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Surface roughness prediction using artificial neural networks when drilling Udimet 720

Marek Vrabel^{a*} Ildiko Mankova^a Jozef Beno^a Jaroslav Tuharský^a^a*Technical University of Košice, Masiarska 74, 04001 Košice, Slovakia*

Abstract

Article deals with design of appropriate control strategy for prediction of surface roughness as one of the important indicators of machined surface quality applying artificial intelligence. Test sample was nickel based super alloy UDIMET 720, which is used as material of jet engines components such as discs etc. Experimental data collected from tests were used as input parameters into neural network to identify the sensitivity among cutting conditions, tool wear and monitoring parameters and surface roughness. Selected parameters were used to design a suitable algorithm for control and monitoring of the drilling process. Moreover, the developed software for implementation to machine tool control system for surface roughness on-line identification through monitoring indices is described.

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Keywords: neural networks, surface roughness, drilling, monitoring strategy.

Nomenclature

CC	cutting conditions
PM	process monitoring
VB	tool flank wear
v_c	cutting speed m/min
f	feed mm
Ra	surface roughness
F	thrust force in drilling

1. Introduction

Production of highly stressed rotating parts of a new generation of aero engine turbines requires the monitoring of the machining process, which should provide the desired surface quality and identification of machined surface defects. One of frequently used construction materials for aero-engine components are nickel based super-alloys like Udimet720 in applications such as turbine disks. Machining of nickel alloys is a relatively difficult process, and already small changes of cutting conditions can contribute to the anomalies of the surface, which in turn cause serious malfunctions of components. Hole-making mainly drilling is one of the most common operation used and usually is carried out as one of the last steps in

* Corresponding author. Tel.: +421-55-6023586; fax: +421-55-6225186
E-mail address: marek.vrabel@tuke.sk

the production process [1, 2]. The effort to reduce operating costs and improve the quality of manufactured parts leads to the introduction of on-line monitoring of machining operations, which significantly contributes to improving the quality of manufactured parts as well as reducing the total cost of production. In spite of that monitoring the hole making process is still unresolved problem in industrial practice. Tool wear is an important factor. Wear development during machining Udimet 720 can reach unacceptable levels very fast resulting in poor surface finish. Generally, monitoring of tool wear has an important role because of the cutting edge wear significantly affects the machined surface quality (surface integrity). Decision making process plays an important role in monitoring. Today developments in computer techniques have made neural network a robust and popular tool in modeling, prediction and decision making process in monitoring. Neural networks have been used extensively mainly to monitor the progress of tool wear in machining Masory [3], to predict tool life Choi [4]; to select optimum cutting conditions Wang and Dornfeld [5]; to ensure the tool replacement cycles and to minimize production time Rahaman and Zhou [6]. Choudhury and Jain [7] as well as Lin and Ting [8] used regression model of cutting force and torque and cutting conditions as an input parameters to the neural network to monitor drill wear. Abu-Mahfouz [9] predicted drill wear using neural network, where vibrations signals transformed into frequency spectra employing Fast Fourier Transformation was used as input data. Singh et al. [10] used a neural network with back propagation (BP) training algorithm for the prediction of high speed steel drill wear when drilling copper alloy. The input parameters were spindle speed, feed rate, drill diameter, force and torque. The output of neural networks – predicted value – was the flank wear of drill. Panada et al. [11] used the BP neural networks to predict tool wear of HSS drills when drilling of steel using as inputs parameters to the networks spindle revolution, feed rate, tool diameter, force, torque and chip thickness and as output parameter the maximum tool wear, and came to the conclusion that chip thickness includes to the input parameters more accurately predict tool wear. Asilturk [12] proposed learning procedure for predicting surface roughness with neural networks. The objective of this research is to develop and test neural network that can predict the drill flank wear in order to prevent anomalies occurring on machined surface as well as to develop and test neural network that can predict surface roughness in order to achieve acceptable surface integrity when drilling Udimet720. Main tasks of this paper is answer on two basic problems; firstly how the ANN model and prediction match with experimental data, secondly, how accurate the ANN model can describe wear behaviour and surface roughness prediction.

2. Artificial neural network proposal for tool wear and surface roughness prediction

In spite of the intensive research being carried out in this field, there is still no clear methodology for developing machining monitoring systems that allows machining processes to be optimized, predicted or controlled. Machining monitoring systems is a process-oriented problem where the selection of the sensor system, sensory features and the modeling approach are closely related to the specific characteristics of the machining process. For hole-making process in turbine discs made from Udimet720 the structure of monitoring system with neural network prediction models have been proposed, fig.1. Proposed system consists of two subsystems: one for tool wear modeling and prediction where the cutting conditions and significant process monitoring features were used as input to neural network. The second subsystem is developed for surface roughness prediction and it employs the same inputs such as cutting conditions and PM features and in addition predicted tool wear.

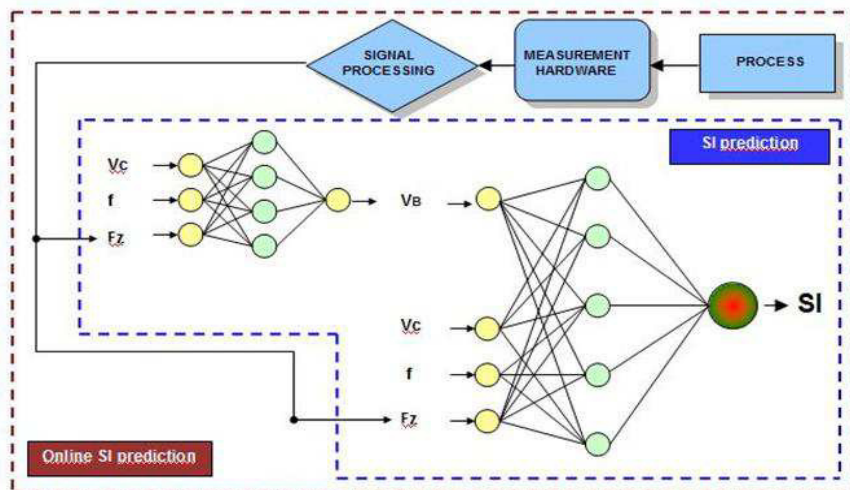


Fig. 1 Illustration of proposed surface roughness prediction.

As known PM features (i.e. cutting force, torque, and vibrations) have good correlation with tool wear and adequately describe tool wear behaviour. On the other hand there is no direct correlation between surface roughness and PM features but tool wear has great impact on machined surface integrity as well as on surface roughness mainly in finishing operations. Therefore tool wear as one of inputs to neural network could bring expected results.

2.1. Neural network structure for prediction of tool wear when drilling Udimet 720

Results from experimental measurements provided at the Laboratoire Génie de Production – ENIT Tarbes - France were chosen for training and testing the neural networks structure [13, 14]. Forged nickel alloy Udimet 720 with diameter of 80 mm was used as test samples; this type of material is mostly used in the manufacture of aircraft turbine discs. The sample has undergone the same heat treatment used as a real disk. For trials drill diameter of $D = 15.5$ mm with a removable cutting head coated with TiAlN have been employed. Length of drilled hole was 37mm, each hole was drilled with a new instrument. All drilling tests were performed on 3-axis vertical milling machine tool with NC Siemens 840D control. The machine tool was fitted with the Kistler 4 components dynamometer (F_x , F_y , F_z and M_z) and three accelerometers were arranged in three main axes X, Y and Z. Tool wear was measured using a laboratory microscope. The cutting conditions were selected according to COM methodology [14]. Table 1 show employed cutting conditions and measured drill flank wear that was used for training procedure of proposed neural network.

Table 1. Cutting conditions and measured values of drill flank wear and surface roughness for Udimet720

v_c (m/min)	f (mm)	VB (mm)	Ra (μ m)	v_c (m/min)	f (mm)	VB (mm)	Ra (μ m)	v_c (m/min)	f (mm)	VB (mm)	Ra (μ m)
20	0,1	0,09	0,38	19	0,15	0,04	2,00	3	0,28	0,04	0,41
15	0,1	0,07	0,42	19	0,3	0,32	1,18	4,94	0,065	0,0007	0,65
17,5	0,1	0,09	0,53	19	0,125	0,06	1,80	1,27	0,15	0,001	0,49
25	0,1	0,1	1,03	19	0,075	0,07	0,67	29,44	0,29	0,32	3,12
22,5	0,1	0,11	0,89	12,5	0,175	0,08	0,98	37,7	0,23	0,322	3,00
10	0,1	0,05	0,94	39,7	0,174	0,26	2,28	36,88	0,25	0,34	3,29
27,5	0,1	0,18	1,12	37,9	0,18	0,257	2,29	36,88	0,29	0,396	3,87
18,75	0,1	0,04	0,48	31,5	0,21	0,24	2,27	21,92	0,29	0,235	2,29
21,25	0,1	0,05	0,47	27	0,23	0,236	2,28	3,75	0,29	0,05	0,46
19	0,1	0,04	0,77	23	0,27	0,23	2,27	32,84	0,23	0,28	2,65
19	0,05	0,07	0,43	11,55	0,276	0,123	1,21				

Cutting conditions and measured thrust force component have been used as input data into neural network in order to predict the drill flank wear. The neural network had three layers – input layer, one hidden layer and output layer. Two types of three-layered feed forward back propagation neural networks have been trained and tested. The elements of hidden layer were varied in the experiments. The first of the two networks had distribution of 3-4-1 (Fig. 2a) and it was configured as follows: Input layer had 3 neurons, because the input vectors had three components: cutting speed v_c , feed f , thrust force component F_z ; hidden layer consisted of 4 neurons; output layer in this case contained only one neuron, because the output was the value of tool wear VB. The second network had five neurons in hidden layer and distribution of 3 – 5 - 1 (Fig. 2 b). The input layer and an output layer were identical with the first network.



Fig. 2 Network structure models with a single hidden layer a) 4 neurons in the hidden layer b) 5 neurons in the hidden layer

The first step of calculation is to normalize all the raw input data to values between 0,1 and 0,9. The activation function in the hidden layer is another important factor influencing the network performance. For developed network a sigmoid function was chosen as activation function in this study. The actual output in the output layer is calculated by applying the same sigmoid function as in the hidden layer. The total number of measured values 42 was divided into two data sets: for testing and training. For training 32 samples was used and remaining 10 samples was applied for testing the neural networks. Constructive learning method has been used for design the proper structure of neural network. Learning process starts from the simplest network to more complex. Sum of squares error (SSE) was used to minimize the training errors. Figures 3a, b.

illustrate testing and training errors expressed as SSE values. In the case of NN structure 3-4-1 the errors (the accuracy of calculation) after 2.10^5 learning cycles achieved value of 0,05 for training and 0,06 for testing procedure, fig.3a. Network with structure 3-5-1 was trained and tested by 4.10^5 cycles and SSE values were obtained for training and testing 0,04 and 0,06, respectively, fig.3b. Values of SSE error determine the suitability of the neural networks to accurate prediction of the output variable. Lower SSE error values were achieved for network structure 3 – 5 – 1 than this for structure 3 – 4 – 1, therefore, the network structure 3 – 5 – 1 was chosen to test the real values of the tool wear.

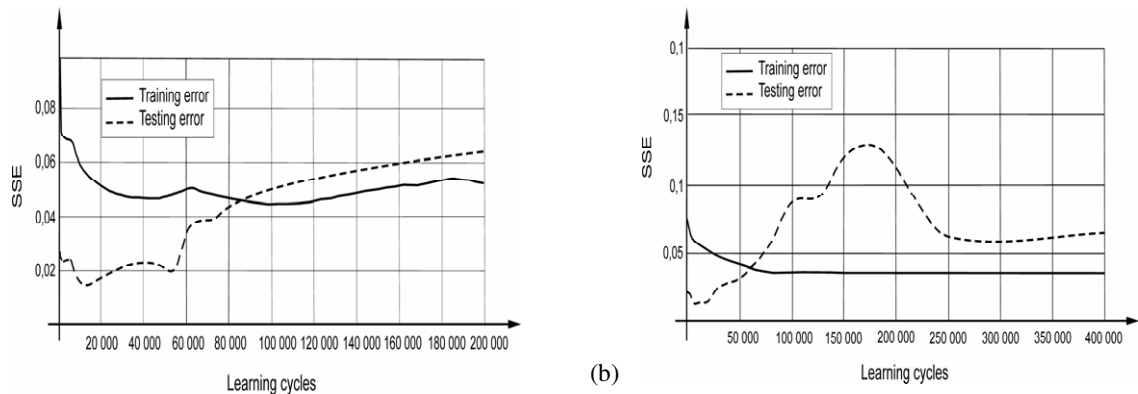


Fig. 3 SSE learning error at network with one hidden layer and structure a) 3-4-1 b) 3-5-1

2.2. Analysis of the proposed neural network and evaluation of tool wear prediction results

Table 2 shows the comparison of the measured values of wear VB and predicted values used for VB neural network learning process.

Table 2. Comparison of predicted and experimentally measured values of tool wear for training set with predicted errors

Hole No	Sample	VB predicted	VB measured	Error	Error (%)	Hole No	Sample	VB predicted	VB measured	Error	Error (%)
1.	1	0,066678	0,09	0,02332	25,91	22.	17	0,262239	0,26	0,00224	0,86
2.	2	0,055767	0,07	0,01423	20,33	23.	18	0,262321	0,257	0,00532	2,07
3.	3	0,061865	0,09	0,02813	31,26	25.	19	0,238186	0,24	0,00181	0,76
5.	4	0,122330	0,1	0,02233	22,33	26.	20	0,225489	0,236	0,01051	4,45
6.	5	0,084242	0,11	0,02575	23,42	27.	21	0,230390	0,23	0,00039	0,17
7.	6	0,055346	0,05	0,00534	10,69	29.	22	0,118941	0,123	0,00405	3,30
9.	7	0,160313	0,18	0,01968	10,94	30.	23	0,048064	0,04	0,00806	20,16
10.	8	0,060097	0,04	0,02009	50,24	31.	24	0,004651	0,0007	0,00395	564,51
11.	9	0,076900	0,05	0,02690	53,80	33.	25	-0,00256	0,001	0,00356	356,44
13.	10	0,046747	0,04	0,00674	16,87	34.	26	0,325786	0,32	0,00578	1,81
14.	11	0,080685	0,07	0,01068	15,26	35.	27	0,314967	0,322	0,00703	2,18
15.	12	0,049456	0,04	0,00945	23,64	37.	28	0,347514	0,34	0,00751	2,21
17.	13	0,316042	0,32	0,00395	1,24	38.	29	0,393967	0,396	0,00203	0,51
18.	14	0,057595	0,06	0,00240	4,01	39.	30	0,240852	0,235	0,00585	2,49
19.	15	0,061324	0,07	0,00867	12,39	41.	31	0,044752	0,05	0,00524	10,49
21.	16	0,083731	0,08	0,00373	4,66	42.	32	0,286637	0,28	0,00663	2,37

Table 3. Comparison of predicted and experimentally measured values of tool wear for training set with predicted errors

Hole No.	Sample	VB (flank wear) predicted	VB (flank wear) measured	Error	Error (%)
4.	1	0,051962154	0,07	0,018038	25,77
8.	2	0,178705808	0,09	0,088706	98,56
12.	3	0,046747704	0,04	0,006748	16,87
16.	4	0,04095599	0,05	0,009044	18,09
20.	5	0,042327856	0,05	0,007672	15,34
24.	6	0,258455184	0,25	0,008455	3,38
28.	7	0,207065879	0,18	0,027066	15,04
32.	8	-0,002746388	0,0009	0,003646	405,15
36.	9	0,27853462	0,29	0,011465	3,95
40.	10	0,141855119	0,15	0,008145	5,43

For each of the compared values was calculated error RMS (Root Mean Square) i.e. numerical value of the difference between actual and predicted values of wear as well as the percentage by which it is possible to quickly and easily assess the quality and performance of the network.

From the data set in Table 2 it can be concluded that the correlation between predicted and experimental data is quite good, because the average percentage of the total RMS error in the training set was 12.7%. The percentage of error is within the permissible values. Some higher values of the errors arise from inaccuracy of measurement; as well as relatively small number of measured values as inputs parameters to the network affect the output error. Table 3 represents a test set of neural networks, where the RMS deviation is higher and the percentage error varies over a wide range in comparison with training set. These errors speak about the appropriateness of the network for prediction of tool wear. From those results conclude that the validation of network irregularities have occurred which could be caused for example with low number of trained samples or improperly selected network architecture.

Comparison of experimental with the NN predicted values for tool wear is shown graphically on Fig. 4. From fig.4a, it is clearly seen that the predicted values in training set almost follow the same trend as that of the corresponding experimental values. On fig.4b some higher differences occurred in one sample, which could be originated from inaccuracy in measurement or by small number of input samples.

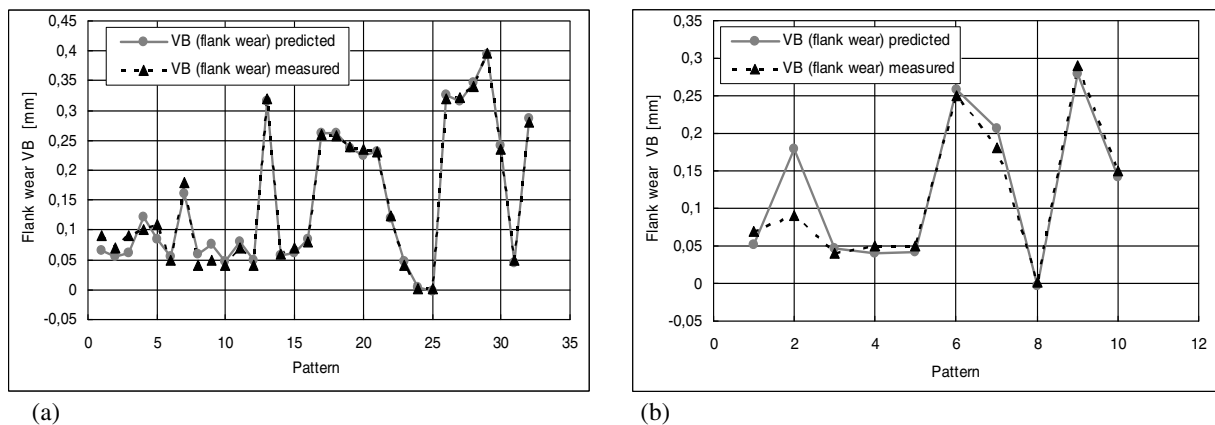


Fig. 4 Comparison of experimental values and NN predicted value of tool wear for a) training set b) testing set

Designed and tested network model with 3-5-1 topology for the prediction of tool wear achieved quite good results and especially in the training set, where the average RMS error percentage was 12.7%. Analysis of experimental data confirmed that the both proposed input to the network (feed f , cutting speed v_c thrust force F) and output parameters (drill flank wear VB) there are an dependency that NN is able to learn.

2.3. Neural network structure for prediction of surface roughness when drilling Udimet 720

The second subsystem for roughness prediction applies the same procedure for artificial neural network development as those for tool wear. Input parameters and architecture of neural network were changed based on proposed algorithm for surface integrity prediction as illustrated on fig.5. Table 1 shows employed cutting condition; measured values of tool flank wear as well as measured values of surface roughness.

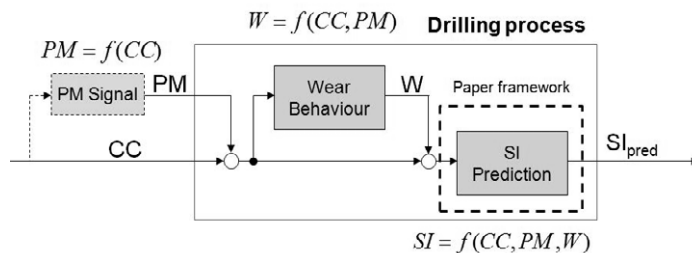


Fig. 5 Proposed algorithm for surface integrity prediction when drilling Udimet 720

Again two types of feed forward back propagation neural networks have been trained and tested. The first of the two networks had distribution of 4-6-1 (Fig. 6a) and it was configured as follows: Input layer had 4 neurons, because the input vectors had four components: cutting speed v_c , feed f , thrust force component F and flank wear VB ; hidden layer consisted of 6 neurons; output layer has only one neuron, corresponding with the output of surface roughness R_a . The second tested network had two hidden layers and distribution of 4-6-4-1 (Fig. 6b). The input layer and an output layer were identical with the first network. Fig. 6b illustrates both input and output layers with normalized values as well as weights in hidden layers.

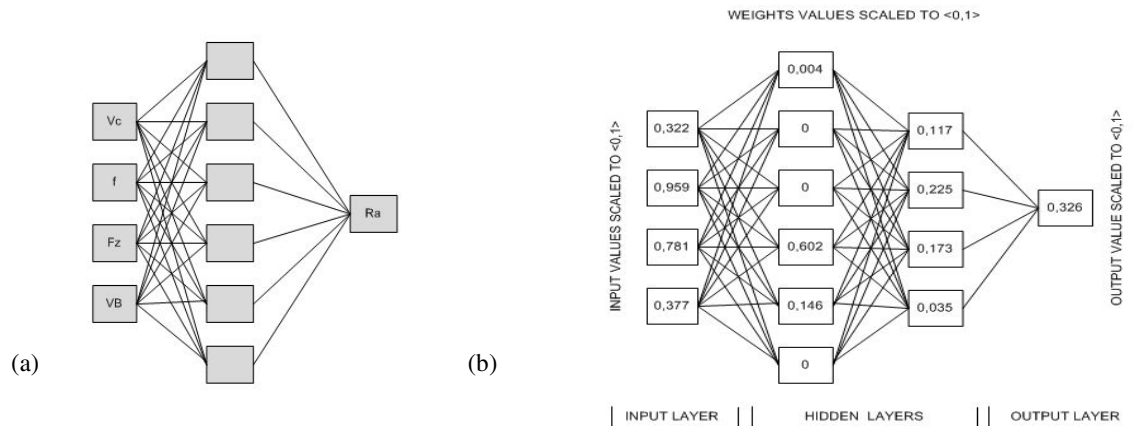


Fig. 6 Neural network models for surface roughness prediction with distribution a) 4-6-1 b) 4-6-4-1

Table 4. Comparison of predicted and experimentally measured values of surface roughness in the testing set with predicted errors

Pattern	Ra predicted	Ra measured	Error	Error (%)
1	0,38	0,36	0,020777	5,77
2	0,44	0,42	0,016794	4,00
3	0,54	0,53	0,014824	2,80
4	1,06	1,03	0,034758	3,37
5	0,87	0,893	0,02552	2,86
6	0,97	0,94	0,032336	3,44
7	1,14	1,12	0,020347	1,82
8	0,45	0,48	0,034061	7,10
9	0,44	0,47	0,03117	6,63
10	0,81	0,77	0,0351	4,56
11	0,42	0,43	0,012045	2,80
12	2,02	2	0,017337	0,87
13	1,19	1,18	0,010912	0,92
14	1,78	1,8	0,024774	1,38
15	0,66	0,67	0,006008	0,90
16	1,01	0,98	0,032459	3,31
17	2,29	2,28	0,014401	0,63
18	2,28	2,29	0,012913	0,56
19	2,24	2,27	0,029044	1,28
20	2,31	2,28	0,028684	1,26
21	2,26	2,27	0,006951	0,31
22	1,18	1,21	0,025238	2,09
23	0,39	0,406	0,01789	4,41
24	0,62	0,65	0,034651	5,33
25	0,46	0,49	0,030362	6,20
26	3,11	3,12	0,011066	0,35
27	2,99	3	0,008762	0,29
28	3,31	3,29	0,020524	0,62
29	3,87	3,87	0,002831	0,07
30	2,32	2,29	0,029793	1,30
31	0,49	0,46	0,032329	7,03
32	2,64	2,65	0,00822	0,31

Sum of squares error (SSE) was used to minimize the training errors. In the case of ANN with one hidden layer structure 4-6-1 the errors (the accuracy of calculation) after $5 \cdot 10^5$ learning cycles achieved value of 0,025 for training and 0,25 for testing procedure. Network with two hidden layers and structure 4-6-4-1 was trained and tested $2 \cdot 10^5$ cycles and SSE values

were obtained for training 0,008 and testing 0,46. Lower SSE error values were achieved for network structure with two hidden layers and distribution 4-6-4-1 than those for structure 4-6-1, thus the network structure 4-6-4-1 was chosen to test the real values of the surface roughness, fig. 6b.

Table 4 shows the comparison of the measured values of roughness Ra and predicted values used for Ra neural network learning process. For each of the compared values was calculated error RMS (Root Mean Square) i.e. numerical value of the difference between actual and predicted values of surface roughness as well as the percentage by which it is possible to quickly and easily assess the quality and performance of the network.

From the data set in Table 4 it can be concluded that the correlation between predicted and experimental data is very good, because the average percentage of the total RMS error in the training set was 2,64 %. The percentage of error is within the permissible values. Comparison of experimental with the NN predicted values for surface roughness is illustrated on Fig. 5. From fig.5a, it is clearly seen that the predicted values in training set almost follow the same trend as that of the corresponding experimental values. On fig.5b some higher differences in testing samples occurred in two patterns (pattern No.2 and No5) , which could probably be originated from inaccuracy in measurement or sometimes from small number of input samples.

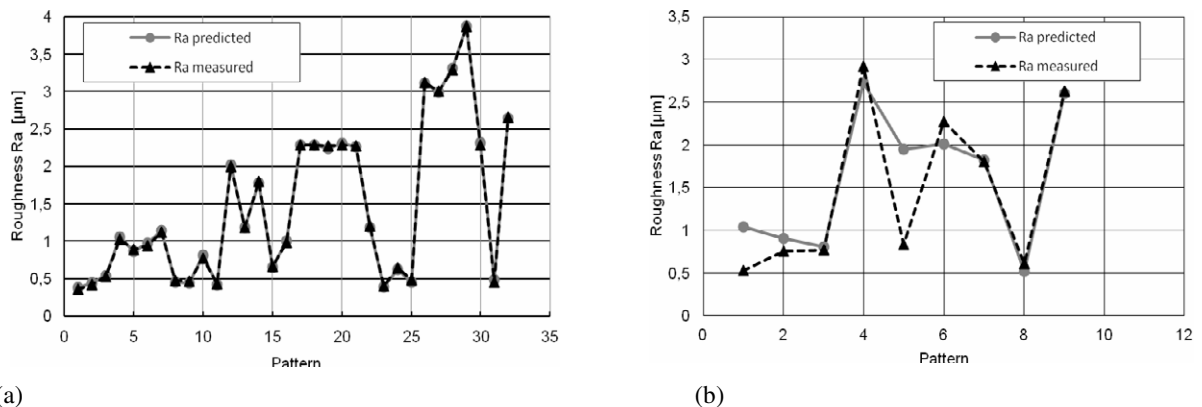


Fig. 7 Comparison of experimental values and NN predicted value of surface roughness for a) training set b) testing set

3. Conclusion

Monitoring systems require reliable models which are able to learn complex non-linear relationships between process performance variables and process variables in machining. Modeling and optimization are necessary for the understanding and control any process. Precise control is a prerequisite to achieve improved quality and productivity. An adequate selection of the artificial intelligence technique is crucial to develop reliable machining models. This selection depends mainly on the number of experimental samples, the stochastic nature of the process, the desired model accuracy, and the explicit or implicit nature of the model and the previous knowledge of the process. Artificial neural network plays an important role in predicting linear and non- linear tasks in machining operation.

The advantage of neural networks lies in their capability to represent both linear and non-linear relationship and their ability to learn these relationships directly from the data being modelled. Article presents two neural network structures that could be employed for decision-making process in monitoring when drilling Udimet 720. Experimental data used for training and testing of network were carried out by Partner University at the Laboratoire Génie de Production – ENIT Tarbes - France in the frame of FP7 project 213855 ACCENT “Adaptive Control of Manufacturing Processes for a New Generation of Jet Engine Components” [2,14].

The algorithm of the feed forward network with back propagation has been used to predict tool wear and surface roughness. From the research results the following conclusions can be formulated:

Neural networks have good generalization ability to process and appear to be useful tools in the cutting tool wear condition monitoring when drilling as well as for surface roughness prediction in monitoring system.

Designed and tested network model with 3-5-1 topology for the prediction of tool wear achieved satisfactory results and especially in the training set, where the average RMS error percentage was 12.7%.

Designed and tested network model with 4-6-4-1 architecture for the prediction of surface roughness achieved good results and especially in the training set, where the average RMS error percentage was 2.64%

Analysis of experimental data confirmed that the both proposed input to the network (feed f , cutting speed v_c thrust force F) and output parameters (drill flank wear VB and surface roughness) there are an dependency that ANN is able to learn.

The type of input data and the number of neuron affect the results of the NN.

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