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DYNAMICAL CONTACT PARAMETER IDENTIFICATION OF SPINDLE-HOLDER-TOOL ASSEMBLIES USING SOFT COMPUTING TECHNIQUES

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Abstract. *In industry, the capability to predict the tool point frequency response function (FRF) is an essential matter in order to ensure the stability of cutting processes. Fast and accurate identification of contact parameters in spindle-holder-tool assemblies is very important issue in machining dynamics analysis. This work is an attempt to illustrate the utility of soft computing techniques in identification and prediction contact parameters of spindle-holder-tool assemblies. In this paper, three soft computing techniques, namely, genetic algorithm (GA), simulated annealing (SA), and particle swarm optimization (PSO) were used for identification of contact dynamics in spindle-holder-tool assemblies. In order to verify the proposed identification approaches, numerical and experimental analysis of the spindle-holder-tool assembly was carried out and the results are presented. Finally, a model based on the adaptive neural fuzzy inference system (ANFIS) was used to predict the dynamical contact parameters at the holder-tool interface of a spindle-holder-tool assembly. Accuracy and performance of the ANFIS model has been found to be satisfactory while validated with experimental results.*

Key Words: *Contact Dynamics, Parameter Identification, Soft Computing*

1. INTRODUCTION

Regenerative chatter is a well-known and undesirable machining phenomenon that could result in cutting process instability, poor surface quality, excessive tool wear and reduced material removal rate. Many research efforts have made significant contributions to modeling of chatter mechanism [1-3]. Their work includes analytical or numerical time-domain techniques for generating stability lobe diagrams as the main tool to identify the stable zone in the machining process. Regardless of the approach used, knowledge of

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the machine tool dynamics, specifically the tool point frequency response function (FRF) is an essential requirement for generation of stability lobe diagrams.

The tool point FRF is traditionally obtained using experimental modal analysis by simple impact testing. However, due to a large number of holder and tool combinations, these tests are expensive and time consuming. Recently, in order to minimize experimentation, researchers have attempted to obtain the tool point FRF semi-analytically. Schmitz et al. [4, 5] propose a method for predicting the tool point FRF using the receptance coupling theory of structural dynamics. Park et al. [6] included the rotational degree-of-freedom at the tool holder-tool joint, which was indirectly identified using translational responses measured from a set of short and long blank tools. Kivanc and Budak [7] modeled complex end-mill geometry in finite elements and practical equations were developed to predict the static and dynamic properties of the tools. Erturk et al. [8] proposed a reliable analytical model for predicting the tool point FRF by using the receptance coupling and structural modification methods where all components of the spindle-holder-tool assembly were modeled with the Timoshenko beam theory. Kiran et al. [9] applied inverse receptance coupling substructure analysis approach in order to compensate mass and damping for accelerometer-based impact testing. Ji et al. [10] proposed a new receptance coupling substructure analysis methodology to predict the tool tip dynamics solving the accuracy problem in the estimation of the rotational/moment receptance. Postel et al. [11] presented a new approach for prediction of tooltip FRFs under operational conditions for arbitrary tool-holder combinations. Qi et al. [12] presented tool point frequency response prediction based on Timoshenko beam model using receptance theory.

Successful application of these models strongly depends on the accurate identification of dynamical contact parameters at the spindle-holder and holder-tool interfaces. Therefore, accurate and fast dynamical contact parameter identification in spindle-holder-tool assemblies has become an important issue for obtaining the accurate tool point FRF. Most researchers [4, 5, 13] used the nonlinear least square error minimization for identifying the contact parameters in spindle-holder-tool assemblies. Schmitz et al. [14] present a finite element modeling approach to determine the stiffness and damping behavior between the tool and the holder in thermal shrink fit connections. Ahmadi and Ahmadian [15] considered the holder-tool interface as a distributed elastic layer between the holder-spindle and the tool shank part. Namazi et al. [16] presents modeling and identification of holder-spindle interface stiffness using translational and rotational springs which were uniformly distributed at the contact zone. Ozsahin et al. [17] proposed identification approach where elastic receptance coupling equations previously used for coupling the spindle-holder-tool assemblies are rearranged to give the complex stiffness matrix at the holder-tool and spindle-holder interfaces in a closed-form manner. Gou et al. [18] developed a static model of BT40 spindle-holder system and presented an identification method based on analysis of the rigid body deformation and elastic modulus of the virtual material layer. Gao et al. [19] proposed an analytical method combining classic elasticity theory with the fractal theory in order to estimate the contact stiffness of spindle-holder joint. Effects of cutting force on contact stiffness at the spindle-holder interface were also investigated in this study. Zhao et al. [20] present a macro-micro scale hybrid model to obtain the contact stiffness at the spindle-holder interface at high speeds. The taper contact surface of spindle-holder joint is assumed flat in macro-scale and the finite element method is used to obtain the pressure distribution at different speeds, while in micro-scale, the topography of contact surfaces is fractal featured and determined by fractal parameters.

Liao et al. [21] developed identification method based on fractal topography theory to determine the contact properties at the holder-tool interface in the shrink-fit connection.

Some researchers use artificial intelligence methods to identify the contact parameters of spindle-holder-tool assemblies. Movahhedy and Gerami [22] present two joint models with linear and rotational springs to model the holder-tool connection. The model is then applied to real machine tool cases and an optimization method based on genetic algorithm is used to identify joint parameters at the tool-holder interface. Wang et al. [23] proposed an identification method to recognize the connection parameters at the holder-tool interface by using receptance coupling substructure analysis and particle swarm optimization. Ganguly and Schmitz [24] also implemented a particle swarm optimization technique to automate the identification of the Euler-Bernoulli beam parameters for each mode. Liu et al. [25] introduced an optimization technique based on particle swarm optimization algorithm to obtain the high contact stiffness of BTF40 spindle-holder joint at the high speed.

Having an accurate prediction of contact parameters in spindle-holder-tool assemblies is very important for obtaining correct tool point FRF. This research aims to illustrate the utility of soft computing techniques in identification and prediction contact parameters in spindle-holder-tool assemblies. Due to high complexity of this optimization problem, three non-traditional algorithms, the genetic algorithm (GA), simulated annealing algorithm (SA), and the particle swarm optimization (PSO) have been employed to resolve this problem. Firstly, in order to verify the proposed identification approaches, numerical analysis of the spindle-holder-tool assembly has been performed and the results were presented. Then, GA identification approach was verified experimentally and obtained results were used to train the ANFIS model for prediction of translational and rotational stiffness at the holder-tool interface of assembly.

2. Mathematical Model of Spindle-Holder-Tool Assembly

It is generally accepted that an analysis of complex dynamical systems can be simplified by disassembling a system into a set of interconnected subsystems. In this sense, the problem referring to dynamic properties of the spindle-holder-tool assembly can be so simplified that instead of viewing it as single, the specified system is regarded as the one composed of three components, namely: a spindle (*S*), holder (*H*), and tool (*T*), as shown in Fig. 1. After obtaining the end-point receptance matrices of spindle (**S**), holder (**H**) and tool (**T**) these components should be elastically assembled through the complex stiffness matrices at the spindle-holder (${}_{SH}\mathbf{K}$) and holder-tool (${}_{HT}\mathbf{K}$) interfaces of assembly. In this paper, the analytical model proposed by Erturk et al. [8] was applied where part of the holder inside the spindle is considered rigidly joined to the spindle and the part of the tool inside the holder is considered rigidly joined to the holder.

The following equation represents the elastic coupling of subsystem spindle and subsystem holder FRFs to obtain the end point FRF of the spindle-holder subassembly at the holder tip:

$$\mathbf{SH}_{ii} = \mathbf{H}_{ii} - \mathbf{H}_{ic} \cdot (\mathbf{H}_{cc} + \mathbf{S}_{cc} + {}_{SH}\mathbf{K}^{-1})^{-1} \cdot \mathbf{H}_{ci} \tag{1}$$

where $\mathbf{H}_{ii}$, $\mathbf{H}_{ic}$, $\mathbf{H}_{ci}$, $\mathbf{H}_{cc}$ and $\mathbf{S}_{cc}$ are submatrices of receptance matrices of the holder and spindle, respectively, that include the point and transfer receptance functions of the segment end point (i) and (c).

Complex stiffness matrix of the spindle-holder interface has the following form:

$$ {}_{SH}\mathbf{K} = \begin{bmatrix} {}_{SH}k_t + i\cdot\omega\cdot {}_{SH}c_t & 0 \\ 0 & {}_{SH}k_r + i\cdot\omega\cdot {}_{SH}c_r \end{bmatrix} \tag{2} $$

where: ${}_{SH}k_t$ is the translational stiffness, ${}_{SH}c_t$ is the translational damping, ${}_{SH}k_r$ is the rotational stiffness and ${}_{SH}c_r$ is the rotational damping at the spindle-holder interface, ω is the excitation frequency and i is the unit imaginary number.

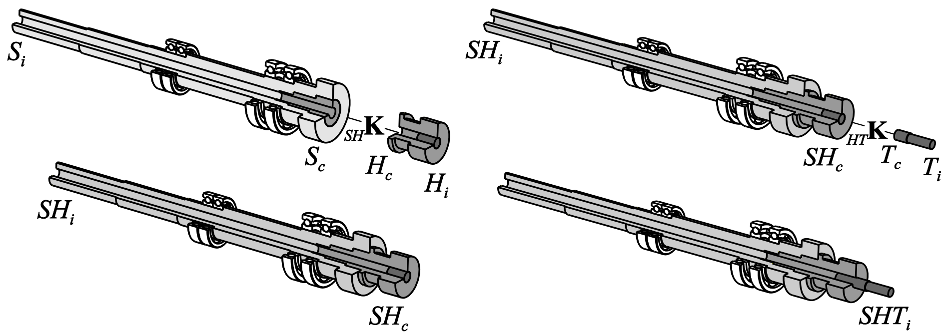

Fig. 1 Elastic coupling of the spindle and holder (left) and elastic coupling of the spindle-holder subassembly and tool (right)

The receptance matrix of the tool can be coupled with the spindle-holder subassembly (Fig. 1) and the resulting matrix of the assembly spindle-holder-tool can be obtained in a very similar manner as follows:

$$ \mathbf{SHT}_{ii} = \mathbf{T}_{ii} - \mathbf{T}_{ic}\cdot(\mathbf{T}_{cc} + \mathbf{SH}_{cc} + {}_{HT}\mathbf{K}^{-1})^{-1}\cdot\mathbf{T}_{ci} \tag{3} $$

where $\mathbf{T}_{ii}$, $\mathbf{T}_{ic}$, $\mathbf{T}_{ci}$, $\mathbf{T}_{cc}$ and $\mathbf{SH}_{cc}$ are submatrices of receptance matrices of the tool and spindle-holder subassembly, respectively, that include the point and transfer receptance functions of the segment end point (i) and (c).

Complex stiffness matrix of the holder-tool interface is defined as:

$$ {}_{HT}\mathbf{K} = \begin{bmatrix} {}_{HT}k_t + i\cdot\omega\cdot {}_{HT}c_t & 0 \\ 0 & {}_{HT}k_r + i\cdot\omega\cdot {}_{HT}c_r \end{bmatrix} \tag{4} $$

Here, ${}_{HT}k_t$ is the translational stiffness, ${}_{HT}c_t$ is the translational damping, ${}_{HT}k_r$ is the rotational stiffness and ${}_{HT}c_r$ is rotational damping at the holder-tool interface.

A very important issue in the receptance coupling theory of structural dynamics is proper modeling of dynamical contact parameters (stiffness and damping) at spindle-holder and holder-tool interfaces which have a significant impact on the dominant elastic modes of the tool point FRF. However, these parameters are very difficult to model adequately and accurately.

In the end point FRF of the spindle-holder subassembly at the holder tip (Eq. 1), ${}_{SH}k_t$, ${}_{SH}c_t$, ${}_{SH}k_r$ and ${}_{SH}c_r$ are all unknowns to be recognized. These parameters can be represented as depicted in Eq. 5.

$$ {}_{SH}\boldsymbol{\alpha} = \left[{}_{SH}k_t, {}_{SH}c_t, {}_{SH}k_r, {}_{SH}c_r \right] \tag{5} $$

When $\omega = \omega_j$, FRF of the spindle-holder subassembly at the holder tip is $\mathbf{SH}_{ii}(\omega_j)$, simplified as $\mathbf{SH}_{ii}$. Meanwhile the measured FRF is $\overline{\mathbf{SH}}_{ii}(\omega_j)$, simplified as $\overline{\mathbf{SH}}_{ii}$. If $\omega_j = \omega_1, \omega_2, \ldots, \omega_m$, there are m frequency measurement points, and an error vector ${}_{SH}\mathbf{e}$ can be constructed by Eq. 6.

$$ {}_{SH}\mathbf{e} = \mathbf{SH}_{ii} - \overline{\mathbf{SH}}_{ii} \tag{6} $$

In Eq. 6 ${}_{SH}\mathbf{e}$ is the nonlinear function of vector ${}_{SH}\boldsymbol{\alpha}$ to be identified. Similarly, in the end point FRF of the spindle-holder-tool assembly at the tool tip (Eq. 3), ${}_{HT}k_t$, ${}_{HT}c_t$, ${}_{HT}k_r$ and ${}_{HT}c_r$ are all unknown to be recognized and these parameters can be represented as

$$ {}_{HT}\boldsymbol{\alpha} = \left[{}_{HT}k_t, {}_{HT}c_t, {}_{HT}k_r, {}_{HT}c_r \right] \tag{7} $$

Error vector ${}_{HT}\mathbf{e}$ is the nonlinear function of vector ${}_{\mathrm{HT}}\boldsymbol{\alpha}$ to be identified:

$$ {}_{HT}\mathbf{e} = \mathbf{SHT}_{ii} - \overline{\mathbf{SHT}}_{ii} \tag{8} $$

where $\mathbf{SHT}_{ii}$ is FRF of the spindle-holder-tool subassembly at tool tip and $\overline{\mathbf{SHT}}_{ii}$ is the measured FRF.

3. Formulation of Optimization Problem

The general approach to the problem of parameters identification is to minimize the differences between the results obtained by measuring and by the mathematical model. An appropriate method of identification depends on the assumptions and knowledge about the errors of measurement. Classical optimization algorithms are not suitable for solving nonlinear and large scale optimization problems. Hence, novel optimization algorithms are emerging to solve these problems. Recently a lot of metaheuristic algorithms have been proposed to find the best global solution and to overcome the restrictions and difficulties of classical optimization algorithms.

The classical nonlinear constrained optimization problem can be written as minimize $f(x)$ subject to $h_j(x) = 0$ ($j = 1, 2, ..., m$), $g_k(x) \leq 0$ ($k = 1, 2, ..., n$), $x_i^{lb} \leq x_i \leq x_i^{ub}$ ($i = 1, 2, ..., p$). In general, objective function $f(x)$ as well as equality constraint function $h_j(x)$ and inequality constraint function $g_k(x)$ are nonlinear implicit functions with respect to the design variables. x_i^{lb} and x_i^{ub} denote the lower boundary condition vectors and upper boundary condition vectors, respectively.

Based on the presented mathematical model of the spindle-holder-tool assemblies, for accurate prediction of the FRF it is necessary to know the exact stiffness matrix at the spindle-holder, and holder-tool interface. The matrix elements are stiffness and damping between these subsystems, and as the specified values cannot be experimentally measured, they need to be determined in other way. Therefore, it is necessary to explore the possibilities of applying different methods for identification of the contact parameters in spindle-holder-tool assemblies. The proposed identification procedure of contact parameters in spindle-holder-tool assemblies using soft optimization techniques is presented in Fig. 2.

The identification procedure estimates the vector of unknown parameters, so that the deviation between the mathematical model and the real system responses to the same input is minimized. In this paper, considerations are limited to identification of dynamical contact parameters only at the holder-tool interface. However, the same procedure can also be applied for identification of other parameters, such as contact parameters at the spindle-holder interface as well as the dynamical parameters of bearings. In the direct tool point FRF (Eq. 3), ${}_{HT}k_t$, ${}_{HT}c_t$, ${}_{HT}k_r$ and ${}_{HT}c_r$ are all unknowns to be recognized (Eq. 4). These parameters can be represented as depicted in Eq. 7. In engineering application of optimization algorithms an important step is to choose the form of the objective function. In this study, the objective function was constructed as Euclidian norm of vector differences between the experimental and analytical responses. Since both response values are complex, they are divided into real and imaginary parts.

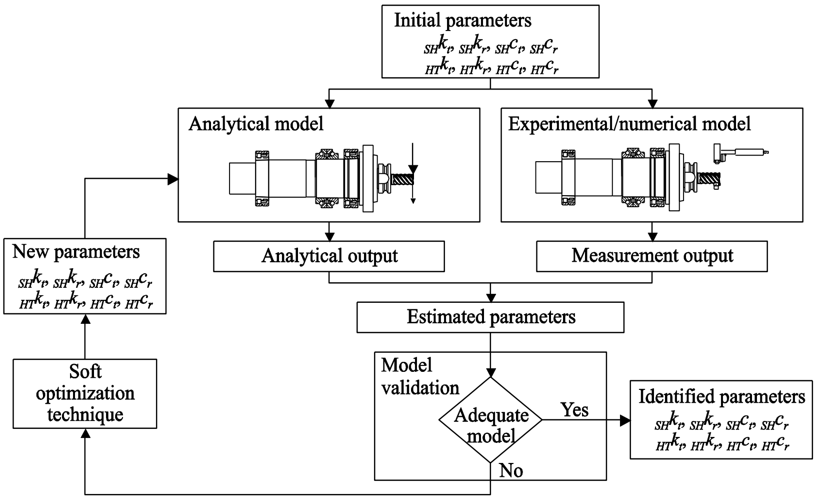

Fig. 2 General identification procedure of dynamical contact parameter in spindle-holder-tool assemblies using soft optimization techniques

The presented dynamical contact parameter identification of spindle-holder-tool assemblies can be solved by means of some optimization methods, such as Newton and quasi-Newton methods, conjugate gradient methods, the simplex method, etc. However, these methods are ill-conditioned, very sensitive to noise, and numerically complicated, resulting in the problem of convergence to a local minimum instead of global one. Another drawback is that the optimum identified parameter values strongly depend on the initial guess of the parameter. As an alternative to these methods, non-traditional optimization techniques based on soft computing have been employed to overcome these disadvantages. This paper considers three soft computing techniques, namely, GA, SA and PSO, for dynamical contact parameter identification in spindle-holder-tool assemblies.

4. NUMERICAL CASE STUDY

To create conditions that will lead to a successful experiment, it is desirable to analyze the possibility of identifying unknown parameters of the spindle-holder-tool assembly using optimization techniques based on soft computing prior to experimental obtaining tool point FRF. Therefore, in this section, a numerical case study for identification of the contact parameters in spindle-holder-tool assemblies is presented. In order to be able to use Eq. 3 to calculate FRF at the tool tip of a spindle-holder-tool assembly, the receptance matrices for each of the components of the spindle-holder-tool assembly are required.

In this section, translational and rotational dynamic responses for each of the components of the spindle-holder-tool assembly are obtained through the FEM analysis. The spindle-holder-tool assembly of the case study (Fig. 3) is modeled using a reliable finite element software ANSYS. Each of the subsystems is composed of several sections with different diameter and lengths which are modeled as multi-segment beams. The dimensions of the subsystems, i.e. spindle, holder and tool, bearings properties, spindle-holder interface dynamics, and holder-tool interface dynamics are given by Cica [26].

Beam element BEAM188 which is based on the Timoshenko beam theory is used for modeling the spindle, holder and tool, since this element supports the effects of rotary inertia and shear deformation. Dynamics of bearings and spindle-holder and holder-tool interfaces, were modeled using combination element COMBIN14, which is a spring-damper element. Material properties of assembly are taken as follows: Young's modulus E = 210 GPa, mass density ρ = 7800 kg/m^3, Poisson's ratio ν = 0.3. The FEM analysis of the spindle-holder-tool assembly is performed in ANSYS and the tool point FRF for the frequency range of 0-3000 Hz with a frequency increment of 1 Hz is obtained.

In this numerical case study, unknown contact parameters at the holder-tool interface were identified using GA, SA and PSO optimization techniques. Optimization routines proceeds by considering a ranges of 10^6 to 10^9 N/m, 10^5 to 10^7 Nm/rad, 1 to 300 Ns/m and 1 to 300 Nms/rad for translational stiffness, rotational stiffness, translational damping, and rotational damping at the holder-tool interface, respectively. The fitness function of optimization algorithms was simply the minimization of the error vector given by Eq. 8. It is noted that the error could be either positive or negative. Therefore, absolute value of the error is used as a fitness function.

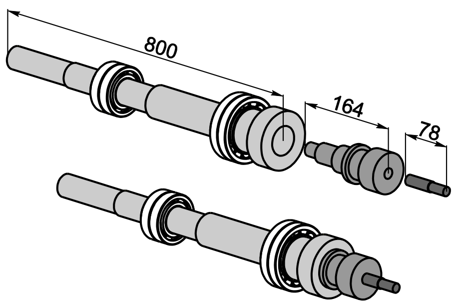

Fig. 3 The spindle-holder-tool assembly for numerical simulation

For each optimization technique a parametric study is carried out so that the value of one parameter is varied at a time, while other parameters have fixed values. In the GA optimization process, the commonly used GA operation parameters were adopted. The optimal values of evolutionary parameters were 2430 and 420 for number of generations and population size, respectively. The genetic operations reproduction, crossover and mutation were also used. Probability of reproduction, crossover and mutation were 0.1, 0.65 and 0.015, respectively. In the PSO optimization process, the commonly used PSO operation parameters were adopted, namely the population size, number of generations, cognitive acceleration, and social acceleration. The optimal values of number of generations, population size, cognitive acceleration, and social acceleration were 280, 120, 0.5 and 1.35, respectively. The SA optimization process takes place with the values of reannealing interval, and initial temperature. The optimal values of reannealing interval, and initial temperature were 50, and 300, respectively. The number of iterations required to find an optimal solution for GA, PSO and SA were 51, 276 and 1020, respectively. The identified contact parameters at the holder-tool interface in the numerical case study using GA, PSO and SA based optimization techniques are shown in Table 1.

Table 1 Identified dynamical contact parameters at the holder-tool interface in the numerical case study

Parameter	Exact value	GA identified value	Rel. error [%]	SA identified value	Rel. error [%]	PSO identified value	Rel. error [%]
${}_{HT}k_t$ [Nm]	$2.1\cdot10^7$	$2.0999663\cdot10^7$	0	$1.8999804\cdot10^7$	9.5	$2.0936593\cdot10^7$	0.3
${}_{HT}c_t$ [Ns/m]	15	$16.^6$	10.7	15.4	2.7	13.6	9.33
${}_{HT}k_r$ [Nm/rad]	$1.4\cdot10^6$	$1.381904\cdot10^6$	1.3	$1.540449\cdot10^6$	10	$7.02672\cdot10^6$	49.8
${}_{HT}c_r$ [Nms/rad]	3	1.2	306.7	89	2866	9	200

As shown in Table 1, the accuracy of the identified parameters is more than satisfactory. Somewhat larger errors are encountered in the identification of the rotational stiffness and rotational damping, but those parameters have no significant impact in the synthesis of dynamic subsystems. The most dominant factor in the synthesis of dynamic subsystems is translational stiffness (${}_{HT}k_t$), and this value was most accurately identified.

In order to show the accuracy of the GA, SA and PSO identification methods, the spindle-holder subassembly receptance matrix is coupled with tool FRFs through the forward coupling equation (Eq. 3). In coupling of the spindle-holder and tool subsystems, the constant values identified from all three methods (Table 1) were used. Fig. 4 shows the comparison of FRF at the tool tip of a spindle-holder-tool assembly with the identified and real values of contact parameters at the spindle-holder interface. It can be seen from these figure that the GA and PSO based identification methods presented in this study give excellent results, while the SA based method yielded somewhat different results.

So far, the implementation of the soft computing identification approach proposed in this paper is demonstrated with an example for extracting the holder-tool interface parameters for a typical spindle-holder-tool assembly. It is observed that accuracy of obtained results allows prediction of the response of the spindle-holder-tool assembly with very high accuracy. An experimental application of the identification approaches is given in the following section.

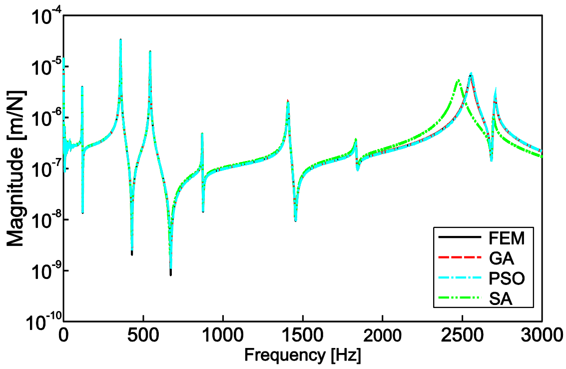

Fig. 4 Comparison between numerically and analytically obtained FRF with identified contact parameters at the holder-tool interface

5. Experimental Details

In this section, an experimental case study for the GA based identification approach is provided. GA was selected because this method provides the best results in terms of identification of translational stiffness ($_{HT}k_t$), which is the most dominant factor in the synthesis of dynamic subsystems. Experiments were performed with ISO 40 type holder, in which different combination of tool diameters (D = 9-30 mm) and different tool overhang lengths (L = 16-83 mm) were inserted, and assembled to the spindle. The spindle-holder-tool assembly shown in Fig. 5 was suspended to obtain free-free end conditions for performing an impact tests.

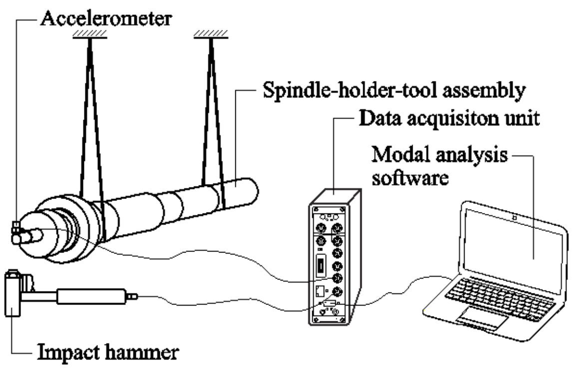

Fig. 5 Schematic layout of experimental setup for dynamical contact parameter identification of spindle-holder-tool assembly

In order to verify the presented identification models, FRF of the spindle-holder-tool assembly was measured or obtained with FE analysis for each of these substructures. Due to the relative complex geometry of the spindle, and since it does not change over time, it is preferred to obtain the FRF of this substructure by modal analysis. On the other hand, the cutting tool usually has a much simpler geometry and FRF of this substructure may be obtained numerically e.g. from an FE analysis. First, FRF of the spindle-holder subassembly (without the tool part outside the holder) is obtained by performing an impact test. Next, the tool is inserted into the holder and the tool point FRF of the assembly is obtained also by performing impact tests. In order to obtain angular displacement or moment-related FRFs of spindle-holder subassembly, the method proposed by Park et al. [6] was used. Finally, the receptance matrices of the tool component in free-free boundary conditions were separately computed using FEM modeling. In this way, 178 measurements were made with different combinations of spindle-holder-tool assembly.

According to the presented mathematical model of the spindle-holder-tool assembly, accurate knowledge of complex stiffness of holder-tool interface dynamics is necessary for accurate prediction of the dynamic response. The GA optimization routine proceeds by considering a range of 10^5 to 10^9 for stiffness and 1-300 for damping coefficients of the holder-tool interface as the feasible range. The obtained experimental results were used to train the ANFIS model for prediction of contact parameters of spindle-holder-tool assembly for different cases. In the present work, the input variables for ANFIS were tool diameters and overhang length of the tools, while the output variables were identified data relating to the translational and rotational stiffness at the holder-tool interface. A 148 sets of data were selected from the total of 178 sets obtained using GA identification method for the purpose of training in ANFIS, while the other 30 sets were then used for testing after the training was completed to verify the accuracy of the predicted values of contact parameters.

Several ANFIS models were developed and tested based on the same training data in order to achieve the maximum prediction accuracy. The models were developed using different shapes of input membership functions (MFs) type which were triangular, trapezoidal, Gaussian, and bell shapes, with a different number of the MFs. The constant and linear output MFs type were employed to produce the stiffness values, while a hybrid of the least-squares method and the back propagation gradient descent method was used to emulate a given training data set.

In order to estimate the prediction capability of the developed ANFIS models, normalized root mean square error, absolute fraction of variance, mean absolute percent error and maximum mean absolute percentage error were used. In the current work, the best ANFIS model was obtained with Gaussian curve built-in membership functions for each input and a linear output function. The number of fuzzy rules is related to the number of fuzzy sets for each input variable. Because the inputs, tool diameters and overhang length of the tools, were classified into 3, and 7 fuzzy sets, respectively, the total number of fuzzy rules formed will be 21. First-order Sugeno fuzzy inference system is used in this work with the hybrid learning rules used in the training

Fig. 6 shows the comparison between the experimental and the ANFIS model results for translational stiffness for test data set. Normalized root mean square error, absolute fraction of variance, mean absolute percent error, and maximum absolute percent error for developed model were 0.09427, 0.99541, 4.5%, and 11.8%, respectively. Referring to Fig. 7 indicates the comparison in prediction of rotational stiffness obtained using the ANFIS model. Normalized root mean square error was 0.08993, absolute fraction of variance was 0.99591, mean absolute percent error was 0.7%, and maximum absolute percent error was 3.2%. Hence, it is obvious that there is good agreement between predicted and experimental values of translational and rotational stiffness. Fig. 8 demonstrates a linear regression between the predicted values and corresponding target values.

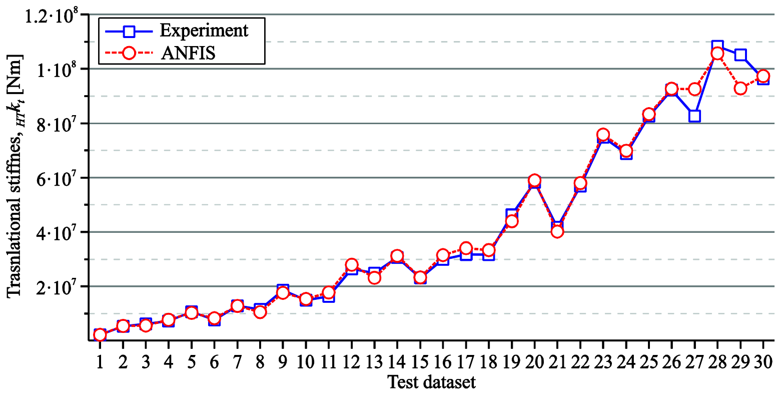

Fig. 6 The experimental and predicted values of translational stiffness at the holder-tool interface in the test data set

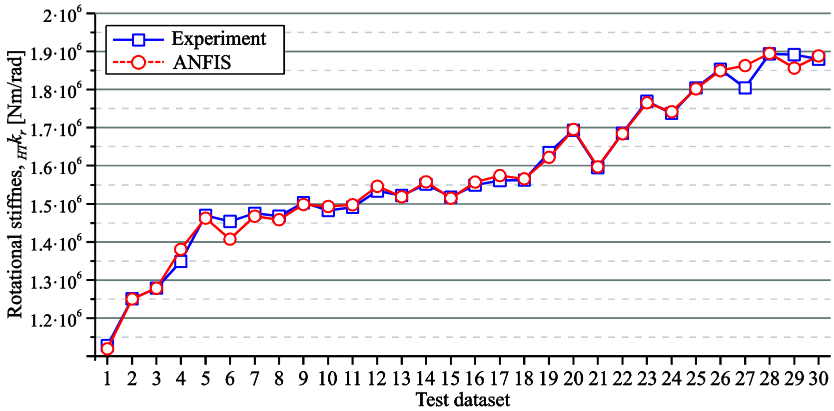

Fig. 7 The experimental and predicted values of rotational stiffness at the holder-tool interface in the test data set

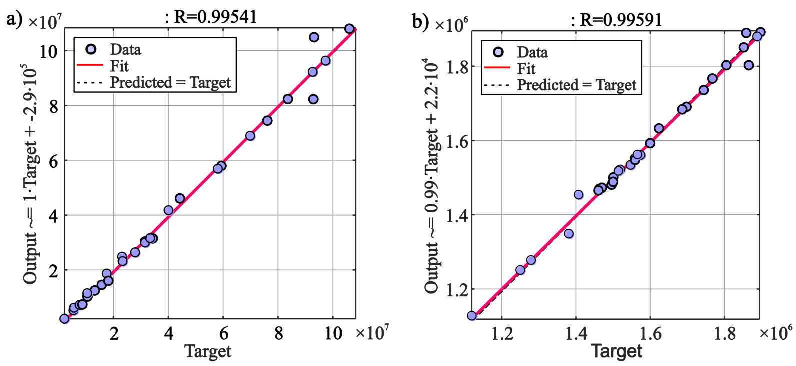

Fig. 8 Regression plot of actual and predicted translational (a) and rotational stiffness (b) at the holder-tool interface in the test data set

6. Conclusions

Soft computing techniques are among the fast-growing and promising research topics that have drawn a great deal of attention from researchers in recent decades. These techniques have excellent learning and generalization abilities on handling ill-defined and complex problems. Various soft computing techniques have been successfully applied to a wide range of applications, and in this paper three techniques, namely, genetic algorithm, simulated annealing, and particle swarm optimization, were used for identification of contact dynamics of spindle-holder-tool assemblies.

Numerical and experimental studies were presented to confirm the effectiveness of proposed methodology. First, a numerical case study for identification of the contact parameters in spindle-holder-tool assemblies (with a focus on the holder-tool interface) was presented. It is observed that the GA and PSO based techniques give exceptional results, while the SA based technique yielded somewhat different results. Furthermore, analysis of the identification results shows that the most dominant factor in the subsystems synthesis of the spindle-holder-tool assembly is translational stiffness, and this value was most accurately identified. Slightly larger deviations were observed at identification of rotational parameters, but these parameters do not have significant impact on the synthesis of dynamic subsystems.

The identification approach based on GA was also experimentally verified in terms of identification contact parameters at the holder-tool interface of a free-free spindle-holder-tool assembly. Finally, the ANFIS model was used to predict identified dynamical contact parameters at the holder-tool interface. The results revealed that the developed ANFIS model can very accurately predict the dynamical contact parameters in spindle-holder-tool assemblies.

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