PREDICTION OF NATURAL FREQUENCIES OF THE TOOL CONTROLLED MODE USING SOFT COMPUTING TECHNIQUES

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Abstract: *The dynamic characteristics of spindle-holder-tool assembly is one of the most important factors that have considerable influence on cutting process stability, quality of machined surface, tool life, material removal rate, etc. In order to determine the stable cutting conditions it is essential knowledge of the tool point frequency response function (FRF). The objective of this study is development of a two different artificial intelligence methods, namely, artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) as a potential modelling techniques for prediction of natural frequencies of tool controlled mode. First of all, the natural frequencies of the tool controlled mode for limited combinations of tool overhang length and tool diameter were identified experimentally. The results were used to train an ANN and ANFIS models and both models were compared for their prediction capability with the experimentally determined data. Regarding the results, ANN and ANFIS models were found to be capable of very accurate predictions of natural frequencies of the tool controlled mode.*

Keywords: ARTIFICIAL INTELLIGENCE, TOOL POINT, NATURAL FREQUENCIES

1. Introduction

The main objective of high performance machining is to produce the high quality parts in the shortest time possible, while respecting the other significant issues such are quality of machined surface, tool life, power requirements, etc. Regenerative chatter developed due to dynamic interactions between the cutting tool and workpiece is one of the major machining problem that could result in inconsistent product quality, process instability, increased tool wear, poor surface finish, excessive noise, etc. In order to determine chatter free machining conditions stability lobe diagrams have been used for decades [1-8]. Forming stability lobe diagrams implies knowing the tool point frequency response function (FRF), which is typically obtained using experimental modal analysis by impact test. However, this approach is time consuming, because measurements must be performed for each spindle-holder-tool combination. In order to reduce modal testing, analytically and semi-analytically approaches [9-14] are used to predict tool point FRF.

In machining operations, it is often required to change the tool and/or holder for practical reasons. It is previously shown that tool overhang length itself is a practical parameter to change the dynamics of the spindle-holder-tool assembly [15, 16]. Moreover, it was concluded that the tool overhang length most strongly affects the natural frequency of the most flexible mode. Similar conclusions were drawn by Cica et al. [17] who deduced that change of the tool overhang length and/or tool diameter have significant impact on the tool point FRF. According to the numerical and experimental study, it is observed that the variations in the tool overhang length and tool diameter mainly alter the natural frequencies of the tool controlled mode and don't have considerable effect on the other modes of the spindle-holder-tool assembly.

In this study, two different artificial intelligence methods, namely, artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) as a potential modeling techniques for prediction of natural frequencies of tool controlled mode were discussed and analyzed.

2. Experimental design and setup

In this section, an experimental study is carried out to provide sufficient data for developing ANN and ANFIS models. The FRF of spindle-holder-tool assembly is obtained by experimental modal analysis. A free-free boundary condition for performing an impact tests was simulated by suspend spindle-holder-tool assembly as is shown in Fig. 1. An impact hammer Endevco type 2302-10 was used for excitation of the spindle-holder-tool assembly, while the response was captured by accelerometer B&K type 4507, mounted on the tip of tool. Tool point FRF of the assembly were collected using the multichannel data acquisition unit Portable Pulse type 3560 C by Bruel&Kjaer, and analyzed in the Pulse LabShop 9.0 software, in the frequency range of 0-3200 Hz. Measurement frequency resolution was chosen to be 1 Hz.

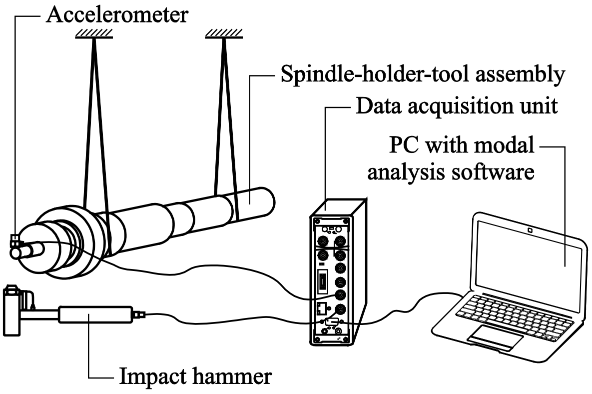

Fig. 1 *Schematic layout of experimental setup.*

Since natural frequencies of tool controlled mode depend on the geometry of the cutting tool, experiments were performed with different combination of tool diameters (D = 10-30 mm) and different tool overhang lengths (L = 19-83 mm). The criteria for selection of a tool diameter in the specified range was based on facts that tools of a diameter less than 10 mm don't provide accurate results due to problems of mounting accelerometer, while tools with a diameter larger than 30 mm are not suitable for the holder ISO 40 which was used during the experimental testing, since the size of this cone define the maximum diameter of tools. Tool overhang lengths are in direct correlation with the used tools, tools with smaller diameters have smaller overhang length, and vice versa. The geometry of the holder is not varied from the simple reason that only collet clamping were analyzed. Therefore, only one configuration of the holder is considered to be sufficiently representative. In this way, 174 measurements of different spindle-holder-tool assembly were performed. The measurements were repeated five times to obtain the average values and to decrease the disturbance of experimental noise. Natural frequencies of tool controlled mode were determined using rational fraction polynomial method.

Fig. 2 shows the result of estimated natural frequencies of the tool mode for different combination of tool diameters and overhang lengths. From these figure it can be concluded that with increasing tool diameter and/or overhang length results in the variations of the same mode, the tool mode. Increasing any of these two parameters reduces the frequencies of tool mode. Therefore, by changing one of these two parameters, the frequency of the tool mode can easily be altered in practical applications for a desired variation in the resulting tool point FRF of the spindle-holder-tool assembly.

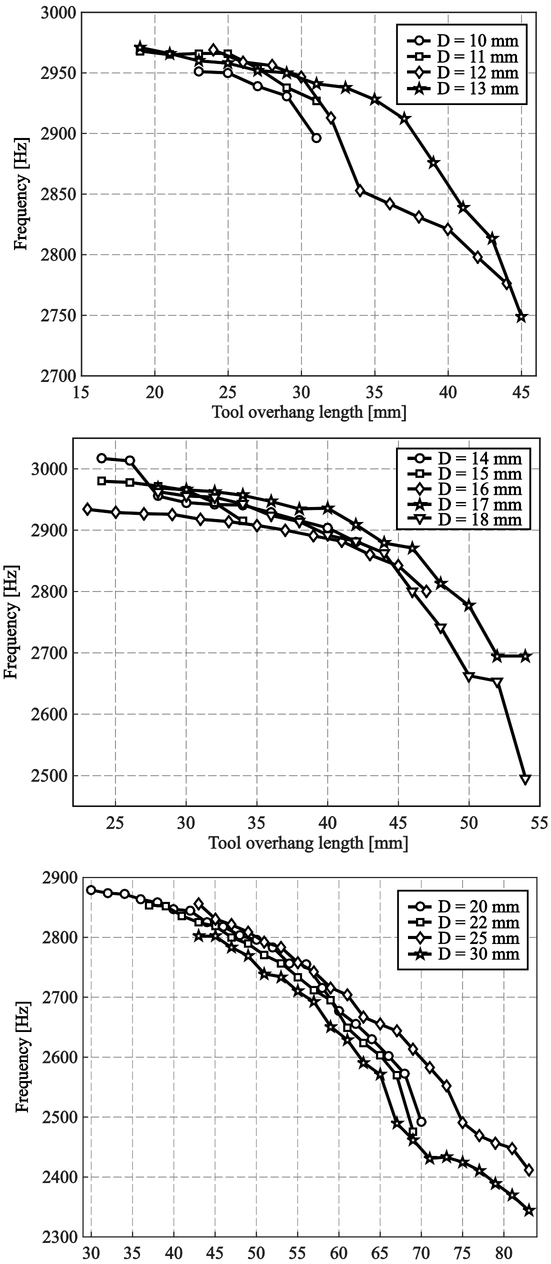

Fig. 2 Estimated natural frequencies of the tool mode for different combination of tool diameters and overhang lengths.

The obtained experimental results were used to train ANN and ANFIS models for prediction of natural frequencies of tool controlled mode of spindle–holder–tool assembly for different cases.

3. ANN based modeling

In last few decades ANN have been verified as an effective tool for providing solutions to a wide range of engineering problems that cannot be solved using conventional methods, including function approximation, optimization, pattern recognition, classification, control, time series modeling, etc. ANN have been designed with the aim of achieving human-like performance and duplicate human brain intelligence by utilizing adaptive models that can learn from the existing data and then generalize what it has learnt.

In this study, a multilayer feed-forward ANN architecture, trained using an error backpropagation algorithm, was employed to develop predictive model for natural frequencies of tool controlled mode of spindle–holder–tool assembly. As shown in Fig. 3, an ANN is made of three types of layers: input, hidden, and output layers. There are two neurons in the input layer (corresponding to two inputs: tool overhang length and tool diameter) and one neuron in the output layer (corresponding to natural frequencies of tool controlled mode).

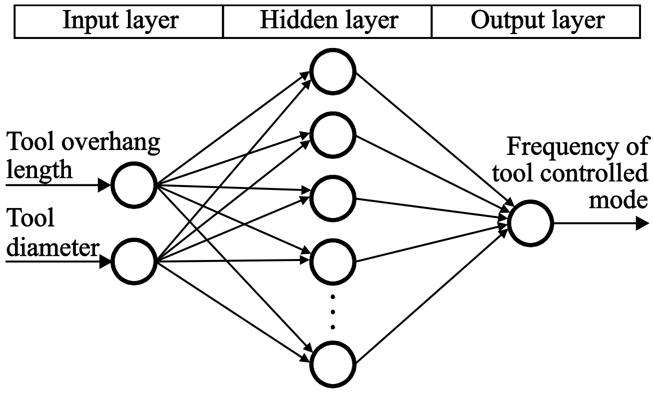

Fig. 3 *Artificial neural networks architecture.*

The first step in developing ANN model is normalization of all the inputs and the desired outputs within the range of ±1. Then, the estimated data, relating to natural frequencies of tool controlled mode for different combinations of tools, were by the random method divided into three datasets: training dataset, validation dataset, and test dataset. The training, validation and test datasets consist of 116, 29, and 29 data, respectively. In order to test how well how well the ANN based on the given input values provides output parameters, in all three datasets errors were analyzed using the following parameters: absolute fraction of variance (R^2), mean absolute percent error (MAPE) and normalized root mean square error (NRMSE). The higher value of R^2 indicate better prediction model (1 denotes perfect), while the smaller values of NRMSE and MAPE means better prediction model (0 denotes perfect).

The performance of supervised training of ANN depends on several factors, such as the number of hidden layers and neurons, activation functions and selection of initial connection weights. Network optimization is usually performed over the optimal number of hidden layers and the number of neurons in the hidden layer. In this study ANN architecture with one hidden layer is selected, and the most favorable number of neurons in the hidden layer was determined by monitoring of errors in the validation dataset and the test dataset. Since there is no exact procedure to determine the optimal number of the neurons on hidden layer, we intentionally chose to start with one neuron and neurons were added to the hidden layer incrementally until there is no further improvement in network performance. According to the evaluation results of various network architectures, an ANN with 9 neurons in the hidden layer provides an optimal values for absolute fraction of variance, mean absolute percent error and normalized root mean square error.

The activation functions are also important factor influencing the network performance. For the developed optimal ANN architecture, tangent of sigmoid activation function has been used in the hidden layer, while linear activation function has been used in the output layer. The weights and biases of the network are initialized with the help of Nguyen-Widrow algorithm. The ANN model was trained with various training variations of back propagation methods and among them the Levenberg- Marquardt method provided the best performance for the adjustment of weighting coefficients. Initial value of the Marquardts parameter was 0.001, reduction factor of the Marquardts parameter was 0.1 and increase factor of the Marquardts parameter was 10. ANN training was stopped when the value of the Marquardts parameter rises above the threshold that is set to 10^{10}.

The developed ANN model was tested by comparing the predicted results with the experimental data and results for test dataset are summarized in Fig. 5. In predicting natural frequencies of tool controlled mode, absolute fraction of variance, mean absolute percent error and normalized root mean square error were 0.9914, 0.57 and 0.1299, respectively, while maximum mean absolute percentage error (MaxAPE) was 1.9%. Hence, it is evident that there is very good agreement between estimated and experimental values of natural frequencies of tool controlled mode.

4. AFIS based modeling

The acronym ANFIS derives its name from adaptive neuro-fuzzy inference system. Utilizing the Sugeno fuzzy inference system (FIS), Jang [18] presented a neuro-fuzzy system that combines the explicit knowledge representation of fuzzy inference systems with the learning capabilities of ANN in a complementary hybrid system called ANFIS. ANFIS is perhaps the most popular hybrid artificial intelligence technique because it has potential to capture the benefits of neural networks and fuzzy logic into a single framework. The integration of excellent learning capability of ANN with FIS overcomes the limitations of a traditional FIS, such as the dependency on the expert for fuzzy rule generation and design of the non-adaptive fuzzy set.

Working principles of ANFIS is based on its architecture which is typical multilayer feed-forward network where each node performs a particular function on incoming signals as well as providing a set of parameters pertaining to this node. However, unlike multilayer feed-forward ANN, in ANFIS no weights are associated with the links which only indicate the flow direction of signals between nodes.

Basically, ANFIS architecture contains a five network layers (input layer, output layer and three hidden layers) which are characterized by the operations that they perform (Figure 4). These layers are used by inference system to perform the following fuzzy inference steps: (i) input fuzzification, (ii) fuzzy set database construction, (iii) fuzzy rule base construction, (iv) decision making, and (v) output defuzzification. Each layer consists of several nodes described by nodes function, which can be in the form of adaptive nodes (denoted by squares) and fixed nodes (denoted by circles).

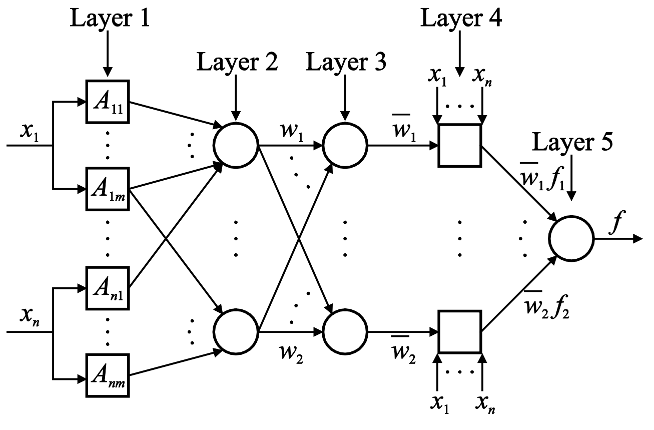

Fig. 4 *General architecture of ANFIS.*

Similar to ANN, first step in developing ANFIS model is partitioning the whole data into training and testing dataset. In this study, the ANFIS model was tested using same test dataset as in ANN to predict an output response. The size of training and test dataset of ANFIS model were 145 and 29 of the total number of experimental data, respectively.

In order to achieve maximum prediction accuracy of ANFIS, the model was tested in terms of the number of membership functions (MFs), their type and the most suitable training options. Each input variable was represented using different numbers and shapes of MFs type in the constructed ANFIS model. Optimal number of MFs which offers best performance of ANFIS and is computationally quite fast, were seven and five for tool overhang length and tool diameter, respectively. The model was developed using different shapes of input MFs type which were triangular, trapezoidal, Gaussian, and bell shapes, while the constant and linear output MFs type were employed to produce the natural frequencies of tool controlled mode value. The best responding models of ANFIS system were those which have Gaussian curve built-in membership functions (gaussMF) for each inputs and a linear output function. Furthermore, a hybrid of the least-squares method and the back propagation gradient descent method was used to emulate a given training data set. A first-order Sugeno FIS was used in this study with the hybrid learning rules used in the training.

The same variables as in ANN, namely, absolute fraction of variance, mean absolute percent error and normalized root mean square error, were used as a criterion for selecting the best ANFIS model.

The predicted values of response by developed ANFIS model were compared with the experimental data and results for testdata set are summarized in Fig. 5. In predicting natural frequencies of tool controlled mode, absolute fraction of variance, mean absolute percent error and normalized root mean square error were 0.99325, 0.48 and 0.1158, respectively, while maximum mean absolute percentage error (MaxAPE) were 1.8%. The predicted values of response from ANFIS model and experimental data are fairly close which indicates that ANFIS can be used effectively to predict natural frequencies of tool controlled mode.

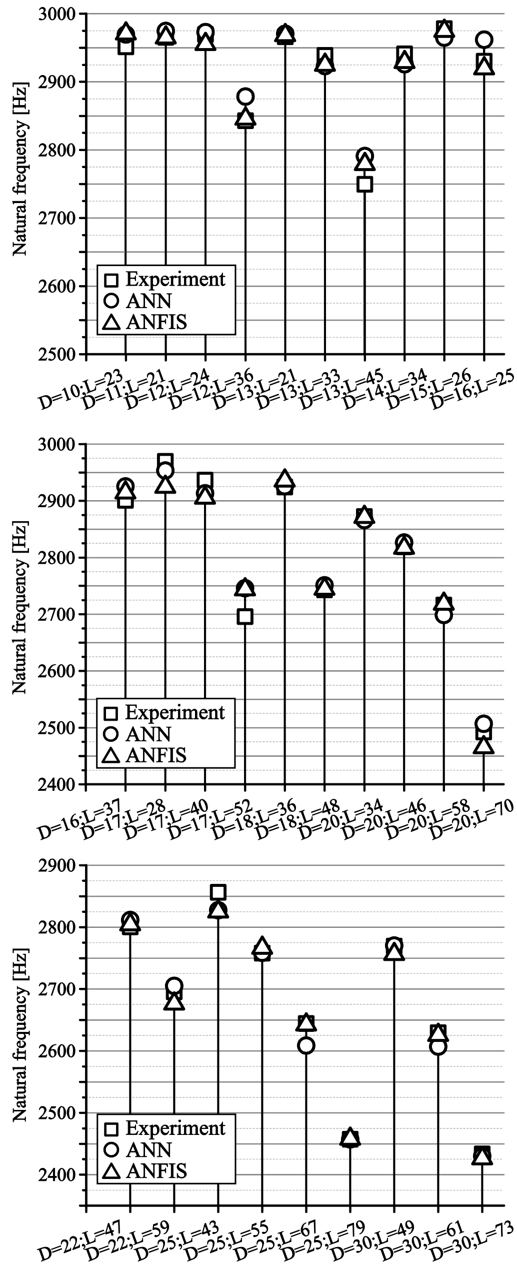

Fig. 5 *Comparison of ANN and ANFIS models with experimental results.*

5. Conclusions

Spindle-holder-tool assembly is one of the most important machine tool elements because its static and dynamic behavior, strength, speed, etc., have a significant impact on machine tools overall performance. Determination of the stable and unstable cutting zone in the machining process implies knowing stability lobe diagrams of spindle-holder-tool assemblies. For generation of these diagrams FRF of the spindle-holder-tool assembly should be achieved firstly using experimental modal analysis. However, tool point FRF is strongly depend on the individual components of the spindle-holder-tool assembly as well as their interactions. Tool geometry is very practical operational parameter which can be controlled by the user to alter the dynamics of the spindle-holder-tool assembly, by primarily altering the natural frequencies of the tool controlled mode.

The present work aims at estimating natural frequencies of the tool controlled mode of the spindle-holder-tool assembly using two different artificial intelligence methods, namely, ANN and ANFIS, as a tools for the prediction. Tool overhang length and tool diameter were considered to be the design variables. The natural frequencies of the tool controlled mode for limited combinations of tool overhang length and tool diameter were firstly identified experimentally. The obtained experimental results were used to develop ANN and ANFIS models for prediction of natural frequencies of tool controlled mode. Both models were compared for their prediction capability with the experimentally determined data. Regarding the results, ANN and ANFIS models were found to be capable of very accurate predictions of natural frequencies of the tool controlled mode, although ANFIS models give somewhat better predictions. Therefore, it can be concluded that ANN and ANFIS models can be used in the determination of the tool point FRF, and thus can be used for the generation of stability lobe diagrams.

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