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Turn-mill Process Plan and Intelligence Machining Operations Selection on STEP

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ABSTRACT

The objective of the study was to present the architect, training system consideration and performance of Levenberg-Marquardt back propagation algorithm for manufacturing operation selection that can be associated with STEP-NC file generation. Here STEP-based product data modeling, EXPRESS representation combined with neural network algorithm using feature based design attributes such as dimension ratio, tolerance and surface finish etc. It describes the details of training algorithm steps, training data pattern and performance output of the system in association with object oriented data model in process plan data generation. It gives required criterion for extending the system for machine tools and cutting tools selection with reference to turn-mill process planning requirements. Finally summarizes on importance and methods of binding STEP representation and intelligent Computer Aided Process Planning (CAPP) system development.

Key words: Artificial intelligence, computer aided process planning, neural network

INTRODUCTION

Computer Integrated Manufacturing (CIM) is generally considered to be effective methodology for improving manufacturing competition and manufacturing enterprise automation strategy through Computer Aided Process Planning (CAPP) system, as it has been listed by Zhang and Alting (1994), they are allocated into four divisions namely; (1) variant CAPP systems (based on Group Technology coding), (2) generative CAPP systems (based on built-in decision making logic), (3) hybrid CAPP systems (which combine variant and generative approaches) and (4) knowledge-based CAPP systems (based on expert systems). CAPP systems have been assisted by advanced artificial intelligence techniques. The information exchange is supported by standard product data model (STEP). However, the integration and implementation of these two CAPP system enhancements is still a significant point to be investigated (Zhang and Alting, 1994).

These artificial intelligent techniques in area of generative CAPP system used to resolve high difficulties in addressing capabilities requirements. These are solving knowledge adoption and modification requirements of users, self learning capability in shop floor decisions and to utilize predetermined function technology knowledge bases (Santochi and Dini, 1996). Jun *et al.* (2001) established experimentally verified flexible feature-based reverse engineering. It uses ANN approach successful for recognition of geometric feature with taught knowledge. The input patterns were typical selection of geometric characteristics such as dimensions and feature orientation. However, the validity for the robustness and efficiency needs means for CAD/CAM integration (Jun *et al*., 2001).

In promoting the effectiveness of CAPP system artificial intelligence techniques such as Neural Network (NN) and fuzzy logic are promising approaches. The study investigated the significance of a neural network technique with implementation of STEP on a turn-mill machining environment for operations selection.

Hence, this can be used with an ISO14649 implementation model using XML and its validation on process plan data interaction between features based design and manufacturing module of turn-mill environment. It promotes the use of process planning knowledge acquisition to an artificial intelligent machining operations selection with back propagation BP algorithm.

ARCHITECT OF THE SYSTEM FRAMEWORK

Design and manufacturing data model: ISO 14649 standardizes CNC machine tool technology (ISO 14649-121, 2005; ISO 14649-11, 2004, ISO 14649-10, 2004) and corresponding cutting tools (ISO 14649-111, 2010; ISO 14649-12, 2005) with an EXPRESS object-oriented data model which can be used as high-level NC language based on the CNC data model of next-generation machining system, as shown in Fig. 1. That is comprised of the three principal components of STEP methodologies (Huang *et al*., 2006). This data model is based on the STEP product model (ISO10303) along with process plan information. ISO 10303 acquires the information requirement for product data and accompanying technologies.

Turn-mill machine tools are appropriate for reducing number of set-ups and combined machining operations. Since the motion of the axis of the machine tool is more complicated than the conventional machines, it has higher dependency on CAM or post processor. This creates process plan data with reference to specific information on the structure of the machine tool, so compatibility and ease of part programming only maintained in generative process planning. Since, the machining information that is based on ISO14649 is related to the manufacturing features and

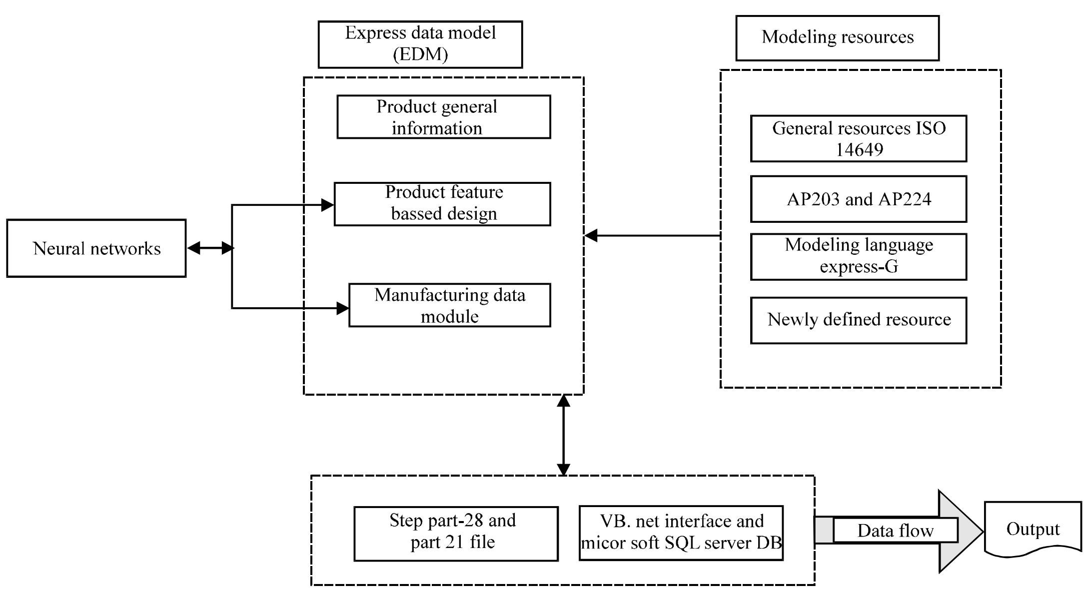

Fig. 1: Neural network framework on STEP based product and manufacturing model

machining operation, compatibility of information can be maintained among different machines and manufacturing system. A 2.5-axis machining data in ISO14649 with tool orientation has been used to describe a 5-axis CNC machining by Mitsui *et al.* (2007), similarly it is used to construct implementation for turning, milling and wireEDM technologies. The EXPRESS data model represented feature based design data and machining feature data with the XML data sharing (Gizaw *et al.*, 2011) and functional methodology as represented on the Fig. 1.

Selection of machining operations: The system receives feature data from the part design decomposition and used to generate corresponding machining operations to realize the form feature found on the part design. Figure 2 shows representation of neutral network model of back propagation algorithm criterion used for machining operation selection.

It consists of five input variables, two hidden layers with eighteen neurons each and twenty outputs variables. The input values are approximately encoded and neutralized to facilitate network training. The output variables associated with machining operations and given a signature matrix with 1 and 0 values.

Each feature type is associated with a set of characterized attributes given in the input layer of the architect. This allows feature representation of the part to the network that can associate with operation output Layer as shown in Fig. 2 and 3 represents MATLAB graphical user interface (GUI) for double layer neural network model.

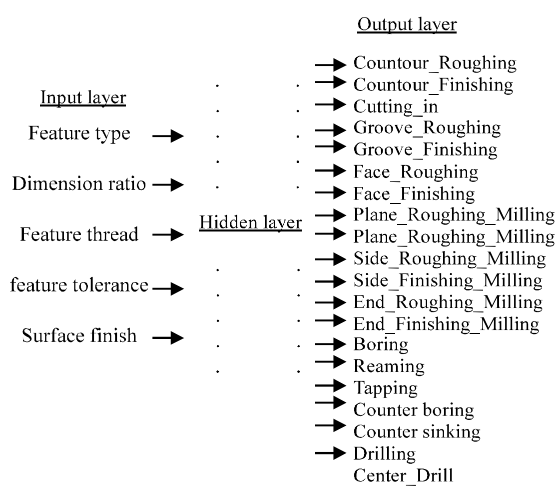

Fig. 2: Operation selection neural network model

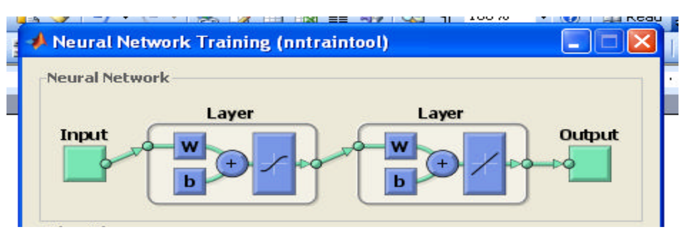

Fig. 3: GUI on the MATLAB

BATCH TRAINING OF NEURAL NETWORK

Training algorithm: In the design of the neural network, the main aim was to prepare function governing predefined pattern of input values for expected output values. This can be accomplished by proper selection of algorithm suitable for the problem at hand. Levenberg-Marquardt back propagation has been selected among different neural network training algorithms. The method recommended since it is relatively simple supervised algorithm which has relatively small sum of square error, requires less memory, updates weight and bias values with Levenberg-Marquardt optimization (Lourakis and Argyros, 2004; Lourakis, 2005). The following steps are adopted for implementing the selected training algorithm (Levenberg, 1944):

Step 1: All network weight are set to be in the range of binary values of (0 to 1)
Step 2: Initializes the iteration (epoch)
Step 3: Apply on training sample to the input layer X and not the corresponding output O maintain the number of neuron for the layer
Step 4: Calculates the Jacobean jX of performance perf with respect to weigh and bias variables X. Each variable is adjusted according to Levenberg-Marquardt:

$$\begin{aligned} jj &= jX*JX \\ je &= jX*E \\ dX &= -(jj+mu)/je \end{aligned} \tag{1}$$

where, E and mu are all errors and I is the identity matrix and adoptive value for changing performance value, respectively.

Step 5: Calculate O output layer matrix or Hessian matrix and g gradient when the function has form of a sum squares:

$$\begin{aligned} O &= J^T J \\ g &= J^T e \end{aligned} \tag{2}$$

where, e and μ are the vector of network error and the gradient descent then the model can approximate the Hessian matrix like Newton update:

$$o_{k+1} = o_k-[J^T J+\mu I]^{-1} J^T e \tag{3}$$

Step 6: Repeat actions from 4 to 6 for every training sample
Step 7: Calculate and compare the average and total sum-square error respectively

Training data patterns: The preparation of an appropriate training set is the major factors affecting the final training network. The data requirement must sufficiently cover the problem area. Training data that are applicable for the design neural networks, number of training patterns have to be generalized for every task in the system. The specified range of the input values and the limitations output parameter values has been maintained.

Training output: The training set performance is maintained to acceptable accuracy after a number of training run and the following training outputs are exhibited. An input signature matrix is assigned for every machining feature and used with a hidden layer signature matrix formed on the characteristic attributes of dimension ratio, surface finish and tolerance trained to deliver an output matrix assigned as a signature for machining operation. Architecture and training parameters of neural network models have been presented in Table 1.

Figure 4 shows how the training mean square error and the testing mean square error are converging to a unit constant value closer to zero. That confirms the accuracy of the prediction of the system developed. It followed by the output of the training state shown on Fig. 5. Where,

Table 1: Architecture and training parameters of neural network models

Activation function	Log-sigmoid
Input neurons	20
Output neurons	21
Hidden neurons	12
Epoch	112
Performance	0.845
Gradient	0.000437
μ	0.0001
Validation checks	6

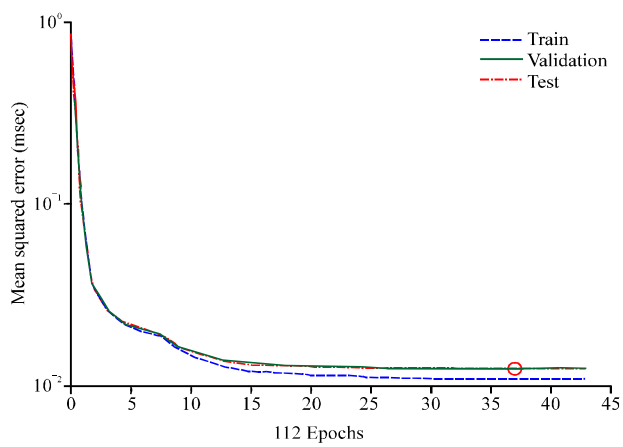

Fig. 4: Mean square errors of 112 Epochs

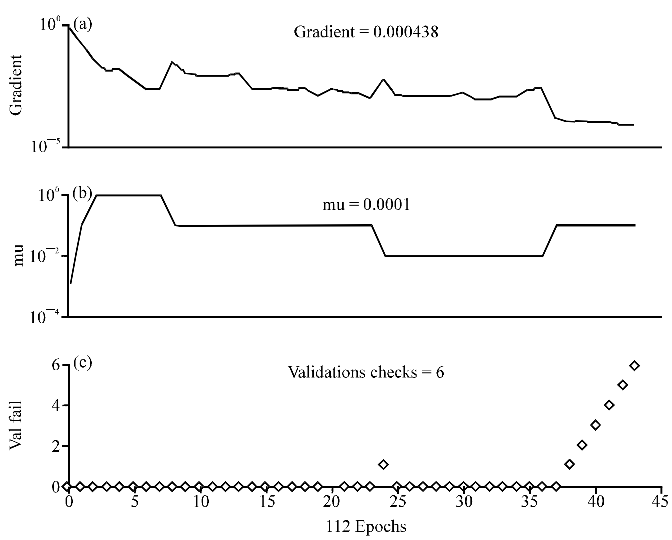

Fig. 5(a-c): The training state for 112 Epoch log-sigmoid (logsig) was used as activation function for input layer and linear (purelin) for hidden layer. In the training state, gradient, performance variation factor parameter mu and validation are given on the within the indicated range for 112 Epochs.

SYSTEM IMPLEMENTATION

An interlink serves to import the operation selection output from the intelligence neural network. The result has been processed based on the input information related to the workpiece such as feature type, tolerance, surface finish etc. STEP-NC interface used to submit requirement for generating process plan file. The supervised learning back propagation algorithm constructed on the requirement and capabilities representing turn-mill machining environment.

Thus, it can facilitate integration and improve efficiency of manufacturing enterprises. Concurrent engineering approach and STEP implementation emphasizes manufacturing data interlink with standard representation. The output process data can be given in text or an XML file representation of part-21 or part-28, respectively.

Machining operation selection has been developed beyond single domain. Lv algorithm used minimizes the total sum square error over the entire training and brings relatively more optimal solution, faster convergence and lower cycle (epoch) of 122 from 5000 performed in previous researches by Amaitik and Kilic (2007) and Devireddy (1999). In this study, additional types of machining operations consideration and STEP implementation for CAPP systems has been introduced.

CONCLUSION

The developed training system performance, training state and regression which are given in figure four and five indicated acceptable Mean Square Error (MSE), gradient and value of μ. This result lead to introducing artificial intelligence system on machining operation selection along with STEP implementation on turn-mill manufacturing environment. The architect of the neural network discussed able to accommodate criterion of machine dynamic characteristics related to cutting tool, machine tool specifications, machine tool configuration and setup. This leads the intelligence system to be extended for knowledge base process plan data output encapsulated by working steps. As it has been represented on the product model and process data associated with neural network with XML repository of EXPRESS. Its output can be delivered with generation of STEP-NC process plan file.

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