INTEGRATED FEED-FORWARD ARTIFICIAL NEURAL NETWORKS SYSTEM FOR MACHINES TOOLS SELECTION

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Abstract: The choice of the machine tools is one of the considerations of manufacturing companies which depend primarily on machining process, by deciding how a finished product will be manufactured. The activity of tools choice is established in geometry of machining features, but it also has a direct impact on workability and execution of machine-tool. We propose in this paper an integration module of the automatic choice of machine tools in the environment of systems CAD/CAM, which consisted in the two neuronal systems NN1 and NN2; NN1 allows the automatic machining machines choice. NN2 makes it possible to choose cutting tools for machining features. In this work, we have worked two complementary parts for the integration of the automatic choice of machine tools. Firstly we developed a neuronal system for selection of machine tools classes. Secondly, we have created an interface of neuronal system integration which exploits machining features geometrical data to be carried out by Visual Basic programming.

1 INTRODUCTION

By reason of the increasing competition to the world market, the manufacturing companies always seek advanced technologies to gain benefit. Indeed, the total integration of computer-aided design and computer-aided manufacture (CAD/CAM) were a goal, for industries as well as for researchers, towards the realization of the concurrent design of the products and the process. However, the automatic machining process planning CAPP "Computer Aided Process Planning" plays a significant role in the integrity of CAD/CAM systems (C. Gologlu, 2004). One of the principal objectives of the automatic system of machining process planning is to interpret the information of design and to prescribe the operations of machining appropriate and conformed to the conditions determined by the designer.

More over, the development of the systems by using the artificial intelligence increased the diversity of representation of knowledge and generalization which approaches generative machining process planning, having as a result the improved execution of the systems of automatic machining process planning.

In this research work, we used multi-layer neural networks for the choice of machines and cutting tools, starting from information extracted from machining features.

However, Neural Networks are powerful to replace the methods of classifications, like their high speed of resolution and their aptitude of training and significant adaptation. We have benefited from these performances to apply neural networks for automatic choice of machines-tools during the generation of machining process planning.

The first part of this communication relates to modeling of the machining features, like their characteristics. The second part is devoted to the development of neuronal system structure for the automatic choice of machine and cutting tools. In the third part of this communication we will present the interface of neuronal system integration. We finish by interpretations of the results of performances of neuronal system for the automatic choice of machines and cutting tools starting from a case study, as well as a conclusion.

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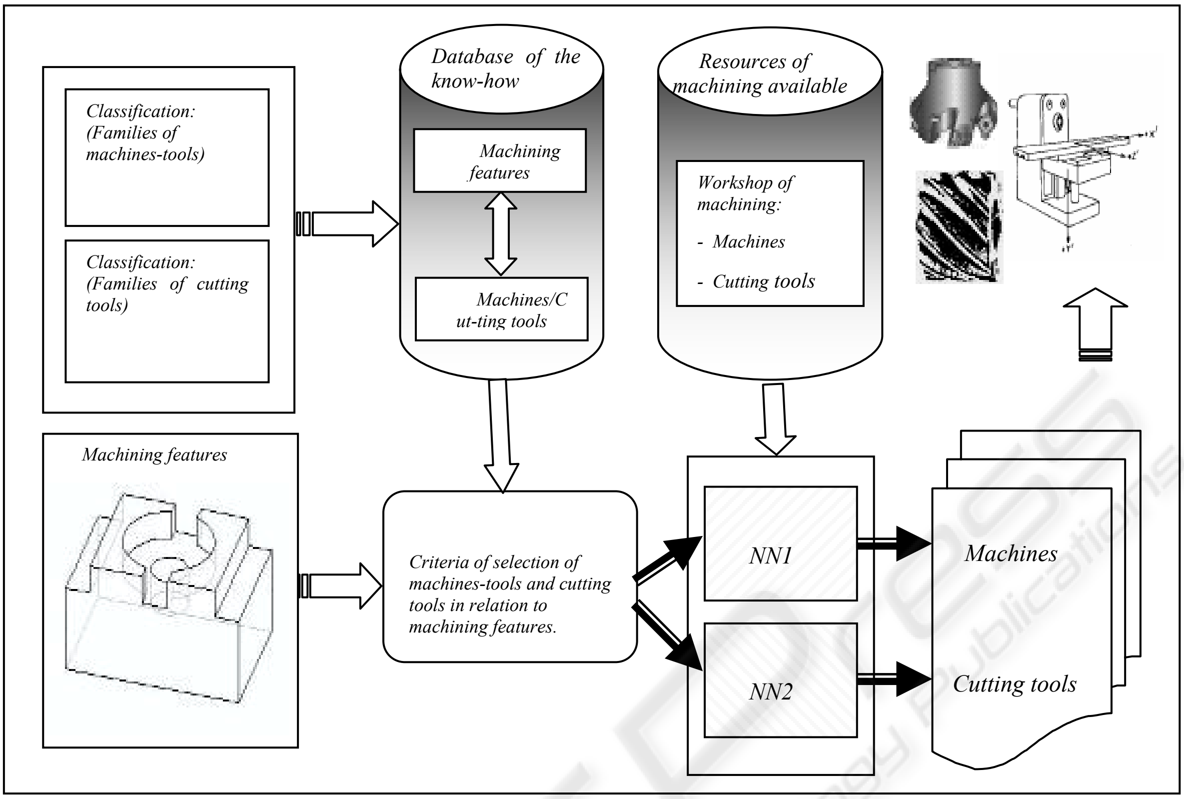

Figure 1: Module of neuronal system for selection of machine-tools and cutting tools

We present in figure 1 the module of the neuronal system for the selection of the classes of machines-tools.

2 DEVELOPMENT OF NEURONAL SYSTEM NN1 FOR THE CHOICE OF MACHINES TOOLS

During the development of this module, we have begun by the creation of database of know-how starting from an investigation in manufacturing mechanical companies, with production specialists, experts, mechanical engineers and skilled workers production in machining, as well as teachers of mechanical production.

Indeed, the method used in the expertise of the production specialists or equivalents is entitled ETED (Emploi Type Etudié dans sa Dynamique: Job kind in dynamic study) (MANDON. N, 1991), which makes it possible to carry out talks and to structure the results of the investigations (W.Eversheim et al., 2001).

There are several manners of classifying the machines tools, such as: by type of employment, by architecture (with horizontal spindle, vertical spindle and directional spindle), by type of order (conventional, automatic, numerical control... etc), and by dimensions (displacement following 3 axes X, Y, Z... etc). In our study we propose a classification of the machines tools according to the number of possible axes in a machine tool (one axis, two axes, three axes, four axes, five axes). This classification is related to morphologies of machining features, like their type of machining and their operations possible (table 1). We show on figure 2 the structure of neuronal system NN1 which is based on the choice of machines tools families in relation to machining features. The inputs of the network are the criteria of selection of machine-tools which are extracted from the basic module of database of know-how.

Table 1: Classification of the rotating tools

Classes of Machines-Tools	***Class 1 (1 axis)***	***Class 2 (2 axes)***	***Class 3 (3 axes)***	***Class 4 (3 axes)***	***Class 5 (4 axes)***	***Class 6 (4 axes) milling***
Motions	***Z***	***X, Z***	***X, Y, Z***	***X, Z, C***	***X, Y, Z, B***	***X, Y, Z, C***
Classes of Machines-Tools	***Class7 (4 axes) turning***	***Class 8 (4 axes)***	***Class 9 (5 axes)***	***Class 10 (5 axes***	***Class 11 (5 axes)***	***Class 12 (5 axes)***
Motions	***X, Y, Z, C***	***2x(X, Z)***	***2x(X, Z), C***	***X, Y, Z, A, C***	***X, Y, Z, B, C***	***X, Y, Z, A, B***

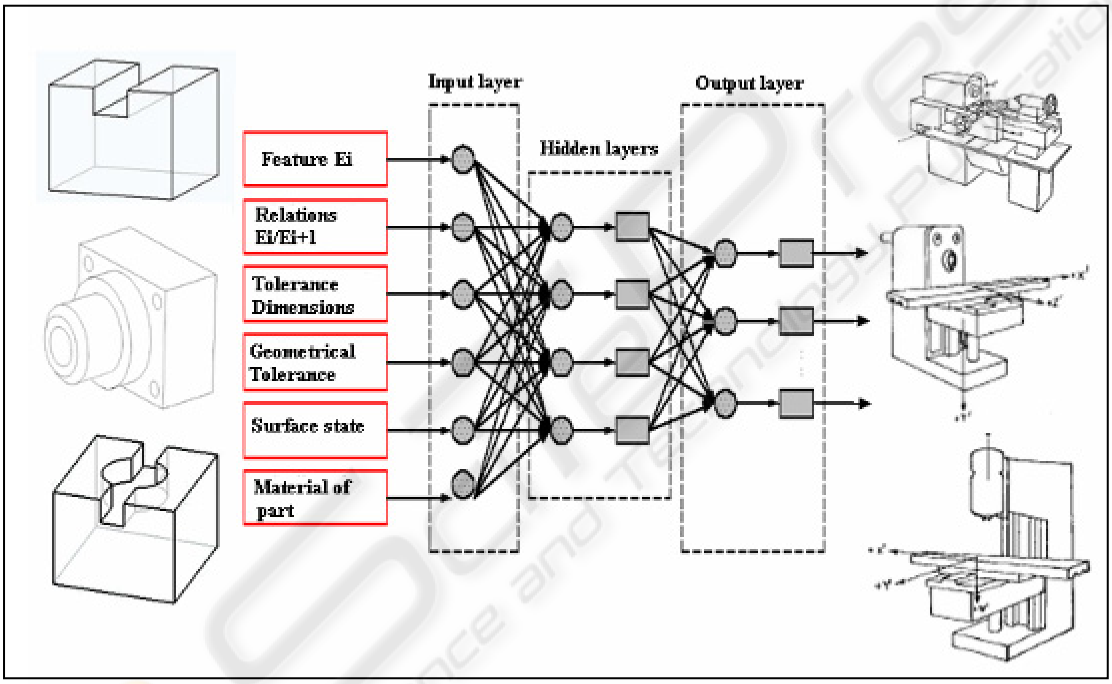

Figure 2*:* Structure of the multi-layer neural networks NN1 for the automatic choice of the machine- tools.

The necessity of the automatic choice of a machine-tool in mechanical manufacturing is today a very interesting stage for the efficiency of a machining operation as well as the reliability of a manufacture process planning (G. Chryssolours et al., 2001) (Chiung Moon et al.,2002). Indeed, to manufacture a machining feature, it exists several possibilities of machine-tool selection, however to optimize this choice we must respect certain number of criteria of the choice of machine-tool (the morphology of the piece to manufacture, measurements, the asked precisions, the dimensional, geometric and technological constraints,…etc) [5].

The automatic system of the choice of machines-tools which we used in this study is based on multi-layer artificial neural networks. They have the advantage to permit with a certain number of tests to select the appropriate machine-tool with the characteristics of proposed machining features (I.Drstvensek et al., 2000). The model of multi-layer neural networks is based on a simple representation of the biological neurons in form of a function of several variables. For this sort of networks, the activity of a neuron is modeled by a real number and the synapses by coefficients. As their name indicates it, the multi-layer neural networks are divided into layers; the first layer is a layer of inputs because it receives the inputs vector, reciprocally the last layer is a layer of outputs, it produces the results. The intermediate layers are called hidden layers, because states of neurons that they contain are not observable. The proposed neural networks are a self-adapting structure, it internally modified until attaining the desired result following the phase of training and generalization. Indeed, the training is a development phase of neural networks during which the behavior of the networks is modified until ottaining the desired behavior. It is done in the context of a task or a behavior to be learned. Information to be treated is coded in the shape of a inputs vector, which is communicated to the inputs neural networks (A. Zouidi et al, 2004). The answer of the network is interpreted starting from the value of activation of its outputs neurons, of which the outputs vector. It is a procedure which consists in estimating the parameters of neural networks, so that this one as well as possible fills the task which is affected for him (J. Dunfied et al., 2004).At the end of this process, the network was to be able to generate the good solutions for examples which were not seen before it is the objective of the generalization phase. This process consists in generalizing the outputs results of the inputs to network do not belong to the training base. Indeed, for the multi-layer neural networks, the training algorithm used is the retro propagation of gradient (A. Zouidi et al 2004).The application that we proposed here for the resolution to machining problems of prismatic interacting features of the type groove /pocket (H.Thomas, 2000).

Indeed, to respect constraints, the geometric tolerances and the state of surface of workpiece registered to the definition drawing of machining feature (Mustafa Yurdakul, 2004), (N. Ahmadi et al., 2002)*;* we affected these features in three different codes:

(1) without constraint,
(2) dimensional requirements,
(3) geometrical requirements and/or state of surface.

Besides, we specified the material of manufacturing workpiece while regrouping materials in three families according to their hardness by three different codes :

(1) alloys of copper and alloys of aluminum,
(2) soft steels ,
(3) hard steels and cast irons.

The outputs of the network consists of a matrix of dimension (5x18), the set of these outputs describes the proposed solutions by possible machine-tools classes according to the desired outputs (S1, S2, S3,…, S11, S12).

For this configuration of the neural networks, we propose the different types of training according to number of epochs, estimate of the gradient of errors and the training function [7]

Table 2: Parameters of the neural networks NN1 for the automatic choice of machines- tools

GA (mm)	a (mm)	GA/a =X	code Cont	Mat. pièce	C1	C2	C3	C4	----	- -	--	C11	C12
>10	>8	2<X<5	1	1	0	0	1	1	----	-	--	0	0
>10	>8	5<X<10	1	1	0	0	1	1	----	-	--	0	0
>10	>8	2<X<5	2	1	0	0	1	1	----	-	--	1	1
>10	>8	5<X<10	2	1	0	0	1	1	----	-	--	1	1
>10	>8	2<X<5	3	1	0	0	1	1	----	-	--	1	1
>10	>8	5<X<10	3	1	0	0	1	1	----	-	--	1	1
>10	>8	2<X<5	1	2	0	0	1	1	----	-	--	0	0
>10	>8	5<X<10	1	2	0	0	1	1	----	-	--	0	0
>50	>30	2<X<5	2	1	0	0	1	1	----	-	--	1	1
>50	>30	5<X<10	2	1	0	0	1	1	----	-	--	1	1
>100	>40	2<X<5	3	1	0	0	1	1	----	-	--	1	1
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---	---	-----	--	---	---	---	-----	-----	----	-	--	---	---
>300	>100	2<X<5	1	3	0	0	1	1	----	-	--	0	0
>300	>100	5<X<10	1	3	0	0	1	1	----	-	--	0	0
>300	>100	2<X<5	2	3	0	0	1	1	----	-	--	1	1
>300	>100	5<X<10	2	3	0	0	1	1	----	-	--	1	1
>300	>100	2<X<5	3	3	0	0	1	1	----	-	--	1	1
>300	>100	2<X<5	3	3	0	0	1	1	----	-	--	1	1

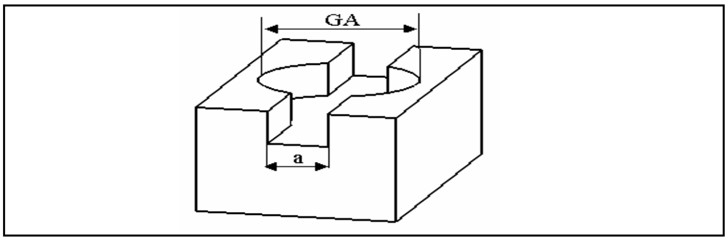

Figure 3: Intersecting features groove / pocket

The graphs represented in the figure 4 shows the evolution of the training mean squared error (TMSE) according to the number of epochs and measurements of machining features. Indeed, it is noticed that the TMSE is weak for the different measurements of the machining features of our application and after 18 epochs according to the proposed measurements, it will have the stability of the network with a training mean squared error (TMSE) minimal lower to 0.1**.**

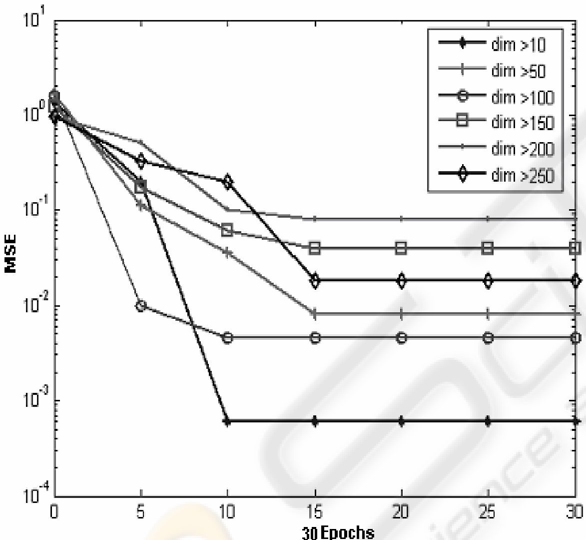

Figure 4: Result of training of the network NN1.

In order to fix an optimal structure of neural network, we must choose the parameters of network well such as the number of the hidden layers, the number of neurons in the hidden layer and the function of training and adaptation. Indeed, the best structure of network is obtained starting from a very weak TMSE and an optimal number of epochs "Kopt" so that the generalization mean squared error (GMSE) is minimal. However, we have presented at the graphs represented in figure 5 show the neural networks system an input vector doesn't belong to the basis of training then we have examine the generalization mean squared error and we have compared it with the one of the training (R. Ben Khalifa et al., 2003), (N.BEN Yahia et al, 2000).

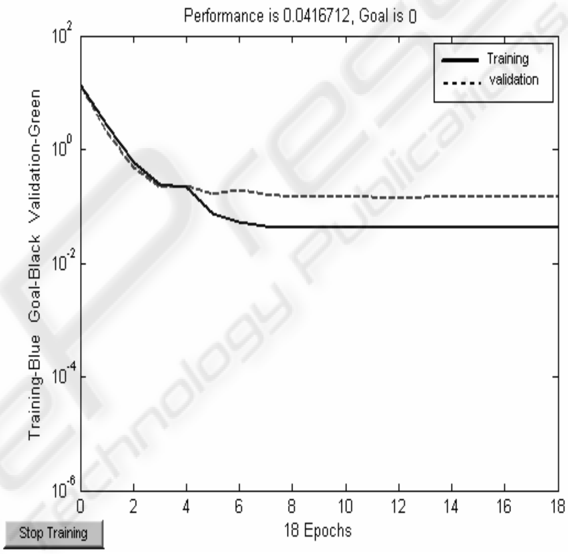

Figure 5: Evolution of the training error and of generalization of the NN1.

Evolution of the error of training (TMSE) and generalization (GMSE) of our neuronal system for the automatic choice of machines tools. We notice that the error of generalization (GMSE) decreases until a number of epochs (or iterations) to be determined well, by this value error (GMSE) increases. This translated it on training of the network. Indeed, it is obliged to stop the training for an optimal number of epochs (Kopt=18)

In order to choose the number of optimal neuron, we made a series of training for the various numbers of neurons in the hidden layer. The choice of the optimal number of epochs corresponds to a minimal GMSE and TMSE.

The number of neurons making it possible to have a minimal TMSE in this case is 20 neurons. This phase we enabled to choose the optimal structure of the network. Lastly, the following structure was fixed:

- inputs and outputs: 5 inputs and 12 outputs,
- number of hidden layers: 1 only hidden layer,
- number of neurons in the hidden layer: 20 neurons,
- activation function : hyperbolic tangent for the set of the neurons in the network.

3 DEVELOPMENT OF NEURONAL SYSTEM NN2 FOR THE CHOICE OF CUTTING TOOLS

The structure of the automated choice system for cutting tools that we used is based on the multi-layer neural networks. They have the advantage of making it possible with a certain number of tests to model the machining process to prismatic features by the proposal of the cutting tools.

The application that we have proposed here for the automatic choice of cutting tools by neural networks is the same that the one for automatic choice of machine-tools, the feature studied consists of prismatic interacting features of type groove / pocket (figure 3).

The study of various solutions of choice of cutting tools proposed by expert production specialist (or equivalent) which will be coded with the nodes of inputs of networks. Indeed, the inputs of the system are coded and organized in a matrix whose columns are a interval of dimensions (GA, a), studied types of constraints and material of features, as well as desired exits are tools classes (c1, c2, c3..., c30). Table 4 shows the parameters of neural networks for the 30 classes which are shared in relation to interval of cutting tools dimensions (diameter and length) (table3).

Table 3: Classification of the rotating tools.

Dim.	Class1 (1 E)	Class 2 (1 E)	Class 3 (1 E)	Class 4 (1 E)	Class 5 (1 E)	Class 6 (1 E)	Class 7 (2 E)	Class 8 (2 E)	Class 9 (2 E)	Class 10 (2 E)
Dia. Leng.	[8, 25] [20, 50]	[25, 50] [20, 50]	[50, 80] [50, 100]	[80, 100] [50, 100]	[100, 160] [20, 80]	[160, 200] [20, 80]	[10, 16] [20, 40]	[16, 30] [20, 40]	[20, 25] [20, 60]	[25, 50] [20, 60]
Dim.	**Class11 (2 E)**	**Class 12 (2 E)**	**Class 13 (2 E)**	**Class 14 (3 E)**	**Class 15 (3 E)**	**Class 16 (3 E)**	**Class 17 (3 E)**	**Class 18 (3 E)**	**Class 19 (1 E)**	**Class 20 (1 E)**
Dia. Leng.	[100, 160] [20, 80]	[160, 200] [20, 80]	[30, 40] [8, 20]	[40, 60] [8, 20]	[40, 63] [10, 40]	[63, 80] [10, 40]	[50, 125] [15, 50]	[125, 160] [15, 50]	[30, 40] [8, 20]	[40, 60] [8, 20]
Dim.	**Class 21 (2 E)**	**Class 22 (2 E)**	**Class 23 (3 E)**	**Class 24 (3 E)**	**Class 25 (3 E)**	**Class 26 (3 E)**	**Class 27 (3 E)**	**Class 28 (3 E)**	**Class 29 (1 E)**	**Class 30 (1 E)**
Dia. Leng.	[30, 40] [10, 40]	[40, 60] [10, 40]	[40, 100] [15, 50]	[100, 160] [15, 50]	[30, 40] [20, 50]	[40, 60] [20, 50]	[60, 80] [20, 50]	[80, 100] [20, 50]	[100, 125] [20, 50]	[125, 160] [20, 50]

Table 4: Parameters of the neural networks NN2 for the automatic choice of cutting tools

GA (mm)	a (mm)	GA/a =X	code Cont.	Mat. pièce	C1	C2	C3	C4	C5	C6	C7	--	--	--	C26	C27	C28	C29	C30
>10	>8	2<X<5	1	1	1	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	5<X<10	1	1	1	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	2<X<5	2	1	1	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	5<X<10	2	1	1	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	2<X<5	3	1	1	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	5<X<10	3	1	1	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	2<X<5	1	2	1	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	5<X<10	1	2	1	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	2<X<5	2	2	1	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	5<X<10	2	2	1	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	2<X<5	3	2	1	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	5<X<10	3	2	1	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	2<X<5	1	3	0	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	5<X<10	1	3	0	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	2<X<5	2	3	0	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	5<X<10	2	3	0	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	2<X<5	3	3	0	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>10	>8	5<X<10	3	3	0	0	0	0	0	0	1	--	--	--	0	0	0	0	0
>50	>30	2<X<5	1	1	1	1	0	0	0	0	1	--	--	--	1	1	0	0	0
>150	>60	2<X<5	1	1	1	1	1	1	0	0	1	--	--	--	1	1	0	0	0
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>250	>100	5<X<10	1	2	0	1	1	1	1	1	0	--	--	--	1	0	1	1	1
>250	>100	2<X<5	2	2	0	1	1	1	0	1	0	--	--	--	0	0	1	1	1
>250	>100	5<X<10	2	2	0	1	1	1	0	1	0	--	--	--	0	0	1	1	1
>250	>100	2<X<5	3	2	0	1	1	1	0	1	0	--	--	--	0	0	1	1	1
>250	>100	5<X<10	3	2	0	1	1	1	0	1	0	--	--	--	0	0	1	1	1

The best solutions of the choice of cutting tools classes for an effective system are obtained by separated 6 networks (NN21, NN22, NN23, NN24, NN25, NN26) (figure 6), every network to a matrix of input and a matrix of output in the same way dimension (5x18) (table 4). Outputs of every network also constitute a matrix of dimension (5x18), the whole of these outputs describes solutions proposed by the possible cutting tools classes according to desired outputs (S1, S2, S3, S4, S5…, S29, S30) (R. Ben Khalifa et al., 2003).

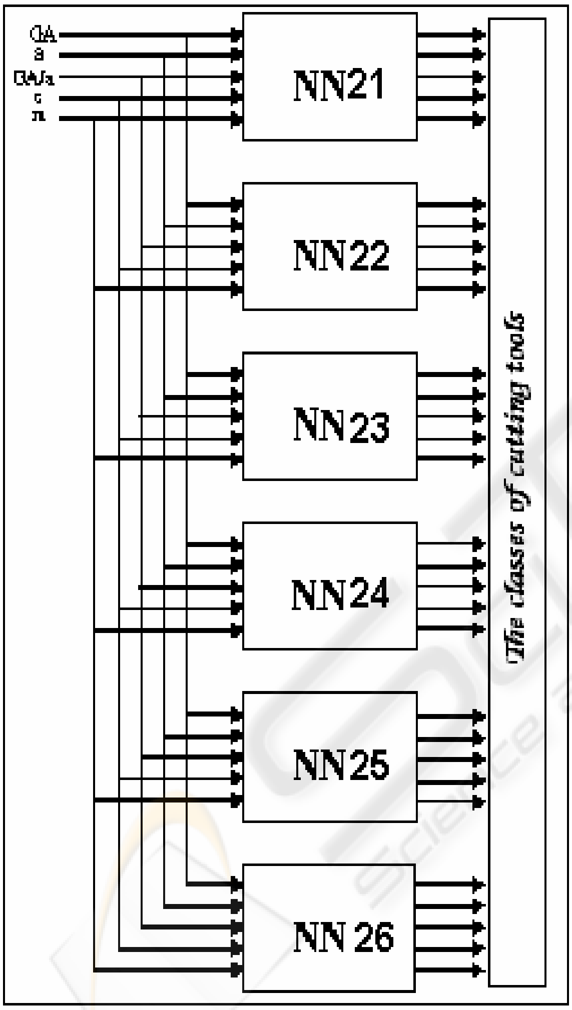

Figure 6: Global architecture of neural system ***NN2***

We have studied the evolution of training error only for the network NN21 since the different results that we have found for other networks are nearly very near. The figure 7 shows the evolution of the training mean squared error TMSE according to number of epochs and measurements of machining features for neural networks NN21.

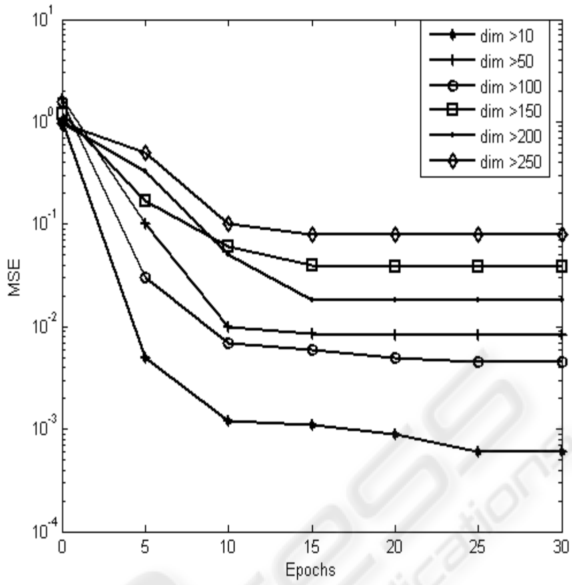

Figure 7: Result of training of the network NN21

Besides, it is noticed that the TMSE is weak for the different measurements of the machining features of our application and after 10 epochs according to the proposed measurements, it will have the stability of the network with a training mean squared error (TMSE) minimal lower to 0.1.

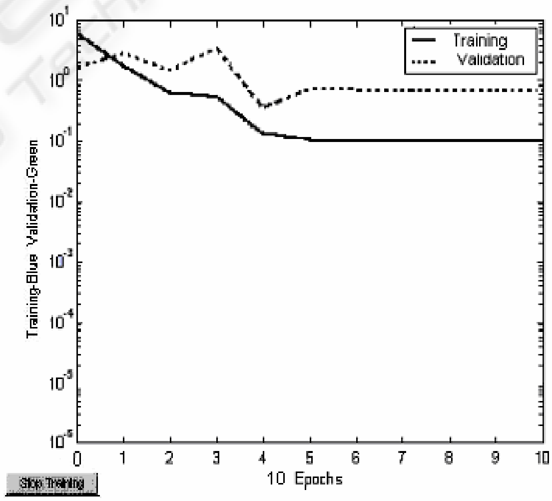

Figure 8: Evolution of the training error and of generalization of the NN21

The graphs represented in figure 8 show the evolution of the error of training (TMSE) and generalization (GMSE) of our neuronal system for automatic choice of cutting tools. The optimal number of epochs in this case is k_{op} =10 epochs.

This phase has permitted us to choose the structure of the optimal network.

Finally, the following structure was fixed:

- inputs and outputs: 5 inputs and 5 outputs,
- number of hidden layers: 3 hidden layers
- number of neurons in the hidden layer: 30 neurons,
- activation functions: hyperbolic tangent for the whole of neurons in the network.

In this application, we have defined a network of neurons that permits a choice efficient of cutting tool classes, a generalization sequence different training sequence permitted to specify performances of the neural networks. Several trainings permitted to fix the optimal structure of the network, permitting it to have a maximal generalization capacity (minimal GMSE). (R. BenKhalifa et al., 2005).

4 DEVELOPMENT OF THE INTERFACE OF NEURONAL STSTEM

In order to model this kind of application, we must create an interfacing-user under CAD/CAM software that allows the process planners to communicate with these applications of a simple and fast manner. We have created a user-interface with Visual Basic language under CAD system software, as well as we have created an interfacing or compilation between MATLAB and VBA under CAD system.

We show in figure 9 the module of neuronal system interface with CAD/CAM systems. This module was to realize with Visual Basic language, it makes possible to facilitate the communication and use of neuronal system for automatic choice of machines and the cutting tools (Mustafa Yurdakul, 2004).

5 CONCLUSION

From the expertise in process planning, we have succeeded in structuring several technological data under shape of arrays (matrixes) that are going to have entered directly in the structure of the network under Matlab by his Tool-box (N.BEN Yahia, 2002).

The validation has been proposed here for the relative cutting tools choice to interaction machining features of type groove / pocket.

The approach neuronal remains promising in relation to approaches of by variants, especially in the speed of implantation and appropriate up to date in industry manufacturing, as well as the precision in the automatic choice of machines-tools of the data base. The proposed system permits as the verification of consistency machine-tools/machining features.

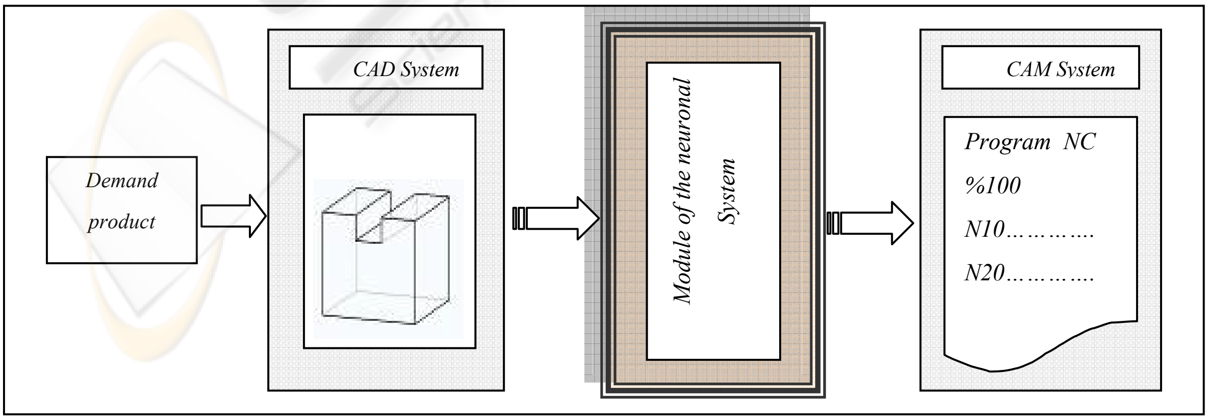

Figure 9: Module of the interface of neuronal system

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