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PREDICTION OF DIMENSIONAL DEVIATION OF WORKPIECE USING REGRESSION, ANN AND PSO MODELS IN TURNING OPERATION

David Mocnik, Matej Paulic, Simon Klancnik, Joze Balic

Original scientific paper

As manufacturing companies pursue higher-quality products, they spend much of their efforts monitoring and controlling dimensional accuracy. In the present work for dimensional deviation prediction of workpiece in turning 11SMn30 steel, the conventional deterministic approach, such as multiple linear regression and two artificial intelligence techniques, back-propagation feed-forward artificial neural network (ANN) and particle swarm optimization (PSO) have been used. Spindle speed, feed rate, depth of cut, pressure of cooling lubrication fluid and number of produced parts were taken as input parameters and dimensional deviation of workpiece as an output parameter. Significance of a single parameter and their interactive influences on dimensional deviation were statistically analysed and values predicted from regression, ANN and PSO models were compared with experimental results to estimate prediction accuracy. A predictive PSO based model showed better predictions than two remaining models. However, all three models can be used for the prediction of dimensional deviation in turning.

Keywords: *artificial neural network, dimensional deviation, particle swarm optimization, regression*

Predviđanje dimenzionalnih devijacija obratka primjenom regresijskih, ANN i PSO modela u postupku tokarenja

Izvorni znanstveni članak

Budući da proizvodna poduzeća traže kvalitetnije proizvode, mnogo svojih napora troše na praćenje i reguliranje dimenzionalne točnosti. U ovom je radu za predviđanje dimenzionalne devijacije obratka pri tokarenju 11SMn30 čelika, primijenjen konvencionalni deterministički pristup, na primjer metoda višestruke linearne regresije i dvije metode umjetne inteligencije, "back-propagation feed-forward" umjetna neuronska mreža (ANN) i optimizacija roja čestica (PSO). Kao ulazni parametri uzeti su brzina osovine, brzina napajanja, dubina rezanja, tlak rashladnog fluida za podmazivanje i broj proizvedenih dijelova , a dimenzijska devijacija obratka kao izlazni parametar. Značaj pojedinih parametara i njihovi međusobni utjecaji na dimenzionalnu devijaciju su statistički analizirani, a vrijednosti predviđene regresijskim, ANN i PSO modelima uspoređene su s eksperimentalnim rezultatima kako bi se ocijenila točnost predviđanja. Model predviđanja zasnovan na PSO pokazao se boljim od druga dva modela. Međutim, sva se tri modela mogu koristiti za predviđanje dimenzionalnih devijacija kod tokarenja.

Ključne riječi: *dimenzionalna devijacija, optimizacija roja čestica, regresija, umjetna neuronska mreža*

1 Introduction

Due to increasing complexity of industrial production, necessity for stronger utilization, better adaptability, higher quality and lower costs, the production has changed over the last years. Production (cutting) process optimization has become a constant of present industrial production. Decisions regarding selection of cutting parameters importantly influence the level of production, production costs and the quality of product.

Thus, in the last years noticeable activities in the use of artificial intelligence methods at tool wear monitoring have been perceived. The tool wear itself is directly connected with a consecutive dimensional deviation of workpiece from the nominal value. On account of tool wear first the quality of treated surface is reduced, followed by increased deviations from required dimension of workpiece. If we are acquainted with the influence of each cutting parameter for tool wear level or dimensional deviation of workpiece and if we know how to predict this influence, we can directly influence the cutting process and by doing so we can assure that the end product will be within defined tolerances.

For this reason, in the present work the emphasis has been on developing a reliable model for predicting dimensional deviation and to experimentally investigate the role of cutting conditions on dimensional deviation of workpiece caused by tool wear in semifinish to finish turning 11SMn30 steel. Multiple linear regression model, artificial neural network model and particle swarm optimization model were developed for predicting dimensional deviation of workpiece in batch production. With the help of prediction of developed models we can change the tool offset value on CNC lathe and minimize dimensional deviation of workpiece from the nominal value.

With the use of artificial intelligence methods for predicting the dimensional deviations of workpieces the quality control costs are considerably reduced and the manufacturing speed is increased. Therefore, in the last years the determination of adequate cutting conditions to monitor dimensional accuracy and above all tool wear has become a field which is a subject of numerous researches.

Section 2 presents a brief literature review related to prediction of dimensional deviation and tool wear, Section 3 describes experimental details, Section 4 presents three models, multiple linear regression, artificial neural network (ANN) and particle swarm optimization (PSO), for predicting dimensional deviation and describes results. A short discussion and conclusions are given in Section 5.

2 State of the art

Literature concerning dimensional deviation prediction caused by tool wear is relatively sparse. A lot of researchers have investigated only tool wear, without researching the influence it has on dimensional deviation of a workpiece. Here, a brief review of tool wear and dimensional deviation, as well, is presented. Dimensional deviation in machining processes is found to be influenced in varying amounts by a number of factors, such as workpiece and cutting tool material, cutting conditions, time of cut, use of cutting fluids, etc. Various researchers studied the correlation of a few out of above mentioned several factors and presented many theoretical models to predict tool wear and/or dimensional deviation.

Sert et al. [1] investigated the correlation between the wear of PVD-TIAlN, CVD-TiN coated and uncoated cermet cutting tool and the change of workpieces dimensional deviation during serial machining of AISI 5140 steel. Kalidass et al. [2] developed a regression and an artificial neural network model to predict tool flank wear in end milling of AISI 304 austenitic stainless steel in terms of machining parameters such as helix angle, spindle speed, feed rate and depth of cut. A similar research was conducted by Palanisamy et al. [3]. In his work cutting speed, feed rate and depth of cut are taken as input parameters, while flank wear is taken as an output variable during milling of AISI 1020 steel. In these two works only the tool wear is investigated. Risbood et al. [4] used neural networks to predict dimensional deviation of slender workpieces ($L/D > 6$) by measuring cutting forces and vibrations in turning operation. His work is based on the definition, that dimensional deviation is the difference between applied depth of cut and obtained depth of cut. In his work a static stiffness of the machine – workpiece system has a significant contribution to dimensional deviation. Shahabi et al. [5] used response surface methodology in combination with design of experiment (DOE) or regression analysis to develop a model for predicting the dimensional deviation for given set of input parameters. Dimensional deviation of workpiece due to the two different feed rates is defined in this work as the difference between maximum heights of two superimposed surface profiles.

Some papers deal with experimental investigation in the role of cooling for dimensional deviation, surface roughness and tool wear in turning of different steels in industrial speed-feed combination by coated carbide inserts [6 ÷ 13]. The results show that cooling leads to better dimensional accuracy in respect of controlling the increase in diameter of finished job with machining time and helps to achieve better surface roughness and reduction of tool wear.

As the tool wear is the best indicator of dimensional deviation and vice versa, researches that are concerned only with the sphere of tool wear or tool life estimation are also very interesting. Özel et al. [14] developed neural networks models and multiple linear regression models for predicting surface roughness and tool flank wear. Experimental data was directly utilized to study the effects of cutting parameters on surface roughness, tool wear and mean machining force. Rafai et al. [15] presented a preliminary study into dimensional accuracy and surface finish achievable in dry turning. The Taguchi method and Pareto ANOVA analysis are used to determine the effects of major controllable machining parameters. Results show that in dry turning, cutting parameters such as cutting speed, feed rate and depth of cut have a significant influence on dimensional accuracy. More about tool wear can be found in [20].

The main purpose of this research is to study the influence of cutting conditions such as spindle speed, feed rate, depth of cut, pressure of cooling lubrication fluid and number of produced parts on tool wear and/or dimensional deviation of finished product and then to develop a prediction model. Although tool wear and surface roughness prediction are well studied and reported, the prediction of dimensional deviation of the workpiece was reported only by a few researchers. Also comparison of regression, ANN and PSO model prediction of dimensional deviation with experimental data has not yet been done for turning. For this reason, it is done in the context of our research and presented below.

Unlike the previous work on the prediction of dimensional deviation in turning, where dimensional deviation was derived from the tool wear (at the tip of the cutting edge), in this work direct experimental data of dimensional deviation for prediction of dimensional deviation of workpiece were used. Tool wear does not only influence dimensional deviation, but it also influences cutting forces and vibrations in the turning process, and for this reason we cannot (directly) generalize that the tool wear at the tip of the cutting edge expresses itself as double in deviation from the workpiece diameter.

3 Experimental details

For conducting the experiments a Dugard Eagle 200 CNC lathe with the motor power of 11 kW was employed and a CVD coated carbide cutting tool DCMT 11T308 (TP1500) was selected. It was clamped on a SDJCL 2020 tool holder.

Material used in experiments (turning) was free-cutting steel DIN 11SMn30 (AISI 1213) which finds application in automotive industries. Workpiece was a round-shaped bar, having diameter 40 mm and length 200 mm. In the test group with depth of cut 2 mm specimens were machined from diameter 40 mm to diameter 32 mm and in group with depth of cut 1 mm from diameter 40 mm to diameter 36 mm. The standard chemical composition of DIN 11SMn30 is listed in Tab. 1.

Table 1 Chemical composition of 11SMn30 (wt. %)

C	Si	Mn	P	S
< 0,14	< 0,05	0,90 –1,30	< 0,11	0,27 – 0,33

Experiments were conducted for various sets of machining (cutting) conditions, i.e. spindle speed (n), feed rate (f), depth of cut (a_p), pressure of cooling lubrication fluid (p) and number of produced parts (m). Input parameters and their levels were selected based on the experience of experts, on the tool manufacturer's recommendation and industrial practices. The parameters were set at two levels. Minimum and maximum levels of each influential factor are shown in Tab. 2.

Table 2 Influential factors and their levels

Influential factor	Units	Notation	Low level	High level
Pressure of cooling lubrication fluid	bar	p	2,5	15
Spindle speed	1/min	n	1800	3000
Depth of cut	mm	a_p	1	2
Feed	mm/rev	f	0,30	0,36
Number of produced parts	part	m	20	50

Dimensional deviations of the specimens from the nominal dimension were measured (and then calculated) by passameter.

4 Prediction of dimensional deviation

This section presents three dimensional deviation models and experimental results. The regression model, the ANN and PSO model were developed to predict dimensional deviation on experimentally measured dimensional deviation.

4.1 Development of regression model

Regression analysis is a statistical forecasting model that is concerned with describing and evaluating the relationship between a given variable usually called dependent variable and one or more other variables known as the independent variables [16]. Details of regression analysis can be found elsewhere [17].

Table 3 Variation design of influential factors according to Yates algorithm and measurement results (*MV*) in μm

Machining parameters in coded form						Influential factors					
Exp. no.	*A*	*B*	*C*	*D*	*E*	*p*	*n*	a_p	*f*	*m*	*MV*
1	-1	-1	-1	-1	-1	2,5	1800	1	0,30	20	9,5
2	1	-1	-1	-1	-1	15	1800	1	0,30	20	4,5
3	-1	1	-1	-1	-1	2,5	3000	1	0,30	20	10
4	1	1	-1	-1	-1	15	3000	1	0,30	20	6
5	-1	-1	1	-1	-1	2,5	1800	2	0,30	20	10,5
6	1	-1	1	-1	-1	15	1800	2	0,30	20	8,5
7	-1	1	1	-1	-1	2,5	3000	2	0,30	20	11,5
8	1	1	1	-1	-1	15	3000	2	0,30	20	8
9	-1	-1	-1	1	-1	2,5	1800	1	0,36	20	10
10	1	-1	-1	1	-1	15	1800	1	0,36	20	5
11	-1	1	-1	1	-1	2,5	3000	1	0,36	20	10
12	1	1	-1	1	-1	15	3000	1	0,36	20	6,5
13	-1	-1	1	1	-1	2,5	1800	2	0,36	20	11
14	1	-1	1	1	-1	15	1800	2	0,36	20	9
15	-1	1	1	1	-1	2,5	3000	2	0,36	20	11,5
16	1	1	1	1	-1	15	3000	2	0,36	20	9
17	-1	-1	-1	-1	1	2,5	1800	1	0,30	50	11,5
18	1	-1	-1	-1	1	15	1800	1	0,30	50	8,5
19	-1	1	-1	-1	1	2,5	3000	1	0,30	50	12,5
20	1	1	-1	-1	1	15	3000	1	0,30	50	9,5
21	-1	-1	1	-1	1	2,5	1800	2	0,30	50	13,5
22	1	-1	1	-1	1	15	1800	2	0,30	50	10
23	-1	1	1	-1	1	2,5	3000	2	0,30	50	15
24	1	1	1	-1	1	15	3000	2	0,30	50	10
25	-1	-1	-1	1	1	2,5	1800	1	0,36	50	12
26	1	-1	-1	1	1	15	1800	1	0,36	50	9
27	-1	1	-1	1	1	2,5	3000	1	0,36	50	13
28	1	1	-1	1	1	15	3000	1	0,36	50	9,5
29	-1	-1	1	1	1	2,5	1800	2	0,36	50	13,5
30	1	-1	1	1	1	15	1800	2	0,36	50	10,5
31	-1	1	1	1	1	2,5	3000	2	0,36	50	15,5
32	1	1	1	1	1	15	3000	2	0,36	50	10,5

The planning of experiments means prior prediction of all influential factors and actions that will result from new knowledge utilizing the rational research [21]. In the present work an experiment was conducted using Design of Experiments (DOE). Regarding the number of selected influential factors (and design order) we have decided on a multifactorial 1st order design. Our multifactorial design was composed of 5 influential factors, each of them appears in two levels, i.e. in low level (−1) and high level (1). The combinations of experiments of design 2^5 and measurement results are shown in Tab. 3. The number of experimental points was 32. Since the experiment was conducted 2 times in each experimental point, the total number of experiments amounts to 64. We gain 2^5 series of experimental results of dimensional deviation measurements, whereat each series is conducted with a selected combination of factors *A*, *B*, *C*, *D*, *E* and comprises two iterations. The average value of both measurements (*MV*) was used for the later work.

On the basis of measurement results the contrasts of main (k_A, k_B, k_C, ...) and all join (k_{AB}, k_{AC}, ...) effects were calculated, the significance of single factors and their interactive influences were statistically analysed, the mathematical regression model of the process (which is valid solely in the field of research) was developed, the adequacy of regression polynomial was tested and the polynomial was decoded. In spite of the fact, that there are quite numerous software programs for processing statistical data available, we have decided to use Microsoft Excel™.

4.1.1 A factor significance test

Using the Yates algorithm [17] the contrast values were calculated first. Contrasts enable more flexibility in the hypothesis testing process. In this way we can simply compare single experimental points or groups of experimental points and obtain for example an answer whether the factor influence at selected levels is significantly different or not. Values of calculated contrasts are shown in Tab. 4.

Table 4 Contrast values

k_o	649	k_{AD}	3	k_{ABC}	−15	k_{BDE}	1
k_A	−113	k_{AE}	−3	k_{ABD}	1	k_{CDE}	−1
k_B	23	k_{BC}	−5	k_{ABE}	−9	k_{ABCD}	1
k_C	61	k_{BD}	−1	k_{ACD}	3	k_{ABCE}	3
k_D	13	k_{BE}	5	k_{ACE}	−23	k_{ABDE}	−5
k_E	87	k_{CD}	1	k_{ADE}	−3	k_{ACDE}	1
k_{AB}	−7	k_{CE}	−9	k_{BCD}	3	k_{BCDE}	1
k_{AC}	7	k_{DE}	−1	k_{BCE}	5	k_{ABCDE}	−1

On the basis of calculated contrasts we carry out a factor significance test – *F*-test. Analysis of variance (ANOVA) is presented in Tab. 5.

The values of test statistics *F* are compared with critical value for the *F* distribution. In our case critical value of *F* at the p = 0,05 level of significance with (1, 32) degrees of freedom is 4,15. Values of *F* larger than 4,15 indicate that the model terms are significant. In this case, *A*, *B*, *C*, *E*, *A*B*C* and *A*C*E* are significant model terms.

The purpose of the analysis of the variance (ANOVA) is to investigate which design parameters significantly affect the quality characteristics [22]. It is evident from Tab. 4 and Tab. 5 that the factor which influences dimensional deviation the most in this concrete example is the pressure of cooling lubrication fluid, followed by the number of produced parts, depth of cut and spindle speed. Also the interaction pressure of cooling lubrication fluid/spindle speed/depth of cut and pressure of cooling lubrication fluid/depth of cut/ number of produced parts, show significance of contribution to dimensional deviation, as given by *F* – values above 4,15 for interactive terms. Interestingly, the feed rate and its interactions with other process parameters, is not significant.

Table 5: Analysis of variance according to F-test for testing the factor significance (ANOVA table)

Source of variation	Sum of squares SS	Degrees of freedom DF	Mean square MS	F - value	P - value
A	199,5156	1	199,5156	311,4390	0,000
B	8,2656	1	8,2656	12,9024	0,001
C	58,1406	1	58,1406	90,7561	0,000
D	2,6406	1	2,6406	4,1220	0,051
E	118,2656	1	118,2656	184,6098	0,000
$A*B$	0,7656	1	0,7656	1,1951	0,282
$A*C$	0,7656	1	0,7656	1,1951	0,282
$A*D$	0,1406	1	0,1406	0,2195	0,643
$A*E$	0,1406	1	0,1406	0,2195	0,643
$B*C$	0,3906	1	0,3906	0,6098	0,441
$B*D$	0,0156	1	0,0156	0,0244	0,877
$B*E$	0,3906	1	0,3906	0,6098	0,441
$C*D$	0,0156	1	0,0156	0,0244	0,877
$C*E$	1,2656	1	1,2656	1,9756	0,169
$D*E$	0,0156	1	0,0156	0,0244	0,877
$A*B*C$	3,5156	1	3,5156	5,4878	0,026
$A*B*D$	0,0156	1	0,0156	0,0244	0,877
$A*B*E$	1,2656	1	1,2656	1,9756	0,169
$A*C*D$	0,1406	1	0,1406	0,2195	0,643
$A*C*E$	8,2656	1	8,2656	12,9024	0,001
$A*D*E$	0,1406	1	0,1406	0,2195	0,643
$B*C*D$	0,1406	1	0,1406	0,2195	0,643
$B*C*E$	0,3906	1	0,3906	0,6098	0,441
$B*D*E$	0,0156	1	0,0156	0,0244	0,877
$C*D*E$	0,0156	1	0,0156	0,0244	0,877
$A*B*C*D$	0,0156	1	0,0156	0,0244	0,877
$A*B*C*E$	0,1406	1	0,1406	0,2195	0,643
$A*B*D*E$	0,3906	1	0,3906	0,6098	0,441
$A*C*D*E$	0,0156	1	0,0156	0,0244	0,877
$B*C*D*E$	0,0156	1	0,0156	0,0244	0,877
$A*B*C*D*E$	0,0156	1	0,0156	0,0244	0,877
Between (groups)	405,2344	31	13,0720	20,4052	
Within (error)	20,5000	32	0,6406		
Total	425,734	63			

4.1.2 Regression mathematical model

When we ascertain, with a test of significance that single factors and their interactive influences are not significant, their effects equal 0 and also the adequate coefficients of regression polynomial equal 0. Hence it follows that the less significant coefficients can be eliminated, without affecting much the accuracy of the model.

For polynomial coefficients calculation the contrast values from Tab. 4 were used. The regression mathematical model for dimensional deviation Y by neglecting the insignificant coefficients will be given by the following Eq. (1):

$$Y = 10{,}140625 - 1{,}765625A + 0{,}359375B + 0{,}953125C + 1{,}359375E - 0{,}234375ABC - 0{,}359375ACE \tag{1}$$

whereat A is the coded value of pressure of cooling lubrication fluid, B is the coded value of spindle speed, C is the coded value of depth of cut and E is the coded value of number of produced parts. The coefficients of the coded values also show which variable affects the output significantly.

4.1.3 Checking the adequacy of the developed model

In order to verify if a developed regression polynomial still predicts the response of a system well enough, the adequacy test is carried out. The predicted dimensional deviation values obtained using Eq. (1) are compared with the measured values and percentage of error for each experiment is given in Tab. 6.

It is evident that in most cases, the error in prediction is smaller than 10 %. The maximum error observed was 13,53 %.

Table 6 Comparison of predicted and measured values of dimensional deviation

Exp. no.	Measured values	Predicted values using regression	% Error
1	9,5	9,828	3,45
2	4,5	5,109	13,53
3	10,0	10,078	0,78
4	6,0	6,297	4,95
5	10,5	10,547	0,45
6	8,5	8,203	3,49
7	11,5	11,734	2,03
8	8,0	8,453	5,66
9	10,0	9,828	1,72
10	5,0	5,109	2,18
11	10,0	10,078	0,78
12	6,5	6,297	3,12
13	11,0	10,547	4,12
14	9,0	8,203	8,86
15	11,5	11,734	2,03
16	9,0	8,453	6,08
17	11,5	11,828	2,85
18	8,5	8,547	0,55
19	12,5	12,078	3,38
20	9,5	9,734	2,46
21	13,5	13,984	3,59
22	10,0	10,203	2,03
23	15,0	15,172	1,15
24	10,0	10,453	4,53
25	12,0	11,828	1,43
26	9,0	8,547	5,03
27	13,0	12,078	7,09
28	9,5	9,734	2,46
29	13,5	13,984	3,59
30	10,5	10,203	2,83
31	15,5	15,172	2,12
32	10,5	10,453	0,45

The F-test is conducted again. Calculation of variance for testing the model adequacy is shown in Tab. 7. In our case critical value of F at the p = 0,05 level of significance with (10, 32) degrees of freedom is 2,14. Based on this, we can determine that calculated F - value is larger than the tabulated value at a 95 % confidence level; hence, the model is considered to be adequate.

Table 7 ANOVA test results

Source	Sum of squares SS	Degrees of freedom DF	Mean square MS	F - value
Lack of fit	9,2656	10	0,9266	1,4463
Pure error	11,2344	22	0,5107	
Total error	20,500	32	0,6406	

4.1.4 Mathematical model decoding

As already written in one of the previous subsections, the variables A, B, C, D, E are coded – defined on scale -1 to +1 in this way that the actual variables n, f, a_p, p and m

are on low level at value -1 and on high level at value +1. The first order mathematical model in decoded form by neglecting the insignificant coefficients of the dimensional deviation Y is given in Eq. (2).

$$\begin{aligned} Y &= 12{,}603125 - 1{,}135p - 0{,}001042n - 3{,}066667a_p \\ &- 0{,}01m + 0{,}0001875pn + 0{,}5683333pa_p \\ &+ 0{,}0115pm + 0{,}0010938na_p + 0{,}0670833a_pm \\ &- 0{,}000125pna_p - 0{,}007667pa_pm. \end{aligned} \tag{2}$$

The polynomial enables the prediction of dimensional deviation as a function of spindle speed (n), depth of cut (a_p), pressure of cooling lubrication fluid (p) and number of produced parts (m). It was found out that feed rate (f) and its interactions with other process parameters are not significant, and for this reason are also not considered in Eq. (2).

Since the experiment introduced in this paper is based on 2^k design, a potential concern is the assumption of linearity in the factor effects. For the purpose of this experiment the 2^k design works quite well, even when the linearity assumption is true only very approximately [17]. The first order regression model is capable to describe some curvature in a response function. This is a consequence of surface bending, which is caused by interaction of influential factors.

4.2 Artificial neural network (ANN)

The principal characteristic of neural networks is that they are capable of finding the rule that connects output and input parameters, during the process of training. When the neural network is trained, it operates also in situations with which it did not encounter during the process of training.

In the present paper, the most commonly used technique, the feed-forward back-propagation neural network is adapted for the prediction of dimensional deviation in turning operation. It consists of an input layer (where the inputs of the problem are received), hidden layers (where the relationships between the inputs and outputs are determined) and an output layer (which emits the output of the problem).

The input parameters for the network are spindle speed (n), feed rate (f), depth of cut (a_p), pressure of cooling lubrication fluid (p) and number of produced parts (m). Input parameters are used to assess the dimensional deviation of turning process which is the output parameter of ANN.

On the basis of these values ANN defines the value of dimensional deviation of the turning process. For learning i.e. training and testing the neural network, which was created with assistance of Alyuda NeuroIntelligence software, all parameters were used, with the exception of the last three from Tab. 3. The last three parameters were used for validation of the neural network quality.

4.2.1 Topology of neural network

The number of neurons in an input layer is determined by the number of input parameters, so the input layer contains 5 neurons, since we have 5 input variables. The number of neurons in an output layer equals the number of output parameters, which, in the presented case, is one and this is the evaluated size of dimensional deviation of workpiece. The number of neurons in a hidden layer was determined by the number of experiments, on the basis of comparison of neural network properties with a diverse number of neurons in the hidden layer. Finally five hidden neurons were selected as the optimum number. Neural network topology of feed-forward three-layered back-propagation neural network is illustrated in Fig. 1.

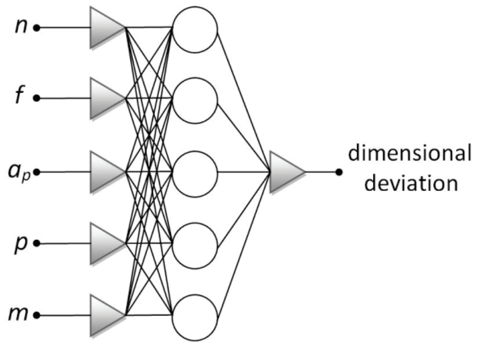

Figure 1 ANN model structure

4.2.2 Neural network training and results

After selecting the appropriate neural network topology we can start with the neural network training. Quite a few training algorithms are available. Irrespective of which algorithm we select, we have additional settings at each of them that enable better results. At selected algorithm of back-propagation a setting of two parameters is available – a learning rate and a momentum. Learning rate influences the stability of training algorithm and is designated with n. Momentum is designated with a and it takes care that we do not get stuck in local minimums during the training process. During the neural network training process we can also define the number of iterations or state the number of training cycles in order to gain final results. The second criterion that also brings us to final results is the setting at which absolute mistake the training should stop. After implementation of these criteria the training is concluded.

Data for training, testing and validating of neural network were selected as presented in Fig. 2.

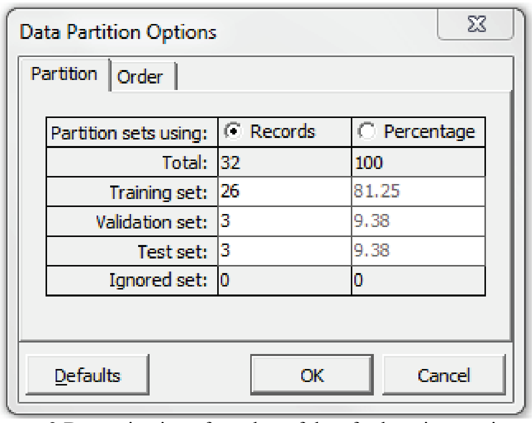

Figure 2 Determination of number of data for learning, testing and validating for our example

4.2.3 ANN model results

The final results were gained with the assistance of several experiments of training neural networks with diverse topologies. Each experiment was carried out with different parameters and settings. We have used the same final criteria for all experiments – conclusion of training by 50000th iteration. The times of training were diverse due to different learning rate settings *n* and momentum *a*. Finally, selected value of learning rate and momentum was 0,1.

The predicted values of dimensional deviation of workpiece by ANN model are given in Tab. 8. The predicted values of response by ANN are compared with experimental values. It is evident that in most cases, the error in prediction is small. Only in one case, the error was more than 10 %. Maximum error observed was 15,83 %.

Table 8 Results of neural network prediction

Exp. no.	Measured values	Predicted values using ANN	% Error
1	9,5	9,48	0,21
2	4,5	5,21	15,78
3	10	10,07	0,70
4	6	6,18	3,00
5	10,5	10,45	0,48
6	8,5	8,41	1,06
7	11,5	11,48	0,17
8	8	8,11	1,37
9	10	9,76	2,40
10	5	5,30	6,00
11	10	10,14	1,40
12	6,5	6,36	2,15
13	11	10,74	2,36
14	9	9,17	1,89
15	11,5	11,79	2,52
16	9	8,75	2,78
17	11,5	11,51	0,09
18	8,5	7,83	7,88
19	12,5	12,39	0,88
20	9,5	9,39	1,16
21	13,5	13,72	1,63
22	10	9,97	0,30
23	15	14,51	3,27
24	10	10,03	0,30
25	12	12,12	1,00
26	9	8,10	10,00
27	13	13,04	0,31
28	9,5	9,46	0,42
29	13,5	13,79	2,15
30	10,5	10,26	2,29
31	15,5	14,46	6,71
32	10,5	10,50	0,00

4.3 Particle swarm optimization (PSO) model

Another artificial intelligence technique for dimensional deviation prediction was used – PSO i.e. optimization with swarm of particles. It does not create an optimal solution, but searches for it [18]. The algorithm was written in Matlab.

PSO is a population-based stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by the social behaviour of a flock of birds [19]. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. Within iteration each particle is updated by following the two best values. The first one is the best solution (fitness) achieved so far. This fitness value is also stored and is called *pbest*. Another "best" value tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population. This best value is the global best and called *gbest*. After finding the two best values, the particle updates its velocity using the Eq. (3):

$$v_i = v_i + c_1\, rand()(p_i - x_i) + c_2\, Rand()(p_g - x_i) \quad (3)$$

and positions by Eq. (4):

$$x_i = x_i + v_i \,. \quad (4)$$

In Eq. (3) and (4), the designations have the following meanings:

- c_1 and c_2 are learning factors
- rand () and Rand() are random numbers between (0,1)
- $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ is a *i*-th particle
- p_i is the best position for the *i*-th particle in the history (p_{best})
- p_g is globally the best position among all particles (g_{best})
- v_i is the particle velocity.

For effective convergence of the system the adequate algorithm parameters must be selected, when using the PSO. For dimensional deviation prediction of workpiece with assistance of PSO-algorithm the following parameters were used:

- Number of swarm particles: 2500
- Number of iterations: 500 000
- Particle size: 26
- Acceleration coefficient c_1 (cognitive parameter): 1,8
- Acceleration coefficient c_2 (social parameter): 2,4.

4.3.1 PSO model results

Through evolution the developed system has searched the optimal coefficient values of the selected polynomial model given by the Eq. (5).

$$\begin{aligned} Y &= k_1 + k_2 p + k_3 n + k_4 a_p + k_5 f + k_6 m + k_7 pn \\ &+ k_8 pa_p + k_9 pf + k_{10} pm + k_{11} na_p + k_{12} nf + k_{13} nm \\ &+ k_{14} a_p f + k_{15} a_p m + k_{16} fm + k_{17} pna_p + k_{18} pnf \\ &+ k_{19} pnm + k_{20} pa_p f + k_{21} pa_p m + k_{22} pfm + \\ & k_{23} na_p f + k_{24} na_p m + k_{25} nfm - k_{26} a_p fm. \end{aligned} \quad (5)$$

The best solution proposed for calculation of dimensional deviation of workpiece *Y*, by algorithm is the following:

$$\begin{aligned}Y &= 7{,}3233-1{,}3288p+0{,}0013n+0{,}8978a_p\\&+10{,}9173f-0{,}0939m+2{,}2019\times10^{-4}pn+0{,}4619pa_p\\&+0{,}0387pf+0{,}0231pm-6{,}5908\times10^{-4}na_p\\&-0{,}0057nf+4{,}4330\times10^{-6}nm-4{,}9267a_pf\\&+0{,}0496a_pm+0{,}3090fm-1{,}2586\cdot10^{-4}pna_p\\&+8{,}4327\times10^{-5}pnf-2{,}5220\cdot10^{-6}pnm+0{,}4362pa_pf\\&-0{,}0077pa_pm-0{,}0183pfm+0{,}0028na_pf\\&+1{,}6631\times10^{-5}na_pm+4{,}4410\times10^{-6}nfm-0{,}1242a_pfm.\end{aligned}\tag{6}$$

With the Eq. (6) we can calculate (predict) the dimensional deviation achieved in turning by the proposed cutting parameters. Tab. 9 presents the prediction of dimensional deviation results with a use of model that is presented by Eq. (5), also for the data which were used in testing (test base) by PSO-algorithm. Test base was composed of three samples (Exp. no. 8, 17 and 27). Deviation of PSO model prediction regarding the conducted dimensional deviation measurements is also calculated.

It is evident from Tab. 9 that in most cases, the error in prediction is smaller than 3 %. Only in one case, the error was more than 25 %. In this case this sample was composing the test base.

Table 9 Results of PSO model prediction

Exp. no.	Measured values	Predicted values using PSO	% Error
1	9,5	9,63	1,37
2	4,5	4,61	2,44
3	10	10,1	1,00
4	6	6,12	2,00
5	10,5	10,75	2,38
6	8,5	8,38	1,41
7	11,5	11,46	0,35
8	8	10,05	25,63
9	10	9,95	0,50
10	5	5,12	2,40
11	10	10,23	2,30
12	6,5	6,52	0,31
13	11	10,99	0,09
14	9	9,15	1,67
15	11,5	11,72	1,91
16	9	9,1	1,11
17	11,5	11,58	0,70
18	8,5	8,57	0,82
19	12,5	12,63	1,04
20	9,5	9,52	0,21
21	13,5	13,39	0,81
22	10	10,15	1,50
23	15	15,28	1,87
24	10	10,05	0,50
25	12	12,16	1,33
26	9	8,93	0,78
27	13	13,03	0,23
28	9,5	9,79	3,05
29	13,5	13,67	1,26
30	10,5	10,54	0,38
31	15,5	15,58	0,52
32	10,5	10,54	0,38

5 Discussion and conclusions

In this work the basic aim of dimensional deviation prediction of workpieces has been fulfilled. With assistance of developed mathematical models and on the base of cutting parameters we can predict the dimensional deviation of workpiece. For prediction the conventional deterministic approach, such as multiple regression and two artificial intelligence techniques ANN and PSO were used. Comparison of results of error calculation results of prediction of dimensional deviation regarding the experimental measurements for each model is interesting and is presented in Fig. 3. This comparison has been depicted in terms of % error in Fig. 3.

The average error of predicted values regarding the experimental measurements of dimensional deviation was also calculated. The average error of regression model prediction equals 3,40 %, for ANN 2,58 % and 1,95 % for PSO.

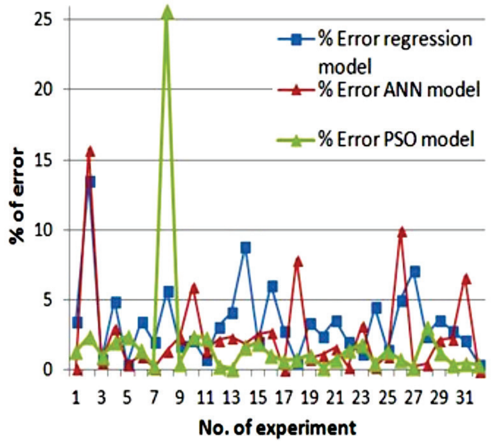

Figure 3 Comparison of errors in dimensional deviation

It is evident that the prediction errors are low, and also the differences among prediction errors of single model are very low, therefore all models are adequate for prediction of dimensional deviation, although the predictive PSO model was found to be capable of better predictions of dimensional deviation within the trained range.

In this work, it has also been shown that in the field of research the cooling lubrication fluid has the most significant effect of the parameters on the dimensional deviation, followed by the number of produced parts, depth of cut and spindle speed.

The ability to predict dimensional deviations caused by tool wear even before machining based on the input parameters, such as spindle speed, feed rate, depth of cut, pressure of cooling lubrication fluid and number of produced parts, will give manufacturers an advantage in terms of cost and time savings and less re-work or rejects. Knowledge about dimensional deviations helps the operator in selecting the appropriate machining parameters in order to maximize dimensional accuracy. This research is a good starting point for development of a system, which would automatically, on the training base, compensate the depth of cut itself and so assure that the end product would be within defined tolerances. In the future it is therefore provided to develop a system for an on-line compensation of the dimensional deviation in a turning process, based on dimensional deviation prediction.

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Authors' addresses

David Mocnik, BSc
Techne d.o.o.
Rakičan, Panonska ulica 36
9000 Murska Sobota, Slovenia
E-mail: david.mocnik@techne.si

Matej Paulic, BSc
University of Maribor
Faculty of Mechanical Engineering
Smetanova ulica 17, 2000 Maribor, Slovenia
E-mail: matej.paulic@um.si

Simon Klancnik, PhD
University of Maribor
Faculty of Mechanical Engineering
Smetanova ulica 17, 2000 Maribor, Slovenia
E-mail: simon.klancnik@um.si

Jože Balic, PhD
University of Maribor
Faculty of Mechanical Engineering
Smetanova ulica 17, 2000 Maribor, Slovenia
E-mail: joze.balic@um.si