ERJ
Engineering Research Journal
Faculty of Engineering
Minoufiya University

NEURAL NETWORK APPROACH TO FEATURE-BASED PROCESS PLANNING

Omar M. EL-Mabrouk* and Saleh M. Amaitik**

*Industrial and Manufacturing Systems Engineering Department, Garyounis University, Benghazi, LIBYA *ommabrouk@yahoo.com and **s_amaitik@garyounis.edu*

ABSTRACT

Machining operations selection is a key issue in today's research of computer aided process planning (CAPP). Traditionally, this task is carried out by process planners and knowledge base systems. Recently, process planners have started using newer artificial intelligent techniques, such as neural networks, fuzzy logic, intelligent agents, etc. to model machining operations. In this study, the problem of machining operations selection for hole making operations is investigated. A neural network model is proposed to generate the needed machining operations and their sequence based on hole attributes and accuracy required. Hole diameter, length to diameter (L/D) ratio, surface finish and tolerances are presented to the network for each feature as input parameters. The network classifies the required machining operations into three steps; hole starting, core making and hole finishing operations. The advantage and effectiveness of the proposed model are verified through a several types of hole features.

يعتبر اختيار عمليات التشغيل من المواضيع التي تبحث اليوم في مجال أنظمة تخطيط عمليات التصنيع بالحاسب الآلي. تقليديا كانت هذه المهمة تنجز من خلال الاعتماد على خبرة المهندسين أو نظم قواعد المعرفة. حديثا قام الباحثون في مجال تخطيط عمليات التصنيع باستخدام تقنيات الذكاء الاصطناعي مثل الخلايا العصبية الذكية والمنطق الغامض والخوزميات الجنية والعديد من الطرق الأخرى في اختيار عمليات التشغيل.

في هذه الورقة تمت دراسة إمكانية استخدام الخلايا العصبية الذكية في اختيار عمليات التشغيل اللازمة لتصنيع الثقوب في الأجزاء الميكانيكية. وبناءً على ذلك تم بتصميم نموذج رياضي لخلايا عصبية ذكية قادرة على اختيار وتسلسل العمليات اللازمة لتصنيع الثقوب معتمدة على ملامح الثقب والدقة الهندسية المطلوبة له. حيث كانت المعطيات لهذا النموذج تتمثل في التالي: قطر الثقب، معدل طول الثقب إلى قطره، نعومة سطح الثقب، والتفاوتات المسموح بها على ملامح الثقب. وبناءً على هذه المعطيات قام نموذج الخلايا العصبية الذكية باختيار وتصنيف عمليات التشغيل اللازمة إلى ثلاثة أقسام على النحو التالي: (١) اختيار عمليات بداية الثقب، (٢) اختيار عمليات عمل الثقب، و (٣) اختيار عمليات تشطيب وضبط الثقب. وقد تم التحقق من فعالية هذا النموذج من خلال تصنيع عدة أنواع من الثقوب.

Keywords: Process Planning, Neural Networks, Hole Making, Backpropagation

1. INTRODUCTION

Modern industry today facing a rapid diminishing of experienced process planners and the time required by junior process planners to gain the necessary experience. It becomes necessary to search for new approaches to capture process planning knowledge in a practical form and act as a training vehicle that disseminates this accumulated knowledge to the junior process planners. The majority of research in the area of automated process planning has focused on the use of algorithmic process planning and expert system approaches. These approaches have shown inflexibility in process planning knowledge acquisition. In previous, papers were published between 1993 and 2000 described the use of genetic algorithms [1] and fuzzy systems [2]. Also, recently, some interest has occurred in using artificial neural networks technology in the development of automated process planning systems [3]. Various efforts are documented in the literature on the application of artificial neural networks in the process planning. These efforts have shown that the implementation of neural networks in process planning has the following advantages;

a- Adaptability to the dynamic manufacturing environment, owing to efficient knowledge acquisition capability.

b- Ability to face unknown situations, without having the explicit rule for the solution. This can be done by training neural networks with new examples.

c- Fast inference and high working efficiency.

This paper studies the implementation of artificial neural networks in machining operations selection of hole making.

2. ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial Neural Networks (ANNs) are biologically inspired models analogue to the basic functions of biological neurons. They have a natural propensity for storing experiential knowledge, and resemble the human brain in the sense that training rather than programming is used to acquire knowledge.

A neural network consists of a number of nodes massively interconnected through connections. The nodes are arranged in layers: an input layer, an output layer, and several hidden layers. The number of hidden layers depends on the type of problem. The nodes of the input layer receive information as input patterns, and then transform the information through the connections to the other connected nodes layer by layer to the output layer nodes. The transformation behaviour of the network depends on the structure of the network and the weights of the connections [4]. Fig. 1 shows a multi-layered neural network.

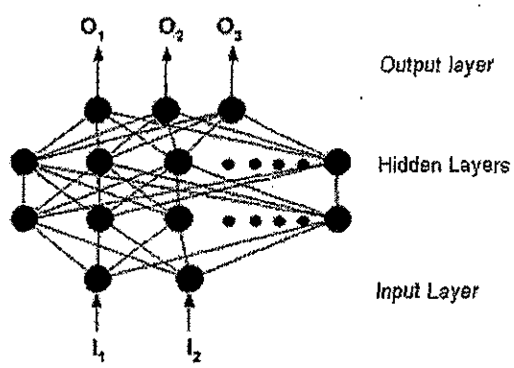

Fig. 1 *Multi-layered neural network.*

ANNs can be classified into unsupervised learning networks and supervised learning networks. The networks can also be classified according to the input patterns, for example binary or continuous values. In any case, a network has to go through two phases: training and application. The training of a network is done by exposing the network to a number of examples, each of them formed by an input vector and a target vector. By means of a training algorithm, the network self-learns the examples by modifying step by step the connection weights in order to reduce as much as possible the network error (difference between the output vector and the design target vector). The capability of the network to obtain a low value of the error depends on several aspects, such as: network architecture, training algorithm, initial values of weights, set of proposed examples, and number of training epochs. The learning of a new knowledge is obtained after having faced a sufficient number of times, just like a human expert does. The desired target vector is related to an input vector without explaining the reason of this relation, and the procedure of acquisition is repeated until the network has understood the mechanism of solution. However, the most relevant feature of a trained network is the capability of generating correct solutions also for new situations different from the examples proposed during the training sessions, this property of ANN is called generalization [5]. This particular procedure of knowledge acquisition and the capability to face unknown situations, without having the explicit rule for solution, make ANNs an effective tool for some typical problems of process planning.

3. APPLICATION ANN IN SELECTION OF MACHINING OPERATIONS

Although the advantages of the application of ANNs are evident, it is clear that their applicability in other areas of process planning has to be still verified [5,6]. One of the important research points in process planning is to develop an intelligent model for automated selection and sequence of machining operations in CAPP systems. In hole making operations, the selection and sequence of machining operations are accomplished by three sets of operations namely; hole starting operations, core making operations and hole improving and finishing operations. For a given hole feature parameters, certain machining operations from each set will be selected. Moreover, this selection is made more difficult by the number of parameters defining the hole feature and the design requirements. ANNs can be used effectively to select the required machining operations for each hole feature. The aim of this research work is to verify the applicability of ANNs in the area of automated selection of machining operations in hole making. Three types of hole feature are considered in this work namely; round hole feature, counterbore hole feature and countersunk hole feature. For each hole feature type, a neural network has been designed to select the machining operations required to generate the feature based upon certain input parameters.

4. DESIGING OF NEURAL NETWORK

The optimal structure of ANN depends on the inputs and output describing the problem. Fig. 2 shows a multilayer perceptron neural network structure used to select machining operations for round hole feature. The network consists of four fully connected layers namely; the input layer, the output layer and the hidden layers. The input layer has 9 inputs which are hole diameter, hole length to diameter ratio, hole diameter tolerance, surface finish required, straightness tolerance, circularity tolerance, location tolerance, taper existence and thread existence. These inputs are normalized to within 0 and 1. Two hidden layers are used in this network. Each hidden layer has 15 neurons which are decided by conducting a number of experiments. The output layer has 11 neurons, each corresponding to a particular machining operation and has either a value of 0 or 1. If the output neuron value is equal to 1, it is interpreted as meaning that the selection of the machining operation is supported.

5. TRAINING OF NEURAL NETWORKS

5.1 Training Algorithm

Once the neural network has been designed, it has to be trained to produce the expected output values in function of a predefined pattern of input values. This training operation is accomplished by selecting a proper training algorithm for the problem to be solved. Several training algorithms have been developed for ANNs. Many of these training algorithms are closely connected with a certain network topology. Among various existing training algorithms, backpropagation algorithm was selected in this research work. It is commonly used algorithm, relatively easy to apply and has been proven to be successful in practical applications [7]. Backpropagation algorithm is a gradient decent method to minimize the total sum of square error over the entire training data set. The convergence to the optimal solution is accomplished by adjusting the weight connections through the partial derivative of the sum-squared error with respect to the weights.

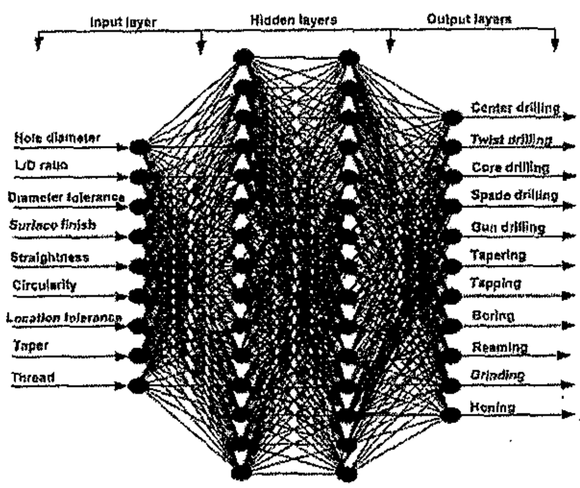

Fig. 2 Round hole feature neural network structure.

The following steps summarize the implementation of this algorithm for training the designed neural networks [8,9,10].

Step 1 Set all the necessary network parameters such as the number of input neurons, the number of hidden layers and the number of neurons included in each hidden layer, the number of output neurons, etc.

Step 2 Set all network weights to small random values, positive and negative (-0.3 to 0.3).

Step 3 Initialize the iteration (epoch) number (m=1) and presentation (example) number (n=1).

Step 4 Apply one training sample to the input layer $[X_1, X_2, \ldots\ldots, X_{N_k}]$ and note the corresponding desired output $[O_1, O_2, \ldots\ldots O_{N_k}]$, where N_k is the number of neurons in layer k.

Step 5 Calculate the output of the neurons layer by layer through the network, from the second layer to the output layer using:

$$O_j^{N_k}(n) = F\left(\sum_{i=1}^{p} W_{ji}(m) O_i^{N_{k-1}}(n)\right) \tag{1}$$

for each neuron j, $1 \le j \le N_k$ and $2 \le k \le L$

where L is the number of layers in the network. F is a sigmoid activation function of the form:

$$F(a) = 1/(1+e^{-a}) \tag{2}$$

$W_{ji}(m)$ is the weight connecting neuron i in layer k to neuron j in layer $k+1$. $O_i^{N_k}$ is the output of neuron N in layer k.

Step 6 Calculate the error gradient δ for every neuron in every layer in backward order from output to the first hidden layer. The error for the output layer neurons is computed by

$$\delta_j^{N_k}(n) = O_j^{N_k}(n)\left(1 - O_j^{N_k}(n)\right)\left(T_j(n) - O_j^{N_k}(n)\right) \tag{3}$$

for every neuron j, $1 \le j \le N_k$, $k=L$ where $T_j(n)$ is the target vector.

Then, successively, the error gradients for all hidden layer neurons are computed from

$$\delta_j^{N_k}(n) = O_j^{N_k}(n)\left(1 - O_j^{N_k}(n)\right)\sum_{i=1}^{N_{k+1}} \delta_i^{N_{k+1}}(n) W_{ij}(m) \tag{4}$$

for every neuron j, $1 \le j \le N_k$, $k=L-1, \ldots\ldots, 2$

At the end of the error backward propagation step, neurons of the network will have error values (except input layer neurons, L=1).

Step 7 Adjust the network weights for every layer. Starting at the output layer neurons and working back to the first hidden layer recursively adjust weights according to the generalized delta rule.

$$W_{ji}(m+1) = W_{ji}(m) + \eta\delta_j^{N_k}(n) O_j^{N_k}(n) + \alpha\left[W_{ji}(m) - W_{ji}(m-1)\right] \tag{5}$$

for every neuron j, $1 \le j \le N_k$, $k=L, L-1, \ldots, 2$

where α is momentum constant (0< α<1) to smooth out the weight change and accelerate convergence of the network. η is learning rate (0< η<1) controls the step size for weight adjustments.

Step 8 Repeat actions in steps 4 to 7 for every training sample.

Step 9 Calculate the average sum-squared error resulted at the end of every training cycle. This error can be evaluated by the following expression.

$$sse = \frac{1}{2N}\sum_{j=1}^{n}\sum_{i=1}^{N_L}\left(T_{ij} - O_{ij}^{L}\right)^2 \tag{6}$$

where T_{ij} is the target value desired for the i^{th} output and for the jth example.

Step 10 Compare the average sum-squared error (*sse*) with the tolerance value (ε) of the error, if it is less then stop. Otherwise, increase number of iterations and randomize the order in the training set and return to step 4.

5.2 Hole Making Operations

Process planners are interested in those features, which are generated by some sequence of machining operations. In this research work, *hole feature*, as shown in Fig. 3, with three types are considered [11]. Each hole feature type is associated with a set of attributes defines it for manufacturing purpose. These attributes include feature dimensions, dimensional tolerances, geometrical tolerances, surface finish requirements and other attributes. Process planners can use these feature attributes to select and sequence the necessary machining operations.

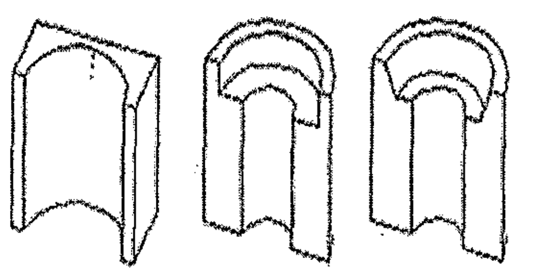

Fig. 3 Hole feature types.

The operations required to produce hole features are categorized to three groups; hole starting operations (center drilling), core making operations (twist drilling, core drilling, spade drilling and gun drilling) and hole improving and finishing operations (boring, reaming, grinding and honing). These operations are selected according to the requirements of the hole feature. Every machining operation in each category has its own limitations. For example, twist drilling operation is not recommended for deep holes (L/D>3), instead gun drilling may be used. Table 1 provides the limitations of hole making operations on each feature attribute.

5.3 Training Data Patterns

A successful neural network requires that the training data set and training procedure be appropriate to the problem. The training data set must span the total range of input patterns sufficiently well so that the trained network can generalize about the data. In order to have extrapolation and interpolation capabilities, neural networks must be trained on a wide enough set of input data to generalize from their training sets. To achieve this goal and demonstrate the applicability of the designed neural networks, a number of training patterns (each pattern is formed by input and output vectors) are generated for each hole feature type. The training patterns used to training the round hole feature network are 200 training patterns. Some of these patterns are presented in Table 2.

The input values of the training patterns are selected from within specified range for each input parameter. The output values are based upon the limitations put on each machining operation. For example, hole starting operations are controlled by hole diameter, hole L/D ratio, and location tolerance. Core making operations are controlled by hole diameter and L/D ratio. Hole improving and finishing operations are controlled by hole diameter, surface finish required, dimensional tolerances and geometrical tolerances.

5.4 Training Experiments

Several training experiments have been performed to select the optimal structure and training parameters of the neural networks. The results obtained for each hole feature type are presented in Table 3.

The graph shown in Fig. 4 represents the training set average error on the y-axis against the number of epochs elapsed on the x-axis. Epochs represent a complete pass through the network of the entire set of training patterns. The graph illustrates downward movement of the error rate as learning progressed, indicating that the average error decreased between actual and predicted results.

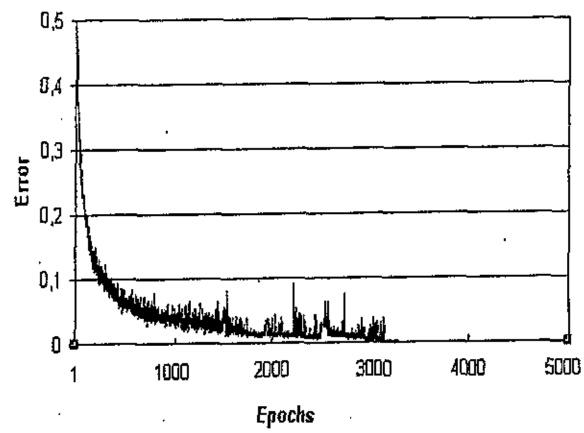

Fig. 4 Training progress of the neural networks.

6. TESTING OF NEURAL NETWORKS

Once the neural network has been trained, its applicability has to be verified. This can be done by presenting to the network several input vectors. Some of these inputs are selected from the training patterns (they are presented to the network before) and the other some are new inputs (first time to be presented to the network). Table 4 shows the results obtained by presenting these input vectors to the round hole feature neural network.

Table 1: Limitations of hole making operations

Operation	Hole size, mm	L/D ratio	S. finish, μm	Hole diameter, mm						
				Dimensional tolerances, mm						
				1-3	3-6	6-10	10-18	18-30	30-50	50-80
Center drilling	-	$>2(D/8)^{0.5}$	-	-	-	-	-	-	-	-
Twist drilling	Over 0 to 50	<3	1.6 - 6.3	.127	.152	.190	.216	.254	.330	.381
Core drilling	Over 13 to 50	<3	1.6 - 6.3	.127	.152	.190	.216	.254	.330	.381
Spade drilling	Over 25 to 150	>0.5	1.6 - 6.3	.127	.152	.190	.216	.254	.330	.381
Gun drilling	Over 0 to 50	>3	1.6 - 6.3	.127	.152	.190	.216	.254	.330	.381
Boring	Over 10	<3	0.8 - 6.3	.052	.060	.072	.086	.108	.127	.146
Reaming	Over 0 to 50	<3	0.8 – 3.2	.020	.024	.029	.033	.040	.052	.061
Grinding	1 to 2000	<5	0.1 - 1.6	.008	.011	.013	.014	.016	.021	.024
Honing	6 to 1000	<300	0.1 – 0.8	.004	.004	.005	.006	.008	.009	.010

Table 2: Training patterns for round hole feature

Input vector									Output vector										
1	2	3	4	5	6	7	8	9	1	2	3	4	5	6	7	8	9	10	11
3	.5	.06	2.5	.05	.15	.04	0	0	1	1	0	0	0	0	0	0	1	0	0
17	1	.02	.5	.05	.15	.06	0	0	0	1	0	0	0	0	0	0	0	1	0
30	3	.2	3	.06	.15	.08	0	0	0	1	1	0	0	0	0	1	0	0	0
46	1.5	.09	1.5	.05	.15	.1	0	0	1	1	1	0	0	0	0	0	1	0	0
62	3	.1	2	.06	.15	.1	0	0	1	0	0	1	0	0	0	0	1	0	0
43	1.5	.19	2.5	.05	.15	.1	1	0	1	1	1	0	0	1	0	1	0	0	0
33	2.5	.1	.8	.06	.15	.1	0	1	1	1	1	0	0	0	1	0	0	0	0

Table 3: Training experiments results

Hole feature type	Training patterns	Hidden layers (neurons)	Learning rate	Momentum	Epochs	Ave. Sum square Error
Round hole	200	2 (15)	0.05	0.9	5000	0.000155
Counterbore hole	200	2 (15)	0.3	0.9	3717	0.0001
Countersunk hole	200	2 (15)	0.3	0.9	3800	0.0001

Table 4: Testing results for round hole feature neural network.

Input vector									Output vector										
1	2	3	4	5	6	7	8	9	1	2	3	4	5	6	7	8	9	10	11
10	.5	.05	1.5	.05	.15	.05	0	0	0	1	0	0	0	0	0	0	1	0	0
17	1	.02	.5	.05	.15	.06	0	0	0	1	0	0	0	0	0	0	0	1	0
50	4	.1	1	.082	.15	.1	0	1	1	0	0	1	0	0	1	0	0	0	0
32	1	.15	1	.05	.15	.1	1	0	1	1	1	0	0	1	0	1	0	0	0
62	3	.1	2	.06	.15	.1	0	0	1	0	0	1	0	0	0	0	1	0	0

7. CONCLUSIONS

This paper proposed a neural network model for selection of machining operations in automated process planning. Several types of hole features are tested through the proposed neural network. The results obtained have demonstrated the applicability of ANNs for this task of process planning. This application has shown a good success in knowledge acquisition and fast inference compared with the traditional approaches of automated process planning. Further work in this research will include more machining operations and implementation of the model in a hybrid neural-fuzzy automated process planning system.

8. ACKNOWLEDGMENT

The authors would like to express their gratefulness and appreciation to the Garyounis University for its support throughout this research.

9. REFERENCES

[1] Qiao, L., Wang, X.Y- & Wang, S.-C., A GA-based approach to machining operation sequencing for prismatic parts, Int. J. Prod. Res., 39, 14, 3283-3303, 2000.

[2] Huang, S.H., Zhang, H-C., Sun, S. & Li H.H., Function approximation and neural-fuzzy approach to machining process selectiony, IEEE Transactions – part C, 19, 9-18, 1996.

[3] Huang, S.H. & Zhang, H.-C., Artificial neural networks in manufacturing: concepts, applications, and perspectives, IEEE Transactions – part A, 17, 212-228, 1994.

[4] Gu, P. & Yan, X., Neural network approach to the reconstruction of freeform surfaces for reverse engineering, Computer Aided Design, 27, 59-64, 1996.

[5] Santochi, M. & Dini, G., Use of neural networks in automated selection of technological parameters of cutting tools, Computer Integrated Manufacturing Systems, 9, 137-148, 1996.

[6] Joo, J., Yi, G-R., Cho, H. & Chio, Y-S., Dynamic planning model for determining cutting parameters using neural networks in feature-based process planning, Journal of Intelligent Manufacturing, 12, 13-29, 2001.

[7] Tsai, Y., Chen, J.C. & Lou, S-J., An in-process surface recognition system based on neural networks in end milling cutting operations, International Journal of Machine Tools & Manufacture, 39, 583-605, 1999.

[8] Amaitik, S.M., and KILIÇ, S.E., An intelligent process planning system for prismatic parts using STEP features, International Journal of Advanced Manufacturing Technology, Vol. 31, 978-993, 2007

[9] Chao, P. & Hwang, Y.D., An improved neural network model for the prediction of cutting tool life, Journal of Intelligent Manufacturing, 8, 107-115, 1997.

[10] Mei, J., Zhang, H.-C. & Oldham, W., A neural network approach for datum selection in computer-aided process planning, Computers in Industry, 27, 53-64, 1995.

[11] Amaitik, S.M. and KILIÇ, S.E., STEP-based Feature Modeler for Computer-aided Process Planning, International Journal of Production Research, Vol. 43, No. 15, 3087-3101, 2005