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Full Length Research Paper

Integrated neural networks approach in CAD/CAM environment for automated machine tools selection

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This paper proposed a new model for integrating neural networks approach in the task of generating process planning for machining features. The main issue of process planning addressed in this paper is the optimization of machine tools selection for mechanical part containing simple and interacting features. First, this proposed method elaborated a knowledge database from the investigation with expert in manufacturing companies. Then, it finds the optimal machine tools selection by neural networks. Most importantly, the preliminary sequence is refined by including attributes of machining features. Two cooperated neural networks NN1 and NN2 are used for selection of machine tools according to machining features proposed; the first neural networks takes in input the attributes of machining features and produces the suitable classes of machine tools, the second neural networks used for optimization of machine tools selection is according to machining workshop capacity. Finally, a mechanical part is used as an example to illustrate the implementation of proposed method.

Key words: CAPP, CAD/CAM, machine-tools, machining features, neural networks.

INTRODUCTION

Due to the increasing competition of 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 (Googol, 2004). One of the principal objectives of CAPP system is to interpret the information of design and to prescribe the appropriate machining operations to the conditions determined by the designer.

Moreover, the development of CAPP system 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 CAPP system. The research of process planning activities by employing of CAPP system is of much interest to these years course. Indeed, it plays a significant role in the integrity of the CAD/CAM systems. One of the principal objectives of automatic machining process planning system is to interpret the information of design and to prescribe the operations of machining appropriate and conformed to conditions determined by the designer.

However, the manufacturing companies usually try to reduce manufacturing costs and production times, and to increase the productivity. These objectives cannot be obtained without consideration of an optimal use of machine tools (Drstvensek et al., 2000). Between design and machining, there are software tools (CAPP) systems for machining planning based on part design. CAPP systems are slowly evolving from traditional capabilities (finding volumes to be machined, cutting parameters selection, tolerance analysis and synthesis) to modern capabilities (automated setup planning, interactive feature finding, equipment/tools selection, tool path generation, and machining simulation). CAPP serves the function of bridging the gap between design and manufacturing. Machine tool automation is an important aspect for manufacturing companies facing the growing demand of profitability and high quality products as a key for

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competitiveness (Yurdakul, 2004). The principle of supervising machining processes is to detect interferences that would have a negative effect on the process but mainly on the product quality and production time (Dura´n and Aguilo, 2008).

Indeed, the automatic choice of machine tool in mechanical manufacture is today a very interesting stage for effectiveness of machining operation as well as reliability of a manufacturing process planning. It is carried out according to workpiece characteristics, as well as quantitative and qualitative workpiece information (Santochi et al., 1996).

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

PROBLEM FORMULATION

The traditional method of process planning is centered on the “process planner”. It needs a diverse applied knowledge in both design and manufacturing and uses this knowledge, past experience, handbooks and/or various databases to translate the product engineering requirements into detailed manufacturing. Indeed, process planning is an engineering task that determines the detailed manufacturing requirements for transforming a raw material into a completed part, within the available machining resources (Chung et al., 2004; Fernandes et al., 2000). Their output generally includes: operations, machine tools, cutting tools, fixtures, machining parameters, etc. With the advent of computer technologies, there is a general demand for computer-aided process planning (CAPP) systems to assist human planners and achieve the integration of computer-aided design (CAD) and computer aided manufacturing (CAM) (Zhang et al., 1997).

Tool and machine selection is one of the most important activities in process planning. It is frequently used to examine an economical and feasible process plan for both planning and scheduling. The selection of tools and machines affects almost all aspects related to process planning (Chung et al., 2004). Indeed, machine tool selection has strategic implications that contribute to the manufacturing strategy of a manufacturing organization. In such case, it is important to identify and model the links between machine tool alternatives and manufacturing strategy (Yurdakul et al., 2009).

Consequently, the integration of machine tools selection with design is a key step towards the goal of a seamless integration between computer-aided design and computer-aided process planning. This integration requires that design be carried out using features (Maropoulos et al., 2000).

Examining the recent developments in CAPP, it can be observed that it is now in a strategic position. Key research issues of CAPP must include:

1. Development of methodologies for complete product definition that captures the design, functional and manufacturing aspects of the part;
2. Automation of process planning knowledge acquisition with artificial intelligence paradigms;
3. Development of intelligent interface between CAD and CAM.

In this original research work, two cooperate neural networks are used: the first, back propagation neural networks, takes in as input the attributes of a feature and proposes machine tools classes; the other, fixed for optimization of machine tools selection according to the machining workshop capacity.

PROPOSED INTELLIGENT SYSTEM FOR MACHINE-TOOLS SELECTION

Knowledge database

The first part of this paper presents a new methodology for the description of the profile aimed job. This method is called Job kind in dynamic study, it is known as ETED. The analysis of a knowledge planner is to extract the know-ledge of the expert that it has acquired in general by an initial training of professional experience displayed on several years. This task of knowledge experts extraction is the spring of an analyst. This analyst is able to identify the different real problem types well often complex that pose. It has to find methods of representation of real closest environment. The analysis of know-how consists in extracting knowledge from the expert. Initially, these experts have a relatively short training but they have professional experience spread out over several years in the forming field.

This task of extraction of expert knowledge falls within the competence of one engineer. This engineer must be able to identify the various types of real difficulties, in manufacturing stamping process. This first step is essential to carry out the expertise analytical and set up an information system and knowledge base. The development of the knowledge base requires several visits to companies manufacturing specialty machining that contribute to the creation of an intelligent system. The method used is based on the description of the human planner activity. This methodological approach is called job kind in dynamic study, it is known as ETED, developed by Research and Studies Centre on Qualification (CEREQ), and it was adopted to define the expert activities in stamping companies. We have applied this method to determine the competences of machining work and to develop the rules of manufacture. Indeed, the results waited of these interviews are:

1. Determination of type and number of possible axes of machine-tool from part data.
2. Classification of criteria of machine-tools selection.
3. Classification of constraints influence on machine-tools selection.
4. Identification of optimization criteria of machine-tools selection

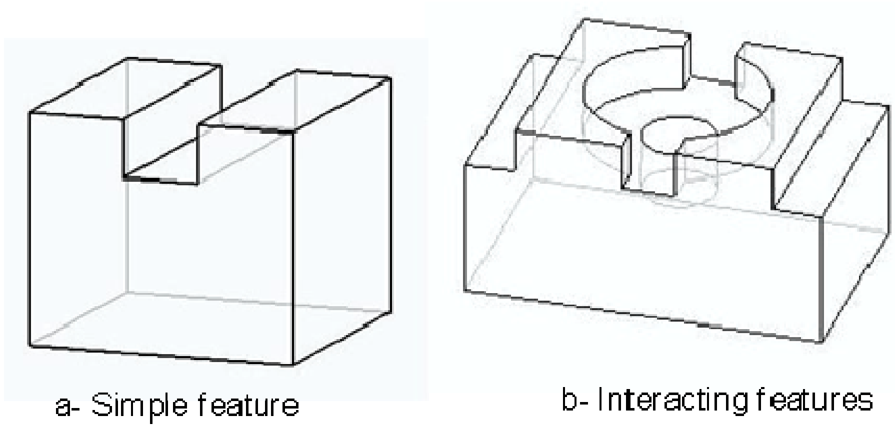
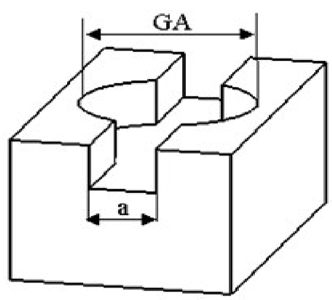


Figure 1. Machining features.



Designation	Attributes
Length	GA
Width	a
Orientation	(0,0,-1)
Tolerance (GA)	IT(GA)
Tolerance (a)	IT(a)
Position	A
Perpendicularity	Pra
Parallelism	Pla
Surface state	Ra
Matter (Hardness)	HB

Figure 2. Machining features attributes.

Machining features representation

The manufacturing process of product is marked by several functions mainly specifications definition, design and manufacture (Park, 2004). In the case of mechanical parts, manufacture function results in process planning generation and efficient machining.

The evolution of production means and the need for reinforcing links between various functions impose today the use of design by features on all the levels of data processing (Oral et al., 2004). Machining feature is defined by geometric shape and set of specifications for which machining process is known, this process is almost independent of the processes of the other features. It is information base that permits to produce the necessary features to identify machining operations, design and manufacture means for workpiece. Besides, it is geometric shape, integrated in the definition part drawing that we want to achieve with a cutting tool and a machine-tool (Figure 1). It can be a simple feature (groove, pocket, hole, and step) or interacting features (slot/ parallel slot, step/ groove, pocket/slot).

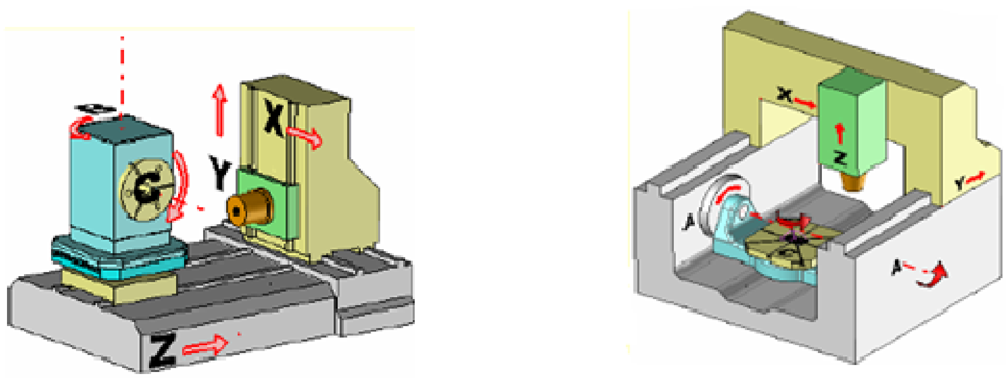
The machining feature is defined as a volume or surface of material that will be removed by machining operations. From the view of machining, the removing of material depends on the cutting movement, feed movement, the tools shape and setup parameters. Those elements consist of engineer semantic of machining feature and will give expression to the machining features para-meters. These parameters describe physical attributes of machining features, including dimension, tolerance and surface finish of the feature, the diameter of a hole and width of a slot and depth of a pocket describe the feature dimension. Tolerances include dimension, position and geometric tolerance and surface finishing includes roughness (Figure 2).

Classification of machine-tools

There are several manners of classifying the machine tools, such as: type of employment, architecture (with horizontal, vertical and directional spindles), by type of order (conventional, automatic, numerical control etc.),

Table 1. Machine-tools classes.

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



a- Machine-tools class (5-Axes XYZBC) b- Machine-tools class (5-Axes XYZAC)

Figure 3. Axes of machine- tools.

and by dimensions (displacement following 3 axes X, Y and Z etc). This study proposes a classification of machine tools according to number of possible axes in a machine tool (one axis, two axes, three axes, four axes and five axes). This classification is related to morphologies of machining features, like their type of machining and their possible operations (Table 1). Figure 3 shows neuronal system structure NN1 which is based on selection of machines tools classes in relation to machining features (Ben et al., 2005).

PROPOSED INTELLIGENT SYSTEM FOR MACHINE-TOOLS SELECTION

The necessity of automatic machine tool selection in mechanical manufacturing is today a very interesting stage for efficiency of machining operation, as well as reliability of manufacture process planning. Indeed, in manufacture machining feature, there exists several possibilities of machine tools selection; however, to optimize this choice we must respect certain number of criteria of machine-tool choice obtained by know-how knowledge, such as: measurements, precisions, dimensional, geometric and technological constraints. The automatic system of machine-tools selection in this study is based on multilayer artificial neural networks. They have the advantage to permit with a certain number of tests to select appropriate machine-tool according to proposed machining features characteristics (Chiung et al., 2002; Chryssolours et al., 2001).

To make sure a correct machines tools selection during generation of machining process planning is done, It must ensures the existing of production means and resources in machining workshop, such as machine tools types (existing and available), their characteristic and their machining capacity. However, to optimize this preparation step of machining process planning, quantitative methods have only been developed with consideration of a simple objective, as minimization of cost or maximization of profit etc. For process of simple objective optimization, several researchers have proposed different techniques as differential calculation, regression analysis, linear, geometric and stochastic programming. However, optimization of machines tools selection is not linear with constraints, so it is difficult with conventional optimization

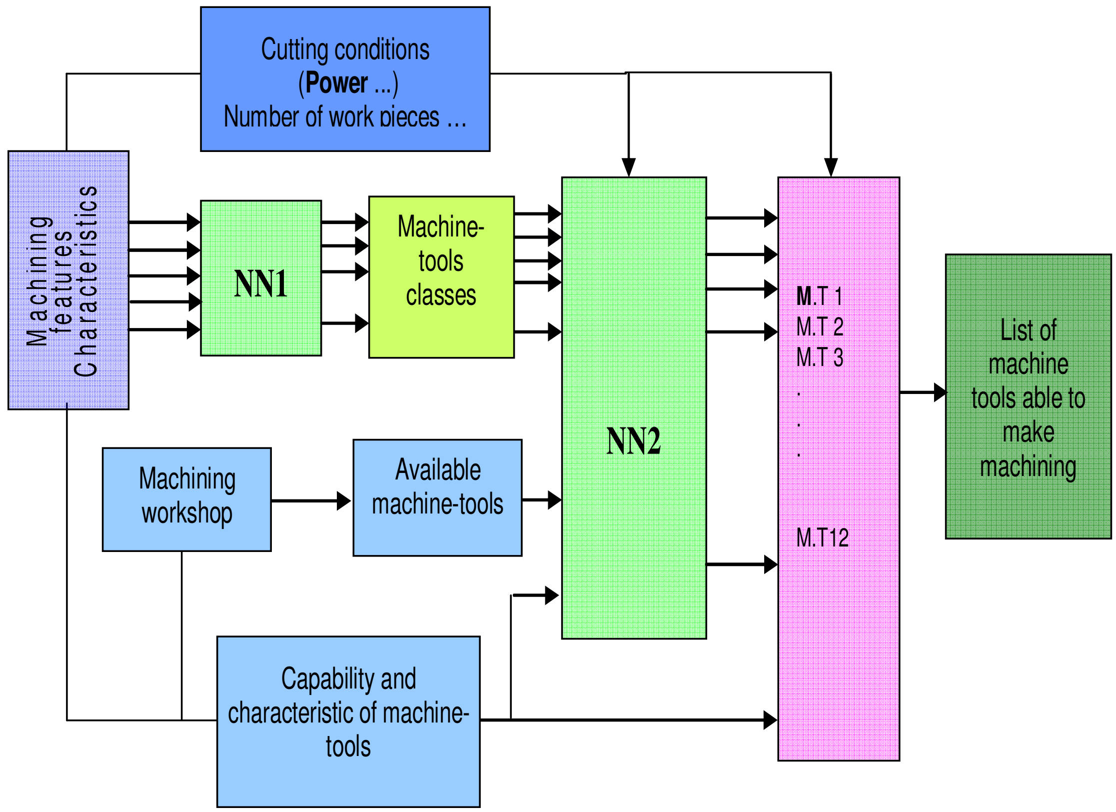


Figure 4. Optimization process of machines tools choice by neural networks.

algorithms to solve this problem because of the presence of a convergence speed problems or precision. Indeed, we present a new optimization method of machines tools selection by using neuronal approach (Figure 4). In fact, for optimization of machine tools selection, we have used second neural networks (NN2) whose desired outputs are machines tools that are able to suggest machining feature according to the machine tools classes selected by first neural networks (NN1), as well as machining workshop capacity. To make sure a correct machines tools selection during generation of machining process planning is done, It must ensures existing of production means and resources in machining workshop, such as machine tools types (existing and available), their characteristic and their machining capacity.

However, to optimize this preparation step of machining process planning, quantitative methods have only been developed with consideration of a simple objective, as minimization of cost or maximization of profit etc.

Structure of neural networks NN1

Artificial neural networks consist of a large number of processing elements, called neurons that operate in parallel. The model of neural networks is based on a simple representation of the biological neurons in form of a function of several variables (Zouidi et al., 2004). For this sort of networks, the activity of a neuron is modelled by a real number and synapses by coefficients.

As their name implies, the neural networks are divided into layers; the first layer is an inputs layer because it receives inputs vectors, reciprocally last layer is an outputs layer, it produces results. The intermediate layers are called hidden layers, because the states of neurons that they contain are not observable (Figure 5). The training phase of the neural networks alters the weights, so that the error of the network is minimized (Dunfied et al., 2004).

Training base

The training base contains 200 machining features cases for training and 50 other different cases that latter for validation and test. The outputs of NN1 are machine tools classes able to machine the suggested features (Table 2). The association of inputs and outputs of NN1 is elaborate starting from the interpreted machining rules to machining know-how knowledge base. The inputs of

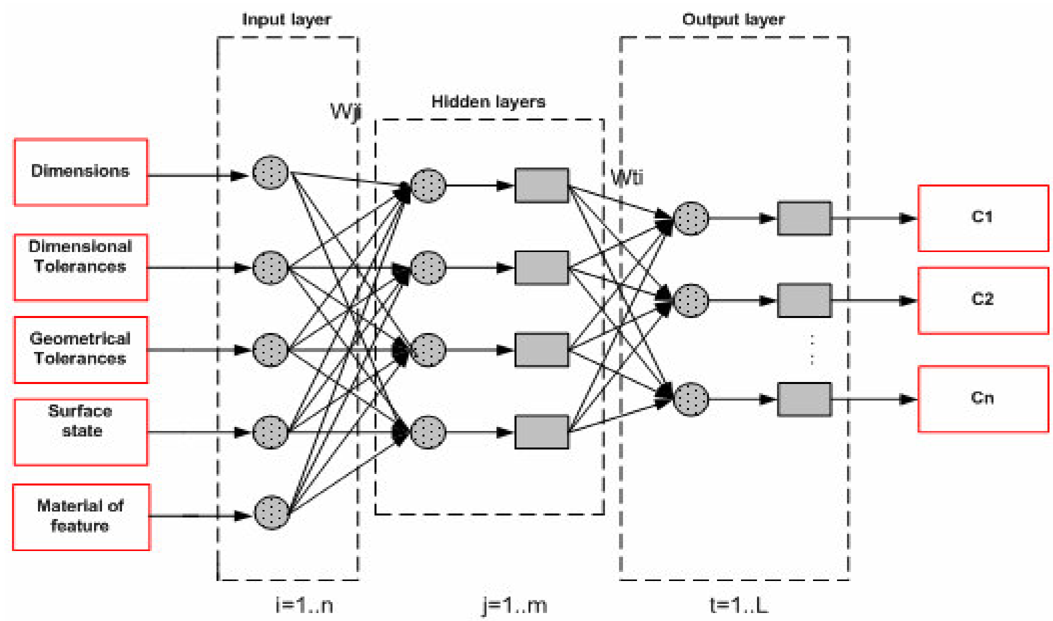


Figure 5. Structure of neural networks NN1.

Table 2. Parameters of the neural networks NN1

Inputs of NN1					Outputs of NN1											
GA (mm)	**a (mm)**	**GA/a**	**code cont.**	**Code mate.**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**
> 10	> 8	< 2	1	1	0	0	1	1	0	1	0	0	0	0	0	0
> 50	> 30	< 2	2	2	0	0	1	1	0	1	0	1	0	0	0	0
> 200	> 80	< 1.5	2	1	0	1	1	1	1	1	0	1	0	0	0	0
-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
> 250	> 100	< 1.5	3	3	0	1	1	1	1	1	0	0	1	1	1	1
> 300	> 150	< 5	2	2	0	1	1	1	1	1	0	0	1	1	1	1

neural networks (NN1) are coded and organized in a matrix whose columns are the dimensions intervals, types of studied constraints and workpiece material, as well as the desired outputs are machine tools classes (c1, c2, c3..., c12). These 12 classes are shared according to the number of possible axes in machine tools. Machining features dimensions are coded by variables (a, GA) in proposed application (Interacting features (pocket/ groove) (Figure 2) and we have affected the relations between features by GA/a. The constraints suggested related to geometrical tolerances are types; associated constraints with simple feature and constraints of relation between pair of interacting features (Table 3). In this work, for respect of geometrical constraints, tolerances and surface quality of workpiece definition in design drawing, it has affected these characteristics to three different codes in Table 3. Moreover, workpiece material is specified by gathering materials into three families according to their hardness by three different codes (Ben khalifa et al., 2005). The output of neural networks consists of a matrix of dimension (12 x 18) (Table 3), the set of these outputs describes proposed solutions by possible machine-tools classes according to desired outputs (C1, C2, C3… C11, C12).

Training and validation of neural networks NN1

The learning process or knowledge acquisition takes place by presenting to neural networks NN1 width a set

Table 3. Constraints and materials code.

Code	Constraints	Code	Materials
1	Without constraint	1	Alloys of copper and alloys of aluminium
2	Dimensional requirements	2	Soft steels
3	Geometrical requirements and/or state of surface.	3	Hard steels and cast irons.

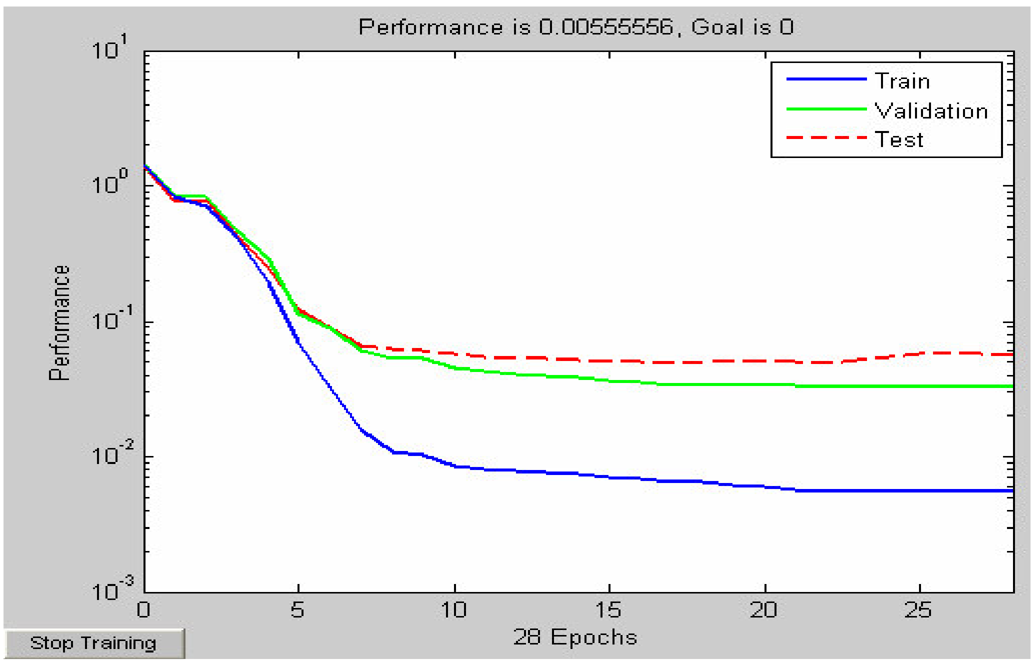


Figure 6 Evolution of training and generalization errors of NN1.

of training examples and NN1 through learning algorithm. It is very difficult to know which training algorithm will be the fastest for a given problem. It depends on many factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal, and whether the network is being used for pattern recognition or function approximation .There are several algorithms for training neural networks that can be deduced in recent applications of neural networks.

The Levenberg-Marquardt algorithm (LM) will have the fastest convergence. This advantage is especially noticeable if very accurate training is required. We have used this algorithm for training NN1 and NN2. The following figures show the evolution of Root of The Mean Squared Error (RMSE) by algorithm LM. It uses a supervised learningmethod (Figure 6), which is a good approach in which the training data also contains classification information. With the solution known, the network is trained to well these target outputs. In order to fix an optimal structure of neural network, it must choose the parameters of network well such as the number of hidden layers, number of neurons in the hidden layer and training and adaptation functions. Indeed, the best structure of network is obtained starting from a very weak training RMSE and an optimal number of epochs so that the test and validation RMSE is minimal. However, we have presented to neural networks system an input vector does not belong to training base then we have examined the test RMSE and we have compared it with training RMSE (Figure 7), The graphs represented in Figure 6 show the evolution of the training RMSE according to the number of epochs. Indeed, it is noticed that the training RMSE is weak for the different measurements of the machining features of this application and after 36 epochs according to the proposed measurements, it will have the stability

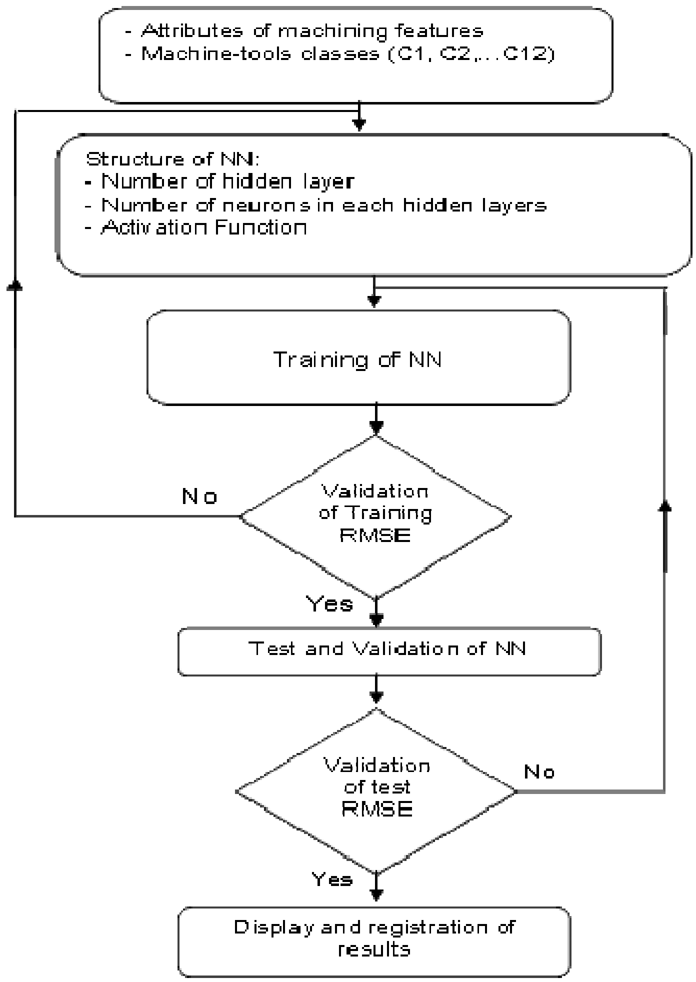


Figure 7. Algorithm of neural networks.

of the network with a training RMSE minimal lower to 0.001. The structure with the minimum training RMSE and test RMSE values is selected to be the optimum architecture. Table 4 shows some structures of NN1 around the optimal structure selected in this study. The choice of optimal number of epochs corresponds to a minimal validation and training RMSE. In this case, the number of neurons making it possible to have a minimal training RMSE is 14 neurons. This phase enabled us to choose the optimal structure of the network (Table 5).

Optimization of machine tools selection

The process of preparing a process plan is mostly experience based. For example, it is not apparent to everyone what is involved in manufacturing a turbine blade. The interpretation of the engineering drawing, the selection of appropriate tools, fixtures and machining parameters, etc., cannot be modeled mathematically.

Many of the decision making rules are based on long term experience in manufacturing. Neural networks, charac-terized by their learning ability, provide a promising approach for automated knowledge acquisition and can be advantageously used in developing intelligent process planning systems.

For optimization of machine tools selection, we have used a second neural network (NN2) whose desired outputs are machines tools able for proposed machining feature which according to inputs are machine tools classes selected by first neural networks (NN1), as well as machining workshop capacity (Figure 4) (Ben et al., 2006). In this optimization case of machines tools selection, the machining workshop is considered as producing

Table 4. RMSE of NN1.

Structure	Training RMSE	Validation RMSE	Epochs
5-8-12	0.0128	0.0513	56
5-10-12	0.0098	0.0381	34
5-14-12*	0.0055	0.0314	28
5-20-12	0.0049	0.0415	37
5-24-12	0.0032	0.0670	41

Table 5. Structure of NN1

Parameters of NN1	Number and type
Inputs	5
Outputs	12
Hidden layers	1
Neurons in the hidden layer	14
Activation function	hyperbolic tangent sigmoid
Learning rate	0.74
Momentum rate	0.03

Table 6. Parameters of the neural networks NN2

Inputs of NN2			Outputs of NN2								
GA (mm)	a (mm)	Classes of machines-tools; machining workshop	M1	M2	M3	M4	M5	--	--	M11	M12
>10	>8	[0 0 1 1 1 1 0 0 0 0 0 0; 1 5 3 0 1 0 0 0 0 1 0 0]	0	0	3	0	1	--	--	0	0
>50	>30	[0 0 1 1 0 1 0 0 1 0 0 0; 1 5 3 0 1 0 0 0 0 1 0 0]	0	0	3	0	0	--	--	0	0
>100	>40	[0 0 1 1 0 1 0 0 1 0 0 0; 1 5 3 0 1 0 0 0 0 1 0 0]	0	0	3	0	0	--	--	0	0
>200	>80	[0 0 1 1 0 1 0 0 1 0 1 0; 1 5 3 0 1 0 0 0 0 1 0 0]	0	0	3	0	0	--	--	0	0
>300	>150	[0 0 0 1 0 1 0 0 1 1 0 0; 1 5 3 0 1 0 0 0 0 1 0 0]	0	0	0	0	0	--	--	0	0

small and mean sets of workpiece. The machining feature proposed for this optimization survey is the same as that proposed for machines tools classes selection, it is a interacting machining features (pocket / groove) (Figure 2).

The training base of NN2 is consisted in inputs vectors representing machines tools classes selected by NN1 and machine tools existing and available in considered machining workshop as well as the wish outputs are machine tools able to machining of proposed machining features (M1, M2, M3..., M12). The set of these outputs describe the possible solutions for optimization machines tools selection, by observing the cutting conditions of studied feature, their capacity of machining workshop and the characteristics of available machines tools (Table 6). Moreover, it has taken into consideration the cutting conditions, which are calculated outside from the neuronal system starting from information of the studied machining features (Figure 2) and the characteristics of machines tools available in machining workshop according to the French standard (NF E 60-010).

The graphs represented in the Figure 8 show the evolution of the training RMSE according to the number of epochs and measurements of machining features. The best structure of NN2 is obtained from a very weak error of generalization (please complete this sentence).

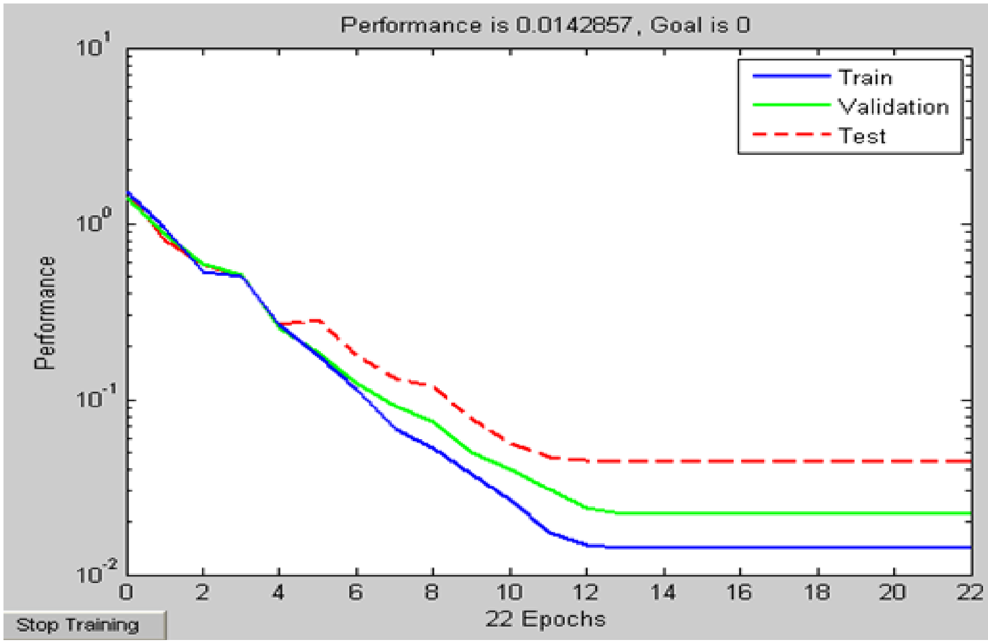


Figure 8. Evolution of training and generalization errors of NN2.

Table 7. RMSE of NN2.

Structure	Training RMSE	Validation RMSE	Epochs
24-10-12-12	0.0986	0.1830	59
24-14-14-12	0.0540	0.0487	46
24-15-14-12	0.0181	0.0354	38
24-16-14-12*	0.0142	0.0225	22
24-21-15-12	0.0123	0.0355	36
24-24-16-12	0.0119	0.0521	60

Indeed, the validation error decreases until a number of epochs were determined. After this value of epochs is obtained, validation of RMSE increases. This translates the on-training of network. Indeed, it is grateful to stop the training for an optimal epochs number (22 epochs).

Table 7 shows some structures of NN2 around the optimal structure selected in this study. Indeed, the optimal structure for NN2 that was fixed during the two phases of training and generalization is shown in Table 8.

Development of user interface for system of machine tools selection

For modelling this intelligent system for machine tools selection, we must create a user interface under CAD systems, which allow the production of routing specialists within office method to communicate with these applications in a simple and fast way. These systems are named “ANNM-Tools” (Artificial Neural Networks for Machine-Tools).

Indeed, a user interface with a language Visual Basic Application (VBA) was created (Figure 10), under Auto-CAD as we have created compilation between MATLAB and VBA in AutoCAD (Ben khalifa et al., 2006).

Until recently much of the work on artificial intelligence was concentrated in research laboratories. This was partly due to the fact that machines for designing such systems have to be powerful with a large memory for storing a vast amount of knowledge. However, with today’s faster and more powerful computers, systems using artificial intelligence techniques are becoming available to more people. Another reason for the lack of industrial applications to date is that obtaining the knowledge or expertise for an AI system is a difficult and tedious task. ANNMTools has many advantages, like the

Table 8. Structure of NN2.

Parameters of NN2	Number and type
Inputs	24
Outputs	12
Hidden layers	2
Neurons in the hidden layer	16, 14
Activation function	hyperbolic tangent sigmoid
Learning rate	1; 1
Momentum rate	0.01; 0.01

Table 10. Machine tools retained by ANNM-Tools system.

Machine-tools	Designation and AFNOR references
Universal milling machine	(3 axes) 315-4.7.1.2.0.2.3.4.5.x-2.4.1.1.2.x.84.2
Horizontal milling machine	(3axes) 315-2.3.1.2.0.2.3.4.5.7-2.4.1.1.2.x.85.2
machining center	(4 axes) 345-2.3.4.1.6.3.6.9.7.2.x 2.4.1.1.1.x.82.2

Table 9. Machining features characteristics.

	Type	Dimensions (mm)	Geometrical tolerances	IT (mm)	Ra (µm)	Material
E1	Pocket	l = 26 r = 7 h = 15		0.1	3.2	
E2	Step	a = 10 b = 40 c = 50	⊥ 0.05	0.1	3.2	CuAl9 (HB=130)
E3	Hole	R = 10 L =20		0.1	3.2	

speed required of suitable machine tool by taking account of all machining constraints, as well as the capacity of machining workshop.

CASE STUDY

Both the changing demands of the market and keen competition among manufacturers call for a more flexible approach to manufacturing. Adopting conventional computing methods is not adequate to meet the sophisticated needs of the modern manufacturing industry. The objecttive of this case study is to present the new methodology of the best alternative of the machine tools and to show to industrialists the results of the available and able machine tools to machine part proposed. The example proposed for the validation of neuronal system of optimization of machine tools selection is a prismatic workpiece, it contains machining features (E1, E2 and E3) (Figure 11). Indeed, the charac-teristics of machining features in proposed prismatic workpiece is to allow machining experts to express necessary information for means of production choice (Table 9).

In the case study, the results determined by developed neuronal system in this paper ANNMTools, for the choice of machine tools, are more precise and correct than the manual choice of a planner or machining specialist, who uses his individual knowledge of the know how to estimate appropriate machine tool selection with the workpiece proposed, without consideration of the machining constraints, capability and availability of selected machine. However, the machine tools retained by ANNMTools are the results of professional experiments of machining experts who are introduced into the training base, by taking account of the constraints of machining and the capacity of the machining workshop.

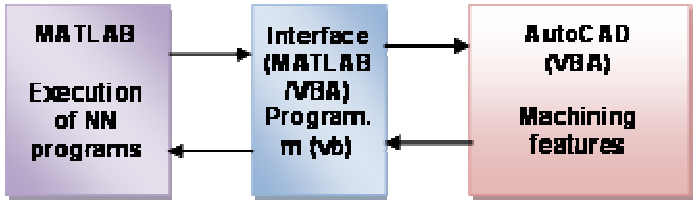


Figure 9. Compilation Matlab / VBA.

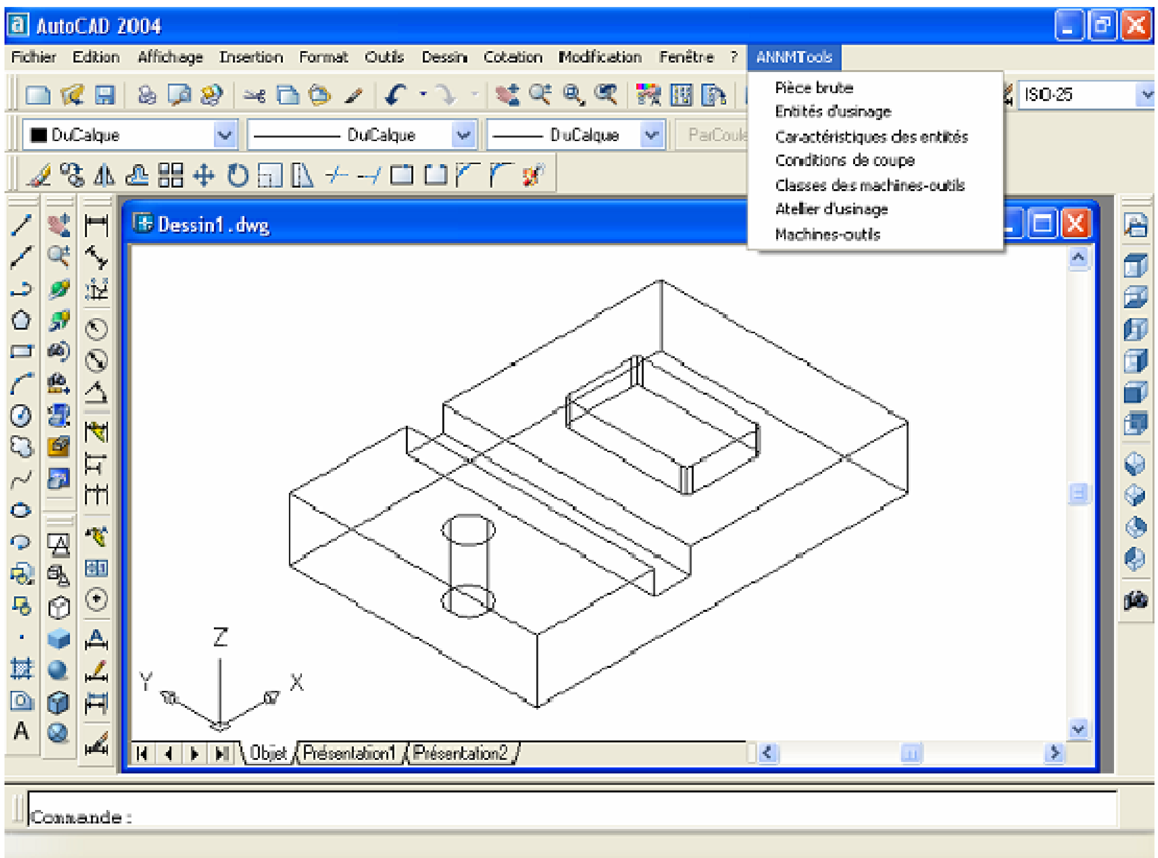
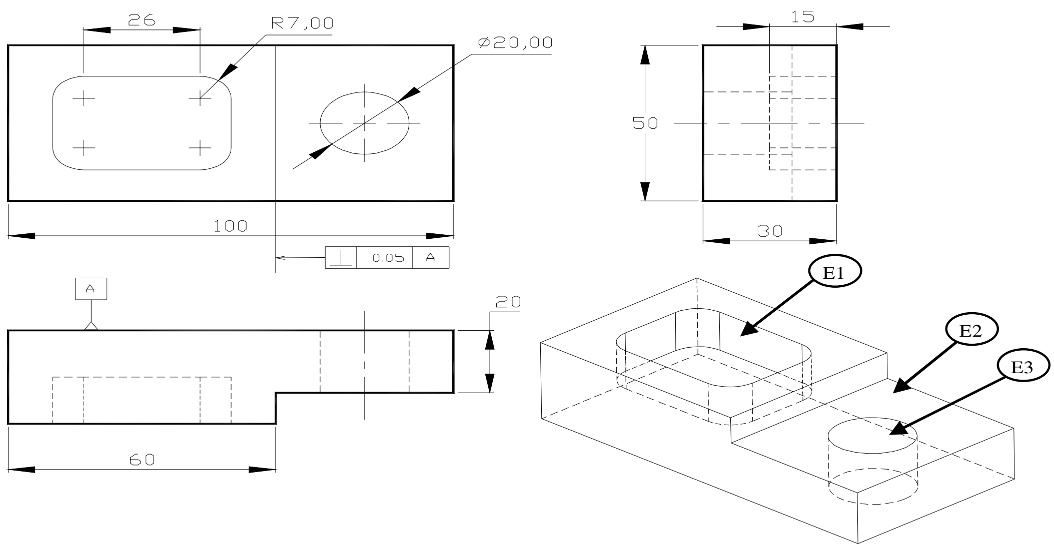


Figure 10. ANNM-Tools system.

Conclusion

Neural networks provide a promising approach for automated knowledge acquisition and can be advantageously used in developing intelligent process planning systems. We have demonstrated in this paper the interest of neural networks for optimization of machine tools choice during generation of machining process planning. The validation has been proposed here for the relative machines tools choice to interaction machining features of type groove/ pocket. The neuronal approach remains promising compared to the approaches group technology and alternatives, especially in speed of establishment and update in manufacturing industry, as well as the precision in the automatic of machine tools choice of the database. Indeed, a very strong benefit of intelligent systems based on neural networks is being able to widely distribute the knowledge of a single expert, or being able to accumulate knowledge of several widely separated experts in one place.

For a future development of this research topic, it is desirable to use neuronal approach for the optimization of



General tolerance ±0.1, all over Ra=3.2

Figure 11. Design drawing of prismatic workpiece.

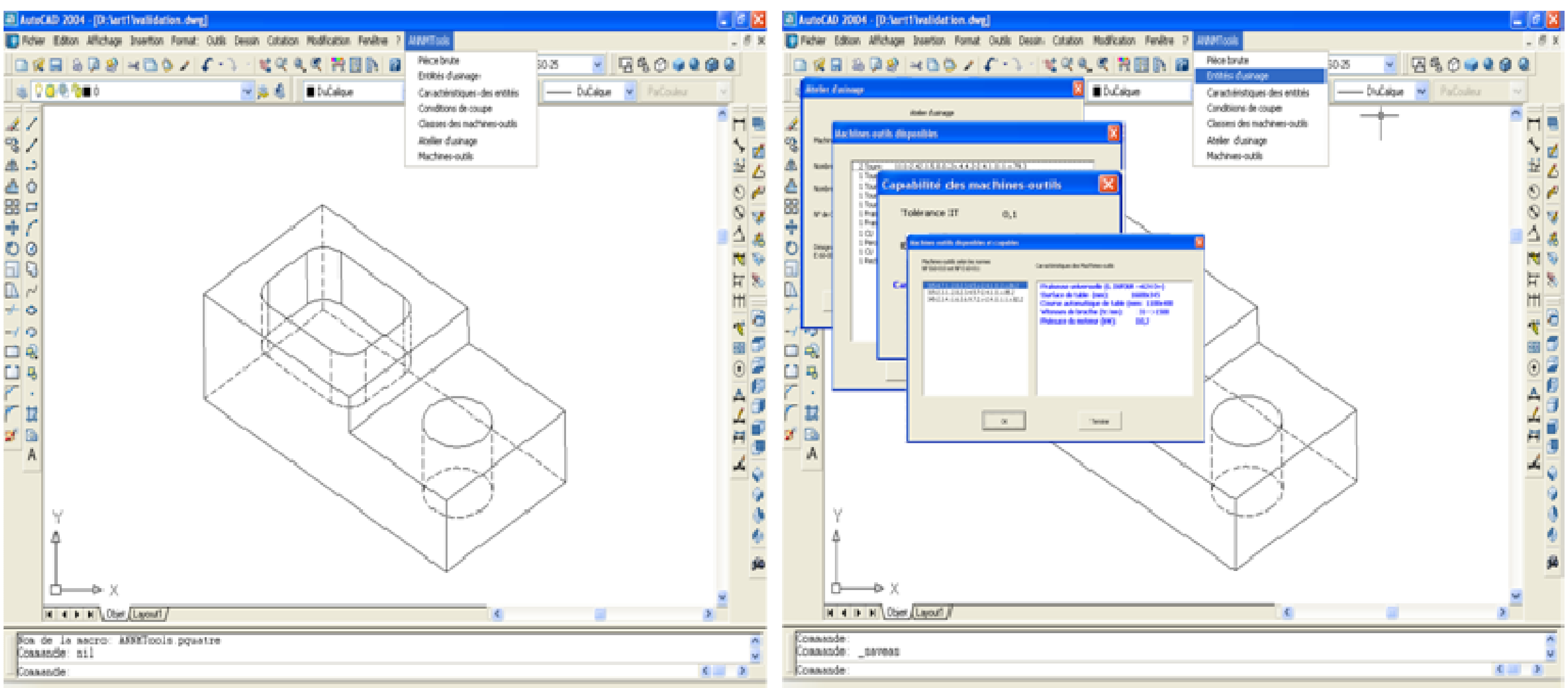


Figure 12. Selection of machine-tools by ANNM-Tools system.

various tasks of preparation and manufacture planning such as resolution of fixture problems of workpiece on table of machine tool, as well as the optimization of cutting parameters and integration of CAD/CAM systems by using optimization hybrid systems.

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