Military Technical College
Cairo, Egypt

12th International Conference
on Applied Mechanics and
Mechanical Engineering (AMME)

DETERMINATION OF MACHINING PROCESS FOR ROTATIONAL PARTS USING NEURAL NETWORKS

EL-AGAMY* M.S. and MOHAMMED**.A.AWAD

ABSTRACT

Computer-Aided Process Planning (CAPP) is the link between CAD and CAM system. CAPP interprets the design information and prescribes appropriate manufacturing processes consistent with the requirements set forth by the designer. Development of a machining process plan is a basic function in manufacturing process. It is a time consuming, and requires significant skills with great deal of experiential knowledge. Process selection and sequencing are also important parts of CAPP. Process selection is a difficult problem in CAPP since it requires productive CAPP system containing a huge amount of knowledge-facts which limits CAPP capability and flexibilityin real manufacturing systems. AI provided some tools for this problem such as artificial neural network (ANN).ANN has the capability of continuous learning and ability to learn arbitrary mappings between input and output spaces. In this paper, a neural network is used for machining process selection in CAPP for cylindrical axis-symmetrical parts. The part features and attributes are the input, and the output is the operation(s) required to produce. Each feature arranged in the same order of logical machining sequences.

KEY WORDS

ANN, CAPP, CAD, CAM and GUI

ABBREVIATIONS

ANN Artificial Neural Network
CAD Computer-Aided Design
CAPP Computer-Aided Process Planning
CAM Computer-Aided Manufacturing
GUI Graphical User Interface

---

* Egyptian Armed Forces
** Associate professor, Dpt. Of Mechanical Engineering, Ain Shams University, Cairo, Egypt.

1. INTRODUCTION

Computer Aided Process planning is a link between computer-aided design (CAD) and computer-aided manufacturing (CAM). Automated process planning in a manufacturing environment is vital to achieve automated and integrated future factories. Many research and development efforts have been devoted to analyze, model, and automate process planning activities for over two decades. However, due to the complexity of the problem involved, a truly generative process planning solution is yet to be found [1].

Today, with the rapidly diminishing number of various experiences in process planning field, there is an urgent need to automate the process planning functions. The complexity and the variety of the tasks in process planning, requires a significant amount of time from even the experienced process planner. In traditional CAPP systems, manufacturing knowledge is coded line by line in program's statements. Any modification to the facts and/or rules would cause rewriting of the whole program. In other words, a traditional CAPP program cannot learn new knowledge unless it is explicitly rewritten [2]. This inflexibility of traditional methodologies limits the implementation of CAPP systems, which is the important link in CAD/CAM systems. Neural Networks, comes as a very suitable tool to overcome the limitations of traditional CAPP systems.

2. LITERATURE REVIEW

Different AI based approaches have been implemented in Computer-Aided Process Planning in manufacturing process .These approaches are classified into three categories: expert system, fuzzy reasoning and neural networks. Several applications of expert systems in CAPP have been reported. A knowledge-based approach for hole machining process selection was reported by Khoshnevis et al [4]. It takes in manufacturing features as input and generates possible sequences of machining operations. Younis [5] used an expert system based approach that generates a sequence of machining operations using production rules, taking into account technological attributes of features of the part. Sabourin et al [6] used an expert system based approach that generates a sequence of machining operations using production rules. Jiang et al [7] developed a CAPP a feature extraction system, represented by a GT coding and automatically generates process plans for prismatic components using a rule based expert system. Radwan [8] developed an expert system based CAPP approach for machining of different kinds of surfaces and holes. Process capability matrices were developed for each surface type and an expert system was employed to generate process plans by matching the surface parametric data and required quality with respect to the capability matrices of each surface type. The knowledge-based expert systems offer a structured knowledge representation in the form of rules and an explicit inference route and therefore, the capability of explanation facility. It, however, suffers from such weaknesses as for example, its inability to infer when information provided is incomplete. Besides it performs exhaustive searches for matching the patterns resulting in increase of execution times with increase in number of process plan rules.

The Application of fuzzy reasoning methods in CAPP was also the subject of many researches. Hashmi et al [9] have developed a fuzzy reasoning method for selection of machining speed for a depth of cut, material hardness. The necessary production rules were constructed based on knowledge extracted from data handbook. The application of fuzzy reasoning methods offers a structured and rule based knowledge representation similar to the expert systems approach. It enjoys a significant advantage over the expert systems in that it is characterized by ability to handle uncertainty and reason with imprecise information. Its main weaknesses are, however, its inability to automatically acquire the inference rules and problem of finding appropriate membership functions for the fuzzy variables.

The application of ANN networks attracted the attention of many researchers in the last 2 decades. Knapp et al [10] used neural network in the process selection and feature process sequencing. In this work, two co-operating neural networks were utilized: the first one takes in as input the feature attributes and proposes a set of machining alternatives; the other network selects one of the alternatives. A neural network approach for automated selection of technological parameters of turning tools is reported by Santochi et al [11].For each parameter, a neural network was designed, trained and validated. The use of neural networks in CAPP overcomes the deficiencies of expert system and fuzzy reasoning methods to a certain extent. They are able to perform inference procedure with heuristic knowledge that cannot be expressed in explicit rule form. It is characterized by high processing speed through its massively interconnected, parallel architecture and adaptability to dynamic manufacturing environment owing to efficient knowledge acquisition capability. Moreover, they are robust and error tolerant and able to approximate human reasoning in the face of uncertainty. In this paper, a neural network based approach was presented for machining process selection and sequencing in CAPP.

3. WORK DONE

The objective of the proposed methodology is automated selection of all machining operation sequences with logical machining sequence by using a neural network based approach. The scope of the present methodology is restricted to features commonly encountered in symmetrical rotational parts.

3.1 Network Design

Till now, there is no clear theory in the selection of the most appropriate configuration of the neural network, the optimum architecture can be only reached through trial and error with progressive adjustments of the weights by varying parameters such as

number of hidden layers, number of nodes in each hidden layer, learning rate and momentum rate in order to obtain the minimum value of the network error.
In this work, (MATLAB Version 7.0.0.19920 -R14) software was used to design and train the neural network , as following :

The selected neural network was feedforward neural network, each layer having full interconnection to the next layer, no connections within a layer and no feedback connections to the previous layer. The standard Back Propagation (BP) algorithm is used as the learning mechanism for the neural network. Input layer has 4 neurons corresponding to 4 inputs which are the feature type (surface code), length, tolerance, and surface finish. The surface codes are: 1 for horizontal, 2 for vertical, 3 for curved and 4 for inclined surface code.

As was mentioned above, the optimum architecture of the network can be only reached through trial and error with progressive adjustments of the network parameters, so neural networks with 1 & 2 hidden layers with number of neurons equals to 1, 5 and10; were designed respectively to find the best network architecture that can reach the minimum designed error between desired output and network output. The output layer has 9 neurons corresponding to 9 machining operations which are rough turning, semi-finish turning, finish turning, facing, taper turning, chamfering, form turning, grinding and lapping. The machining operations are arranged such that their order follows the selected logical machining sequence as shown in table2 such that the output pattern simply gives the required machining operation in order. The selected transfer functions are sigmoid at input & hidden layers and purelin at the output layer. The input layer activations are set equal to the corresponding elements of the input vector. The activations propagate to the hidden layer via weighted connections. Then the hidden layer outputs propagate to the output layer activations of the output layer neurons form the networks response pattern. The inputs and desired output patterns for network training were made according to the process capability and possible operations logic shown in table 1&2.The Selected error level is 0.005

Table1. Process capability matrix

Parameter	Rough turning	Semi-finish turning	Finish turning	Facing	Taper turning	Chamfering	Form turning	Grinding	Lapping
Surface finish (μm)	**6.3 ≤**	**3.2 ≤**	**0.8 ≤**	**0.8 ≤**	**3.2 ≤**	**0.8 ≤**	**0.8≤**	**0.1≤**	**.05**
Tolerance. (mm)	**0.125 ≤**	**.03 ≤**	**0.02 ≤**	**0.02 ≤**	**0.125 ≤**	**0.02 ≤**	**0.02 ≤**	**0.003 ≤**	**0.003 ≤**

Table2. Operations

Surface type	Possible operations
Vertical	1- Rough turn. 2- Semi- finish Turn. 3 – Facing 4- Grinding 5- Lapping
Horizontal	1- Rough turn. 2- Semi- finish Turn .3- Finish turning 4- Grinding 5- Lapping
Curved	1- Rough turn. 2- Semi finish Turn. 3- Form turning
Inclined	1- Taper turn. 2- Grinding 3- Lapping

Notes:
*Selection of one or more operation will be according the Capability table.
*The order of operations corresponding to each surface type is set in the logical machining order.

3.2 Network Training

In training phase, the actual output is compared to a desired output for a given input to calculate error terms for each output neuron. The weights leading into the hidden nodes are then adjusted by reducing the product of learning rate, error term of the output layer and actual activation of hidden neuron. The error terms are then back propagated to the hidden layer to calculate the error terms in hidden layer. A momentum term is used to increase the rate of convergence by preventing the search from falling into shallow local minima during the search process
The training error graphs that were obtained for different network architectures are as following:
Training & testing sets are prepared in Excel data file, 1023 input training patterns and 102 testing patterns representing different examples and their corresponding desired patterns were prepared in Excel file ,the vertical columns represent the input patterns, the desired outputs(machining operations in the logic sequence) and the network simulation (predicted machining operations in the logic sequence) as shown in tables 3,4 and 5.

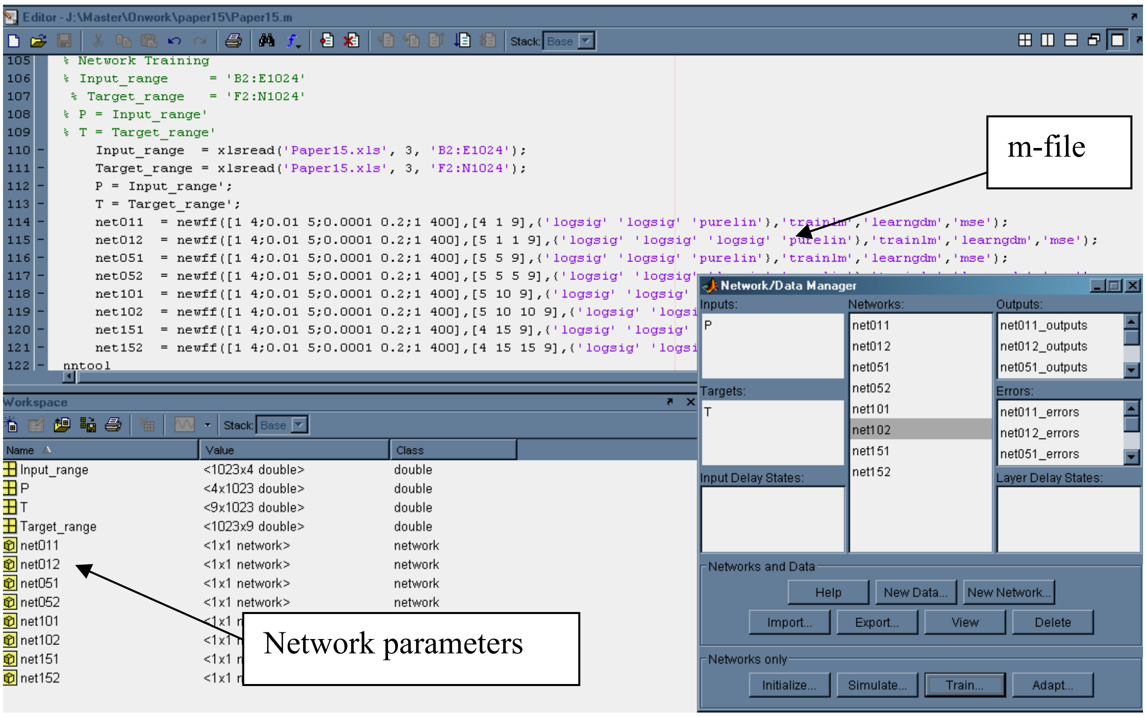

Fig.1 (sample screen from the program)

3.2.a Matlab programs were created to establish different architectures of the neural networks, training and testing them. a part of the program screens is shown in Fig.1.

3.2.bThe Graphical User Interface (GUI) was used to import the designed networks with their inputs, outputs parameters to carry out the training process and its demonstrations ,and for network simulation also as shown in Fig .2

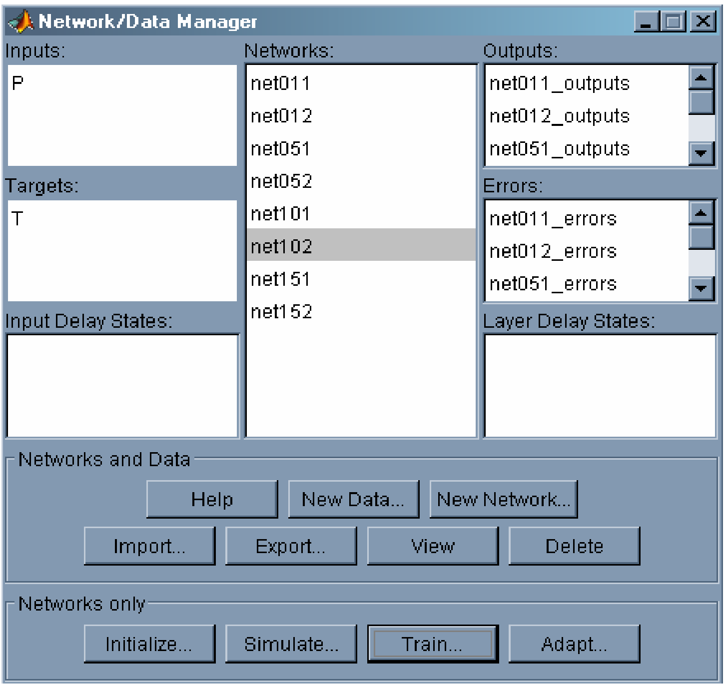

Fig .2 GUI

3.2.cThe training parameters values are selected such that network reach its stabilization within the training process in as shown in the Fig.3

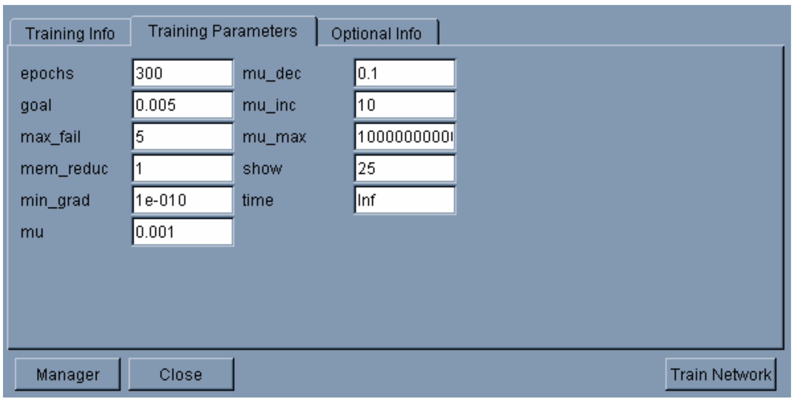

Fig .3 Training parameters

3.2.d Using the above parameters, each network is trained, the networks will be identified as (net ij): where i is the number of hidden neurons in each hidden layer and j is the number of the hidden layers . as an example net011 means network with 1 neuron and one hidden layer.. training curves that represent each network parameters were obtained are shown in appendix[I].

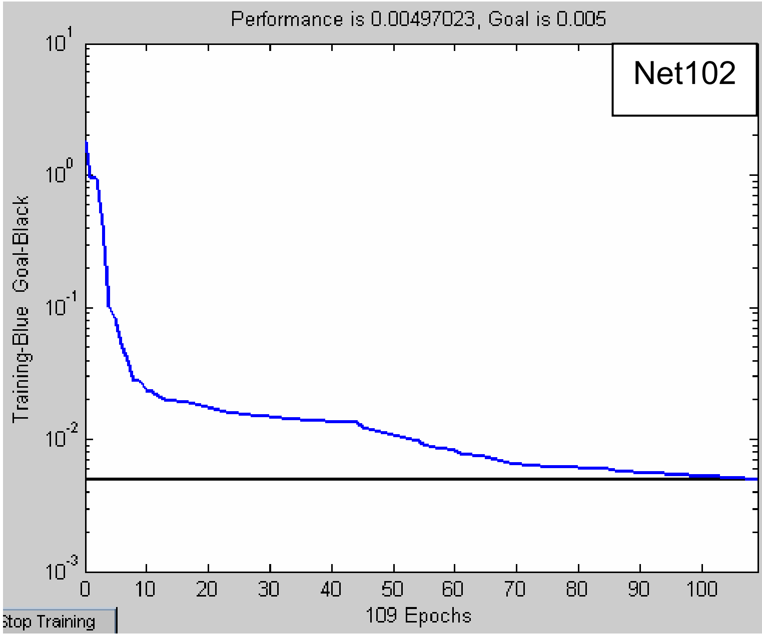

Fig.4 Network training curve

3.3 Training Results& Final Network Selection

The required design of the neural network was (net102) which has 10 neurons and two hidden layers , the required network performance was met and the network was stabilized after 109 epochs after the desired error (0.005)was achieved. The final selected network architecture is shown in Fig .5

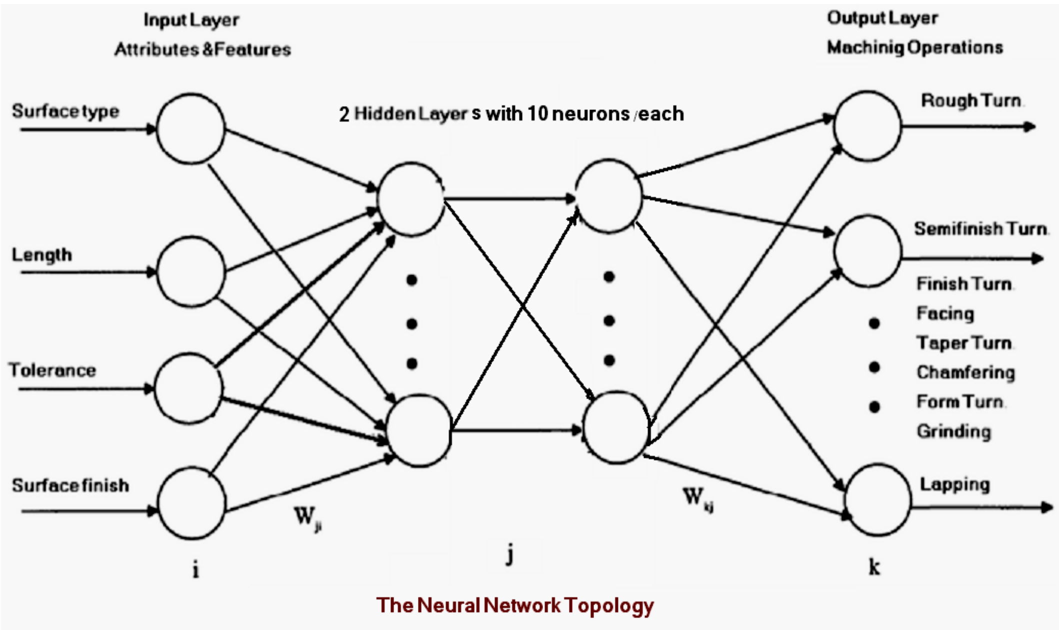

Fig.5 Neural network architecture

The generalization capability of the network is verified by validation tests presenting intermediate situations with respect to those proposed during training.

4. ILUSTRATIVE EXAMPLES

To demonstrate the network capability, 3 illustrative examples are discussed to show how the network can predict the machining operations for3 rotational parts.
An example is discussed in details hereinafter, then appendix [II] will show drawings and results of the other two examples.

A rotational part shown in Fig.6 was created using MasterCam 9.0 software . as shown in the Fig., The features are assumed to be present in a certain order from the left face of the part. the above half section of the part was drawn in 2D drawing , the start and the end of each feature are numbered for identification starting from the left hand side

The corresponding codes and attributes are written in Excel file representing the inputs to the network, followed by the desired operations and the predicted ones in the following columns.

The network (net102) is run and simulated after the attributes and features of each example were presented as inputs to the network. By exporting the network simulation results against the desired one, the results shown in table 3 were obtained. As shown from the table, the network could predict the required machining operation with high accuracy, since the table columns are already arranged in a logic machining sequence shown in table3, so both the required machining operations in the logic machining sequence could be obtained. Additional two examples are attached to the paper for more demonstration.

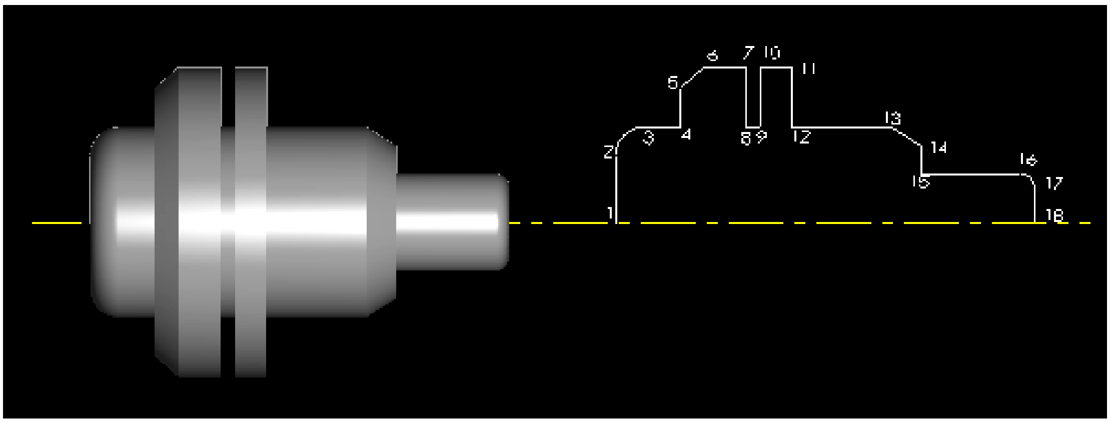

Fig. 6 Example 1

Table 3 Network inputs and outputs

Type Of surface	Part Inputs Features & Attributes				Target (Desired Output) Machining Operations									Network Simulation Predicted Operations								
	Surface code	Length (mm)	Tolerance (mm)	Surface finish (μm)	Rough turning	Semi-finish turning	Finish turning	Face	Taper turning	Chamfer	Form turning	Grind	Lap	Rough turning	Semi-finish turning	Finish turning	Face	Taper turning	Chamfer	Form turning	Grind	Lap
Vertical	2	119	0.08	1.8	1	1	0	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0
curved	3	80	0.00	1.4	1	1	0	0	0	0	1	1	0	1	1	0	0	0	0	1	1	0
Horizontal	1	68	0.01	0.1	1	1	1	0	0	0	0	1	0	1	1	1	0	0	0	0	1	0
Vertical	2	71	0.00	0.8	1	1	0	1	0	0	0	1	0	1	1	0	1	0	0	0	1	0
Inclined	4	55	0.13	1.3	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1	0
Horizontal	1	80	0.13	1.8	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
Vertical	2	107	0.00	0.4	1	1	0	1	0	0	0	1	0	1	1	0	1	0	0	0	1	0
Horizontal	1	25	0.01	1.9	1	1	1	0	0	0	0	1	0	1	1	1	0	0	0	0	1	0
Vertical	2	107	0.00	0.2	1	1	0	1	0	0	0	1	0	1	1	0	1	0	0	0	1	0
Horizontal	1	74	0.00	1.3	1	1	1	0	0	0	0	1	1	1	1	1	0	0	0	0	1	0
Vertical	2	107	0.13	0.8	1	1	0	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0
Horizontal	1	183	0.01	0.1	1	1	1	0	0	0	0	1	0	1	1	1	0	0	0	0	1	0
inclined	4	64	0.13	1.4	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1	0
Vertical	2	50	0.13	1.2	1	1	0	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0
Horizontal	1	203	0.02	0.8	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
Inclined	4	3	0.13	3.2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
Vertical	2	84	0.13	0.8	1	1	0	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0

Differences between target (desired) output and the simulated output of the neural network

(1) corresponds to Selected operations , (0) Unselected operations

5. CONCLUSION

In this paper, a new CAPP methodology for machining of rotational symmetric parts using a neural network approach was implemented successfully. The proposed CAPP methodology takes in as input the attributes and features of the part and automatically generates machining processes required to produce this feature. The advantages of using neural network based CAPP methodology is: (a) Its efficient knowledge acquisition capability owing to its ability to implicitly derive the rules from sample machining cases presented to the neural network. (b) Its capability to generalize beyond the original machining cases to which it is exposed during the training and face intermediate situations with reasonably good accuracy with respect to those proposed during the training. (c) High processing speed once the neural network is trained. The network faults in the presented examples were 0.006,0.016 and 0.02 respectively which represent promising results for using neural networks in determination of machining process for rotational parts.

REFERENCES

[1] Chang, T. C, Editorial, Journal of Design and Manufacturing, 1992.

[2] Nafis, A. and Anwarul H., “Artificial neural network based process selection for cylindrical surface machining” ,P. Of Int. Conf. on Manufacturing, pp321-326,(2002).

[3] Edward, G., "The analysis of methods for computer aided process planning", Provo, Utah, USA. 1998.

[4] Khoshnevis, B. and Tan Wei, “Automated process planning for hole-making”, American Society of Mechanical Engineers, Manufacturing Review,8,2. (1995).

[5] Younis, M.A. and Waheb, M.A.,"A CAPP expert system for rotational components", Computers Ind. Eng., 33, 3-4, pp509 -512, (2002).

[6] Sabourin, L. and Villeneuve, F.O, “An Expert CAPP System”, Advances in Engineering Software, 25, pp51 -59 ,(1996).

[7] Jiang, B. ,Lau H., Chang Felix T.S., Jiang H., “An automatic process planning system for the quick generation of manufacturing process plans directly from CAD drawings, “Journal of Materials Processing Technology” , 87, pp97 -106. ,(1999).

[8] Radwan A., “A Practical Approach to a Process Planning Expert System for Manufacturing Processes”, “Journal of Intelligent Manufacturing 11, pp75 -84., (2000).

[9] Hashmi K., El Baradie M. A., Ryan M., “Fuzzy Logic Based Intelligent Selection of Machining parameters”, Computers Ind. Eng. , 1135, pp571 -574., (1998).

[10] Knapp, G. M, Wang, H., "Acquiring, storing and utilizing process planning knowledge using neural networks", Journal of Intelligent manufacturing, 1, pp1-15. (1992).

[11] Santochi M., Dini G., “Use of neural networks in automated selection of technological parameters of cutting tools”, Computer Integrated Manufacturing Systems, , 9, 3, pp137 -148, (1996).

.

Appendix [I]

Training Curves of Neural Networks

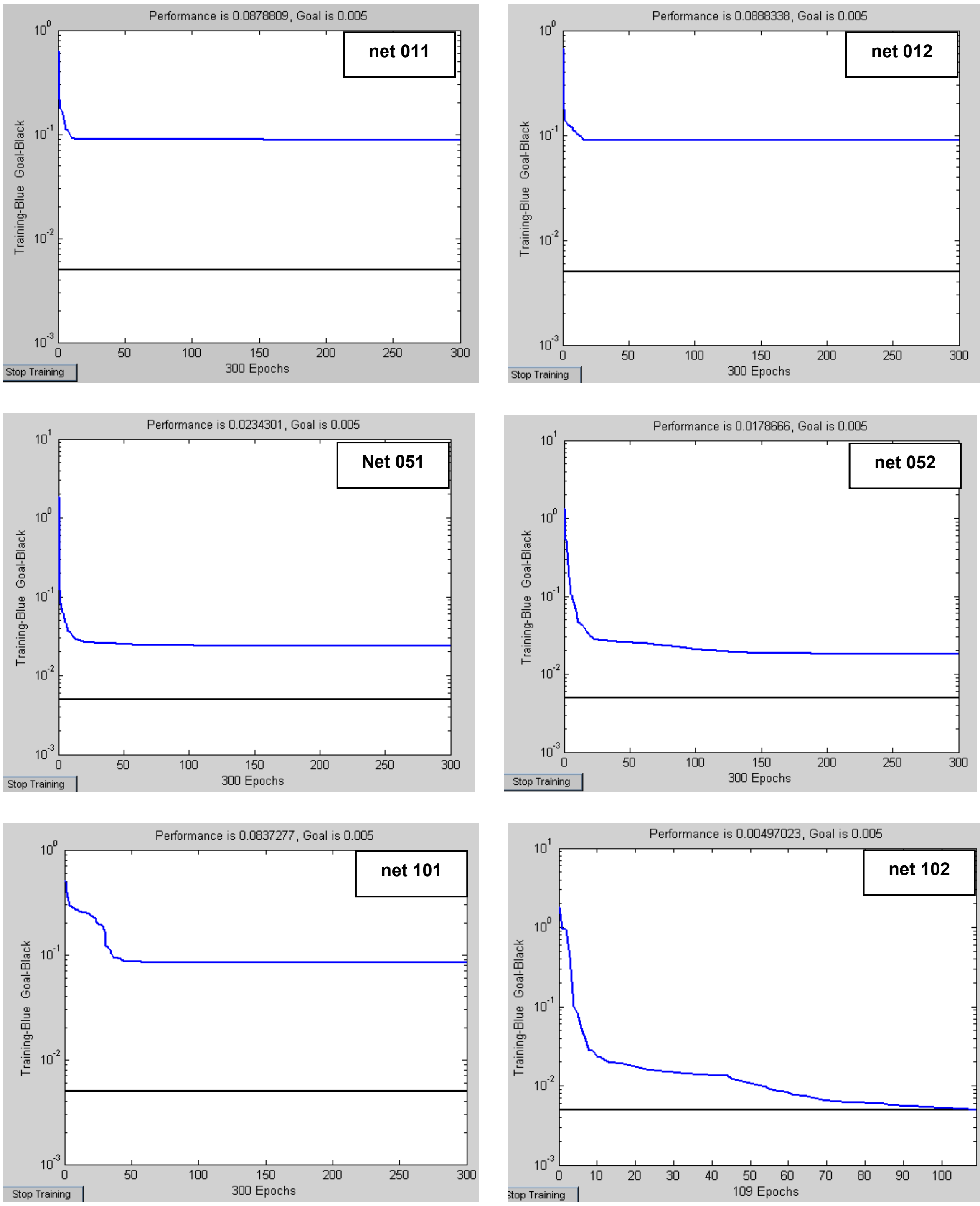

Fig.7 Training Curves for different neural networks designs

APPENDIX [II]

Example no.2

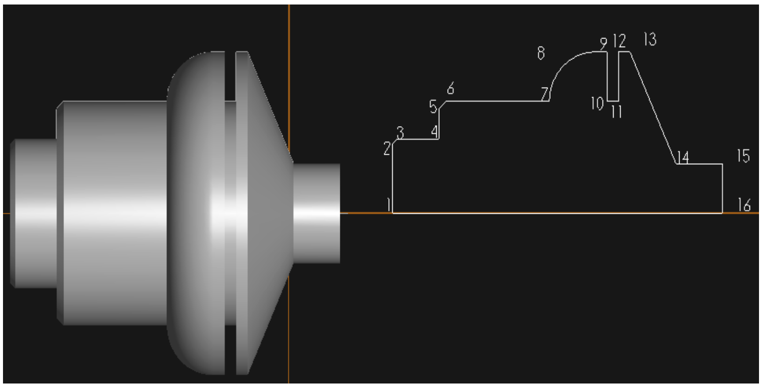

Fig. 4

Table 4

Type Of surface	Part Input Features& Attributes				Target (Desired Output) Machining Operations									Network Simulation Predicted Operations								
	Surface code	Length (mm)	Tolerance (mm)	Surface finish (µm)	Rough turning	Semi-finish turning	Finish turning	Face	Taper turning	Chamfer	Form turning	Grind	Lap	Rough turning	Semi-finish turning	Finish turning	Face	Taper turning	Chamfer	Form turning	Grind	Lap
Vertical	2	28	0.03	0.8	1	1	0	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0
Inclined	4	3	0.13	1.6	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0
Horizontal	1	18	0.02	0.4	1	1	1	0	0	0	0	1	0	1	1	1	0	0	0	0	1	0
Vertical	2	12	0.02	1.6	1	1	0	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0
Inclined	4	4	0.05	1.3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
Horizontal	1	45	0.13	0.1	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0	1
Curved	3	31	0.25	0.8	1	1	0		0	0	1	0	0	1	1	0	0	0	0	0	0	0
Vertical	2	20	0.03	0.1	1	1	0	1	0	0	0	1	0	1	1	0	1	0	0	0	1	0
Horizontal	1	5	0.25	1.7	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
Vertical	2	20	0.13	0.4	1	1	0	1	0	0	0	1	0	1	1	0	1	0	0	0	0	0
Horizontal	1	5	0.00	1.9	1	1	1	0	0	0	0	1	0	1	1	1	0	0	0	0	1	0
Inclined	4	49	0.01	0.2	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1	0
Horizontal	1	20	0.05	1.3	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
Vertical	2	20	0.23	3.2	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0

Differences between target (desired) output and the simulated output of the neural network

(1) corresponds to Selected operations , (0) Unselected operations

APPENDIX [II]

Example no.3

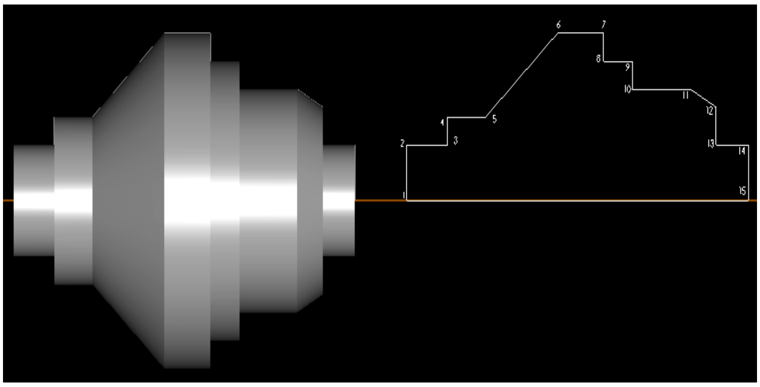

Fig .5

Table 5

Type Of surface	Part Input Features & Attributes				Target (Desired Output) Machining Operations									Network Simulation Predicted Operations								
	Surface code	Length (mm)	Tolerance (mm)	Surface finish (µm)	Rough turning	Semi-finish turning	Finish turning	Face	Taper turning	Chamfer	Form turning	Grind	Lap	Rough turning	Semi-finish turning	Finish turning	Face	Taper turning	Chamfer	Form turning	Grind	Lap
Vertical	2	41	0.02	1.3	1	1	0	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0
Horizontal	1	36	0.13	0.1	1	1	1	0	0	0	0	1	0	1	1	1	0	0	0	0	0	1
Vertical	2	20	0.02	0.8	1	1	0	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0
Horizontal	1	33	0.13	1.3	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
Inclined	4	86	0.13	0.1	0	0	0	0	1	0	0	1	0	0	0	1	1	0	1	0	1	0
Horizontal	1	40	0.02	0.8	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
Vertical	2	20	0.03	1.3	1	1	0	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0
Horizontal	1	25	0.13	0.1	1	1	1	0	0	0	0	1	1	1	1	1	0	0	0	0	1	1
Vertical	2	20	0.03	0.4	1	1	0	1	0	0	0	1	0	1	1	0	1	0	0	0	1	0
Horizontal	1	50	0.13	1.9	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
Inclined	4	25	0.02	0.2	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1	0
Vertical	2	28	0.02	1.3	1	1	0	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0
Horizontal	1	28	0.01	0.1	1	1	1	0	0	0	0	1	1	1	1	1	0	0	0	0	1	1
Vertical	2	46	0.13	0.8	1	1	0	1	0	0	0	1	0	1	1	0	1	0	0	0	0	0

Differences between target (desired) output and the simulated output of the neural network

(1) corresponds to Selected operations , (0) Unselected operations