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METHODOLOGY OF DEVELOPING OPTIMAL BP-ANN MODEL FOR THE PREDICTION OF CUTTING FORCE IN TURNING USING EARLY STOPPING METHOD *

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Abstract. *Predictive modeling is essential for better understanding and optimization of the machining processes. This paper presents the modeling methodology for predicting the cutting force in turning AISI 1043 steel based on artificial neural networks (ANNs). Based on the previous theoretical and experimental studies, a comprehensive analysis of the ANN training and architectural parameters is carried out in order to develop an optimal ANN model of high predictive performance. In order to improve generalization capabilities of the ANN models, early stopping (ES) method is used in ANN training. The ANN models trained with backpropagation (BP) training algorithm are developed using experimental machining data. The optimal 3-2-1 BP- ANN model is selected based on multiple statistical criteria. It was found that the 3-2-1 ANN model has very good prediction performance in terms of agreement with experimental data.*

Key words: *Artificial Neural Networks, Modeling, Early Stopping Method, Prediction, Turning, Cutting Force*

1. INTRODUCTION

Machining is one of the most important and widely used manufacturing processes. Predictive modeling is essential for better understanding and optimization of the machining processes. In turning processes, modeling and prediction of cutting performance such as cutting forces, tool wear and surface quality is of high importance. Study of cutting forces is critically important in turning operations [1] because cutting forces are directly related to surface quality, machined piece dimensions, tool wear, tool breakage, cutting temperature, self-excited and forced vibrations, and, moreover, with power requirements of the machine tool. The cutting forces are influenced by geometrical, dynamical, material and tool surface properties. In developing the performance prediction models there are three main modeling approaches: multiple regression technique, mathematical modeling

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based on the physics of the process, and artificial intelligence (AI) based modeling. AI based models are developed using artificial neural networks (ANNs), fuzzy logic (FL) and genetic algorithm (GA). In recent years, ANN models have become the preferred trend and are being applied by most researchers. ANNs offer a number of attractive features which makes them very popular for modeling complex processes. The learning ability of nonlinear relationship in a cutting operation without going deep into the mathematical complexity, or prior assumptions on the functional form of the relationship between inputs, in-process parameters and outputs makes ANNs an attractive alternative choice for many researchers to model cutting processes [2].

It should be noted that there are some drawbacks and limitations when using ANN modeling. Firstly, model parameters may be hard to interpret; identification of influential observations, and significance of various predictors may not be possible. Furthermore, when modeling with ANN some of the issues related to ANN architecture and training parameters need to be adequately solved, in order to prevent well known over-fitting and over-training problems. Only in this way is the development of high performance ANN models provided.

There are numerous applications of ANN based modeling of machining processes reported in the literature. The prediction of cutting forces in turning using the ANN approach can be found in [3][4][5]. In [3] BP-ANN was used for the selection of machining parameters and for the prediction of machining performance in terms of cutting forces, surface finish, and tool life using the data from handbooks. The authors noted that there is a lack of guidance on ANN design. Modeling of cutting forces using ANN methodology using experimental machining data is given in [4]. In model development, various training and architectural parameters are varied in order to obtain optimal values. Modeling of cutting forces in hard turning using experimental data is given in [5]. The optimization of ANN training and of architectural parameters is approximated by the regression equations obtained using data from training process.

In this paper the ANN modeling methodology is applied to the development of prediction model for cutting force in turning using early stopping (ES) method. With detailed analysis of ANN training and architectural parameters, ANN models are developed and trained using the backpropagation (BP) algorithm. Prediction accuracy of the all developed ANN models is statistically tested, and optimal ANN model is selected. The predicted cutting force values of selected optimal ANN model and experimental results are then compared.

2. EXPERIMENTAL DESIGN AND SETUP

The cutting force, during the cutting process, occurs due to resistance of work pieced material. The cutting force in turning is found to be affected in varying amounts by the parameters such as: cutting parameters, tool related parameters, properties of work piece material, environment parameters and size and shape of chip section. In the turning process, the resultant cutting force can be decomposed in three cutting force components which are acting on a single point tool as shown in Fig. 1. F_c is the cutting force (tangential force) acting on the rake face of the tool in the direction of motion of the work piece, F_f is the feed force (axial force), acting on the tool in the direction of tool movement and F_p is the passive force (radial force), acting on the tool in the radial direction, normal to the machined surface.

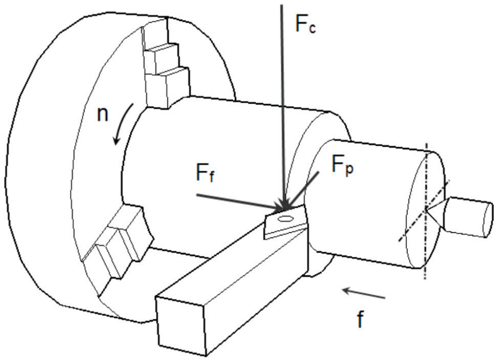

Fig. 1. Cutting forces in turning

The workpiece material used in this experiment is AISI 1043 steel: ultimate strength R_m=650 MPa, Brinell hardness HB=206. The cylindrical bar specimen that is utilized in these experiments has a diameter of 62 mm and length of 500 mm. Longitudinal turning is conducted on the universal lathe "Potisje" PA-C30, with a power of 11 kW. The workpiece is held in the machine with chuck and center to minimize run-out and maximize rigidity. Cutting tool is SANDVIK Coromant tool holder PCLNR3225P12 with insert CNNM120408P25 (4025), rake angle γ=-6˚, angle of inclination λ=-6˚, corner radius r_ε=0.8 mm. In order to ensure constant cross-sectional area of cut the cutting parameters are set as presented in Table 1.

Table 1. Cutting conditions

Cutting speed, v	[m/min]	97						
Feed rate, f	[mm/rev]	0.124	0.142	0.16	0.196	0.249	0.321	0.499
Depth of cut, a_p	[mm]	4	3.5	3	2.55	2	1.55	1
Cutting edge angle, κ	[degree]	45, 50, 55, 60, 65, 70, 75, 80, 85, 90						
Lubrication and cooling		None						

With the cutting parameters defined and according to their levels, 70 experiments were realized. The cutting force is measured with a three-component force dynamometer Kistler type 9441, mounted on the lathe via a custom designed adapter for the tool holder creating a very rigid tooling fixture. The signal generated at the dynamometer is amplified using amplifier Kistler type 5007A. The amplified signal is acquired and sampled by using computer Hewlett Packard HP 9000/300.

3. ANN BASED MODELING

ANNs are mathematical representations of the human brain function. They represent a new generation of information processing systems. ANNs are systems consisting of highly interconnected processing elements (neurons or nodes) that usually operate in parallel. The neurons, as basic elements of every ANN, are linked by weighted connections where the knowledge possessed by the networks is held.

In order to solve numerous problems a number of ANNs and training algorithms have been developed in the past years. There are about 30 different ANN architectures, which are being employed in research at present. The most used ANNs in modeling of machining processes are: multilayer perceptrons (MLP) also known as multilayer feedforward networks, adaptive resonance theory models (ART), self-organizing maps (SOM), radial basis function network (RBFN), etc. There are also numerous training algorithms. Especially used are some variations of back propagation (BP) training algorithm, conjugate gradient algorithms, quasi-Newton algorithms and Levenberg–Marquardt (LM) method.

The most popular ANN for modeling machining processes is MLP. There are a great number of training algorithms which can be used to train MLP such as: backpropagation algorithm (BP) and its variations, conjugate gradient algorithms, quasi-Newton algorithms and Levenberg–Marquardt (LM) algorithm.

The proposed ANN used for mathematical modeling of cutting force is a three layer feedforward backpropagation neural network (BP-ANN). Among the various neural networks models, back propagation is the best general-purpose model and probably the best at generalization [6]. A complete description of the algorithm and its derivations can be found in numerous sources, including [7][8].

The feedforward ANN is composed of many interconnected neurons which are grouped into input, hidden and output layer. The ANN knowledge is held by the interconnection weights which are adjusted during training process. The number of input neurons to the ANN model is equal to the number of independent variables, while the number of output neurons is equal to the number of functions being approximated by the model. Here, the inputs to the ANN model are the cutting parameters, namely depth of cut, feed rate and approaching angle. The ANN model output parameter is cutting force. Graphical representation of the proposed ANN model is shown in Fig. 2. For developing the ANN models software package MATLAB is used.

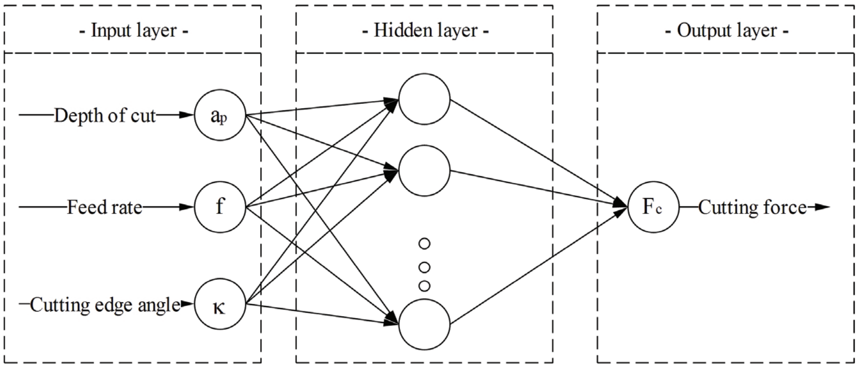

Fig. 2. ANN used for predicting cutting force

In ANN modeling, the choice of the ANN training and architectural parameters is the most important criteria that determine the degree of success of a ANN model. The selection of these parameters is basically problem dependent. However, there are some guides that help in ANN model development.

Generally, in order to develop optimal ANN model of high performance the following modeling steps must be considered carefully: 1) collection and preparation of data for training, validation and testing the ANN models, 2) selection of ANN training and architectural parameters, 3) ANN models training, and 4) testing the ANN models and analysis of the results.

3.1. Collection and preparation of data

Data collection and preparation is the first and crucial step in developing of ANN. Data preparation is an indispensable step in order to convert various data forms and types into proper format that is meaningful to the ANN. Usually the data preparation is done in the form of data normalization (scaling) to some standard ranges such as 0 to 1 or -1 to 1. In order to normalize the raw data of input and output the following normalization equation is used:

$$x_{norm} = 2 \cdot \frac{(x - x_{\min})}{(x_{\max} - x_{\min})} - 1 \qquad (1)$$

where x is the data to be normalized, i.e. depth of cut, feed rate, approaching angle, and x_{min} and x_{max} are minimum and maximum values of the raw data. In such a way, all the inputs and the desired outputs are normalized within the range of ±1. The recorded experimental data is given in Table 2. These data are divided into the three data sets: training data set, validation data set and test data set. The training, validation and testing data sets consist of 40, 20 and 10 data respectively. Selection of data for training, validation and testing is done by random method. The data is presented in Table 2.

Table 2. Training, validation and test set for ANN models

Trial	a_p [mm]	f [mm/rev]	κ [°]	F_c [N]	Trial	a_p [mm]	f [mm/rev]	κ [°]	F_c [N]
1**	0.5	0.499	45	511.2	36*	0.5	0.499	70	531.7
2*	0.775	0.321	45	491.9	37***	0.775	0.321	70	501.4
3*	1	0.249	45	519.3	38***	1	0.249	70	511.1
4**	1.25	0.196	45	538.8	39*	1.25	0.196	70	546.7
5*	1.5	0.16	45	600.1	40*	1.5	0.16	70	548.0
6***	1.75	0.142	45	601.5	41**	1.75	0.142	70	600.3
7**	2	0.124	45	662.7	42*	2	0.124	70	620.3
8*	0.5	0.499	50	567.7	43**	0.5	0.499	75	514.4
9**	0.775	0.321	50	501.7	44**	0.775	0.321	75	532.0
10**	1	0.249	50	530.4	45*	1	0.249	75	518.0
11*	1.25	0.196	50	547.8	46***	1.25	0.196	75	533.5
12*	1.5	0.16	50	575.5	47*	1.5	0.16	75	553.2
13***	1.75	0.142	50	618.3	48*	1.75	0.142	75	586.6
14**	2	0.124	50	634.8	49*	2	0.124	75	617.5
15***	0.5	0.499	55	527.9	50*	0.5	0.499	80	564.4
16***	0.775	0.321	55	521.2	51**	0.775	0.321	80	489.9
17*	1	0.249	55	500.7	52*	1	0.249	80	531.0
18*	1.25	0.196	55	553.6	53*	1.25	0.196	80	537.6
19*	1.5	0.16	55	570.0	54*	1.5	0.16	80	553.8
20**	1.75	0.142	55	583.1	55*	1.75	0.142	80	579.6
21*	2	0.124	55	627.6	56**	2	0.124	80	615.0
22*	0.5	0.499	60	526.1	57*	0.5	0.499	85	527.6
23*	0.775	0.321	60	536.8	58**	0.775	0.321	85	521.4
24*	1	0.249	60	522.0	59***	1	0.249	85	535.0
25*	1,25	0.196	60	522.7	60*	1.25	0.196	85	549.3
26**	1,5	0.16	60	576.4	61*	1.5	0.16	85	544.9
27**	1,75	0.142	60	615.9	62**	1.75	0.142	85	593.3
28***	2	0.124	60	622.3	63*	2	0.124	85	608.9
29*	0.5	0.499	65	538.8	64*	0.5	0.499	90	529.6
30**	0,775	0.321	65	514.3	65*	0.775	0.321	90	503.4
31**	1	0.249	65	518.4	66*	1	0.249	90	558
32**	1.25	0.196	65	539.1	67**	1.25	0.196	90	556.9
33*	1.5	0.16	65	556.5	68*	1.5	0.16	90	546.7
34*	1.75	0.142	65	609.3	69***	1.75	0.142	90	616
35*	2	0.124	65	619.2	70*	2	0.124	90	643.1

*, **, *** denotes training, validation and test data respectively

3.2. Selection of ANN training and architectural parameters

ANN training and architectural parameters have to be appropriately selected so that an optimal ANN model for the prediction of cutting force is developed. The most elementary method for selection of parameter settings is the use of a trial/error method. The most important training and architectural parameters are: learning rate, momentum, number of hidden layers, and number of neurons in hidden layer.

Learning rate and momentum control the speed and efficiency of the training process. Learning rate is the rate, at which the ANN adjusts its weights during training, hence it primarily affects the training speed. A high learning rate provides for faster convergence but the training process may become unstable and divergent oscillations may occur. With a small learning rate, the training time is increased, but the probability of reaching the global minimum is increased. Momentum is a training parameter used for the reduction of training as well as for the enhancement of the training stability. Typically, the learning rate is between 0.01 and 0.1 and the momentum rate is set to a value between 0.5 and 0.99 [9]. Some preliminary investigations have been carried out; it is decided to use average values for learning rate and momentum given in [9].

Determining the number of hidden layers and the number of neurons in each hidden layer can be a considerable task. It has been shown [10][11] that a multilayer ANN with one hidden layer and sigmoid transfer functions can approximate any function with arbitrary accuracy and this, therefore, reduces the problem of defining the ANN architecture to one of choosing the number of hidden neurons.

The number of neurons in the hidden layer is a primary parameter of the ANN architecture. Due to the full interconnection used between neurons, any increase in the neuron number leads to increasing net complexity as well as training speed. On the other hand, networks with more neurons in the hidden layer may solve more complex problems. However, an ANN with too many hidden neurons will generalize very badly which is a reflection of well known over-fitting problem.

The number of hidden neurons is a problem dependent. However, many researchers have proposed some empirical rules for addressing this problem. Reviewing the literature, one can see that recommended number of hidden neurons (h) is: $2 \cdot i+1$ [12], $2 \cdot i$ [13] i [14], $3/4 \cdot i$ [15], $o \div (i+1)$ [16], $(i+o)/2$; $N/10-i-o \leq h \leq N/2-i-o$ [17], $i \div o$ [18], where i, o are the number of input and output neurons and N is the number of training data.

It should be noted that the number of neurons in the hidden layers is data dependent. If an ANN has more degrees of freedom (the number of weights between neurons) than the number of training data, the ANN is mathematically undetermined. The number of weights is equal to the sum of the product between the numbers of neurons in each layer. It is easy to calculate that for three inputs and one output, the upper limit of number of hidden neurons is 10 for 40 training data.

Keeping in mind the previous suggestions the number of hidden neurons is varied. Six ANN architectures are developed, which are 3-1-1, 3-2-1, 3-3-1, 3-4-1, 3-6-1 and 3-7-1. However, in order to deeply examine the influence of the number of hidden neurons to the ANN model performance, it is decided to develop additional models which are 3-5-1, 3-8-1, 3-9-1 and 3-10-1.

3.3. ANN models training

The training of the ANN models is performed using the training data given in Table 2. The training data represents the input-output information which is used to modify the weights according to the BP algorithm. The initial values of weights are usually set by randomization within a specified interval, like ±0.5 or ±1. Prior to ANN training, the initial values of weight were set according to Nguyen-Widrow method [19] which is also one of the most popular ones. The data from the training data set are repeatedly presented in a random order to the ANN; the ANN weights are updated according to BP algorithm. When all the data points have been presented to the ANN, one epoch (iteration through the entire training data set) has taken place. It may take hundreds or thousands of epochs for ANN training. Increasing the number of epochs above needed may result in problem of "over-training". An ANN which is over-trained will learn the details of the training data rather than the underlying input-output relationship and is therefore likely to perform poorly (bad generalization) when given new data which it has not previously seen (the test data).

Two commonly used methods applied to overcome over-training problem, i.e. to decide when to stop training process, are early stopping (ES) and regularization methods. ES is widely used because it is simple to understand and implement and has been reported to be superior to regularization methods. In order to use the ES method, the available data must be divided into three sets:

1. Training set, used to determine ANN weights.
2. Validation set, used to check the ANN performance and decide when to stop the training process.
3. Test set, used to assess performance capabilities of developed ANN model.

A more detailed description of the ES method can be found in [20]. The methodology of ES method is graphically illustrated in Fig. 3.

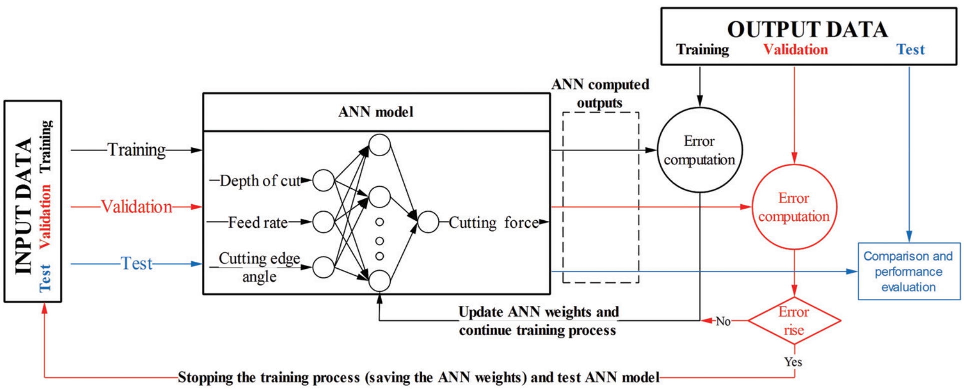

Fig. 3. Role of training and validation set in training process using ES method

The training of the ANN models for the cutting force prediction is carried out using the procedure "traingdm"[1] in MATLAB. The accuracy of the ANN models is evaluated by mean sum of squared error (MSE) between the measured and the predicted values for

[1] MATLAB command for the corresponding function

the training data set. Table 3 summarizes the ANN training parameters and architectural parameters used for developing the ANN models.

Table 3. ANN training parameters

Number of input neurons	3
Number of hidden neurons	1-10
Number of output neurons	1
Initial weights set by	Nguyen-Widrow method
Algorithm	BP
Learning rate	0.055
Momentum	0.745
MSE goal	0
Number of training epochs	1000
Transfer function in hidden layer	tan-sigmoid ("tansig")
Transfer function in output layer	linear ("purelin")

Fig. 4 shows the performance function as a function of the training epochs. As it can be seen, using the ES method, the training process for 3-2-1 ANN models is terminated at 621 training epochs when MSE reaches the value of 0.0485319.

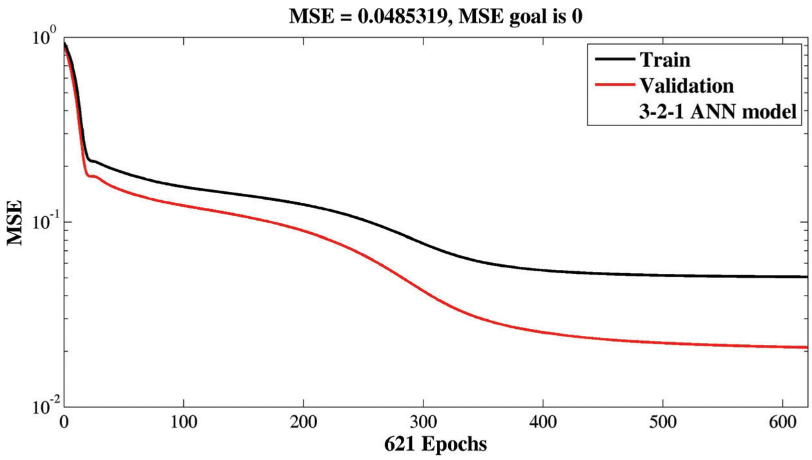

Fig. 4. ANN training performance graph

3.4. Testing the ANN models and analysis of the results

In order to estimate the prediction capability of the developed ANN models, the test data set is now used. Before estimating the performance of ANN models all the ANN outputs are renormalized by using:

$$x_{denorm} = \frac{1}{2} \cdot (o+1) \cdot (x_{\max} - x_{\min}) + x_{\min} \tag{2}$$

where o is the cutting force obtained from ANN model, and x_{min} and x_{max} are minimum and maximum values of the raw data for cutting force.

The statistical methods of root mean square error (RMSE), absolute fraction of variance (R^2) and mean absolute percent error (MAPE) values are used for estimating the prediction errors. These values are mathematically defined by the following equations:

$$RMSE = \sqrt{\frac{1}{p}\sum_{i=1}^{p}\left|t_i - o_i\right|^2} \tag{3}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{p}(t_i - o_i)^2}{\sum_{i=1}^{p}(o_i)^2} \right) \tag{4}$$

$$MAPE = \left(\frac{1}{p}\sum_{i=1}^{p}\left|\frac{t_i - o_i}{t_i}\right| \right) \times 100\% \tag{5}$$

where t is the i-th target value, o is the i-th predicted value and the p is the number of data. The smaller values (0 denotes perfect) of RMSE and MAPE indicate better prediction. On the other hand, the higher value of R^2 means better prediction (1 denotes perfect).

Table 4 illustrates the performance function of developed ANN models during training process as well as the predictions errors using the test data set.

Table 4. Statistical errors for the cutting force using various ANN models

Number of hidden neurons	Training performance function MSE	Test data set RMSE	R^2	MAPE
1	0.0632115	19.85085	0.998699	3.221093
2	0.0485319	**14.05298**	**0.999358**	**1.998486**
3	0.0865176	33.22376	0.996463	5.226565
4	0.0944527	27.24229	0.997596	4.480935
5	**0.0421309**	14.80886	0.999291	2.268626
6	0.0524625	15.62727	0.999203	2.055127
7	0.0674621	23.10197	0.998231	2.865835
8	**0.0444403**	21.66052	0.998471	2.613266
9	**0.0447151**	16.73396	0.999095	2.402412
10	**0.0337169**	13.74286	0.999407	2.177599

As it can be seen from Table 4, the best performance in training process does not guarantee the best prediction results when using the test data. It is obvious that the best performance function is achieved when training the ANN models with 5, 8, 9 and 10 neurons in the hidden layer. But when the developed models are tested using test data, it is clear that these models do not give the best prediction results. The ANN models with 2, 5, 6 and 10 hidden neurons have outperformed all developed models. Another criterion used for the ANN model selection is the training time. ANNs of smaller architecture have a smaller number of free parameters and hence require less training time. Generally, for both practical and theoretical reasons it is always desirable to use as smaller models as possible. Therefore, in the absence of a good reason to use the more complicated ones, the simpler 3-2-1 ANN model is chosen as optimal selection.

The prediction performance of the selected ANN model can be also analyzed based on the correlation coefficient (R) between the model predictions and the experimental values using both test data set and whole data set as presented in Fig. 5.

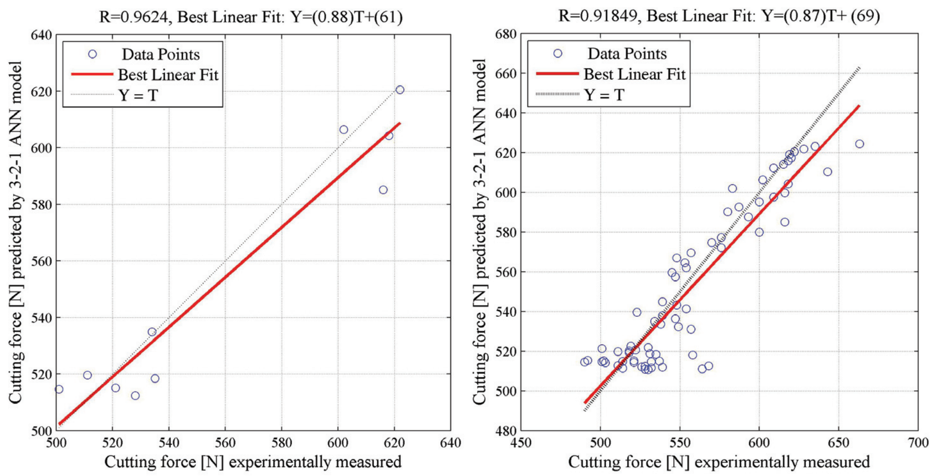

Fig. 5. The prediction performance of 3-2-1 ANN model for cutting force: (a) for test data set and (b) for whole data set

The correlation coefficient is a statistical measure of the strength of correlation between actual and predicted values. For example, the value of R=1 denotes perfect correlation. High value of R obtained for the whole data set, and R=0.96 obtained on test data set confirms good generalization capability of the selected 3-2-1 ANN model. Experimentally measured and predicted values of cutting force for 3-2-1 ANN model are compared in Fig. 6.

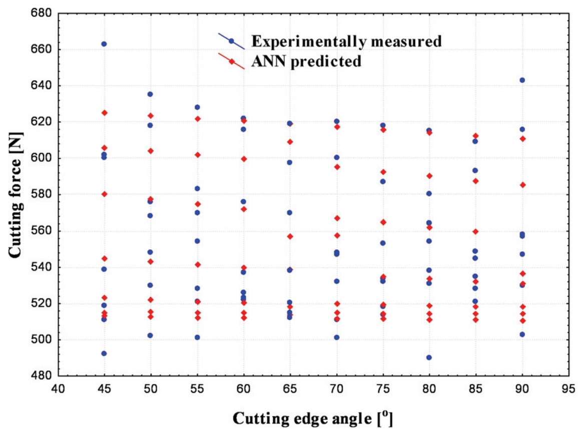

Fig. 6. Comparison of experimentally measured and ANN predicted cutting forces

4. Conclusion

In this paper the methodology of ANN based modeling, as a potential modeling technique, for developing optimal cutting force prediction model has been discussed. The discussion focuses upon ANN training and architectural parameters that have a huge impact on the performances of the developed models. In order to improve generalization performances of the developed ANN models, the ES method is applied. A series of experiments have been carried out in order to collect data for ANN training. The effects of depth of cut, feed and approaching angle on cutting force are used for developing ANN models. The investigation is particularly focused on determining the number of hidden neurons. Ten ANN architectures is created and trained using BP training algorithm with constant learning rate and momentum of 0.055 and 0.9 respectively. It is found that all the developed models have more or less good performance. However, the optimal 3-2-1 BP-ANN model is selected on the basis of three statistical criteria. A good performance is achieved with the selected BP-ANN model, with correlation coefficient between the model prediction and experimental values of 0.9624 for cutting force prediction using test data.

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METODOLOGIJA KREIRANJA OPTIMALNOG BP-VNM MODELA ZA PREDIKCIJU GLAVNOG OTPORA REZANJA KOD STRUGANJA PRIMENOM METODE RANOG ZAUSTAVLJANJA

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Predikciono modelovanje je od suštinske važnosti za bolje razumevanje i optimizaciju obradnih procesa. U ovom radu predstavljena je metodologija modelovanja za predikciju glavnog otpora rezanja kod struganja AISI 1043 čelika zasnovana na veštačkim neuronskim mrežama (VNM). Na osnovu prethodnih teorijskih i eksperimentalnih istraživanja, izvršena je sveobuhvata analiza VNM parametara strukture i treniranja, a sve u cilju kreiranja optimalnog VNM visokih predikcionih performansi. U cilju poboljšanja generalizacije modela VNM, primenjena je metoda ranog zaustavljanja (RZ) u procesu treniranja VNM. Treniranje modela VNM izvršeno je backpropagation (BP) algoritmom korišćenjem eksperimentalnih podataka. Optimalni 3-2-1 BP-VNM model je izabran na osnovu nekoliko statističkih kriterijuma. Utvrđeno je da 3-2-1 VNM model ima veoma dobre predikcione performanse u smislu slaganja sa eksperimentalnim podacima.

Ključne reči: *veštačke neuronske mreže, modelovanje, metoda ranog zaustavljanja, predikcija, struganje, otpori rezanja*