.612245	0.387755
0.000000	0.000000	0.000000	1.000000	0.000000	86.699997	

0.750000	0.250000	0.000000	0.846939	0.153061	0.000000	0.000000
0.000000	1.000000	0.000000	0.000000	0.000000	9.200000	
0.250000	0.750000	0.000000	0.000000	0.000000	0.734694	0.265306
0.000000	0.000000	0.000000	0.500000	0.500000	83.400002	
0.000000	0.250000	0.750000	0.295918	0.704082	0.000000	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	28.799999	
0.500000	0.500000	0.000000	0.020408	0.979592	0.000000	0.000000
0.000000	0.000000	0.000000	0.500000	0.500000	41.299999	
0.000000	1.000000	0.000000	0.000000	0.316327	0.683673	0.000000
0.000000	0.000000	0.500000	0.500000	0.000000	62.500000	
0.000000	0.000000	1.000000	0.000000	0.000000	0.244898	0.755102
0.000000	0.500000	0.500000	0.000000	0.000000	95.900002	
0.000000	0.500000	0.500000	0.051020	0.948980	0.000000	0.000000
0.000000	0.000000	0.000000	0.500000	0.500000	40.700001	
0.000000	0.250000	0.750000	0.000000	0.000000	0.826531	0.173469
0.000000	1.000000	0.000000	0.000000	0.000000	75.800003	
0.250000	0.750000	0.000000	0.000000	0.000000	0.918367	0.081633
0.000000	0.500000	0.500000	0.000000	0.000000	73.400002	
0.000000	0.500000	0.500000	0.295918	0.704082	0.000000	0.000000
0.000000	1.000000	0.000000	0.000000	0.000000	27.700001	
0.000000	0.750000	0.250000	0.000000	0.438776	0.561224	0.000000
1.000000	0.000000	0.000000	0.000000	0.000000	53.599998	
0.000000	0.250000	0.750000	0.000000	0.775510	0.224490	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	45.799999	
0.000000	0.000000	1.000000	0.387755	0.612245	0.000000	0.000000
0.000000	0.000000	0.500000	0.500000	0.000000	27.900000	
0.250000	0.750000	0.000000	0.540816	0.459184	0.000000	0.000000
0.000000	0.000000	0.000000	1.000000	0.000000	23.400000	
1.000000	0.000000	0.000000	0.000000	0.000000	0.428571	0.571429
0.000000	0.000000	0.000000	0.000000	1.000000	94.099998	
0.000000	1.000000	0.000000	0.632653	0.367347	0.000000	0.000000
0.000000	0.000000	1.000000	0.000000	0.000000	18.500000	
1.000000	0.000000	0.000000	0.000000	0.714286	0.285714	0.000000
0.000000	0.000000	0.500000	0.500000	0.000000	49.099998	
0.000000	0.500000	0.500000	0.000000	0.867347	0.132653	0.000000
0.000000	0.000000	0.000000	0.000000	1.000000	47.700001	
0.000000	1.000000	0.000000	0.000000	0.316327	0.683673	0.000000
0.000000	0.000000	0.000000	1.000000	0.000000	63.500000	
0.750000	0.250000	0.000000	0.173469	0.826531	0.000000	0.000000
0.500000	0.500000	0.000000	0.000000	0.000000	31.200001	
0.000000	0.500000	0.500000	0.000000	0.928571	0.071429	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	40.700001	
0.000000	1.000000	0.000000	0.000000	0.000000	0.887755	0.112245
1.000000	0.000000	0.000000	0.000000	0.000000	71.500000	

0.000000	0.750000	0.250000	0.000000	0.714286	0.285714	0.000000
0.000000	0.000000	0.000000	0.500000	0.500000	51.599998	
0.500000	0.500000	0.000000	0.081633	0.918367	0.000000	0.000000
0.500000	0.500000	0.000000	0.000000	0.000000	34.299999	
1.000000	0.000000	0.000000	0.000000	0.000000	0.704082	0.295918
0.000000	0.000000	1.000000	0.000000	0.000000	81.099998	
0.250000	0.750000	0.000000	0.000000	0.132653	0.867347	0.000000
1.000000	0.000000	0.000000	0.000000	0.000000	63.400002	
0.000000	0.250000	0.750000	0.000000	0.622449	0.377551	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	50.799999	
0.000000	0.750000	0.250000	1.000000	0.000000	0.000000	0.000000
0.000000	1.000000	0.000000	0.000000	0.000000	4.600000	
0.000000	1.000000	0.000000	0.000000	0.000000	0.214286	0.785714
0.000000	0.000000	1.000000	0.000000	0.000000	97.500000	
0.000000	0.500000	0.500000	0.000000	0.000000	0.489796	0.510204
0.000000	0.000000	0.500000	0.500000	0.000000	89.699997	
0.750000	0.250000	0.000000	0.204082	0.795918	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000	0.000000	28.200001	
0.250000	0.750000	0.000000	0.540816	0.459184	0.000000	0.000000
0.000000	0.000000	0.000000	1.000000	0.000000	23.400000	
0.000000	0.250000	0.750000	0.000000	0.836735	0.163265	0.000000
0.000000	0.000000	0.000000	0.500000	0.500000	47.799999	
0.500000	0.500000	0.000000	0.000000	0.000000	0.612245	0.387755
0.000000	0.000000	0.500000	0.500000	0.000000	85.300003	
0.000000	1.000000	0.000000	0.000000	0.102041	0.897959	0.000000
0.000000	1.000000	0.000000	0.000000	0.000000	66.500000	
0.000000	0.000000	1.000000	0.693878	0.306122	0.000000	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	15.900000	
0.000000	0.500000	0.500000	0.000000	0.928571	0.071429	0.000000
0.500000	0.500000	0.000000	0.000000	0.000000	38.700001	
0.000000	0.250000	0.750000	0.000000	0.683674	0.316327	0.000000
0.000000	0.000000	0.000000	0.000000	1.000000	53.799999	
0.250000	0.750000	0.000000	0.081633	0.918367	0.000000	0.000000
0.000000	0.000000	0.000000	1.000000	0.000000	38.400002	
0.000000	0.500000	0.500000	0.000000	0.000000	0.153061	0.846939
0.000000	0.000000	0.500000	0.500000	0.000000	100.699997	
0.000000	0.750000	0.250000	0.000000	0.000000	0.061224	0.938776
1.000000	0.000000	0.000000	0.000000	0.000000	98.599998	
0.000000	0.250000	0.750000	0.000000	0.000000	0.826531	0.173469
0.000000	0.000000	0.000000	0.000000	1.000000	81.800003	
0.000000	0.000000	1.000000	0.000000	0.469388	0.530612	0.000000
0.000000	1.000000	0.000000	0.000000	0.000000	54.900002	
0.250000	0.750000	0.000000	0.000000	0.867347	0.132653	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	42.400002	

1.000000	0.000000	0.000000	0.000000	0.438776	0.561224	0.000000
0.500000	0.500000	0.000000	0.000000	0.000000	54.099998	
0.000000	1.000000	0.000000	0.510204	0.489796	0.000000	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	31.500000	
0.750000	0.250000	0.000000	0.357143	0.642857	0.000000	0.000000
0.000000	0.000000	1.000000	0.000000	0.000000	27.200001	
0.500000	0.500000	0.000000	0.000000	0.714286	0.285714	0.000000
0.000000	0.000000	0.000000	0.000000	1.000000	52.299999	
0.000000	0.000000	1.000000	0.785714	0.214286	0.000000	0.000000
1.000000	0.000000	0.000000	0.000000	0.000000	9.900000	
0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	1.000000
0.000000	0.000000	0.000000	0.000000	1.000000	108.500000	
1.000000	0.000000	0.000000	0.000000	0.316327	0.683673	0.000000
0.000000	0.000000	0.000000	1.000000	0.000000	63.099998	
0.000000	0.500000	0.500000	0.000000	0.775510	0.224490	0.000000
0.000000	1.000000	0.000000	0.000000	0.000000	44.700001	
0.250000	0.750000	0.000000	0.387755	0.612245	0.000000	0.000000
0.000000	0.000000	0.500000	0.500000	0.000000	27.400000	
0.500000	0.500000	0.000000	0.000000	0.000000	0.857143	0.142857
0.000000	0.500000	0.500000	0.000000	0.000000	75.300003	
0.000000	0.750000	0.250000	0.000000	0.000000	0.948980	0.051020
0.500000	0.500000	0.000000	0.000000	0.000000	70.599998	
0.000000	1.000000	0.000000	0.000000	0.989796	0.010204	0.000000
0.000000	0.500000	0.500000	0.000000	0.000000	38.500000	

Appendix B: CMM fuzzy knowledge database from the NeuFuz method

```
# 1   A
(0    0    0    30   1   a)
(30   30   30   0    1   b)
# 2   Beta
(0    0    0    20   1   a)
(20   20   20   0    1   b)
# 3   Alpha
(   10    10    0    10   1   a)
(   20    20    10   10   1   b)
(   30    30    10   10   1   c)
(   40    40    10   10   1   d)
(   50    50    10   10   1   e)
(   60    60    10   10   1   f)
(   70    70    10   10   1   g)
(   80    80    10   10   1   h)
(   90    90    10   10   1   i)
(   100   100   10   10   1   j)
(   110   110   10   10   1   k)
(   120   120   10   10   1   l)
(   130   130   10   10   1   m)
(   140   140   10   10   1   n)
(   150   150   10   10   1   o)
(   160   160   10   10   1   p)
(   170   170   10   10   1   q)
(   180   180   10   10   1   r)
(   190   190   10   10   1   s)
(   200   200   10   10   1   t)
(   210   210   10   10   1   u)
(   220   220   10   10   1   v)
(   230   230   10   10   1   w)
(   240   240   10   10   1   x)
(   250   250   10   10   1   y)
(   260   260   10   10   1   z)
(   270   270   10   10   1   aa)
(   280   280   10   10   1   ab)
(   290   290   10   10   1   ac)
(   300   300   10   10   1   ad)
(   310   310   10   10   1   ae)
(   320   320   10   10   1   af)
(   330   330   10   10   1   ag)
(   340   340   10   10   1   ah)
(   350   350   10   10   1   ai)
(   360   360   10   0    1   aj)
~ 1   Error
```

(	-0.011085	-0.011085	0.001	0.001	1	a)
(	-0.009103	-0.009103	0.001	0.001	1	b)
(	-0.009423	-0.009423	0.001	0.001	1	c)
(	-0.007552	-0.007552	0.001	0.001	1	d)
(	-0.008436	-0.008436	0.001	0.001	1	e)
(	-0.006701	-0.006701	0.001	0.001	1	f)
(	-0.005884	-0.005884	0.001	0.001	1	g)
(	-0.006592	-0.006592	0.001	0.001	1	h)
(	-0.005506	-0.005506	0.001	0.001	1	i)
(	-0.00507	-0.00507	0.001	0.001	1	j)
(	-0.004695	-0.004695	0.001	0.001	1	k)
(	-0.006003	-0.006003	0.001	0.001	1	l)
(	-0.006121	-0.006121	0.001	0.001	1	m)
(	-0.005681	-0.005681	0.001	0.001	1	n)
(	-0.003364	-0.003364	0.001	0.001	1	o)
(	-0.002742	-0.002742	0.001	0.001	1	p)
(	-0.00342	-0.00342	0.001	0.001	1	q)
(	-0.003189	-0.003189	0.001	0.001	1	r)
(	-0.004117	-0.004117	0.001	0.001	1	s)
(	-0.005005	-0.005005	0.001	0.001	1	t)
(	-0.00563	-0.00563	0.001	0.001	1	u)
(	-0.007794	-0.007794	0.001	0.001	1	v)
(	-0.008981	-0.008981	0.001	0.001	1	w)
(	-0.011382	-0.011382	0.001	0.001	1	x)
(	-0.011702	-0.011702	0.001	0.001	1	y)
(	-0.010575	-0.010575	0.001	0.001	1	z)
(	-0.010201	-0.010201	0.001	0.001	1	aa)
(	-0.007865	-0.007865	0.001	0.001	1	ab)
(	-0.006525	-0.006525	0.001	0.001	1	ac)
(	-0.006491	-0.006491	0.001	0.001	1	ad)
(	-0.00662	-0.00662	0.001	0.001	1	ae)
(	-0.006785	-0.006785	0.001	0.001	1	af)
(	-0.006855	-0.006855	0.001	0.001	1	ag)
(	-0.007086	-0.007086	0.001	0.001	1	ah)
(	-0.008265	-0.008265	0.001	0.001	1	ai)
(	-0.007448	-0.007448	0.001	0.001	1	aj)
(	-0.008944	-0.008944	0.001	0.001	1	ak)
(	-0.006657	-0.006657	0.001	0.001	1	al)
(	-0.006615	-0.006615	0.001	0.001	1	am)
(	-0.00538	-0.00538	0.001	0.001	1	an)
(	-0.006182	-0.006182	0.001	0.001	1	ao)
(	-0.005136	-0.005136	0.001	0.001	1	ap)
(	-0.004967	-0.004967	0.001	0.001	1	aq)
(	-0.005549	-0.005549	0.001	0.001	1	ar)

(	-0.005381	-0.005381	0.001	0.001	1	as)
(	-0.00526	-0.00526	0.001	0.001	1	at)
(	-0.004858	-0.004858	0.001	0.001	1	au)
(	-0.005731	-0.005731	0.001	0.001	1	av)
(	-0.005649	-0.005649	0.001	0.001	1	aw)
(	-0.005555	-0.005555	0.001	0.001	1	ax)
(	-0.002844	-0.002844	0.001	0.001	1	ay)
(	-0.002239	-0.002239	0.001	0.001	1	az)
(	-0.003602	-0.003602	0.001	0.001	1	ba)
(	-0.003136	-0.003136	0.001	0.001	1	bb)
(	-0.004596	-0.004596	0.001	0.001	1	bc)
(	-0.004891	-0.004891	0.001	0.001	1	bd)
(	-0.005198	-0.005198	0.001	0.001	1	be)
(	-0.006502	-0.006502	0.001	0.001	1	bf)
(	-0.007457	-0.007457	0.001	0.001	1	bg)
(	-0.009911	-0.009911	0.001	0.001	1	bh)
(	-0.010017	-0.010017	0.001	0.001	1	bi)
(	-0.008671	-0.008671	0.001	0.001	1	bj)
(	-0.00788	-0.00788	0.001	0.001	1	bk)
(	-0.005754	-0.005754	0.001	0.001	1	bl)
(	-0.004938	-0.004938	0.001	0.001	1	bm)
(	-0.005384	-0.005384	0.001	0.001	1	bn)
(	-0.00582	-0.00582	0.001	0.001	1	bo)
(	-0.00531	-0.00531	0.001	0.001	1	bp)
(	-0.005373	-0.005373	0.001	0.001	1	bq)
(	-0.006085	-0.006085	0.001	0.001	1	br)
(	-0.006306	-0.006306	0.001	0.001	1	bs)
(	-0.007095	-0.007095	0.001	0.001	1	bt)
(	-0.008444	-0.008444	0.001	0.001	1	bu)
(	-0.009662	-0.009662	0.001	0.001	1	bv)
(	-0.012138	-0.012138	0.001	0.001	1	bw)
(	-0.010255	-0.010255	0.001	0.001	1	bx)
(	-0.009071	-0.009071	0.001	0.001	1	by)
(	-0.008517	-0.008517	0.001	0.001	1	bz)
(	-0.007437	-0.007437	0.001	0.001	1	ca)
(	-0.0074	-0.0074	0.001	0.001	1	cb)
(	-0.007	-0.007	0.001	0.001	1	cc)
(	-0.003855	-0.003855	0.001	0.001	1	cd)
(	-0.003768	-0.003768	0.001	0.001	1	ce)
(	-0.003247	-0.003247	0.001	0.001	1	cf)
(	-0.004629	-0.004629	0.001	0.001	1	cg)
(	-0.005178	-0.005178	0.001	0.001	1	ch)
(	-0.007689	-0.007689	0.001	0.001	1	ci)
(	-0.007553	-0.007553	0.001	0.001	1	cj)

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(	-0.006384	-0.006384	0.001	0.001	1	cn)
(	-0.006723	-0.006723	0.001	0.001	1	co)
(	-0.00612	-0.00612	0.001	0.001	1	cp)
(	-0.005598	-0.005598	0.001	0.001	1	cq)
(	-0.006088	-0.006088	0.001	0.001	1	cr)
(	-0.006875	-0.006875	0.001	0.001	1	cs)
(	-0.007982	-0.007982	0.001	0.001	1	ct)
(	-0.009256	-0.009256	0.001	0.001	1	cu)
(	-0.010306	-0.010306	0.001	0.001	1	cv)
(	-0.007579	-0.007579	0.001	0.001	1	cw)
(	-0.007827	-0.007827	0.001	0.001	1	cx)
(	-0.007741	-0.007741	0.001	0.001	1	cy)
(	-0.007903	-0.007903	0.001	0.001	1	cz)
(	-0.007978	-0.007978	0.001	0.001	1	da)
(	-0.00787	-0.00787	0.001	0.001	1	db)
(	-0.008214	-0.008214	0.001	0.001	1	dc)
(	-0.008518	-0.008518	0.001	0.001	1	dd)
(	-0.007269	-0.007269	0.001	0.001	1	de)
(	-0.009879	-0.009879	0.001	0.001	1	df)
(	-0.011411	-0.011411	0.001	0.001	1	dg)
(	-0.010409	-0.010409	0.001	0.001	1	dh)
(	-0.00959	-0.00959	0.001	0.001	1	di)
(	-0.00878	-0.00878	0.001	0.001	1	dj)
(	-0.006629	-0.006629	0.001	0.001	1	dk)
(	-0.006339	-0.006339	0.001	0.001	1	dl)
(	-0.005095	-0.005095	0.001	0.001	1	dm)
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(	-0.00239	-0.00239	0.001	0.001	1	do)
(	-0.002455	-0.002455	0.001	0.001	1	dp)
(	-0.002937	-0.002937	0.001	0.001	1	dq)
(	-0.003453	-0.003453	0.001	0.001	1	dr)
(	-0.006197	-0.006197	0.001	0.001	1	ds)
(	-0.00624	-0.00624	0.001	0.001	1	dt)
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(	-0.004839	-0.004839	0.001	0.001	1	dv)
(	-0.004179	-0.004179	0.001	0.001	1	dw)
(	-0.004184	-0.004184	0.001	0.001	1	dx)
(	-0.004675	-0.004675	0.001	0.001	1	dy)
(	-0.004502	-0.004502	0.001	0.001	1	dz)
(	-0.004068	-0.004068	0.001	0.001	1	ca)
(	-0.004247	-0.004247	0.001	0.001	1	cb)

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(    -0.005343     -0.005343     0.001  0.001  1     cc)
(    -0.006787     -0.006787     0.001  0.001  1     cd)
(    -0.009483     -0.009483     0.001  0.001  1     ce)
(    -0.010703     -0.010703     0.001  0.001  1     cf)
(    -0.007381     -0.007381     0.001  0.001  1     cg)
(    -0.007834     -0.007834     0.001  0.001  1     ch)
(    -0.00681      -0.00681      0.001  0.001  1     ci)
(    -0.007604     -0.007604     0.001  0.001  1     cj)
(    -0.007851     -0.007851     0.001  0.001  1     ck)
(    -0.007286     -0.007286     0.001  0.001  1     cl)
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(    -0.007413     -0.007413     0.001  0.001  1     cn)
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(2	2	35	143	)
(2	2	36	144	)

Appendix C. One hundred and twenty pole examples.

	premises			MOR
	age	damage	humidity	
1	10	3	19	0.81
2	3	1	21	1.07
3	13	4	14	0.93
4	4	2	30	0.93
5	7	2.5	21	0.99
6	11	4	25	0.72
7	13	8	18	0.78
8	2	4	20	0.83
9	12	6	30	0.61
10	2	7.5	21	0.69
11	8	5.5	19	0.88
12	13	7	22	0.66
13	14	7	30	0.63
14	3	9	30	0.44
15	3	6	20	0.74
16	21	3	30	0.53
17	4	1	23	1.12
18	6	9	19	0.39
19	6	9	17	0.49
20	9	1	20	1.00
21	8	1	20	0.94
22	2	3.5	23	0.78
23	8	2.5	16	0.89
24	23	8	26	0.65
25	22	6.5	27	0.63
26	15	1	13	1.48
27	8	2	15	0.94
28	8	5.5	22	0.77
29	12	1.5	14	0.82
30	16	6.5	18	0.43

	premises			MOR
	age	damage	humidity	
61	3	1	30	1.02
62	3	1.5	21	1.00
63	12	7	18	0.73
64	3	3.5	29	0.81
65	16	1	18	0.98
66	16	1.5	18	0.86
67	15	3	30	0.79
68	6	4	30	0.79
69	4	4	15	0.89
70	3	2.5	30	0.83
71	2	4	25	0.87
72	13	6	30	0.47
73	4	1.5	23	0.98
74	11	3.5	25	0.75
75	2	8	20	0.57
76	6	1	22	0.87
77	6	6	28	0.60
78	5	1.5	30	0.92
79	12	8	30	0.62
80	4	3	20	0.79
81	2	7	24	0.53
82	4	3.5	21	0.79
83	4	2	30	0.94
84	3	5.5	26	0.92
85	4	2	24	0.87
86	4	1	19	0.95
87	8	6.5	21	0.63
88	4	2	30	0.78
89	2	3	19	0.92
90	2	2.5	30	0.79

31	16	2	12	0.73	**91**	6	4.5	20	0.67
32	16	4	13	0.88	**92**	6	3.5	15	1.02
33	16	4	12	0.70	**93**	4	1.5	15	0.98
34	16	3	12	1.09	**94**	19	3	11	0.92
35	16	7.5	12	0.55	**95**	6	3	30	0.82
36	16	3	27	0.74	**96**	14	6	30	0.67
37	13	4	17	0.76	**97**	14	2	19	0.81
38	16	7.5	14	0.71	**98**	14	3	30	0.71
39	16	1	17	0.83	**99**	13	3	17	0.89
40	20	8	17	0.57	**100**	14	1	21	0.85
41	9	4	16	0.95	**101**	12	3	30	0.83
42	17	3.5	30	0.64	**102**	13	4.5	30	0.51
43	17	2	22	1.12	**103**	13	6	30	0.64
44	17	2.5	16	0.87	**104**	4	4	14	0.78
45	9	4	13	0.88	**105**	6	4.5	30	0.69
46	6	8	22	0.47	**106**	16	4.7	23	0.61
47	11	6	28	0.57	**107**	4	3	30	0.95
48	11	3	30	0.80	**108**	23	8	30	0.68
49	11	7	30	0.69	**109**	17	8	23	0.66
50	11	9	30	0.58	**110**	13	7	20	0.58
51	11	5	28	0.88	**111**	14	5	30	0.32
52	11	8	13	0.92	**112**	4	4	30	0.69
53	8	4	30	0.53	**113**	14	8	30	0.57
54	25	7.5	26	0.25	**114**	11	2	29	1.17
55	2	4	19	1.03	**115**	11	4	19	1.01
56	2	3.5	30	1.18	**116**	9	6	30	0.53
57	9	8.5	30	0.66	**117**	16	5	23	0.88
58	8	6	30	0.61	**118**	10	3	30	0.97
59	16	5.5	13	0.64	**119**	13	6	30	0.50
60	8	3	28	1.03	**120**	12	4	30	0.93

IMAGE EVALUATION TEST TARGET (QA-3)

150mm

6"

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Rochester, NY 14609 USA
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Fax: 716/288-5989