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Prediction of thrust forces and hole diameters using artificial neural networks in drilling of AISI D2 tool steel with cemented carbide tools

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Abstract

In this study, the effects of cutting speed, feed rate and different types of coating materials on thrust force and hole diameter were investigated in drilling of AISI D2 cold work tool steel. In addition, the thrust forces and hole diameters were predicted by artificial neural networks (ANN) using experimental data. Uncoated, TiN, TiAlN monolayer and TiAlN/TiN multi-layer coated cemented carbide drills with diameter of 5 mm were used in drilling experiments. The holes were drilled at different combinations of four cutting speeds (50, 55, 60, 65 m/min), two feed rates (0.063 and 0.08 mm/rev), and fixed depth of cut (7 mm). Experimental results showed that the lowest thrust forces and hole diameters were obtained with TiAlN/TiN multi-layer coated drills. After ANN training, it was found that the R^2 values are very close to 1 for both training and test sets. RMSE values are smaller than 0.03, and mean error values are smaller than 5% for the test set. This case shows that ANN is a powerful method for prediction of thrust forces and hole diameters.

Key words: Coatings, Thrust force, Hole diameter, Artificial neural network

1. Introduction

Cutting force is one of the most critical outputs in cutting process. Cutting forces affects many results such as power consumption, surface roughness, roundness error and hole diameter [1]. Therefore, it is very important to specify ideal cutting parameters in measurement of lower cutting forces [2, 3]. Through improvements in coating technology, high speeds are reached in metal cutting process. In addition, tool coatings provide longer tool life, better surface finish and lower cutting forces. For example, due to TiN coatings with high hardness, the tool has a good crater wear resistance and low coefficient of friction [4-6]. In addition to the high hardness, TiAlN coatings have chemical stability, longer tool life and excellent machining performance. [7, 8]. The TiAlN coatings have also shown some interesting properties such as high fracture toughness, corrosion and wear resistance [9]. Also, the multilayer coatings were developed to provide higher wear resistance and hot hardness and lower chemical affinity with any work piece material [10]. It was reported that multi-layer TiN/TiAlN coatings had lower wear rate than monolayer TiAlN [11].

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ANN is an algorithm developed to predict new data by means of learning from some series of experimental data without external help [12, 13]. In recent years, ANN is frequently used the industrial field. [14, 15]. Aykut et al. [16] used ANN for modeling the effects of machinability on cutting parameters for face milling of stellite 6 in asymmetric milling processes. Results showed that the ANN can be effectively used for predicting the effects of machinability on cutting parameters. Benardos et al. [17] presented a neural network modeling approach for the prediction of surface roughness in CNC face milling. ANN predicted the surface roughness with a mean squared error equal to 1.86%. Mounayri et al. presented an integrated product development system for optimized CNC ball end milling. First, the developed model was extended from flat-end milling to ball-end milling. Second, the optimization was extended from 2D (speed and feed) to 3 (1/2) D (speed, feed, radial and axial depths of cut). Third, the modeling and simulation of the flat-end milling was extended to include more input variables. Finally, a new, more efficient and practical, neural network technique was introduced to replace the back-propagation neural network, and was successfully implemented for the case of ball-end milling. A very good match between predicted and experimentally measured process parameters was found [18].

The objectives of this study are to investigate the effects of cutting parameters on the thrust force and hole diameter, and to reduce number of complex and time-consuming experimental studies using ANN predictions.

2. Materials and Method

During experiments, AISI D2 cold work tool steel was used as workpiece material. In order to perform thrust force measurements, Kistler 9257B model dynamometer (Figure 2) was rigidly mounted to table of CNC vertical machining center.

Figure 2. Kistler 9257B trademark dynamometer

In order to fix workpiece to dynamometer, the specimens were cut with 170x100x12 mm dimensions, and two holes with 125 mm distance and 13mm diameter were drilled. Considering the hardness distribution around drilled hole, the distance between holes was carefully designed to be equal. So it was aimed to distribute the heat as equally as possible. The diameters of drills (d) were determined as 5 mm. In order to achieve ideal results at the end of drilling process, the length of hole was determined as 7 mm which is less than 15 mm (d x 3) [19, 20]. The chemical composition of AISI D2 cold work tool steel is given in Table 1.

Table 1. The chemical composition of AISI D2 cold work tool steel

C%	Si%	Mn%	Cr%	Ni%	Mo%	V%
1.003	0.134	0.271	11.88	0.193	0.693	0.713

During the experiments, 4 different sets of drills belonging to Guhring Company (uncoated, PVD-TiN, PVD-TiAlN monolayer, and PVD-TiAlN/TiN multilayer coated). The dimensions of drills used in experiments are given in Figure 1 and Table 2.

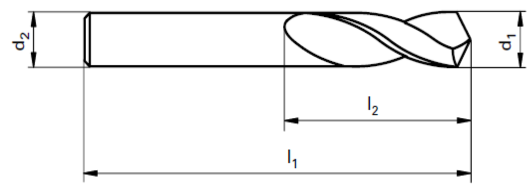

Figure 1. Drill dimensions

The properties of sets with same dimensions are in Table 2.

Table 2. Tool properties

	Properties
Tool type	Twist drill
Standard	DIN 6539
Coatings	Uncoated, TiN, TiAlN, TiAlN/TiN
Diameter (d_1, d_2)	5 mm
Tip angle	135º
Helix angle	35º
Helix length (l_2)	26 mm
Length (l_1)	62 mm

Additional to set properties, the properties of different coating materials are in Table 3 with details.

Table 3. Coating properties of the coated drills.

	TiN-PVD	TiAlN-PVD	TiAlN/TiN -PVD
Tool material	Cemented carbide	Cemented carbide	Cemented carbide
Tool diameter (mm)	5	5	5
Coating thickness (μm)	2.5	2.5	4
Hardness (HV 0.05)	2200	3300	3600
Coating type	Monolayer	Monolayer	Multi-layer
Number of layers	1	1	6
Friction coefficient	0.25	0.3	0.3

The experimental studies were performed in Johnford VMC–550 trademark CNC vertical machining center. The measurement of diameter of holes was performed with Mitutoyo trademark CRT-A C544 model 3D CMM (Coordinate Measuring Machine). Cutting speed and feed rate were determined after preliminary drilling experiments and examination of the catalogue of Guhring Company. During the experiments; 4 different drills, 4 different cutting speeds (50, 55, 60, 65 m/min), 2 different feed rates (0.08 mm/rev for 0.063), and constant depth of cut (7 mm) were used, totally 32 experiments were performed.

2.1. Artificial neural network

ANN consists of artificial neurons. ANN has three main layers (input, hidden and output layers) [21]. Neurons in input layer transfer data from external world to hidden layer. In hidden layer, outputs are produced by using data from neurons in input layer, bias, and summation and activation functions. In the output layer, the output of network is produced by processing data from hidden layer and sent to external world. The summation function calculates net input coming to a cell. The most common function is to calculate the weighted sum. Inputs are the knowledge from other cells or external world to the input cells. Weights (w_1, w_2 …w_n) are the values which determine the effect of input set or another processing element in previous layer on the processing element. Each input value is multiplied by weight value which connects it to the processing element, and then it is combined by summation function. Thus, net input of the network can be found. Activation function provides a curvilinear match between input and output layers. In addition, it determines the output of the cell by processing net input to the cell. Selection of appropriate activation function significantly affects network performance. Recently, logistic sigmoid transfer function has been commonly used as an activation function in multilayer perceptron model. For this reason, the logistic sigmoid transfer function was used in this study. There are many learning algorithms in order to determine weights in artificial neutral network. One of the most common learning algorithms is back propagation. The back propagation method updates the weights in accordance with difference between available data and network output. Learning parameter used in the method has a great importance in order to reach the optimal results. Learning parameter can be constant or dynamically updated in the model. There are various training functions such as Bayesian regularization, gradient descent with adaptive learning rule, gradient descent with momentum and adaptive learning rule, scaled conjugate gradient and Levenberg–Marquardt. In order to acquire the closest output values to experimental results, the best learning algorithm and optimum number of neurons in hidden layer was determined. For this reason, both SCG and LM learning algorithms and different numbers (3-10) of neurons in hidden layer were used in the built network structure for thrust force [22].

Table 4. Statistical data for the thrust force

Learning algorithm	Network structure	THRUST FORCE					
		Training data			Test data		
		R^2	RMSE	MEP	R^2	RMSE	MEP
SCG	3-3-1	0.018629	0.998214	6.454113	0.032572	0.993781	7.584499
	3-4-1	0.006953	0.999752	2.217500	0.024632	0.996319	8.218417
	3-5-1	0.009279	0.999558	2.605711	0.026415	0.995239	11.449130
	3-6-1	0.006191	0.999803	2.150960	0.020266	0.997291	9.010987
	3-7-1	0.006200	0.999803	1.917535	0.012098	0.999053	6.129984
	3-8-1	0.006173	0.999805	2.061780	0.025690	0.995700	12.296259
	3-9-1	0.006131	0.999807	2.037776	0.038658	0.990367	15.969927
	3-10-1	0.006004	0.999815	1.981031	0.026479	0.995166	11.053018
LM	3-3-1	0.015192	0.998814	4.865211	0.029990	0.994247	10.803812
	3-4-1	0.005517	0.999843	1.667968	0.028017	0.995080	10.860849
	3-5-1	0.006091	0.999809	2.045453	0.017124	0.998177	5.767293
	3-6-1	0.006107	0.999809	2.165246	0.016875	0.998160	6.068789
	3-7-1	***0.005758***	***0.999830***	***1.782205***	***0.009454***	***0.999408***	***4.686014***
	3-8-1	0.005768	0.999831	1.645321	0.021584	0.997086	10.074594
	3-9-1	0.005818	0.999826	1.782259	0.022330	0.996934	10.294473
	3-10-1	0.005137	0.999865	1.164660	0.029407	0.994842	12.308946

In consequence of trials, the best learning algorithm and network architecture for prediction of thrust force became LM: 3-7-1. Determination of the best learning algorithm and optimal number of neurons for the thrust force is demonstrated in Table 4. The best learning algorithms and ANN architecture for the hole diameter are given as LM: 3-5-1, respectively. Determination of percentages of training and test data has an important role for building of ANN architecture. 32 experimental results were prepared for training and test data of ANN. In this context, 6 data for test and 26 data for training were randomly selected. The digits for the cutting tool to be entered into the ANN were denoted as TiN = 1 TiAlN, = 2, TiAlN/TiN = 3 and uncoated = 4 because they do not have numerical values [23]. All the values measured in the experiments are given in Table 5.

Table 5. All experimental data

Experiment no	Coating material	Cutting speed (m/min)	Feed rate (mm/rev)	Thrust force (N)	Hole diameter (mm)
1	TiN	50	0.063	575	5.0039
2	TiN	55	0.063	570	5.0029
3	TiN	60	0.063	568	5.0016
4	TiN	65	0.063	576	5.0024
5	TiN	50	0.08	694	5.0049
6	TiN	55	0.08	674	5,0035
7	TiN	60	0.08	668	5.0022
8	TiN	65	0.08	669	5.0030
9	TiAlN	50	0.063	585	5.0045
10	TiAlN	55	0.063	581	5.0034
11	TiAlN	60	0.063	578	5.0025
12	TiAlN	65	0.063	590	5.0033
13	TiAlN	50	0.08	705	5.0052
14	TiAlN	55	0.08	685	5.0044
15	TiAlN	60	0.08	680	5.0032
16	TiAlN	65	0.08	690	5.0037
17	TiAlN/TiN	50	0.063	573	5.0026
18	TiAlN/TiN	55	0.063	565	5.0016
19	TiAlN/TiN	60	0.063	554	5.0009
20	TiAlN/TiN	65	0.063	568	5.0013
21	TiAlN/TiN	50	0.08	686	5.0041
22	TiAlN/TiN	55	0.08	671	5.0025
23	TiAlN/TiN	60	0.08	665	5.0018
24	TiAlN/TiN	65	0.08	669	5.0023
25	Uncoated	50	0.063	771	5.0044
26	Uncoated	55	0.063	755	5.0035
27	Uncoated	60	0.063	747	5.0024
28	Uncoated	65	0.063	731	5.0023
29	Uncoated	50	0.08	900	5.0062
30	Uncoated	55	0.08	875	5.0052
31	Uncoated	60	0.08	850	5.0042
32	Uncoated	65	0.08	820	5.0041

In back propagation model, scaling of inputs and outputs dramatically affects performance of artificial neural network. As mentioned above, logistic sigmoid transfer function was used in this study. One of the characteristics of this function is that only a value between 0 and 0.9 can be produced. In this study, the input and output values were normalized between 0 and 0.9 using formula in Eq. 4.

$$nd_i = 0.8 \times \left(\frac{\mathrm{d}_{\min} - \mathrm{d}_{\mathrm{i}}}{d_{\min} - d_{\max}} \right) + 0.1 \qquad (4)$$

Where, d_i and nd_i *are* i_{th} data and i_{th} normalized data, respectively; d_{min} and d_{max} are minimum and maximum data in whole data, respectively. To understand whether an ANN is making good predictions or not, the test data that has never been presented to the network is used, and the results are checked at this stage. RMSE (root mean square error), R^2 (determination coefficient) and MEP (mean error percentage) values have been used for comparisons [13].

3. Experimental results and discussion

3.1. Cutting Forces

While the measured thrust force values were evaluated in drilling the AISI D2 cold work tool steel (Figure 3), the lowest thrust force values were obtained with TiAlN/TiN multilayer coated drills in all measurements due to their higher wear resistance. For all cutting conditions, it was found that thrust forces were always higher in uncoated drills than those in coated drills. The thrust forces obtained in TiN coated drills were better than those obtained in TiAlN coated drills. It is thought that thrust forces were found low as a result of low friction coefficients of TiN coatings [2, 4, 5]. The lowest value measured with a TiAlN/TiN coated drill is 554 N at feed rate of 0.063 mm/rev and cutting speed of 60 m/min. When evaluating the thrust forces according to feed rates (Figure 3), thrust force values remarkably increased with increasing feed rate. It can be thought that increasing chip section as a result of increasing feed rates affected thrust forces negatively. Although there are many effects affecting thrust forces, cutting speed and feed rate affect at most [24, 25]. Considering the thrust force, 0.063 mm/rev is the ideal feed rate.

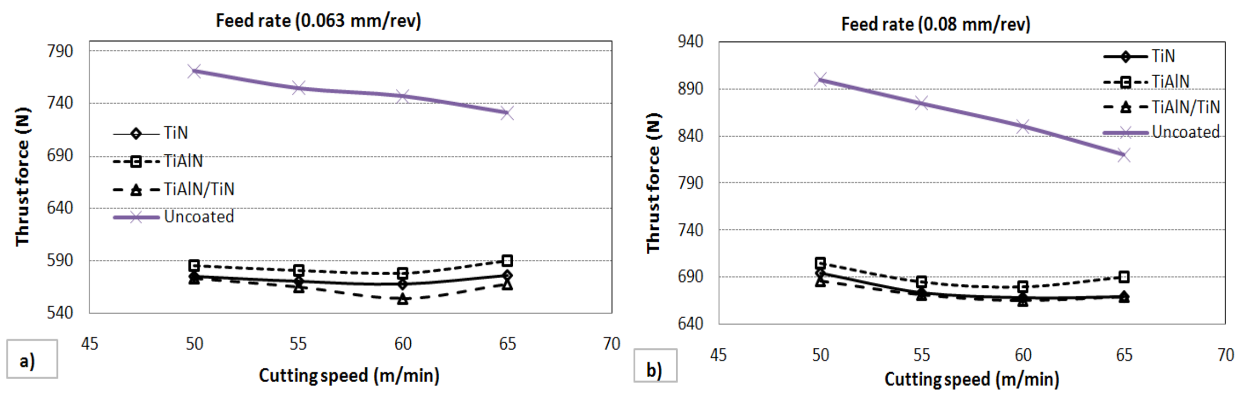

Figure 3. Thrust forces according to cutting speeds and drill types, a) 0.063 mm/rev b) 0.08 mm/rev.

The decrease of cutting speed increases the amount of temperature transferred to work piece, so it increase the temperatures in cutting zone [2]. The thrust forces slightly decreased until cutting speed of 60 m/min because plastic deformation facilitated with increasing temperatures in cutting zone. In addition, certain high levels of cutting speed are important lifetime of the drills [24-26]. At especially cutting speed of 65 m/min, the thrust forces increased owing to rapid tool wear. The best result was obtained at cutting speed of 60 m/min.

3.2. Hole diameters

When analyzing the hole diameters measured at the end of experiments, it is seen that there is a relationship between hole diameters and thrust forces. Higher cutting force leads to lower hole quality. When considering the values obtained in higher feed rates (Figure 4.), it is seen that increasing feed rates lead to increases in a hole diameter. In parallel with increasing cutting forces, hole diameter values also increased as a result of increasing feed rate. Higher feed rates lead to higher thrust forces. It can be said that the vibration as a result of increasing thrust forces may affect hole diameters negatively. The temperatures occurring as a result of increasing cutting speed lead to easy plastic deformation and removing of chips more fluently. So, the hole quality improves. It can be said that good hole diameter can be obtained with better chip removal. As a result of experiments, the hole quality was found better at cutting speed of 60m/min.

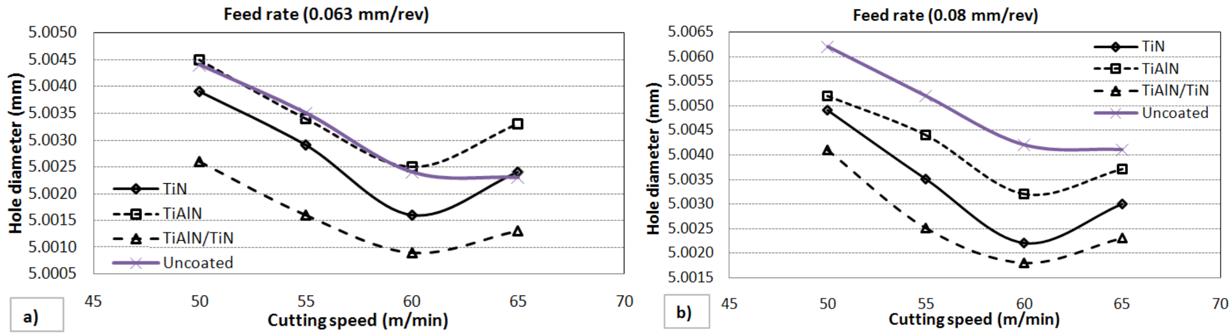

Figure 4. Holes diameters according to cutting speed and drill types, a) 0.063 mm/rev b) 0.08 mm/rev.

When comparing the diameters of holes drilled using different drill types, the quality of holes drilled with multilayer coated drills was found as better due to their lower thrust forces. Also it was seen that the hole quality was worse in uncoated drills. The best hole diameter value (Ø5.0009 mm) was obtained with TiAlN/TiN coated drill at cutting speed of 60 m/min and feed rate of 0.063 mm/rev.

3.3. Prediction of thrust force and hole diameter with ANN

The aim of using the ANN model is to test the ability to the thrust force and hole diameter. In this study, a computer program was developed in MATLAB platform to predict the thrust force and hole diameter. The network has three input parameters. These are coating type (Ct), cutting speed (V) and feed rate (f). Optimal statistical values obtained for each output parameter are given in Table 6. As shown in Table 6, it was shown that R^2 are close to 1 for both training and test data. Similarly, RMSE and mean error percentage are fairly low. All MEP results for training and testing data are within acceptable error limits (±5%).

Table 6. Optimal results for thrust force and hole diameter

			Training set			Test set		
Goal	**Learning**	**Network**	**RMSE**	**R^2**	**MEP**	**RMSE**	**R^2**	**MEP**
Ff	LM	3-7-1	0.005758	0.999830	1.782205	0.009454	0.999408	4.686014
Dh	LM	3-5-1	0.011883	0.999455	2.808310	0.028303	0.994872	4.481558

The equations of the thrust force and hole diameter are given in Eq. (2-3). Also, the thrust force and hole diameter can be accurately calculated by these formulas.

$$Ff = \frac{1}{1+e^{-(-1.1078x\boldsymbol{F1}+3.5702x\boldsymbol{F2}+0.5028x\boldsymbol{F3}-0.1297x\boldsymbol{F4}+3.9356x\boldsymbol{F5}-2.5484x\boldsymbol{F6}-2.1454x\boldsymbol{F7}+0.8390)}} \tag{2}$$

$$Dh = \frac{1}{1+e^{-(-13.5631x\boldsymbol{F1}+1.3177x\boldsymbol{F2}+29.1978x\boldsymbol{F3}+38.6710x\boldsymbol{F4}-3.7014x\boldsymbol{F5}-18.9595)}} \tag{3}$$

Where Fi (i = 1, 2, 3, ... , 6 or 7) can be calculated according to Eq. (11).

$$Fi = \frac{1}{1+e^{-Ei}}$$

Where *Ei* is the weighted sum of the inputs, and is calculated via the equations in Table 6 and 7, respectively. The weight values of the input and hidden layers are given in the Table 6 and 7.

Table 7. The weights for the thrust force

	$E_i = w_1 x Ct + w_2 x V + w_3 x f + \theta i$			
i	w_1	w_2	w_3	θ_i
1	-6.4684	-2.7617	-4.3080	16.4871
2	10.6469	-1.4917	3.8784	-12.8674
3	-3.5996	-7.1583	0.1896	2.3666
4	-7.4703	-5.2997	-4.5306	9.4656
5	11.4510	-0.4933	-1.0716	-8.9492
6	7.0288	-0.4474	-3.4970	-2.2664
7	-10.2174	-0.7649	-3.0773	2.1160

Table 8. The weights for hole diameter

	$E_i = w_1 x Ct + w_2 x V + w_3 x f + \theta i$			
i	w_1	w_2	w_3	θ_i
1	-2.1053	-0.8394	1.6019	17.2975
2	3.8276	51.1579	0.1055	-36.6803
3	-5.2896	0.3984	-0.7148	2.7084
4	3.4728	-0.5955	1.0886	-1.9598
5	-7.5575	2.7807	11.3536	-3.9671

The comparisons of the thrust force and hole diameter values between the experimental values and ANN predictions are shown in Fig 6 and 7, respectively. As shown in these figures, the prediction capacities of the networks for the thrust force and hole diameter were fairly satisfactory.

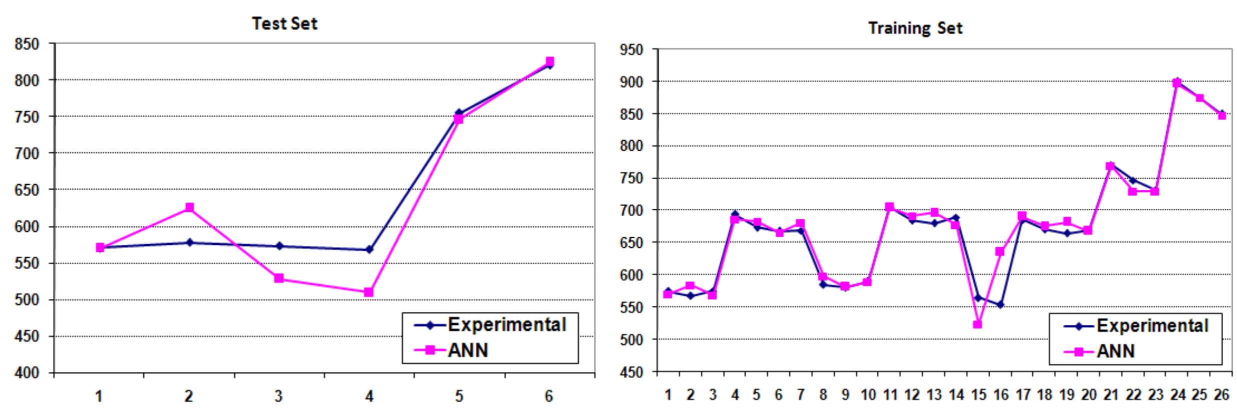

Figure 5. The performance of ANN for the thrust force

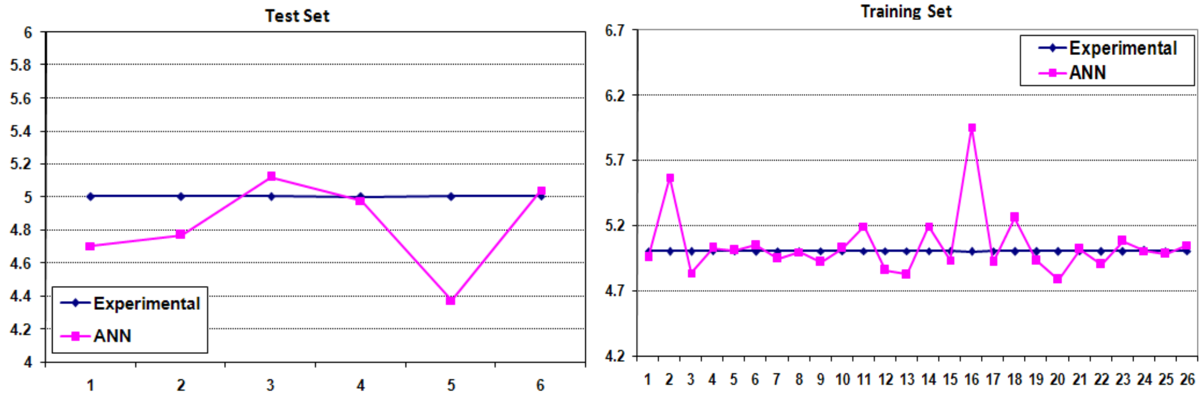

Figure 6. The performance of ANN for the hole diameter

4. Results

In this study, an ANN was used to predict the thrust force and hole diameter in drilling of AISI D2 cold work steel with uncoated, TiN, TiAlN monolayer and TiAlN/TiN multi-layer coated cemented carbide drills. The results can be drawn as follows:

- It was found that the lowest thrust force value was obtained with the TiAlN/TiN multi-layer coated drills due to its higher wear resistance. The optimal thrust force value was 554 N at the feed rate of 0.063 mm/rev and the cutting speed of 60 m/min in the conducted drilling experiments.

- The lowest value of hole diameter was also obtained with TiAlN/TiN multi-layer coated drills due to its lower thrust forces. The measured optimal hole diameter value was Ø5.0009 mm at a feed rate of 0.063 mm/rev and cutting speed of 60 m/min.

- The optimal prediction results for the thrust force and hole diameter were obtained by network architectures of 3-7-1 and 3-5-1 with LM learning algorithms, respectively. In the ANN model, the determination coefficients for the thrust force and hole diameter were more than 0.99. MEP values for them values were within acceptable limits (±5%). The ANN results for both the thrust force and hole diameter were very satisfactory.

The prediction results showed that ANN is notably powerful in prediction of thrust force and hole diameter. So, the use of ANN is highly recommended in prediction of them instead of the experimental set ups to measure thrust force and hole diameter.

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