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ADAPTIVE NETWORK BASED INFERENCE SYSTEM FOR CUTTING FORCE SIMULATION IN MILLING OF MULTI-LAYERED METAL MATERIALS

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Abstract: *This paper outlines the experimental research on cutting forces produced during ball-end milling of multi-layered metal materials manufactured by the laser engineered net shaping (LENS) process. The research employs an adaptive neuro-fuzzy inference (ANFIS) modelling technique for simulating the dynamic cutting force components during the machining of 16MnCr5/316L four-layered metal material with a solid carbide ball-end mill. A Kistler dynamometer was used to measure the actual cutting force, which was compared with the estimated one obtained via suggested procedure. Hardness and thickness of the particular manufactured layer in above mentioned advanced material have been considered during developing of the ANFIS models. Analysis of the developed models has been performed to test their validity. Model predictions were compared with experimental data and were found to be in good agreement. Experimental results demonstrate that this method can accurately predict cutting force within a maximum prediction error of 4.1%.*

Key words: *end-milling, cutting forces, functionally graded material, LENS, ANFIS.*

1. INTRODUCTION

The machining of multy-layerd functionally graded metal materials manufactured by LENS technology lead to undesirable effects such as tool breakage, rapid cutting tool wear, surface deterioration and shelling of the cladded layers (delayerization). These effects, especially delayerization, are directly connected to the cutting tool forces acting on the workpiece. Therefore, there is an interest to predict precisely the cutting forces during milling of these materials.

In milling the relationship between process characteristics and cutting forces is difficult to capture. This is due to the complexity of the relationship between cutting forces and process characteristics. In workshops, inspection of cutting forces is accomplished by on-line measurements. This approach is uneconomical. Therefore, an in-process method based on prediction model is required. Several models have been proposed to estimate the cutting forces. These include classical statistical approaches as well as fuzzy systems [1] and neural networks. No work has been found for multy-layered functionally graded metal materials in literature. Most of the research work reported in this regard, which is based on either analytical or semi-empirical approaches, has in general shown only limited levels of accuracy and generality. For instance researchers [2, 3] developed an approach based on regression for estimating cutting forces in machining while [4] have, respectively, used genetic programming for estimating cutting forces over a limited range of cutting conditions.

The capacity of artificial neural networks to capture nonlinear relationships in a relatively efficient manner has motivated a number of researchers to pursue the use of these networks in developing cutting force prediction models [5]. But in such models, the nonlinear relationship between sensor readings and cutting forces embedded in a neural network remains hidden and inaccessible to the user [6].

In this research we attempt to solve this situation by using the ANFIS system to predict the cutting forces. This model offers ability to estimate cutting forces as its neural network based counterpart but provides an additional level of transparency that neural networks fails to provide.

2. PREDICTIVE CUTTING FORCE MODELING

The aim of this research is to develop precise and reliable models for predicting cutting force components produced during machining of four-layered functionally graded metal materials. This chapter outlines the adaptation of the ANFIS topology to cutting force prediction problem. The cutting force prediction models are built according to the ANFIS method. The ANFIS method seeks to provide models for the prediction of cutting forces from the knowledge stored in the trained neural network. By given input/output data set, the ANFIS method constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using a backpropagation algorithm. This allows fuzzy systems to learn from the data they are modeling. FIS Structure is a network-type structure similar to that of a neural network, which maps inputs

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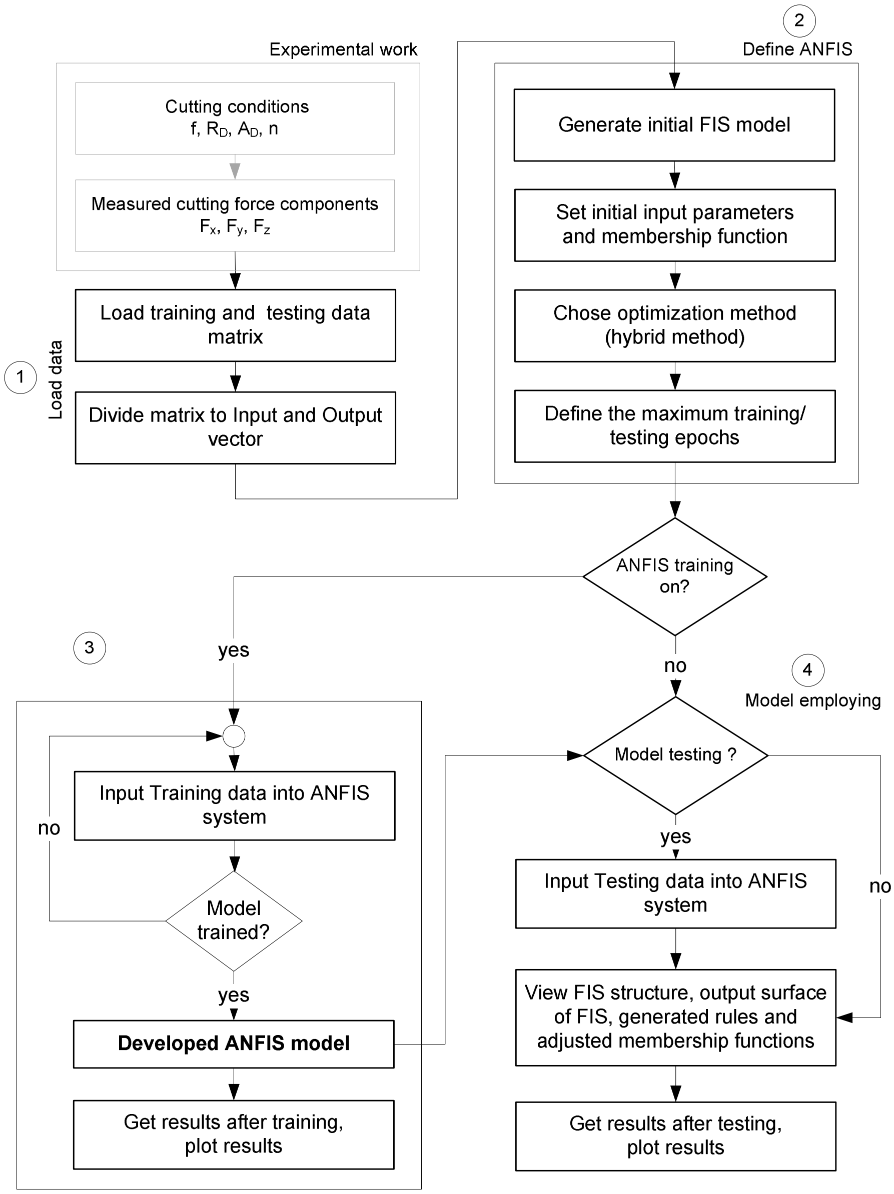

Fig. 1. Flow chart for training and employing the ANN based cutting force model.

through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs.

Fig. 1 shows the basic flow chart for predicting the cutting forces via ANFIS.

Four steps are required to develop an ANFIS system. In step 1, the training and testing data are loaded to the system. The process variables are spindle speed (*n*), feed rate (*f*), axial depth of cut (A_D), radial depth of cut (R_D), cutting tool diameter (*D*), hardness of the machined material (HV) and the layer thickness of functionally graded material (*d*). The inputs are the cutting conditions and LENS process parameters. The output is cutting force sensor signalThe whole data set is divided into the training and the testing set. 400 data points were used in this study. The training data set is used to find the initial premise parameters for the membership functions by equally spacing each of the membership functions. A threshold value for the error between the actual and desired output is determined. The FIS architecture and training parameters were defined in step 2. The optimization method, the tolerance error, the maximal number of epoch, the number of membership functions and the membership functions types are defined. The optimum training parameters were determined by the simulations. The optimum ANFIS model contains 36 if-then rules. The output from the ANFIS is one cutting force component; therefore, three ANFIS models are necessary.

In step 3, the training phase is accomplished. With the input–output data, the neuro-fuzzy algorithm is trained, and the unknown parameters are identified.

Figure 2 shows the inputs, membership functions, and the fuzzy inference system for cutting force prediction. During the training stage, the ANFIS adjusts its internal structure to give correct output results according to the input features. The process is terminated when the error becomes less than the threshold value.

During training in ANFIS, 400 sets of experimental data are used to conduct 500 cycles of learning. Training of the ANFIS can be stopped by two methods. In the first method, ANFIS will be stopped to learn only when the

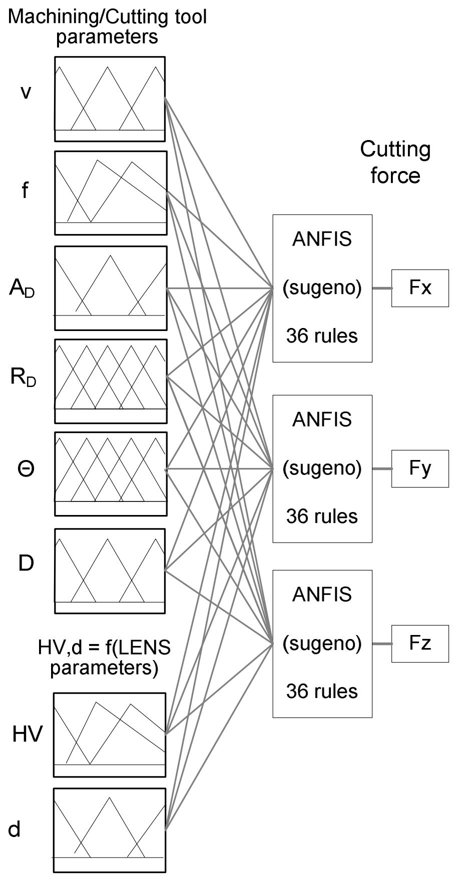

Fig. 2. Architecture of ANFIS cutting force models.

testing error is less than the tolerance limit. This tolerance limit would be defined at the beginning of the training. It is obvious that the performance of a ANFIS that is trained with lower tolerance is greater than ANFIS that is trained with higher tolerance limit. In this method the learning time will change with the architecture of the ANFIS. The second method to stop the learning is to put constraint on the number of learning iterations. In our study, the ANFIS architecture is stopped to learn after 400 training iterations. After the ANFIS models had been trained there were applied to 150 additional input-output data pairs that were excluded from the training process. This time the cutting force components (values of output vector) were not supplied, so that the trained network had to predict them. The predictions were compared to the cutting force measurements and the prediction errors were calculated. It was found out that the error of testing for the 150 examples was converged to 4.1%, which is higher than error of training (2.8%). The lowest error of testing is reached at iteration 350.

Finally, in the fourth step the trained ANFIS models are used to predict cutting forces. After the training, the inference system could estimate cutting forces from selected cutting conditions in real time. The developed ANFIS models can guide system or operator in tool change decisions making.

3. EXPERIMENTAL EQUIPMENT

To develop the cutting force prediction models, experimental results were used. Experiments were performed on a CNC machining platform Heller, under dry cutting conditionsv with FAGOR CNC controller.

The solid end milling cutter tornado with two cutting edges, of 8 mm diameter and 29.9° helix angle was selected for machining. The radius of the cutter edge is 4 mm. The cutter is made of a sintered tungsten carbide material (rode) K88UF with the hardness of 1770 HV in Emo orodjarna d.o.o. The cutting edges were coated with PVD-TiAlN coating.

The cutting forces were measured with a piezoelectric dynamometer (Kistler 9255) mounted between the workpiece and the machining table. The cutting force signals were monitored by using a fast data acquisition card (National Instruments NI 9215 A) and software written with the National Instruments CVI programming package.

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. These settings were limited by the available random access memory (RAM) of the computer. The digital data from the A/D board were then acquired and stored by the LabVIEW software into three files for the three force components. The data were also displayed on the computer monitor for inspection. The resultanat cutting force was then determined.

The data acquisition package used was LabVIEW. The experimental set up can be seen in Fig. 3.

The four-layered functionally graded metal material was used in experiments. The workpiece material is made of a 16MnCr5 basic material and 4 stainless steel (316L) layers with a singular 0.8–1.5 mm thickness, length of 50 mm and width of 15 mm.

The overall thickness of the multidirectional layer was 3 mm with length of 50 mm and width of 15 mm.

Nine such belts of stainless steel layers were welded on a singular workpiece with the 60 mm thickness, length of 180 mm and with of 70 mm.

By varying the two LENS process parameters (Laser power, speed of laser head), 9 different test workpieces of four-layered metal material with different layer hardness and thickness were produced on the Optomec LENS 850-R machine located in Emo orodjarna d.o.o.

In order to minimize the porosity of multilayered material the laser head trajectories during welding of two consecutive layers were programmed to be perpendicular.

These workpieces serve for the purpose of demonstrating the predictive model capabilities in milling a stack of layers of different directions. The weld overlapping in all layers was set to 40%. The diameter of laser ray was 0.8 mm.

The Vickers hardness of welded layers was measured by 7061 Zwick 3212 hardness tester.

Layer thickness (d) of the manufactured four-layered functionally graded metal material is measured by a visual layer thickness measurement algorithm. The developed algorithm is using cross-section metallographic images of cladded layers for thickness measuring.

The metallographic microscopic images for all manufactured test workpieces were obtained by a

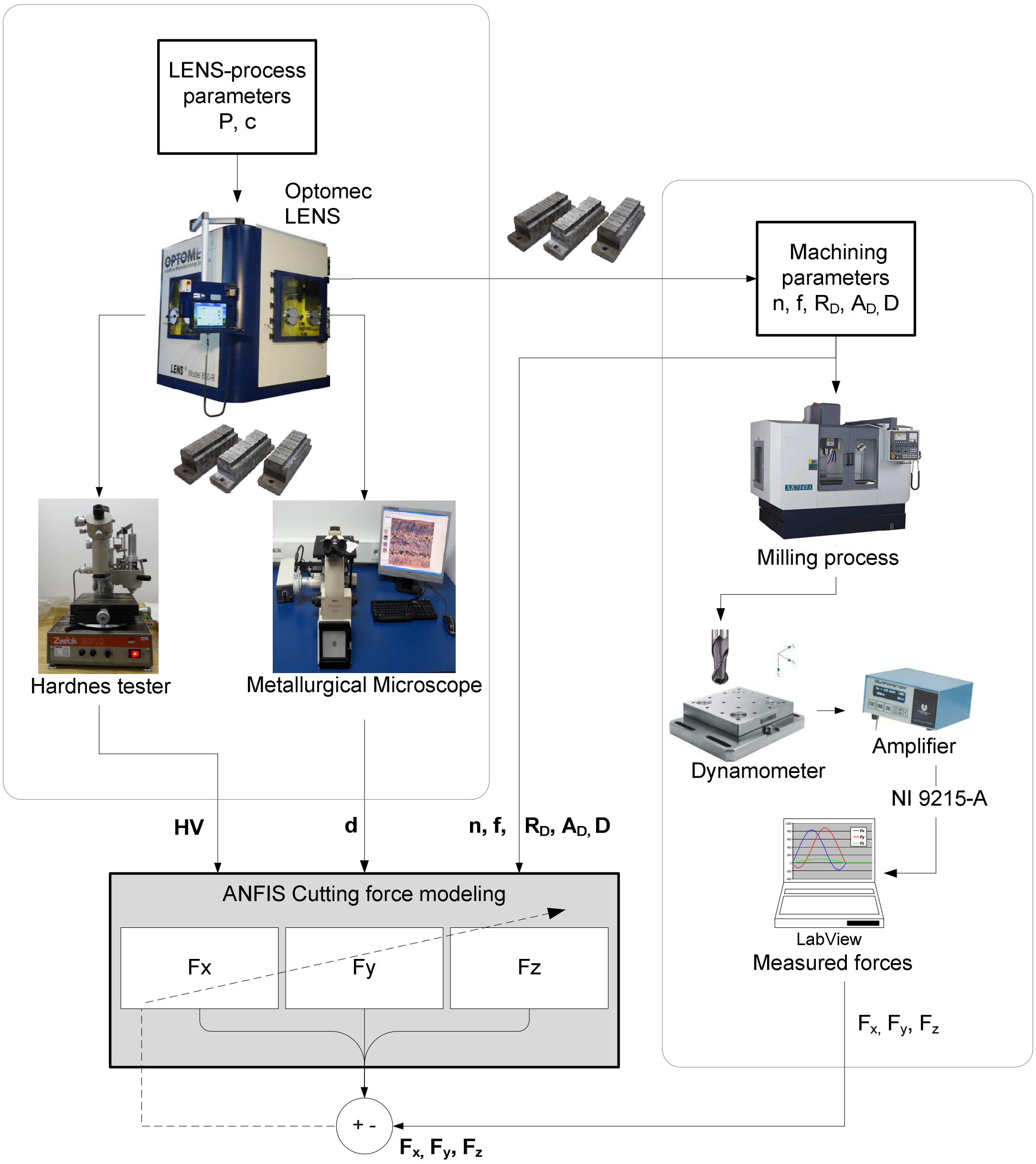

Fig. 3. Experimental set-up for cutting force modelling.

versatile Nikon Epiphot 300 Inverted Metallurgical Microscope.

4. EXPERIMENTAL PLAN

The experiments were carried out for all combinations of machining parameters and LENS process parameters.

Four and/or seven values for the radial and axial depth of cut have been selected: R_{D1} = 1.5 mm, R_{D2}=2 mm, R_{D3}=2.5 mm, R_{D4}=3 mm; A_{D1} = 0.1 mm, A_{D2}=0.2 mm, A_{D3}=0.3 mm, A_{D4}=0.4 mm, A_{D5}=0.5 mm, A_{D6}=1 mm, A_{D7}=1.5 mm.

The following values for spindle speed and feedrate have been selected: n_1 = 3000 min^{-1}, n_2 = 3200 min^{-1}, n_3 = 3600 min^{-1}, n_4 = 4000 min^{-1}; f_1 = 100 mm/min, f_2 = 150 mm/ min, f_3= 200 mm/ min, f_4= 250 mm/ min, f_5 = 300 mm/ min.

The combination of four values for the Laser power (P) and the cladding speed (c) was used to make the four-layered functionally graded material: P_1 = 300 W, P_2 = 360 W, P_3 = 380 W, P_4 = 400 W; c_1 = 30 mm/s, c_2 = 48 mm/s, c_3 = 55 mm/s, c_4 = 60 mm/s.

5. RESULTS AND DISCUSSION

This section presents the results of experiments and the comparison and analysis of results between the experimental and ANFIS models depending on the cutting parameters.

The results and/or the values of cutting forces are graphically represented by means of diagrams depending on cutting tool angle rotation. A total of 300 sets of data were selected from the total of 400 sets obtained in the end milling experiments for the purpose of training in ANFIS.

The other 100 sets were then used for testing after the training was completed to verify the accuracy of the predicted values of cutting forces.

The best results were obtained when triangular membership functions were chosen for the neuro-fuzzy models.

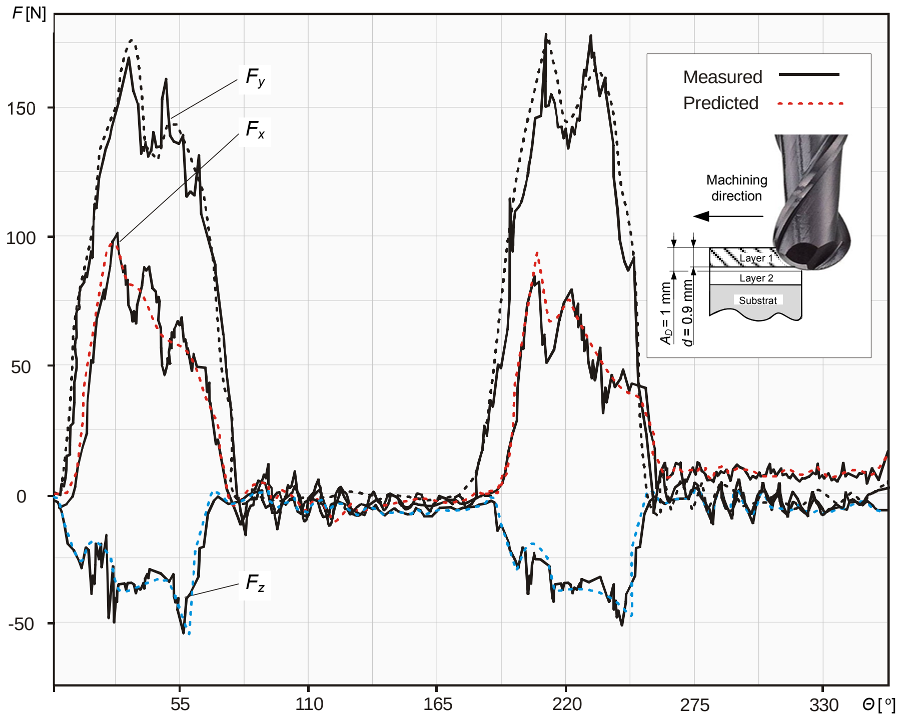

Fig. 4. Comparison between experimental and predicted forces for 16MnCr5 / 316L four-layered functionally graded material at high depth of cut; $A_D \approx d$; (Test No. 3).

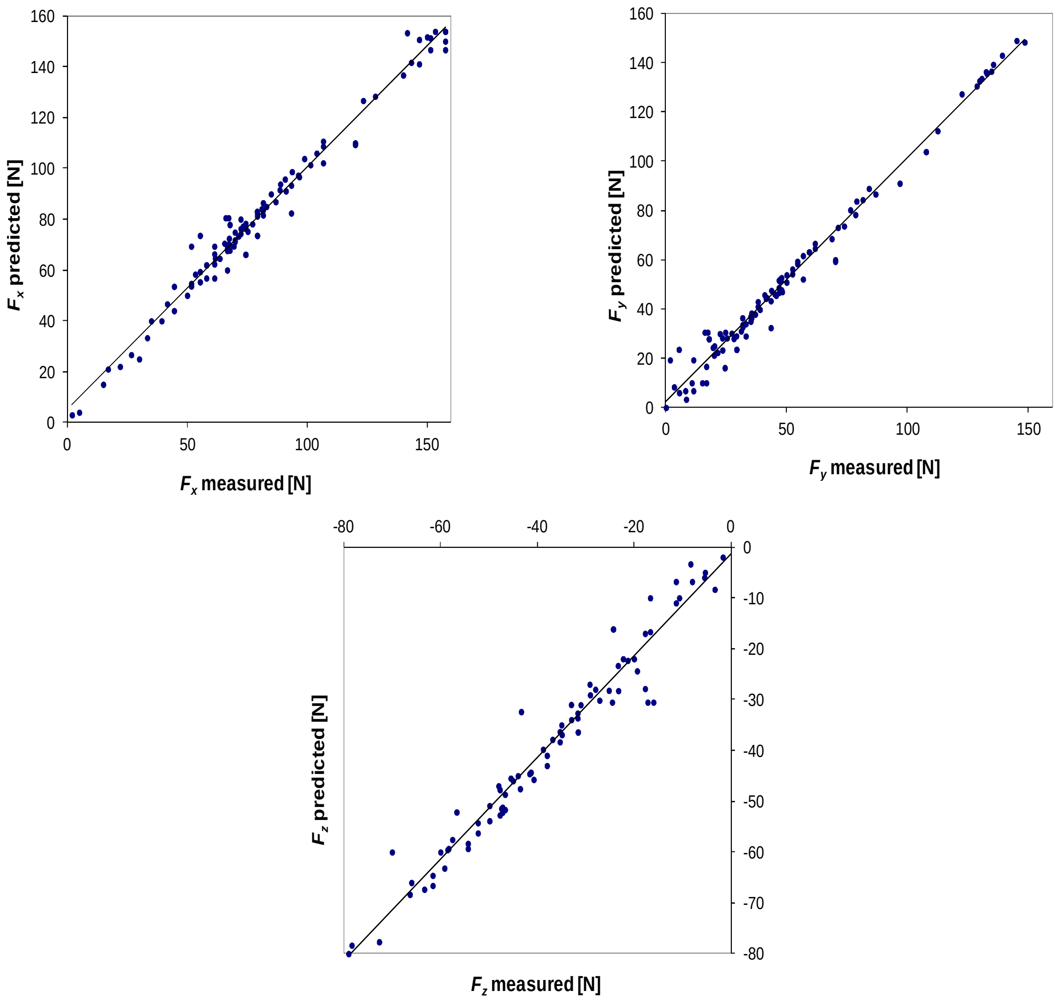

Fig. 5. Scatter diagram of measured and predicted forces for the testing data: *a* – Comparison of ANFIS predicted F_x with measured data; *b* – comparison of ANFIS predicted F_y with measured data; *c* – comparison of ANFIS predicted F_z with measured data.

During training of the neuro-fuzzy algorithm the parameters of membership functions, the optimal rules and the output weights were determined The smallest error of testing (ETest) is reached at iteration 145 (traingular Mf) and at iteration 107 for the Gaussian Mf.

Samples of the cutting forces obtained during ball-end milling of the four-layered functionally graded metal material are represented by continuous line. The directions of F_x, F_y and F_z are along the normal, feed and axial direction. The force signals outline the tool engagement in one revolution.

Fig. 4 shows the comparison of the predicted forces when triangular membership functions is used in ANFIS and the measured cutting forces.

By comparing the results predicted by ANFIS with the results of experiments the 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, with only slight differences in the peak and valley regions of F.

The cutting forces for milling at low axial depths of cut $A_D \approx 0.5d$ are higher than those for milling when the $A_D \approx d$. (Fig. 4). Force signals also exhibit more fluctuation. This is probably due to the material porosity at the border between separate stainless steel layers. The greatest difference between model predictions and experimental results appear in the normal force on the boundary region between two cladded stainless steel layers (Fig. 4).

The slight differences between the simulated and measured results are believed to be caused by the cutter runout, which is evident from the repeated tooth passing patterns in the measured forces.

Figue 5 shows the scatter diagram of the predicted values and measurement values of the F_x, F_y and F_z cutting forces of 100 sets of testing data. It shows that the predicted values of cutting forces follow the 45. line very closely. The predicted values are very close to the experimental measurement values.

The average error of the prediction of cutting forces is around 4.1% when triangular membership function is used in ANFIS.

The training was very fast, and the error reached a constant value after about 90 epochs. In this case, there were 36 rules in the fuzzy inference system. The prediction accuracy of ANFIS when the triangular membership function is used is higher than that when the trapezoidal membership function is used.

The maximum percentage prediction cutting force error is found to be less than 4.1% for all the cases tested.

In other words, the predicted values are not far from the experimental measurement values.

The system with incorporated ANFIS models was capable of predicting the cutting forces in real time. Wrong predictions accrued when the feed rate and rotational speed were low.

6. CONCLUSIONS

The research outlines an experimental investigation on the measurement of cutting forces during CNC end-milling operation of four-layered functionally graded metal material. Based on the experimental data an adaptive neural fuzzy inference models were developed to predict the cutting force components. The correlation between cutting force components, cutting conditions and LENS process parameters were determined via ANFIS modeling.

The solid carbide ball-end mill cutter with two flutes was used. Hardness (HV) and thickness (d) of the particular manufactured layer in multy-layered functionally graded material has been additionally included into the input vector of the prediction models in order to improve the accuracy of predictions.

The presented ANFIS model predicts cutting forces with 96% accuracy.

The trained ANFIS models are capable to predict cutting forces for various cutting conditions, LENS process parameters and tool parameters. The sensor signals and the measured cutting force was analyzed off-line and applied to a neuro-fuzzy method to determine the membership functions and rules.

An effort is made to include only the most significant machining/proces parameters that influence the cutting forces. The training of ANFIS with the triangular membership function obtains a higher accuracy rate in the prediction of cutting force. Comparison between the actual cutting forces and the simulated results from the neuro-fuzzy method showed good agreement.

The trained model can be used to monitor milling operations and provide warnings to an operator.

The following conclusions can be drawn from the study:

- The layer thickness has a significant influence on predicted cutting forces.
- Cutting forces for milling at low axial depths of cutting $A_D \approx 0.5d$ are higher than those for milling when the $A_D \approx d$. The force signals exhibit more fluctuation, probably due to the material porosity at the border between separate metal layers.
- The maximum prediction cutting force error is found to be less than 4.1% for all the cases tested.

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