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ON-LINE CUTTING FORCE MODELLING FOR COPY ENDMILLS BASED ON MULTILAYER PERCEPTRON

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Abstract: *This paper uses the artificial neural networks (ANNs) approach to evolve an efficient model for estimation of cutting forces in copy-end milling. Supervised neural network are developed for use as a direct modelling method. The training of the networks is performed with experimental machining data. The predictive capability of using analytical and neural network approaches are compared using statistics, which showed that neural network predictions for three cutting force components were for 4% closer to the experimental measurements, compared to 11% using analytical method.*
Key words: *machining, cutting forces, modeling, neural network.*

1. INTRODUCTION

Ball-end milling cutters have been used extensively in CNC machining of critical parts in the aerospace and motor industries. The cutting forces that are developed during the end milling process, can directly or indirectly estimate process parameters such as tool wear, tool life, surface finish, etc. The capability of modeling cutting forces therefore provides an analytical basis for machining process planning, machine tool design, cutter geometry optimisation, and on-line monitoring/control. A large amount of work has been carried out on force modeling. These modeling methods can be divided into three types: Experience modeling, plasticity modeling, and geometry modeling (Milfelner, 2002). As the machining process is nonlinear and time-dependent, it is difficult for the traditional identification methods to provide an accurate model. Compared to traditional computing methods the artificial neural networks (ANNs) are reliable, accurate and global. Researchers (Mursec & Cus, 1999), in their ANN implementations, evolve knowledge of the machining environment by training these networks on run-time data.

2. PRESENTATION OF THE EXPERIMENTAL EQUIPMENT

In order to develop the cutting force component model, experimental results were used. The three components of cutting force were measured with a piezoelectric dynamometer (Kistler 9255) mounted between the workpiece and the machining table. The force measurements were sampled at 20000 points/second, and then digitally low-pass filtered at a cut-off frequency of 250 Hz to eliminate the high-frequency components resulting from the machine tool dynamics. The experiments with the copy end milling cutter were carried out on the NC milling machine (type HELLER BEA1). Material Ck 45 and Ck 45 (XM) with improved machining properties were used for tests. The ball-end milling cutter with interchangeable cutting inserts of type R216-16B20-040 with two cutting edges, of 16 mm diameter and 10° helix angle was selected for machining of the material. The cutting inserts R216-16 03 M-M with 12° rake angle were selected. The cutting insert material is P30-50 coated with TiC/TiN, designated GC 4040 in P10-P20 coated with TiC/TiN, designated GC 1025. The coolant RENUS FFM was used for cooling. The cutting tool flank wear was measured with an instrument microscope of 0.01 mm accuracy. The data acquisition package used was LabVIEW. The set up can be seen in Figure 1. The experiments were carried out for all combinations of the chosen parameters, which are radial/axial depth of cut, feedrate, and spindle speed. Other parameters such as tool diameter, rake angle, etc. are kept constant.
Three values for the radial/axial depth of cut have been selected for use in the experiments: RD_1 = 1d, RD_2=0.5d, RD_3=0.25d; AD_1 = 2mm, AD_2=4mm, AD_3=8mm; d- cutting parameter (16 mm). In the experiments the following values for feedrate have been selected: f_1= 0.05 mm/tooth, f_2= 0.2 mm/tooth, f_3= 0.4 mm/tooth. Three values of spindle speed have been selected: $vc_1=125$ min^{-1}, $vc_2=185$ min^{-1}, $vc_3=250$ min^{-1}.

3. PREDICTIVE CUTTING FORCE MODELING

Artificial neural networks consist of a large number of processing elements, called neurons, which operate in parallel. Computing with neural networks is non-algorithmic. They are trained through examples rather than programmed by software. Detailed information concerning artificial neural networks can be found in (Lee &Lin, 2001), (Liu & Wang, 1999).

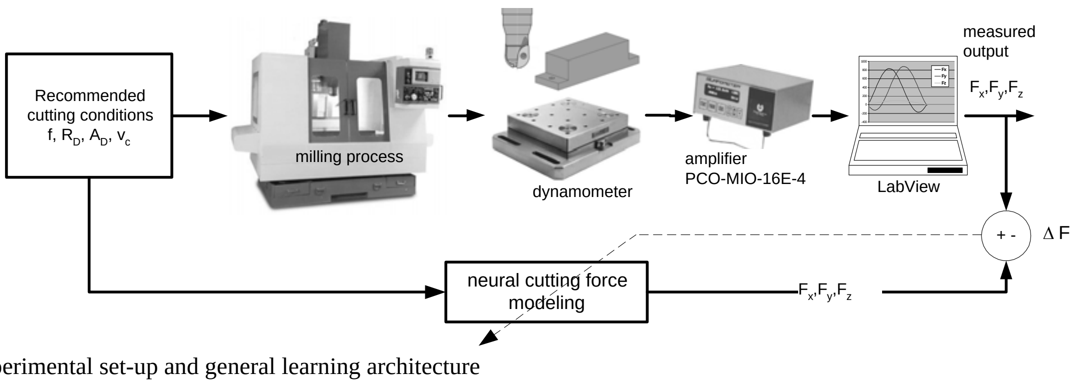

Fig. 1. Experimental set-up and general learning architecture

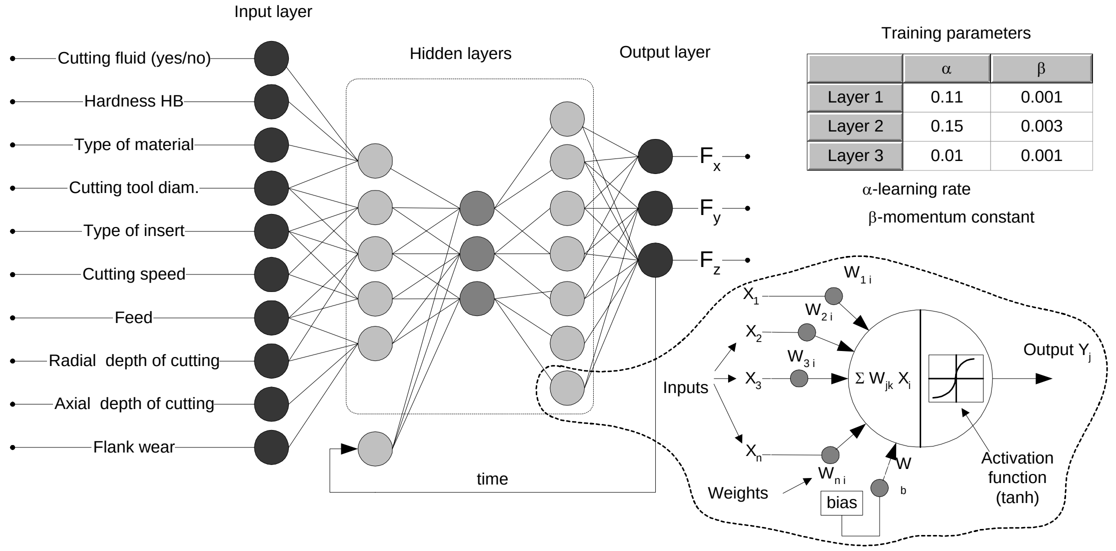

Fig. 2. Predictive force model topology

The Multi-Layer BP network is a supervised, continuous valued, multi-input and multi-output feedforward multi-layer network that follows a gradient descent method.

The gradient descent method alters the weight by an amount proportional to the partial derivative of the error with respect to the weight in question. The backpropagation phase of the neural network alters the weights w_{ji} so that the error of the network is minimized.

This is achieved by taking a pair of input/output vectors and feeding the input vector into the net which generates an output vector, which is compared to the output vector supplied, thus gaining an error value. The error is then passed back through the network (backpropagation process), modifying the weights due to this error using the equations. Hence, if the same set of input/output vectors are presented to the network, the error would be smaller than previously found. For modeling the cutting force components, three-layer feed-forward neural networks were used (Figure 2). They contained 10 neurons in the input layer, and three in the output layer. The number of neurons in the hidden layer was varied in different experiments. The detailed topology of the used ANN with optimal training parameters and mathematical principle of the neuron is shown on Figure 2. The ANN were trained with the following parameters: type of machined material, hardness of the machined material, cutting tool diameter, type of insert, cutting speed, feed, radial and axial depth of cutting, tool wear and the presence of the cutting fluid.

Network training involves the process of interactively adjusting the interconnection weights in such a way that the prediction errors on the training set are minimized. The back- propagation algorithm is applied to each pattern set, input and target, for all pattern sets in the training set. Since the learning process is iterative, the entire training set will have to be presented to the network over and over again, until the global error reaches a minimum acceptable value. The basic goal in training any neural network is to minimize the overall error of the network. Matlab Network Tool Box and Thinks-Pro software were used as a platform to create the networks.

Figure 3 shows the uniform falling of the value of all errors (ETst, ETstMax, ETrn, ETrnMax) with the number of iterations during the training and testing process for described network configuration (Figure 2). The smallest error of testing (ETst) is reached at iteration 1780. It can be seen in the Figure 3 that errors converge not to zero but to 0.04 (4%). This is caused by the presence of some contradicting examples in the training set. The prediction of a network trained with tanh transfer function and optimum parameters of 7-6 hidden nodes, learning rate (0.1) and a momentum rate (0.001) are shown on Fig. 4. The predictions of a non-optimum networks with non-optimal parameters are also shown in the same figure.

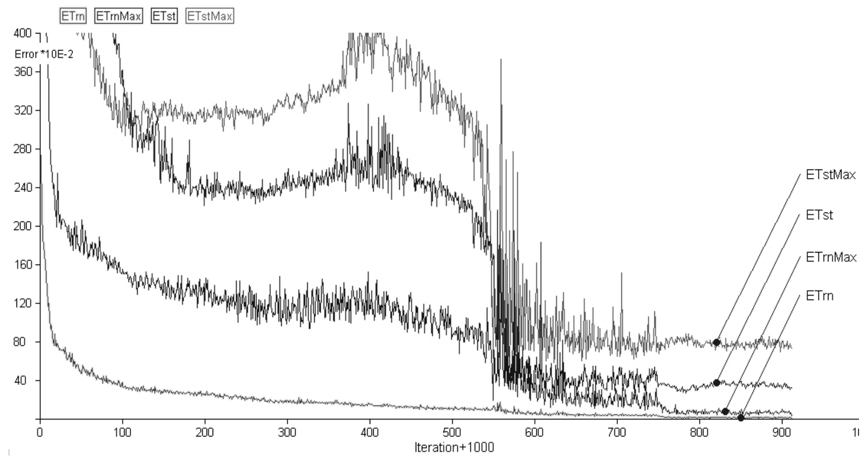

Fig. 3. Decrease of errors during supervised training of neural network

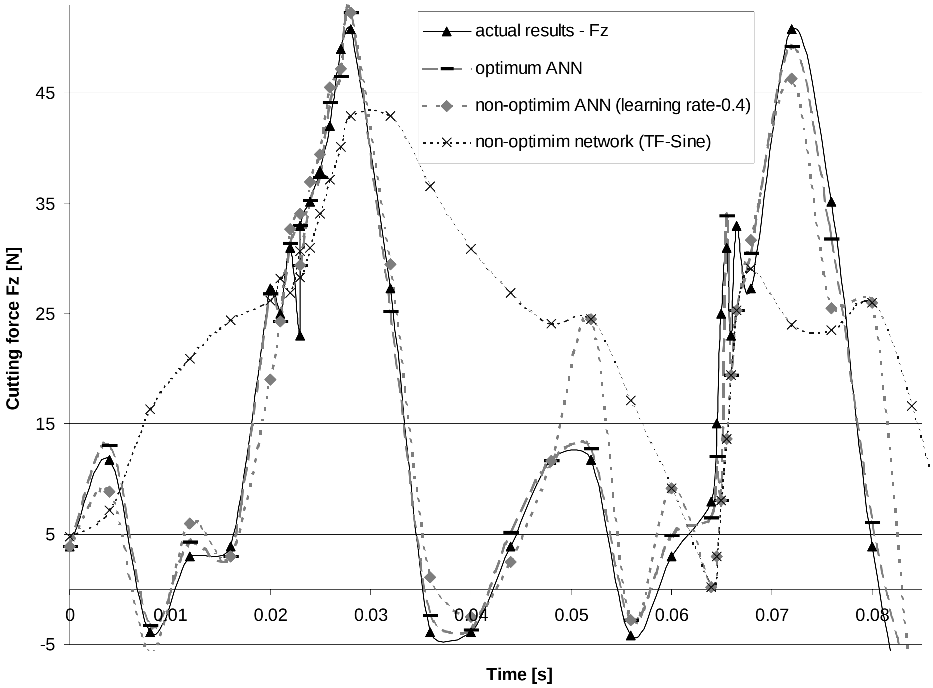

Fig. 4. Decrease of errors during supervised training of neural network

The ANN registers the input data only in the numerical form therefore the information about the tool, cutting insert and material must be transformed into numerical code. The type of the cutting insert is indicated with an 8-digit systematization code containing the data on the cutting insert shape, rake angle, free angle, tip radius, base material, cutting insert coating and length of the insert cutting edge.

4. DISCUSSION OF RESULTS

Verification experiments are conducted to evaluate feed forward and Radial Basis networks. It is found that the Radial basis network is superior. The radial basis neural networks require more neurons than the standard feed forward neural networks with the Back Propagation (BPN) Learning Rule, but conceiving of radial basis neural networks lasts only a part of time necessary for training of the feed forward network. The feed forward neural networks give more accurate results, but they require more time (70%) for training and testing. An extensive number of tests were made on the milling machine to confirm the neural model with different cutting parameters. This chapter presents the results of experiments and the comparison and analysis of results between the experimental and ANN model depending on the cutting parameters. The results and/or the values of cutting forces are graphically represented by means of diagrams depending on the angle of rotation of the milling cutter (Fig. 5 and 6). By comparing the results predicted by ANN with the results of experiments the

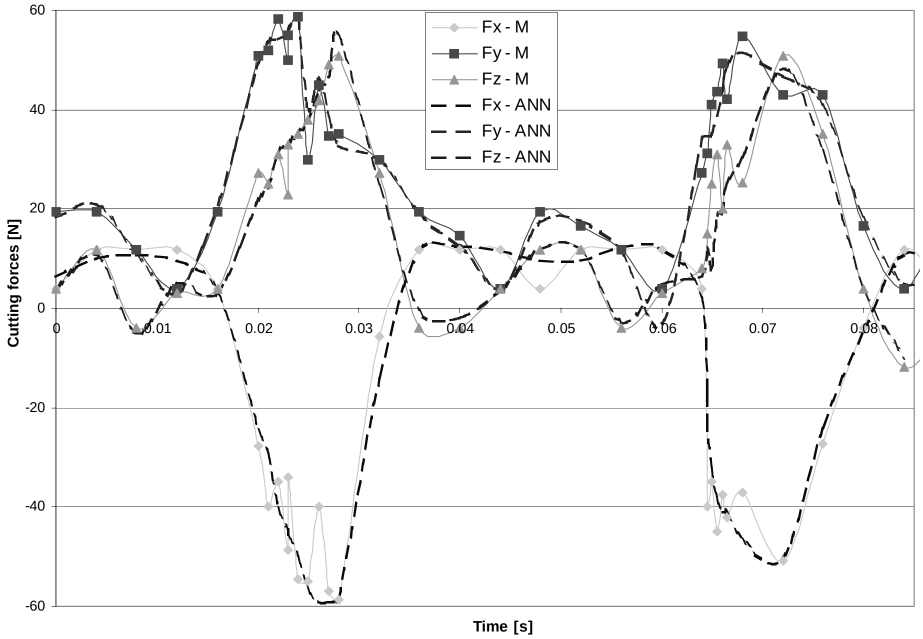

Fig. 5. Representation of measured (Fx-M, Fy-M, Fz-M) and predicted (Fx-ANN, Fy- ANN, Fz- ANN) cutting forces. Copy-end milling cutter R216-16B20-040, cutting insert R216-16 03 M-M GC 4040, material Ck 45, milling width R_D=4 mm, milling depth A_D=2 mm, feeding f=0.05 mm/tooth and cutting speed v_c=125 min^{-1}

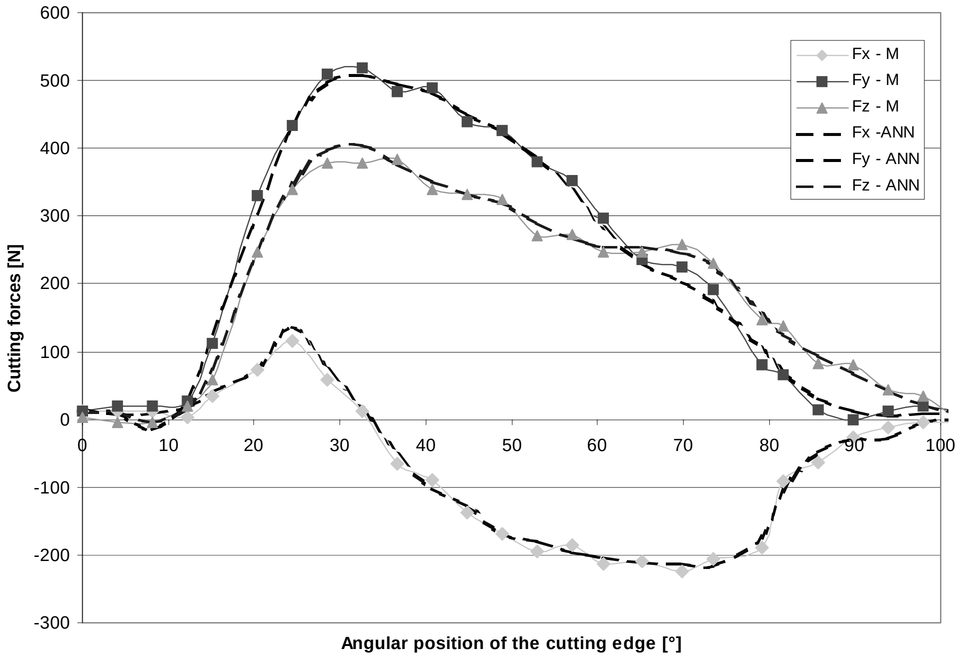

Fig. 6. Representation of measured (Fx-M, Fy-M, Fz-M) and predicted (Fx-ANN, Fy- ANN, Fz- ANN) cutting forces. Copy-end milling cutter R216-16B20-040, cutting insert R216-16 03 M-M GC 4040, material Ck 45, milling width R_D=8 mm, milling depth A_D=2 mm, feeding f=0.4 mm/tooth and cutting speed v_c=125 min^{-1}

following was established: the values from prediction coincide well with the values from experiments and in addition, the process of the change of the cutting force with respect to the angle of rotation of the milling cutter and the amplitude agree well. Fig. 5 shows the comparison of the predicted forces and the measured forces. Also the comparison of maximum values of the cutting forces from simulation with the experimental values in case of different cutting conditions was made.

5. COMPARISON OF THE NEURAL NETWORK-BASED MODEL TO THE ANALYTICAL MODEL

In this paper, supervised neural networks are used to successfully estimate the forces developed during end milling process. The comparison between the predicted cutting forces and measured cutting forces was made (Cus & Balic, 2000). It can be claimed that the comparison of the results obtained from the neural model and of the experimental results confirms the accuracy of the model for predicting the cutting forces. By using a multi-layer perception with backpropagation training method, the neural network is trained to an accuracy of ±2% error for all three forces. In testing the model, the three force components in oblique cutting were predicted to an accuracy of ±4%. An effort is made to include as many different machining conditions as possible that influence the cutting process. Due to high speed of processing, low consumption of memory, great robustness, possibility of self-learning and simple incorporation into chips the approach ensures estimation of the cutting forces in real time. Future work could be directed to application of other preference models and neural networks to machining process optimization and extension of the proposed approach to adaptive control of machining operations or on-line adjustment of cutting parameters based on information from sensors.

6. CONCLUSION

In this paper, supervised neural networks are used to estimate the forces developed during end milling process. The comparison between the predicted cutting forces and measured cutting forces was made.

It can be claimed that the comparison of the results obtained from the neural model and of the experimental results confirms the efficiency and accuracy of the model for predicting the cutting forces.

In testing the model, the three force components in oblique cutting were predicted to an accuracy of ±4%.

7. ADDITIONAL DATA ABOUT AUTHOR

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