Neural Network Approach to Cutting Tools Selection

Saleh M. Amaitik
University of Misurata, Department of Industrial and Manufacturing Engineering
Misurata, Libya
saleh.amaitik@eng.misuratau.edu.ly

Abstract—**Cutting tools 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 cutting tools. In this study, the problem of cutting tools selection for milling and drilling operations is investigated. A neural network model is proposed to select the needed cutting tools and their geometry based feature type and machining operation. Feature type, feature condition, dimension ratio, feature taper and machining operation are presented to the network for each feature as input parameters. The network selects the required cutting tool. The advantage and effectiveness of the proposed model are verified through a several types of machining features.**

Index Terms: **Cutting tools, Neural networks, CAPP, Machining operations, Process planning**.

I. INTRODUCTION

Cutting tool selection is perhaps one of the most important functions in a process planning system because the selection of a cutting tool affects the selection of machining parameters, production rate, cost of product, and the resulting accuracy [1]. Within the field of traditional process planning, cutting tools are chosen by human intuition, but such a means of selection can be faulty, as it depends too much on the process planner's experience in determining the type and size of cutting tools and lacks a logical approach and consistent standard [2, 3]. 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. Therefore, in order to eliminate these problems; so as to be able to achieve machining automation, the development of computer-aided intelligent tool selection models are needed [4].

Received 8 October 2016; revised 26 November 2016; accepted 27 December 2016.

Available online 28 December 2016.

Recently, some interest has occurred in using artificial neural networks technology in the development of automated process planning systems [5]. 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 cutting tools selection of drilling and milling operations.

II. 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 [6]. Figure 1 shows a 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 [7]. 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.

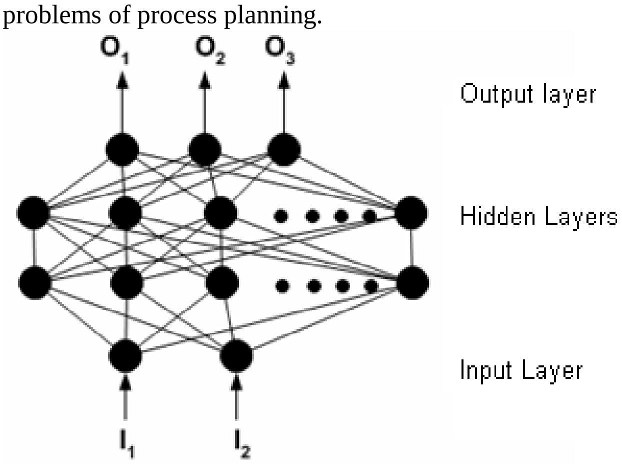

Figure 1. Multi-Layered Neural Network.

III. Application of ANN in Selection of Cutting Tools

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 [7,8]. One of the important research points in process planning is to develop an intelligent model for automated selection of cutting tools in CAPP systems.

The tool selection process in this work is carried out in three overall steps. The first step is utilized a main neural network model to select the proper cutting tool for each machining feature. The selection is based upon machining feature and its associated machining operation. Figure 2 shows the neural network model for cutting tool selection. It consists of five input variables, two hidden layers with fifteen neurons each and twenty output variables. The input variables correspond to feature type, feature attributes and machining operation type. The input values are appropriately encoded and scaled to facilitate the network training. The output variables are corresponding to the cutting tool types. Each output variable has a value of 1 or 0. If the output variable value is equal to 1 then it is interpreted as that the selection of the cutting tool is supported.

The second step in cutting tool selection is then to search the cutting tools database to find standard tool dimensions that fit the machining setup. The search criteria implemented depends on the application of the cutting tool in machining the selected feature. The following are some guidelines used for this purpose.

- Drilling type tool dimensions are selected based on the hole diameter to be drilled. The criterion is to find a cutting tool diameter equal to the hole diameter and the corresponding tool dimensions are then retrieved.
- Milling type cutter dimensions are selected based mainly on machined width and other secondary parameters. The criterion is to find a milling cutter diameter equal to or greater than the machined width and the corresponding tool dimensions are then retrieved.

The third step deals with selecting cutting tools geometry. For each cutting tool a neural network model was designed and trained to select the proper tool geometry. These proper tool geometry values are based on the recommendations collected from different machining handbooks and research outputs. These values can be treated as values obtained from a process planner expert on the shop floor. The users of the proposed models do not have to stick to these values rather they can consider them as a guide to obtain the optimum cutting tool for a specific operation. The selection of these values is based on information about workpiece material and feature size.

IV. Designing of Neural Networks

The optimal structure of ANN depends on the inputs and output describing the problem. Figure 2 shows a multilayer perceptron neural network structure used to select cutting tools for drilling and milling operations. The network consists of four fully connected layers namely; the input layer, the output layer and the hidden layers. The input layer has 5 inputs which are feature type, feature condition, dimension ratio, feature taper and machining operation. 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 20 neurons, each corresponding to a particular cutting tool 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 cutting tool is supported.

In the third step of the selection process, several neural network models have been developed. For each cutting tool a neural network was designed and trained to select the proper tool geometry. For demonstration purpose, figure 3 shows the neural network model designed to provide the proper values of the twist drill geometry. The input parameters to the network are workpiece material type and hole diameter, while the output parameters are helix angle, point angle, land width, lip clearance, margin height and width, shank type, chisel edge, and web thickness. The input and output parameters of the other cutting tools neural networks are summarized in Table 1.

Table 1.Inputs and Outputs of Cutting Tools Neural Networks

Input parameter	Output parameter
Spade drill neural network	
Workpiece material	Web thickness Radius
Hole diameter	Point angle Circular land Radius offset
Material hardness	Primary relief angle Secondary relief angle
Reamer neural network	
Hole diameter	Primary relief angle Secondary relief angle Margin width Flute type Chamfer angle Primary chamfer relief
Hole bottom condition	Secondary chamfer relief Chamfer length Helix angle Number of flutes
Boring tool neural network	
Workpiece material	Back rake angle Side rake angle End relief angle Side relief angle
Workpiece hardness	End cutting edge angle Side cutting edge angle
Tap neural network	
Workpiece material	Point style Flute style
Thread major diameter	Rake (hook) angle Number of flutes
Workpiece hardness	Chamfer relief angle
Thread pitch	Spiral point angle
Milling cutters neural network	
Workpiece material	Helix rake angle Radial rake angle
Tool diameter	Radial relief angle Radial clearance angle
Material hardness	Cutting edge angle End relief angle

V. Training of Neural Networks

A. 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 [9].

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.

The following steps summarize the implementation of this algorithm for training the designed neural networks [10,11,12].

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 $[X_1, X_2, \ldots\ldots\ldots, X_{N_k}]$ 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.

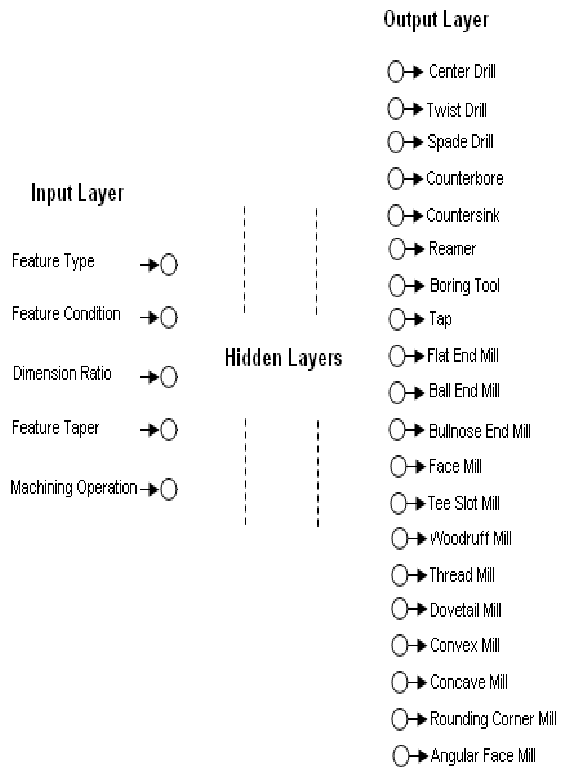

Figure 2. Cutting Tools Selection Neural Network Model

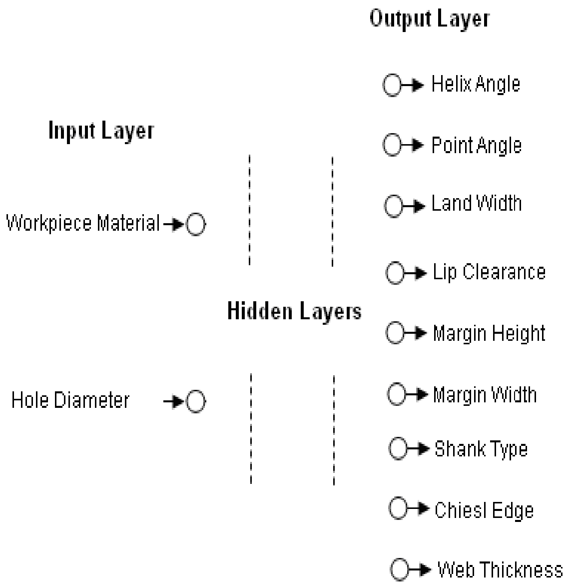

Figure 3. Twist Drill Neural Network Model

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

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

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:

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

$W_{ji}(m)$ 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

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

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

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

(4)

for every neuron j, $1 \le j \le N_k$, *k=L-1,……,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.

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

(5)

for every neuron j, $1 \le j \le N_k$, *k=L,L-1,…,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.

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

where T_{ij} is the target value desired for the *i*th output and for the *j*th 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.

B. 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 feature type. The training patterns used to train the cutting tools selection network are 74 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 cutting tool. The basic idea in the selection process is that for each machining feature and machining operation combination there is a corresponding cutting tool to be used to generate that feature. For example, for square slot to be machined with an end milling operation, a flat end mill might be selected, while for round slot to be machined with the same machining operation, a ball end mill might be used. The neural network is trained based upon this criterion.

Table 2: Training Patterns for Cutting Tools Selection

Input parameter	Input vector					
Feature type	15	15	20	30	55	60
Feature condition	6	1	2	1	1	1
Dimension ratio	0	0	0	0	0	0
Feature taper	0	1	0	0	0	1
Machining operation	60	50	45	45	50	45
Output parameter	**Output vector**					
Center drill	0	1	0	1	0	0
Twist drill	0	0	1	0	1	1
Spade drill	0	0	0	0	0	0
Counterbore	0	0	0	0	0	0
Countersunk	0	0	0	1	0	0
Reamer	1	0	0	0	0	0
Boring tool	0	0	0	0	0	0
Tap	0	0	0	0	0	0
Flat end mill	0	0	0	0	0	0
Ball end mill	0	0	0	0	0	0
Bullnose end mill	0	0	0	0	0	0
Face mill	0	0	0	0	0	0
Tee slot mill	0	0	0	0	0	0
Woodruff mill	0	0	0	0	0	0
Thread mill	0	0	0	0	0	0
Dovetail mill	0	0	0	0	0	0
Convex mill	0	0	0	0	0	0
Concave mill	0	0	0	0	0	0
Round corner mill	0	0	0	0	0	0
Angular face mill	0	1	0	0	0	1

C. 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 cutting tool type are presented in Table 3.

The graph shown in Figure 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.

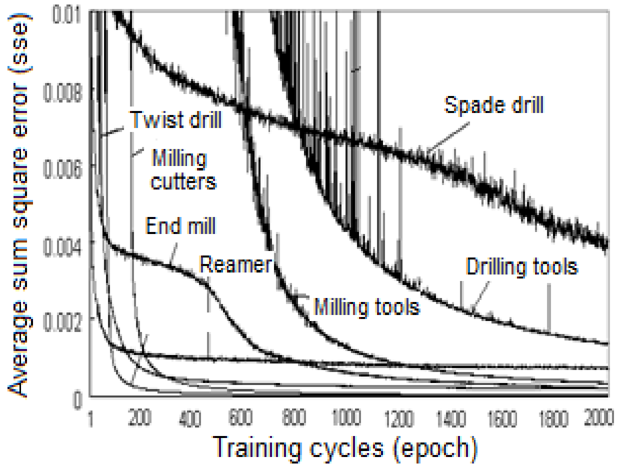

Figure 4. Training Progress of the Neural Networks

Table 3: Training Experiments Results

Network Name	Inputs	Outputs	Hidden Layers	Hidden neurons	Learning rate	Momentum	Train Pattern	Epoch	sse
Twist drill	2	9	2	12	0.4	0.6	135	3000	0.00018
Drilling tools	5	12	2	15	0.1	0.9	198	2000	0.00019
Milling tools	5	13	2	15	0.3	0.8	74	2000	0.000082
Spade drill	3	7	2	15	0.2	0.8	183	3000	0.00326
End mill	3	7	2	15	0.5	0.8	324	3000	0.00012
Reamer	2	10	2	15	0.3	0.8	122	3000	0.00072
Milling cutters	3	6	2	15	0.4	0.6	189	370	0.00001

VI. 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.

VII. CONCLUSIONS

This paper proposed a neural network model for selection of cutting tools in automated process planning. Several types of milling and drilling 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 cutting tools and implementation of the model in a hybrid neural-fuzzy automated process planning system.

Table 4. Testing Results for Cutting Tools Selection Neural Network

Input parameter	Input vector					
Feature type	15	15	20	60	25	50
Feature condition	3	6	2	1	0	1
Dimension ratio	0	0	0	0	0	0
Feature taper	0	0	0	1	0	1
Machining operation	50	60	45	45	60	50
Output parameter	**Output vector**					
Center drill	1	0	0	0	0	0
Twist drill	0	0	1	1	0	1
Spade drill	0	0	0	0	0	0
Counterbore	0	0	0	0	0	0
Countersunk	0	0	0	0	0	0
Reamer	0	1	0	0	0	0
Boring tool	0	0	0	0	0	0
Tap	0	0	0	0	1	0
Flat end mill	0	0	0	0	0	0
Ball end mill	0	0	0	0	0	0
Bullnose end mill	0	0	0	0	0	0
Face mill	0	0	0	0	0	0
Tee slot mill	0	0	0	0	0	0
Woodruff mill	0	0	0	0	0	0
Thread mill	0	0	0	0	0	0
Dovetail mill	0	0	0	0	0	0
Convex mill	0	0	0	0	0	0
Concave mill	0	0	0	0	0	0
Round corner mill	0	0	0	0	0	0
Angular face mill	0	0	0	1	0	1

REFERENCES

[1] Usher, J.M. and Fernandes, K.J., 1999, "An object-oriented application of tool selection in dynamic process planning", International Journal of Production Research, Vol. 37, No. 13, pp.2879-2894.

[2] Lin, A.C. and Wei, C.-L, 1997, "Automated selection of cutting tools based on solid models", Journal of Materials Processing Technology, Vol. 72, pp. 317-329.

[3] Maropoulos, P.G., Baker, R.P., 2000, "Integration of tool selection with design Part 1. Feature creation and selection of operations and tools", Journal of Materials Processing Technology, Vol. 107, pp. 127-134.

[4] Zhao, Y., K. Ridgway, K., Al-Ahmari, A.M.A., 2002, "Integration of CAD and a cutting tool selection system", Computers & Industrial Engineering, Vol. 42, pp. 17-34.

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

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

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

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

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

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

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

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

BIOGRAPHIES

Saleh M. Amaitik is an associate professor in the Department of Industrial and Manufacturing Engineering at the University of Misurata. He received His MSc degree in Manufacturing Engineering from the University of Garyounis in 1994 and PhD degree in Mechanical Engineering from Middle East Technical University in 2005. His main research interests are Computer Aided Process Planning - CAPP, Feature-based Modeling, CAD/CAM Integration, Product Data Modeling using STEP and Intelligent Manufacturing Systems