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Original scientific paper

Modelling and Prediction of Surface Roughness in CNC Turning Process using Neural Networks

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Abstract: The paper presents an approach to solving the problem of modelling and prediction of surface roughness in CNC turning process. In order to solve this problem an experiment was designed. Samples for experimental part of investigation were of dimensions ϕ30 × 350 mm, and the sample material was GJS 500 - 7. Six cutting inserts were used for the designed experiment as well as variations of cutting speed, feed and depth of cut on CNC lathe DMG Moriseiki-CTX 310 Ecoline. After the conducted experiment, surface roughness of each sample was measured and a data set of 750 instances was formed. For data analysis, the Back-Propagation Neural Network (BPNN) algorithm was used. In modelling different BPNN architectures with characteristic features the results of *RMS* (Root Mean Square) error were controlled. Specially analysed were the *RMS* errors realised by different number of neurons in hidden layers. For the BPNN architecture with one hidden layer the architecture (4 – 8 - 1) was adopted with *RMS* error of 3,37%. In modelling the BPNN architecture with two hidden layers, a considerable amount of architectures was investigated. The adopted architecture with two hidden layers (4 - 2 - 10 - 1) generated the *RMS* error of 2,26%. The investigation was also directed at the size of the data set and controlling the level of *RMS* error.

Keywords: CNC turning; Neural Networks; prediction; surface roughness

1 INTRODUCTION

At the present time of the fourth industrial revolution contemporary manufacturing processes integrate methods of artificial intelligence. The methods of artificial intelligence are the tools that enable intelligent production i.e. they make it possible for technologists to plan technological processes quicker and more efficiently. As every technological process is planned among others also according to the requirements of quality, the quality of machined surface (surface roughness) needs to be also pointed out. The quality of machined surface is directly correlated with the manufacturing process which usually contains various influencing parameters (variables). The manufacturing processes being multivariable, they are usually hard to be modelled as optimal. While modelling and investigating the surface roughness dependence on the parameters of a manufacturing process, the investigators designed various models. In paper [1] authors investigated the surface roughness prediction for turning operations using computer vision and artificial neural networks (ANN) with evolutionary algorithm. For the purposes of investigation, they designed a model in which the surface roughness was the output parameter while the model input parameters were: cutting speed, feed, depth of cut and average grey level of the surface image of the workpiece (acquired by computer vision). Computer vision and soft computing approach were also used in paper [2] as the methodology for recognizing the errors of surface roughness in the CNC turning process. For the purposes of investigation a model was designed which contained the following input parameters: feed, depth of cut, cutting speed, frequency range, grey scale value. Based on the given model, training and implementation of neural networks, an efficient methodology was obtained for discovering the error rate of surface roughness in the CNC turning process. A predictive model for various kinds of materials (austenitic, martensitic and duplex stainless steels) in CNC turning process was designed in paper [3] for investigation with the following input parameters: cutting speeds (120, 150, 180 and 210 m/min), feed (0,1 mm/rev) and depth of cut (1 mm) and using coated cemented carbide tools. The following parameters were defined as the model output parameters: cutting forces and surface roughness. Based on the proposed model and the parameters obtained during experimental work these were used in the process of the application of ANNs and for the comparison of obtained results.

In modelling and optimization of the machining parameters in the turning process, the authors of paper [4] proposed a model with the following input parameters: tangential cutting force, cutting power and the material removal rate, and with surface roughness as the output parameter. In experimental part of collecting data during the turning process, coated and uncoated silicon nitride ceramic tools were used while for the process of prediction the approach using neural networks and response surface methodology (RSM) was applied. In the process of optimization genetic algorithm (GA) was used. It was proven that a coated ceramic tool provides better surface quality and minimal cutting force in comparison with those obtained with an uncoated ceramic tool. Authors [5] use ANNs in estimating surface roughness by forming a model in which the machining parameters, cutting forces, sound and vibrations of the turning process were used as input parameters. Regression models were used for comparison. It was proven that neural networks estimated the state of surface roughness with more than 98% accuracy in relation to the formed regression models with more than 90% accuracy.

Comparison of three machine learning methods was suggested by authors [6] for prediction of output parameters of high speed turning process. The analysed output parameters were surface roughness (Ra), cutting force (F_c), and tool life (T). Different methods of machine learning were used for the process modelling: Support Vector Regression (SVR), polynomial (quadratic) regression, and ANNs. The best results in predicting F_c and Ra were obtained by polynomial regression while in predicting T the best results were obtained by ANN. The investigation presented in [7] dealt with the obtaining of surface roughness by the use of fuzzy inference system (FIS) and comparing the results, among others, with the results derived by ANNs. Modelling and prediction of

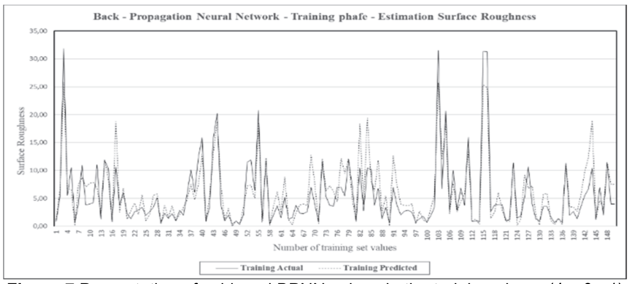

Figure 7 Presentation of achieved BPNN values in the training phase (4 – 8 - 1)

Analysing the data sample (Fig. 2) and the amount of data, in the continuation of experimental work the impact of the amount of data (instances) on the level of *RMS* error will be investigated. The investigation is designed in two steps. In the first step, the data sample is halved and two data sets, identical by the amount of data, are designed. Each data sethad 225 instances in the training phase, while for the testing, 75 instances. For validation purposes, two data sets of 75 instanceseach were also designed. The division of the data sample was made according to the stochastic principle.

For the accepted architecture (4 – 8 - 1) and the realised BPNN characteristics the network was trained again with new data sets, in two steps. In the first step, the training was realised with the first data set (training, testing and validation) and after that with the second data set (division scheme was 225 – 75 - 75 instances). The BPNN network was trained for each data set and the level of *RMS* error (%)was controlled. The results realised in the training phase in the first step were:

- The first data set RMS_{I} = 4,32%
- The second data set RMS_{II} = 5,78%.

The *RMS* error range is 1,46%.

In the second step, the datasample was divided in three data sets using the previously described principle. Each data set was modelled according to the established principle: training, testing and validation with the following subset scheme: 150 – 50 - 50 instances. For each data set the BPNN network training process was separately conducted and the level of *RMS* (%) error was controlled. The results realised in the training phase (second step) were the following:

- The first data set RMS_{I} = 7,09%
- The second data set RMS_{II} = 6,71%
- The third data set RMS_{III} = 6,25%.

Range of *RMS* error "min tomax" is 0,84%.

From this modelling and researchingof *RMS* error in the function of the amount of data, for investigated and accepted BPNN architecture (4 - 8 - 1) it can be concluded that reducing the amount of data in the training phase results in increasing the *RMS* error.

The remaining experimental work is aimed at modelling a larger number of BPNN architectures with two hidden layers in the form (4 - x - x - 1). The BPNN architecture with adopted and accepted features in previous phases will be investigated. In the results of earlier investigations [23] the architectures with two or three hidden layers did not prove more successful than those with one hidden layer. It has been proven by investigations that nonlinear problems can be very well approximated with one hidden layer.

Tab. 3 shows the realised results of modelling different BPNN architectures in the training process with a whole (complete) data sample of 450 instances and 150 instances in the testing phase.

Table 3 Results of realised BPNN architectures and *RMS* error

NN architecture	*RMS* / %	NN architecture	*RMS* / %	NN architecture	*RMS* / %	NN architecture	*RMS* / %
4 - 2 - 1 - 1	6,59	4 - 3 - 1 - 1	6,70	4 - 4 - 1 - 1	4,73	4 - 5 - 1 - 1	6,13
4 - 2 - 2 - 1	6,70	4 - 3 - 2 - 1	5,75	4 - 4 - 2 - 1	2,68	4 - 5 - 2 - 1	7,64
4 - 2 - 3 - 1	9,57	4 - 3 - 3 - 1	8,06	4 - 4 - 3 - 1	4,62	4 - 5 - 3 - 1	5,46
4 - 2 - 4 - 1	2,67	4 - 3 - 4 - 1	4,66	4 - 4 - 4 - 1	6,21	4 - 5 - 4 - 1	4,70
4 - 2 - 5 - 1	7,83	4 - 3 - 5 - 1	6,10	4 - 4 - 5 - 1	4,73	4 - 5 - 5 - 1	3,46
4 - 2 - 6 - 1	4,12	4 - 3 - 6 - 1	6,13	4 - 4 - 6 - 1	4,89	4 - 5 - 6 - 1	5,46
4 - 2 - 7 - 1	5,45	4 - 3 - 7 - 1	7,64	4 - 4 - 7 - 1	6,09	4 - 5 - 7 - 1	5,59
4 - 2 - 8 - 1	7,77	4 - 3 - 8 - 1	3,75	4 - 4 - 8 - 1	6,83	4 - 5 - 8 - 1	5,31
4 - 2 - 9 - 1	5,49	4 - 3 - 9 - 1	3,48	4 - 4 - 9 - 1	6,16	4 - 5 - 9 - 1	4,39
4 - 2 - 10 - 1	**2,26**	4 - 3- 10 - 1	2,38	4 - 4 - 10 - 1	6,03	4 - 5 - 10 - 1	4,60
NN architecture	*RMS* / %	NN architecture	*RMS* / %	NN architecture	*RMS* / %	NN architecture	*RMS* / %
4 - 6 - 1 - 1	3,13	4 - 7 - 1 - 1	5,64	4 - 8 - 1 - 1	4,23	4 - 9 - 1 - 1	4,66
4 - 6 - 2 - 1	4,10	4 - 7 - 2 - 1	5,48	4 - 8 - 2 - 1	6,87	4 - 9 - 2 - 1	7,15
4 - 6 - 3 - 1	5,10	4 - 7 - 3 - 1	5,47	4 - 8 - 3 - 1	3,98	4 - 9 - 3 - 1	2,85
4 - 6 - 4 - 1	5,37	4 - 7 - 4 - 1	5,93	4 - 8 - 4 - 1	6,01	4 - 9 - 4 - 1	5,80
4 - 6 - 5 - 1	5,94	4 - 7 - 5 - 1	5,45	4 - 8 - 5 - 1	4,92	4 - 9 - 5 - 1	4,49
4 - 6 - 6 - 1	2,46	4 - 7 - 6 - 1	2,90	4 - 8 - 6 - 1	5,48	4 - 9 - 6 - 1	3,69
4 - 6 - 7 - 1	3,46	4 - 7 - 7 - 1	7,09	4 - 8 - 7 - 1	2,59	4 - 9 - 7 - 1	6,43
4 - 6 - 8 - 1	6,01	4 - 7 - 8 - 1	3,80	4 - 8 - 8 - 1	4,74	4 - 9 - 8 - 1	4,84
4 - 6 - 9 - 1	3,84	4 - 7 - 9 - 1	6,58	4 - 8 - 9 - 1	4,24	4 - 9 - 9 - 1	3,54
4 - 6 - 10 - 1	7,27	4 - 7 - 10 - 1	6,50	4 - 8 - 10 - 1	6,33	4 - 9 - 10 - 1	4,67

From the results shown in Tab. 3 it can be concluded that in accordance with the least realised *RMS* error the BPNN architecture (4 - 2 - 10 - 1) is selected with two hidden layers and *RMS* error of 2,26% in the training phase (Fig. 8). This BPNN architecture is adopted as the architecture proposed for solving the suggested problem. The process of validation was conducted on the adopted BPNN architecture.

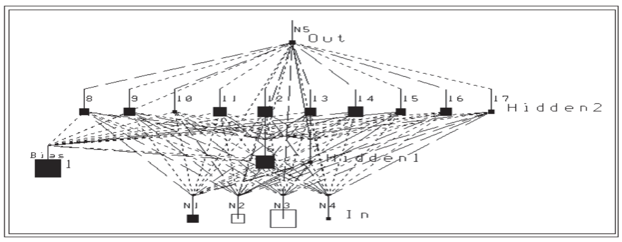

Figure 8 Adopted architecture (4-2-10-1) BPNN

The process of validation is conducted on the new data sample which neural network did not have a chance to use in the training phase and which is an integral part of the results achieved during conducting the experiment (Fig. 2). In the process of validation the *RMS* error of 4,24% was realised. Display of the achieved results in the training phase is given in Fig. 9, and the results achieved in the validation phase are given in Fig. 10.

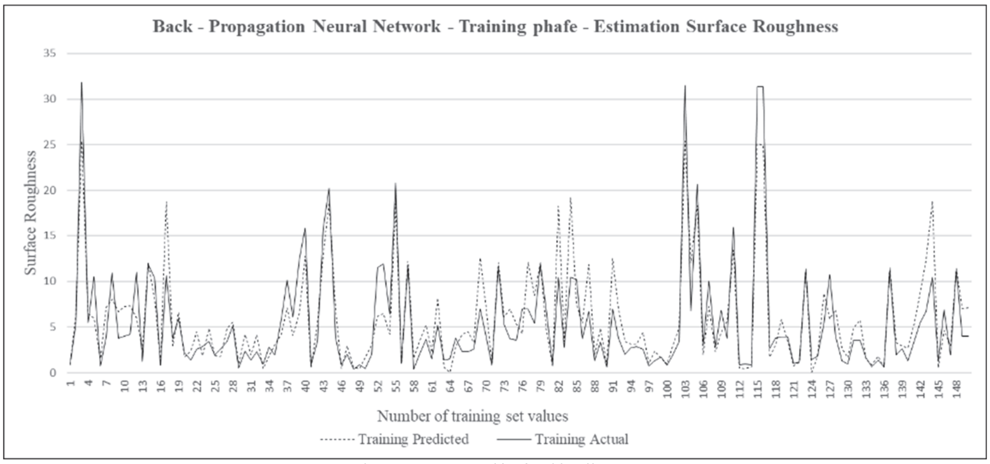

Figure 9 Presentation of realised BPNN (4 - 2 - 10 - 1) values in the training phase

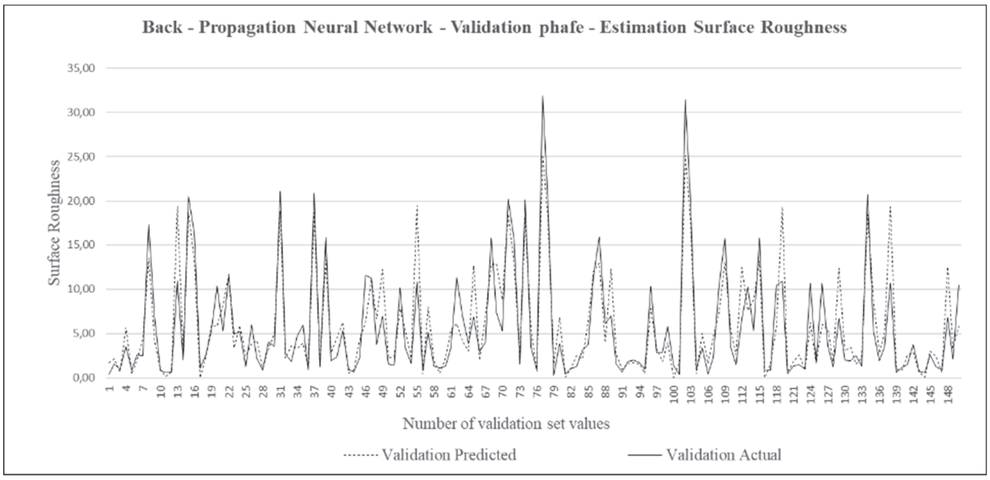

Figure 10 Presentation of realised BPNN (4 - 2 - 10 - 1) values in the validation phase

4 CONCLUSIONS

The investigation carried out in the research of influencing parameters in chip-forming machining process at CNC turning is presented in the paper. In the analysis of the factors of influence on the machining process, cutting speed, feed and depth of cut were selected along with the selected cutting inserts of the tool. The design of experiment defined six cutting inserts and levels of cutting speed (200; 225; 250; 275 and 300 m/min), feed (0,1; 0,2; 0,3; 0,4 and 0,5 mm/rev) and depth of cut (0,5; 1; 1,5; 2 and 2,5 mm) on CNC lathe DMG Moriseiki-CTX 310 Ecoline. The experimental design defined the experimental work conducted on samples of dimension ø30 × 350 mm, and the sample material GJS 500 - 7. In accordance with the experimental design, 125 samples were defined with the variations of cutting speed, feed and depth of cut. The complete conducted experimental work was composed of a set of 750 instances. Surface roughness *Ra* measurement was carried out on each sample. The unified data set formed the basis for continuation of experimental work with the BPNN algorithm. The data were prepared before the work on studying acceptable architecture of a neural network began. Various structures were modelled and the BPNN algorithm parameters varied. Particularly separated and presented were the results of the level of *RMS* error in the function of the hidden layer number of neurons. During the neural network training different training algorithms were also varied which along with the accepted Sigmoid transfer function gave the following results for *RSM*: the Delta rule algorithm 4,82%; the Delta-Bar-Delta rule algorithm 4,73%; the extended Delta-Bar-Delta rule algorithm 3,37% and the Norm. Cum. Delta rule algorithm 4,80%.

The accepted architecture was (4 - 8 - 1) with the Sigmoid transfer function and the algorithm of extended Delta-Bar-Delta rule of the neural network training. After ending and accepting the *RMS* error with one hidden layer, the investigation could continue into the influence of the data set size on *RMS* error. With the accepted BPNN architecture the network training was continued on different amounts of data in two steps. In the first step the data sample was divided in two data sets and the *RMS* errors of 4,32% and 5,78% were realised. In the second step the data sample was divided in three equal data sets. The realised levels of *RMS* error were 7,09%, 6,71% and 6,25%, which leads to the conclusion that by reducing the amount of data the *RMS* error increased for the given problem of investigation. In continued investigation different BPNN structures were modelled with two hidden layers which generated a smaller error than the structure with one hidden layer. The adopted architecture was the one with two hidden layers (4 - 2 - 10 - 1) and *RMS* error of 2,26% in the training phase, i.e. 4,24% in the validation phase. The adopted BPNN architecture (4 - 2 - 10 - 1) was suggested for solving the problem.

There is a plan for the future research to also investigate the other algorithms of neural networks which successfully solve the problems of prediction.

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