Annals of the Academy of Romanian Scientists
Series on Engineering Sciences
ISSN 2066-8570 Volume **10**, Number **1**/**2018**

ROUGHNESS ESTIMATION OF A MILLED SURFACE BY USING NEURAL NETWORK BASED ON MINIMUM NUMBER OF EXPERIMENTAL MEASUREMENTS

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Rezumat. *Rețeaua neuronală artificială este un instrument puternic pentru predicția valorilor parametrilor, care prezintă un set de date de intrare redus, mai ales din punct de vedere al reducerii costurilor și timpului de efectuare a măsurătorilor. Predicția rugozității suprafeței în funcție de tipul de traiectorie al frezei pe suprafața de prelucrat în fazele de finisare se poate realiza atât prin unificarea rezultatelor cât și prin împărțirea setului de date în multi-clase. Lucrarea prezintă, pentru parametrul rugozitate, modul în care un set de date de intrare redus, obținut prin măsurare, este utilizat pentru predicție, precum și pentru extinderea setului de date. Testele efectuate au fost pentru prelucrarea unei suprafețe planare înclinate la un unghi constant pentru o piesă de probă din Aluminium 7075.*

Abstract. *Artificial Neural Network is a powerful tool for the prediction of parameter values, which presents a set of low input data, especially in terms of reducing costs and time for making measurements. The prediction of surface roughness according to the different tool trajectories of the finishing phase in the milling process can be achieved both by unifying the results and dividing the set of data into multi-classes. The paper presents, for the roughness parameter, how a set of low number of input data obtained by measurement is used for prediction as well as data set extension. The experimental tests were made for machining an aluminium 7075 part with plane surfaces at constant angle. The milling process was made without cooling.*

1. **Keywords:** prediction, artificial neural networks, roughness, milling trajectory.

1. Introduction

With the recent increase in energy demand and constraints in carbon emissions, energy saving has become a priority for the manufacturing industry. In the milling

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process energy savings up to 6-40% can be obtained based on the optimum choice of cutting parameters, tools and optimum tool path [1], [2].
With the development of computers and digital environments a paradigm shift in manufacturing from 'real' to 'virtual' production has resulted in a build-up of research interests in the field. With the aid of computers, simulating and modelling a physical manufacturing system become possible in virtual environments. The objective of simulating manufacturing technologies in virtual reality systems is to design a completely digital factory. The part is modelled and produced in a computer simulation environment with predicted errors in order to achieve the best accuracy in the produced part by choosing optimized process parameters [3].

Optimum machining parameters are of great concern in manufacturing environments, where the economy of machining operations plays a key role in competitiveness in the market. Although NC machines can reduce lead times considerably, the machining time is almost the same as in conventional machining when machining parameters are selected from machining databases or handbooks [4].

The use of many methods has been reported in the literature to solve optimization problems for machining parameters. All the methods use different procedures in optimizing the machining parameter with the same objective i.e. minimum production cost, minimum production time, maximum metal removal rate and maximum profit rate. These algorithm models for optimization include: Feasible directions, Particle Swarm Optimization, Memetic Algorithm, Taguchi Method, Genetic Algorithm, Tribes Algorithm, Immune Algorithm, Ant Colony Optimization, Simulated Annealing, Simulation Procedure, Genetic Expression Programming [6].

Metaeuristic algorithm models have good prediction precision for particular applications. Because ANN with backpropagation is suitable for general applications due to the flexibility in building architecture as well as the backpropagation learning of the error to the weight between the hidden node connections in the hidden layers was used in the case study presented in this paper.

2. The Concept of ANN with Backpropagation

The use of ANN for prediction is a modern and complex means of identifying the values of target parameters / indicators that are of interest in the production process. The major advantage is the ability of ANN prediction through learning based on a set of inputs determined experimentally, both values within and outside the scope of representation. An ANN of complex type with superior performance is performed with total backpropagation connected with several hidden layers and nodes per hidden layer. Figure 1 shows the architecture of an ANN with backpropagation totally connected, with h(x) hidden layers, NHL(y) **n**eurons in the **h**idden **l**ayer with the weights of the connection between two

neurons W. The resulting signals, represented by the output layer errors, are unified and used to run the entire network back to the hidden layers, thus enabling ANN to learn. The backpropagation algorithm is used to find a local minimum of the error function. The number of hidden layers neurons contributes to the most accurate identification of the algorithm contained in the training phase. This desideratum has its limits because between the number of hidden layers and the number of neurons per hidden layer there must be a balance to avoid the following situations:

- *a large number of hidden neurons on the hidden layer* negatively influences the generalization capacity and allocates a high processing time to the training phase;
- *a small number of hidden neurons on the hidden layer* is not enough to produce an appropriate ANN resulting in an increase in the mean square error and the training data error.

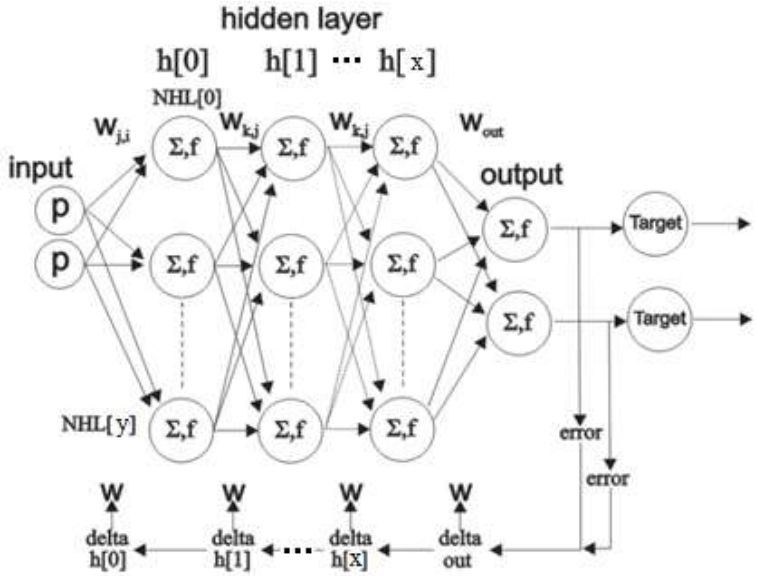

Fig. 1. ANN Architecture with total backpropagation connected. *Source:* [14], [15].

The most used ANN types with backpropagation are:

- **Hopfield** which are recurrent, symmetric, totally connected and self-assembled networks [8] and are designed so that no synchronization is required, each unit having a kind of elementary system in complex interaction with the rest of the assembly [9].
- **Elman** which can be configured on multiple levels of functional units, including forward-to-back network connections and inverse connections (linking hidden layers to input layers). The storage of hidden layer outputs is achieved by inserting context units similar to short-term memory [10].

In order to achieve the most accurate predictions, which supposes the identification of the algorithm underlying the analyzed data set, linear regression is used by the regression slope with parameter - r^2.

3. Method of Application of ANN with Backpropagation in the Prediction of Surface Quality

Step 1. Establish the input data set. This step removes the rough values in the measured field. Eliminating these values serves to increase the degree of identification of the algorithm to predict the values of interest and implicitly to reduce ANN learning time with backpropagation.

Step 2. Choosing how to use the data set. Depending on the concentration level of the data set values, for each test, choose one of the modes of use:

- in the initial order as measured by the measurements;
- by arranging the ascending / descending order of the data set;
- by dividing the data set in the ANN configuration.

Step 3. De-multiplication data sets containing values outside the range [-1, 1]. Since VGD works with data series in the range [-1, 1], the values must be scaled so that they have to be subunits. The de-multiplexing is performed for the entire set of data in that test, so it does not apply only to individually de-multiplexing values that exceed the range.

Step 4. Establishing the data set for training / validation and the prediction.

Step 5. Determination of the optimal simulation of the ANN architecture for the best predictions are obtained. At this stage experimentally determine the optimal architecture of ANN with backpropagation on:

a) the number of hidden layers and the number of nodes per hidden layer;
b) the number of cycles for validation and prediction;
c) the sum of errors and the average of the errors per data set is as small as possible;
d) learning rate and transfer function.

Step 6. Multiply the values in data sets that have been scaled to the same coefficient.

Step 7. Analysis and interpretation of predicted values.

4. Case Study on Roughness Prediction for Milling Surfaces.

One of the main goals in finishing operations is to achieve a very low work piece surface roughness. However, surface irregularities, which are always present in all machined parts, depend on several factors. In milling operations, surface quality

improves at higher cutting speeds. Depth of cut indirectly affects surface quality, since the cutting force, vibration and cutting temperature increase with an increase in the depth of cut. Other factors that influence surface roughness are feed rate, tool nose radius, tool wear, cutting strategy, the tool's trajectory during cutting, the work piece material, the cooling/lubrication system and the dynamic parameters of machining, such as the cutting force, tool deflection, vibration and several thermal phenomena. The machining parameters in milling operations consist of the cutting speed, depth of cut, feed rate and number of passes. These machining parameters significantly impact on the cost, productivity and quality of machining parts. The effective optimizations of these parameters affect dramatically the cost and production time of machined components as well as the quality of final products.

The goal of this paper is to find a way to predict a global roughness of a machined surface based on a minimum number of measurements. We use these results for the accurate calculus of federate based on the tool trajectory type [1] in order to optimize the machining time and surface quality (Figure 1).

Fig. 2. Finishing test for 9 trajectories type.

The roughness obtained on the 7075 aluminium surface was measured in the case of 9 milling trajectories (Figure 2).

A number of 6 measurements was performed (3 longitudinal/3 transversal) for each test (Figure 3). For these measurements we obtained a variation of the longitudinal roughness between 0.42-1.32 and the cross-sectional roughness between 0.45-1.22, so we have an average longitudinal roughness of 0.87 and for the cross-section of 0.835 [5].

Based on the measured data set, we want to predict the roughness magnitude for intermediate values, so expanding the data set from 27 to 80. To predict we use the artificial intelligence component - artificial neural network with backpropagation (ANN-BP) implemented in the software Visual Gene Developer 1.7 (Build 763). VGD works with numbers in the closed range [-1, 1], which

implies the de-multiplexing of unit numbers to obtain subunit numbers (e.g. 93 must be scaled by 100 and 0.93 is obtained).

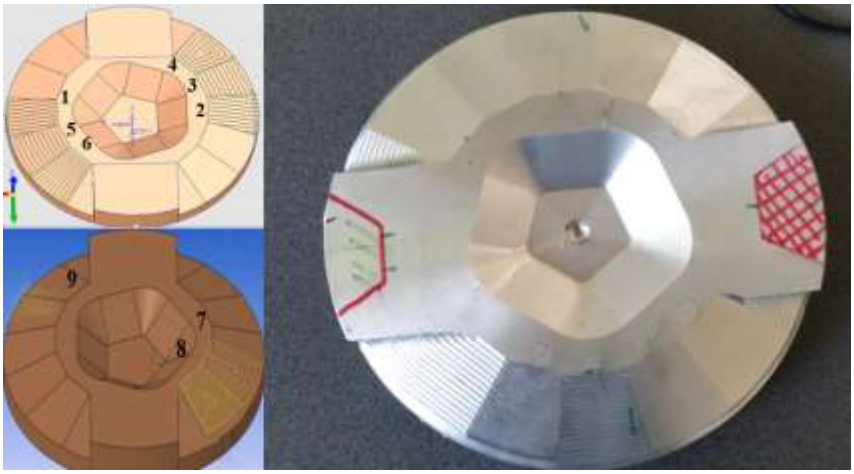

Fig. 3. Tool trajectories used for test : 1 – perpendicular on machine *Y* axis bottom → top; 2-perpendicular on machine *Y* axis top → bottom; 3–parallel top → bottom curves ; 4–spiral from outside to inside; 5–between curves – top→ bottom ;6 – between curves – lateral; 7–3D drive curve finishing; 8–3D finishing; 9–Spiral/radial finishing.

Fig. 4. Roughness measurement.

The data set for the 9 milling trajectories was analyzed as follows:

a) for trajectories 9, 6 and 5, the input data set was made from the first two measurements and the third input variable was used for validation and prediction (Table 1). For Trajectory 9, a **simple configuration** of ANN was used with 2 hidden layers and 3 nodes per hidden layer. In contrast, the roughness prediction for trajectories 6 and 5 required an ANN of **complex configuration** with 5 hidden layers and 10 nodes per hidden layer.

Table 1. Partitioning of the input data set for test number 9

	Measured values		Predicted values with ANN-BP	
No. Test	longitudinal	transverse	longitudinal	transverse
9	**0,46**	**0,98**	**0,46**	**0,98**
	0,56	**0,76**	**0,56**	**0,76**
	0,69	***0,67***	0,58	0,7943757
			0,60	0,7743953
			0,62	0,7533252
			0,64	0,7312565
			0,66	0,7082964
			0,68	0,6845647
			0,69	***0,6724498***

b) for trajectories 2, 7 and 8, the input data set was made from the 3 measurements and the prediction was for values within the data set. For trajectory 2 an **average configuration** ANN was used with 2 hidden layers and 10 nodes per hidden layer. The roughness prediction for trajectories 7 and 8 required a 5-layer **complex configuration** RNA configuration and 10 nodes per hidden layer.

c) for trajectories 1, 3 and 4, the input data set was divided into two classes and the prediction was for values within the class set. For trajectory 1an ANN with **simple configuration** was used with 1 hidden layer and 10 nodes per hidden layer. Roughness prediction for trajectories 3 and 4 required an **average configuration** ANN with 2 hidden layers and 10 nodes per hidden layer.

The nine cases are dominated by 4 mixed-type models (with male human-female biological thinking) and 4 female models (with human feminine biological thinking) [11].

ANN models with **simple configuration** works with an informational flow of numbers close to ± 1 (Figure 5) [12], [13].

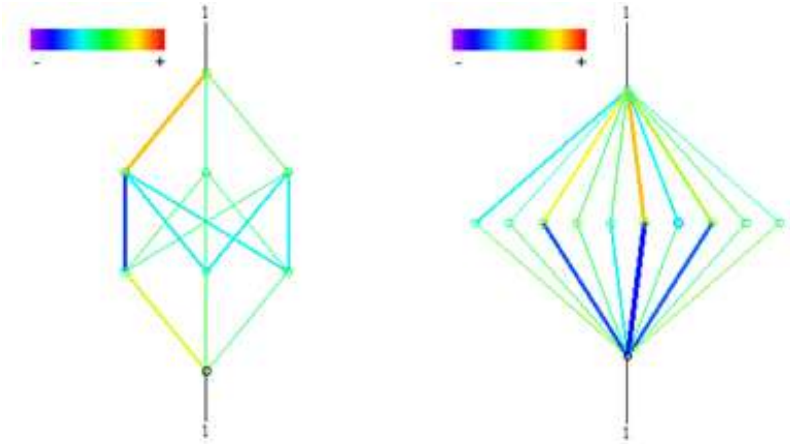

Fig. 5. ANN model with **simple configuration** and propagation of the information flow with numbers to the extremes of the domain.

ANN models with medium and complex configuration works with an informational flow of numbers close to ± 0 (Figure 6).

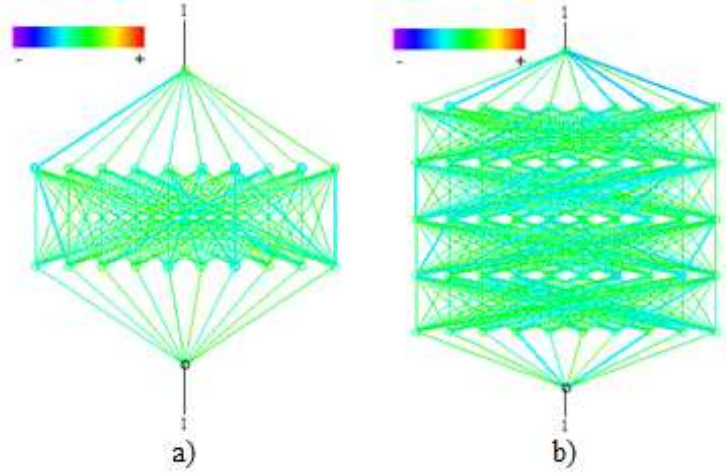

Fig. 6. ANN models with **medium (a) / complex (b) configuration** and propagation of the information flow with numbers to the centre of the domain.

Figure 7 presents the regression slope distribution modes for which the values of the r^2 determination coefficient of 1.000188 were obtained in the case of a) (over-assessment of 0.02%), of 0.9999992 in case b) (precise assessment of 0.00008%) and 0.61842 for c) (imprecise valuation of 38.16%). The higher the value of the coefficient of determination, r^2, is closer to the maximum value 1, the variance of the response variable can be explained by the explanatory variables, the difference being attributable to some unknown variables or variables inherent. It can be observed that in 3 cases (1, 2 and 3), although the regression slope has high imprecision in terms of the coefficient of determination, r^2, the predicted roughness average is very close to the average roughness measured (Table 2).

Conclusion: Not in all cases where the coefficient of determination, r^2, is greater than or equal to 0.93 leads to very accurate predictions.

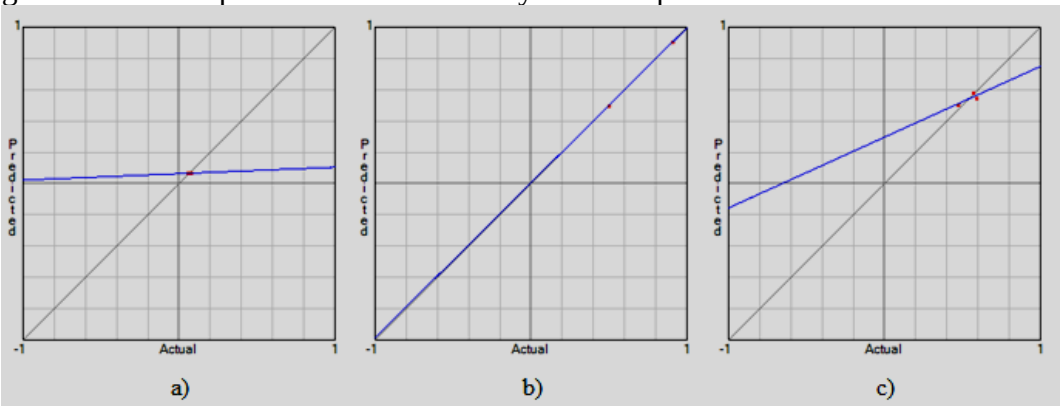

Fig. 7. Modes of data set distribution on regression slope.

It can be seen from Table 2 that the difference between the average of roughness obtained from measurements (classic average) and predicted (mean ANN) is a very small difference of 0.00663 (0.97% <1%). This denotes that the way of realizing the prediction characterized by: the input data set allocation module, the ANN-BP (hidden layers, nodes per hidden state) configuration, the ANN-BP training and the validation of the data were correctly performed.

Table 2. Comparison of experimental and predicted average with ANN-BP. Synthesis of predictive features

No. Test	Measured Average	Average ANN-BP	Regr. Coef.	Slope	y-intercept
9	0,69	0,6860	0,999996	0,343	0,552
6	0,60	0,5863	1,000148	0,091	0,750
5	0,90	0,9342	1,000188	0,041	0,063
2	0,59	0,5816	0,873848	0,873	0,066
7	0,79	0,7835	0,999992	0,536	0,345
8	0,90	0,8469	0,999999	0,991	0,005
1	0,53	0,5260	0,618420	0,453	0,297
3	0,65	0,6417	0,826680	0,521	0,247
4	0,50	0,4958	0,999984	0,947	0,028
Average	0,6824	0,6758			

The comparison between the mean measured for each test and the average predicted by ANN-BP is shown in Figure 8. In 4 cases the difference is in the order of the suits, in 3 cases of the order of the milliams and in 2 cases in the order of the ten thousands, focuses on differences in the order of suits and millet.

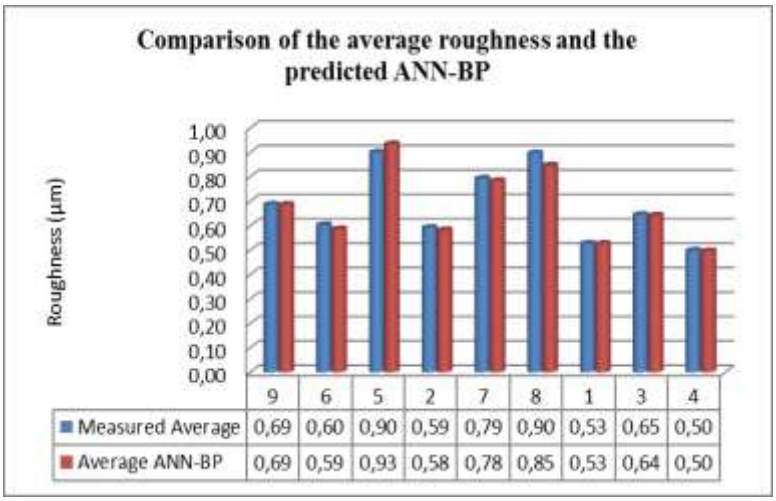

Fig. 8. Comparison between the average roughness and the predicted ANN-BP.

The precision of roughness prediction with the proposed algorithm is also reinforced by the graphical representation of the two sets of data that are very similar (Figure 9).

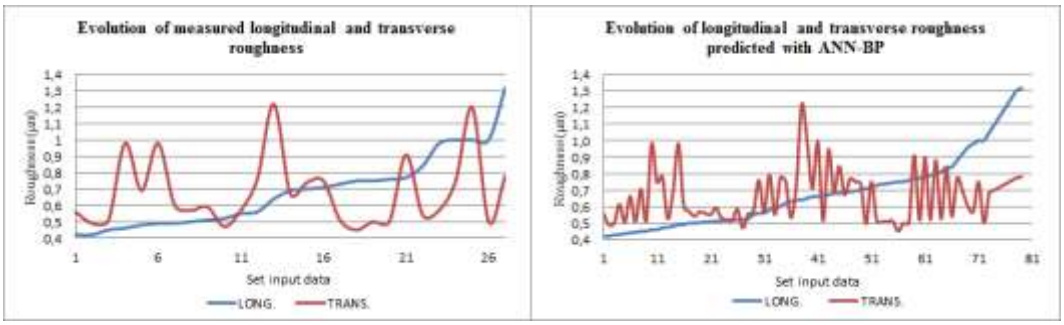

Fig. 9 The comparative evolution of measured vs. predicted rugosity with ANN-BP.

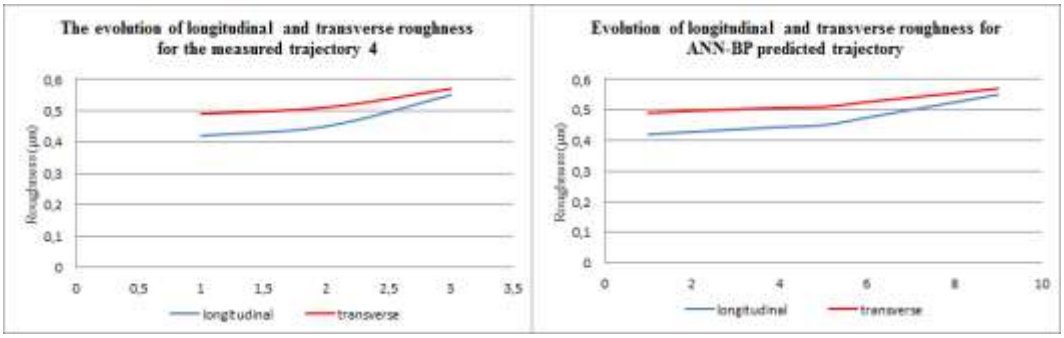

Fig. 10. The comparative evolution of the measured vs. predicted rugosity for the milling trajectory number 4.

In the case of 8 trajectories, the resulting graph is identical to the ANN-BP predicted chart. Figure 10 illustrates the comparative vs. predicted roughness versus milling trajectory number 4 which demonstrates that the two graphs have identical patterns.

The ANN-BP predicted data set for trajectory 8 (Figure 11) makes a distinct prediction, which is evidenced by the evolution of the transversal roughness that is descending to the pre-measured roughness value 7 followed by the trend of the measured data set.

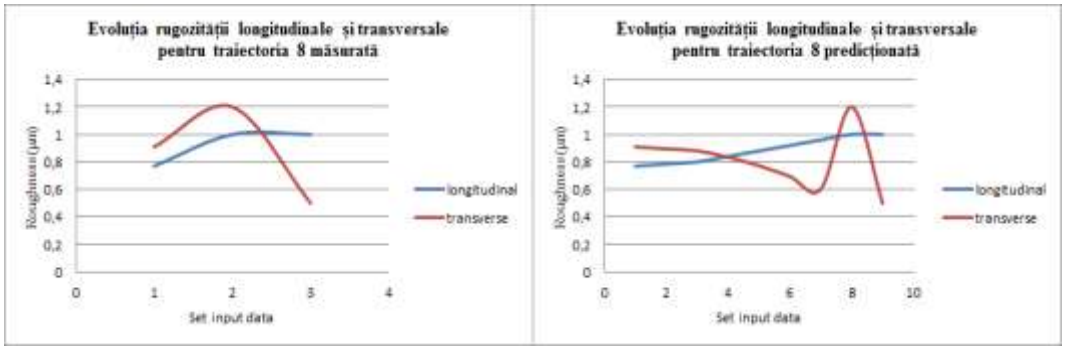

Fig. 11. The comparative evolution of the measured vs. predicted rugosity for the milling trajectory number 8.

5. Conclusions

For predictive predictions, simple, medium and complex ANN-BP architecture configurations with varying number of hidden layers, nodes per hidden layer, learning rates, learning times, experimentally determined characteristics.

There are also exceptions when the determination coefficient, r^2, has values below 0.93 and the predictions obtained are very good because the realization of the ANN-BP architecture identifies the global minimum solution through a rapid learning convergence.

The case study presented in this paper on predicting roughness for different milling trajectories is based on a modern analysis tool highlighted by the performance of the algorithm on which ANN-BP is based.

The precision of predictions with ANN-BP demonstrates that they are robust instruments that lend themselves to prediction: the behaviour of the equipment during the production process, the quality of the products, the maintenance of the equipment, the performance of a real flow line.

Future studies will focus on Fuzzy Logic-ANN type hybrid analyses, each with individual and not ANFIS.

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