

# Optimum Process Parameters in Superfinishing Process using Artificial Neural Networks

Badea Lepadatescu

**Abstract**— The work reported describes application of artificial neural networks (ANN) for the purpose of deriving a complex nonlinear relationship among several factors that influence the roughness of part surfaces obtained through superfinishing process according with different process parameters. The relationship is necessary to optimize the process parameters and predict the optimum values to obtain the roughness surfaces that are needed for the part manufactured. A feed forward two-layers ANN is designed and trained using experimental data. The model is tested for generalization and simulated in MATLABM environment. The results are used to determine the best process parameters that must be used to have a high surface finish according with the technical requirements.

**Keywords**— Surface finish, Reliability, Wear, Cost-performance, Two-Layer ANN, Back propagation, MATLABM Simulation.

## I. INTRODUCTION

The majority of processes that take place in manufacturing processes are difficult to describe by simple, useful and at the same time precise models that can be used in prediction and optimization. Often the reason is their complexity, the impact of various disturbances and many factors [3]. The main areas of application of artificial neural networks (ANN) are related to modeling from experimental data when other techniques are not applicable, the relationships is highly nonlinear and rather complex, the factors to be considered many [5]. The advantage of ANNs is derivation of reliable models by simple approach.

The aim of the present investigation is to apply neural network approach in achieving the process parameters in superfinishing operation in order to easily determine the optimal parameters for obtaining the surface finishes of part manufactured that are required by technical documentation.

## II. THEORETICAL BACKGROUNDS

Surface finishing and surface treatment have been a challenge to the machining industry and material engineers in light of the burdens related to application costs and the time it takes to superfinish a coated mechanical part.

The need for new and more advanced solutions for minimizing the process time required to improve metal

surfaces and reduce friction has been accelerated in recent years for two main reasons: fierce competition between engine manufactures and automotive makers, which constantly requires suppliers to lower their prices, and maintaining long service life and durability in spite of reduced prices. This paper discusses a new approach that addresses both issues in a single process that saves time and cost.

These contradictory requirements drive our researches and development towards solutions that will enable price reduction throughout the superfinishing process and will fit mass production applications. The key to the development presented in the paper was based on combining two main factors [1]:

- a process that can be used in existing production machines;
- a solution that will dramatically shorten the finishing process on coated (hardened surface) or uncoated metal surfaces.

Any superfinishing process involves three elements: the part (or specifically the surface) that should be machined; the abrasive particles that actually machine the surface and reduce its roughness; and the superfinishing tool that exerts the force required affecting the machining operation with the abrasive particles.

In superfinishing, an abrasive stone, shaped to the contour of the workpiece, removes surface fragmentation or smeared metal from previous finishing processes. Superfinishing uses very low pressure and speeds to produce a controlled low stress surface finish.

## III. PROCESS SCHEMATIC

Superfinishing requires the bonded abrasive to oscillate over the rotating symmetrical workpiece. As the workpiece rotates, very fine oxidized chips are removed from its surface [3]. Lubricant is required to cool the workpiece and to wash away the chips from the abraded area (Fig.1).

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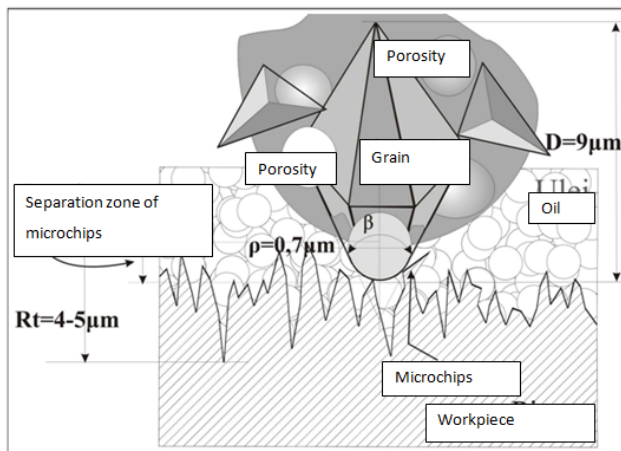


Fig. 1 Schematic illustration of superfinishing process.

Superfinishing is used when grinding alone is not sufficient, or is too expensive, to achieve a required roundness and surface finish. The oscillations movement is produced electro-mechanically or by compressed air (contact pressure is normally made by compressed air). Hardness and grain of the superfinishing stones are selected to suit the job requirement.

Examples of use include for highly loaded surfaces and sliding surfaces, anti-friction bearing elements and friction bearing shafts, contact areas of sealing rings and collars. The abrasive is either aluminum oxide widely used for steel, or silicon carbide for finishing cast iron and non-ferrous metals. If the work is longer than the stone, then a traverse motion is also required parallel to the axis of work. It should be noted that the stone gradually wears in to the average radius of the part. The early stages of the operation consist of the abrasion of the peaks and ridges of the workpiece. The stone will have contact with the workpiece at isolated points (Fig.2).

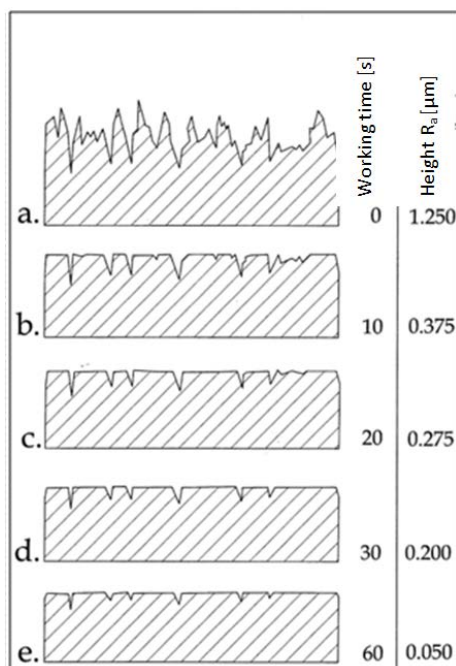


Fig. 2 Evolution of workpiece' roughness during superfinishing process.

However, as the work approaches nearer to a true cylinder the area of contact increases thus reducing the pressure on the unit area. Cutting fluids used in superfinishing are light mineral oil or kerosene oil together with a heavier cutting oil.

Process characteristics:

- Involves no appreciable production of heat to alter metallurgical properties;
- Produces a controlled surface finish, typically less than 0,02 microns  $R_a$ ;
- Utilizes low speeds (15 to 40 meter/minute) and low pressure (10 to 40 psi);
- Removes only a thin layer of smear metal, usually less than 5 microns.

#### IV. TESTS REGARDING THE FACTORS THAT INFLUENCE THE PART SURFACE FINISH

The main factors that have influence on the superfinishing process are: grain size of abrasive stone, time of superfinishing process, pressure of abrasive stone on the part surface, the rotational speed of the part.

The tests were made with a superfinishing attachment mounted on a tool post of a grinding machine as is shown in Fig.3 [12].

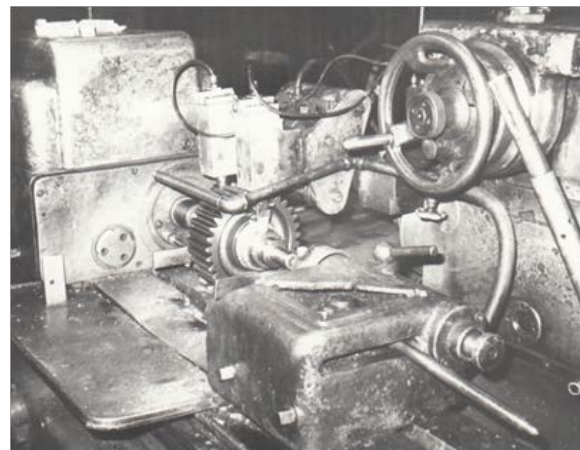


Fig. 3 The superfinishing unit mounted on a grinding machine.

##### A. The influence of grain size of abrasive stone on the surface finish

The size of abrasive stone is an important factor to obtain a high surface finish of the workpiece. During the tests were used the abrasive stones with a grain size between 600 and 1000. The workpiece that was used for the tests had a hardness of 58-62 HRC and a diameter of 75 mm.

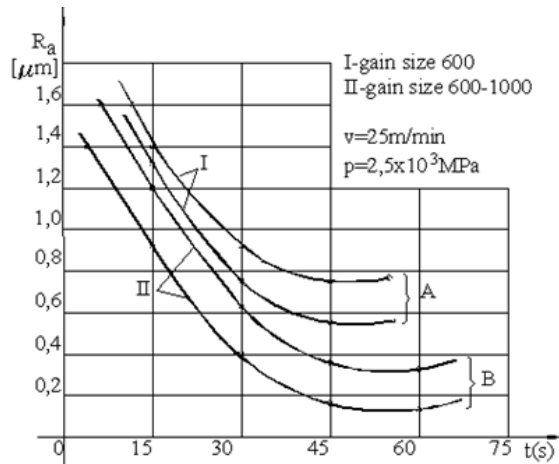


Fig. 4 The influence of the abrasive grain size on the surface finish.

The rotational speed of the workpiece was of 25 m/min and the force of the abrasive stone on the part surface had a constant value of 15 daN, 22 daN, and 30 daN, obtained by different values of the contact pressure between the abrasive stone and part surface.

The results of these tests are shown in the Fig.4 [13].

The graph A was obtained when was used a part with a surface roughness after grinding of  $R_a = 1, 7 \mu\text{m}$ , and the graph B with a part with surface roughness of  $R_a = 1, 2 \mu\text{m}$ .

It results that if is necessary to obtain a surface finish of high quality is important the previous surface finish obtained usually by grinding.

Based on mathematical programs was obtained the value of surface roughness  $R_a$  according with the grain size of abrasive stone:

$$R_a = 7,622178 * (\text{grain size})^{-0} \quad (1)$$

with an error compared with the experimental values of:

$$E_r = 7, 8632 * 10^{-3} \quad (2)$$

**B. The influence of processing time on the part surface finish**

Superfinishing is a machining process where the tool cutting action is interrupted automatically after a specific time. This time have different values according with the factors as: the initial roughness of the part, the abrasive stone grade, the part material and the surface finish value that has to be obtained.

In Fig.5 is presented the test results of the surface roughness  $R_a$  according with the processing time where used three values of stone pressure on the part surface were. It was used an abrasive stone with grain size of 400 and the rotational speed was of 20 m/min.

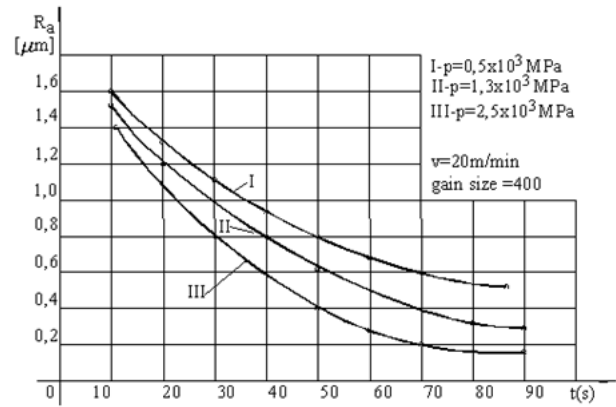


Fig. 5 The influence of the processing time on the part surface finish.

As it is shown in Fig.5 the initial surface roughness of the part was  $R_a = 1.6 \mu\text{m}$ , obtained after grinding operation. The time of machining process is different according with the force between the abrasive stone and the part surface. This force is given by the pressure of pneumatic stone contact, and if is used a bigger value of this pressure the time of superfinishing process is shorter. This time of superfinishing process is obtained by tests for each material and part surface roughness required because when is achieved a high value of bearing surface the process of cutting action is automatically interrupted and is not necessary to continue the superfinishing operation. Depending on the stock removal value and the surface finish required the time of superfinishing process is between 50-90 seconds.

The value of roughness surface according with the processing time can be obtained with the equation:

$$R_a = 0, 00404 * t^2 - 0,036634 * t + 0,937818 \quad (3)$$

with an error compared with the tests results of:

$$E_r = 1, 24441 * 10^{-2} \quad (4)$$

**C. The influence of the cutting speed on the part surface finish**

The cutting speed is an important parameter in superfinishing process that influences in a great manner the surface finish of the part. These different values of cutting speed can be obtained by varying the rotational speed of the part being machined and the oscillating movement of the superfinishing stone.

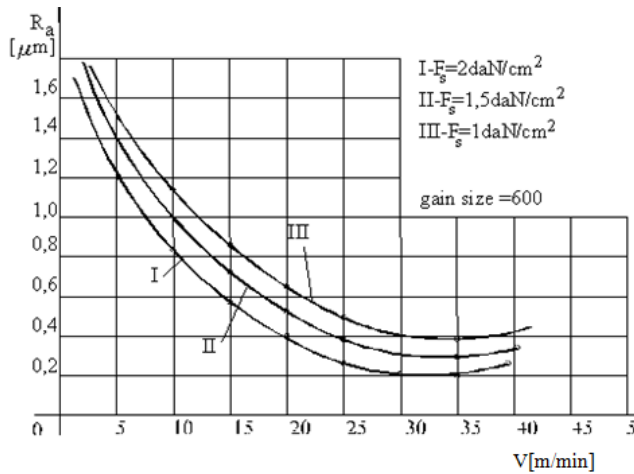


Fig. 6 The influence of the cutting speed on the part surface finish.

In Fig.6 is presented the test results of the part surface finish according with different values of the cutting speed and for different values of the force between the superfinishing stone and part surface. The abrasive grain size used was of 600 the other cutting parameters being constant.

It is noted that the optimum range of cutting speed is between 25-35 m/min, and if the value of cutting speed is increasing the surface finish of the part have a greater value.

This thing is happen because the angle between the path of the abrasive grains is lower of 300, which is considered minimum to maintain the cutting capacity of abrasive stone [2]. The values of specific forces between the abrasive stone and part surface was of  $F_s = 1-2$  danN, and if is used the bigger value of this force is obtained the smaller value of part surface roughness.

The last researches in the field of superfinishing process were indicated that to obtain a high surface finish of the workpieces is recommended to use two type of oscillating movements, with different values of amplitude and frequency.

As an example is recommended for the amplitude of oscillation 1-5 mm with a frequency of 1000-1500 strokes/min and other oscillating motion with an amplitude of 5-10 mm and a frequency of 50-70 strokes/min. by the combination of these two oscillation motions the surface finish of the part being machined is obtained in a shorter time by increasing productivity of machining process.

The value of surface roughness depending on the cutting speed is giving by the equation:

$$R_a = 0,00026 * F_s^2 - 0,006408 * F_s + 0,474286 \quad (5)$$

With an error compared with test results of

$$E_f = 2,5463 * 10^{-3} \quad (6)$$

### Conclusions

By using superfinishing process the roughness average ( $R_a$ ) is improved to a value of 0,02 microns and the bearing area curve characteristics are significantly improved, while surface geometry remains unchanged.

The superfinishing process meets new market demands both in superior results and in competitive cost-performance, compared with other finishing processes. In addition, the superfinishing process reduces friction, wear, and energy consumption, and leads to savings in service and maintenance costs.

## V. APPLICATION OF ARTIFICIAL NEURON NETWORK FOR MODELING, ANALYSIS, PREDICTION AND OPTIMIZATION

Artificial neural networks (ANN) have gained popularity in many engineering applications for their capability to model non-logical data, classify, store and present numerous sensors readings and experimental knowledge in terms of logical symbolic structures. ANNs perform function approximation/mapping as well, being tolerant of data imprecision and noise, which can be successfully applied for interpolation and prediction [10].

A two-layer neural network with nonlinear differentiable and monotonic increasing activation functions in the hidden layer can be off-line trained to reproduce any deterministic nonlinear input-output relationship using vectors of representative input-target training couples and applying the back propagation rule. The matrix block diagram of a network with  $Q$  batching input vectors  $p$  and with logistic sigmoid activation functions in both layers  $F1$  and  $F2$  is shown in Fig.7. The output  $A_i$  ( $i=1, 2$ ) of each 1 log-sigmoid function  $F_i$  in the  $i$ -th layer is given by:

$$A_i = (1 + e^{-N_i})^{-1}, \quad N_i = \sum_k W_{ikl} \cdot p_k + b_{i1} \quad (7)$$

where  $N_i$  is the function input and the weight  $W_{ikl}$  and the bias  $b_{i1}$  are the adjustable ANN parameters. The log-sigmoid function allows to map the input from the interval  $(-\infty, +\infty)$  into the interval  $(0, 1)$ . The number of the inputs  $R$  corresponds to the number of the geometrical factors,  $Q$  is the number of measurements available.

While the number of the output layer neurons  $S2$  depends on the number of problem outputs (here  $S2=1$  - the roughness of part surface which is manufactured), the number of the neurons in the hidden layer  $S1$  can be freely selected in order the optimization problem to have a satisfactory with respect to time and accuracy solution.

The weight matrices  $W1$  and  $W2$  and the bias vectors  $b1$  and  $b2$  are being continually adjusted in the direction of the steepest descent with respect to minimization of the mean squared error (MSE) of the network. Derivatives of error called delta vectors  $\delta$  are calculated for the network's output layer and then back propagated through the network until delta vectors are available for each hidden layer.

The error  $E$  is the difference between the target  $T$  vector of measured/desired values and the ANN output  $A$  vector ( $E=T-A$ ) that corresponds to a given input vector from the batch of input vectors.

The steepest descent method is used with adaptive learning rate in order to increase convergence of the gradient procedure in the surroundings of the minimum, to decrease the number of iterations, and to avoid local minima and instability at large rates. Initialization of the network is provided by a random number generator that produces values within the range (-1, 1). The new weights  $W_{ij}$  connecting neurons from layer  $i$  to layer  $j$  and the biases  $b_i$  at the  $k+1$  iteration are calculated according to the back propagation rule:

$$W_{ij}(k+1) = W_{ij}(k) + \Delta W_{ij}(k) = W_{ij}(k) + \alpha \cdot \delta_i \cdot p_j \quad (8)$$

$$b_i(k+1) = b_i(k) + \Delta b_i(k) = b_i(k) + \alpha \cdot \delta_i, \quad (9)$$

where  $\delta_i$  is the delta vector for the current  $i$  layer,  $p_i$  is the corresponding input vector,  $\alpha$  is the learning rate.

The calculations move from the output to the input layer of the network. When a desired accuracy is reached in the target points, the network is tested with more input vectors than the ones used in training to see if it has learned to generalize the function it is learning. If the approximated function is smooth and monotonic in-between the target points, the training is considered to have ended successfully.

Else, it should be started from different initial conditions, or else the number of the neurons in the hidden layer or the number of hidden layers should be increased. Often more inputs and corresponding targets are added to the training vectors. Specialized software assists the design and training of the ANN.

The ANN used for modeling the relationship between the roughness of part surface on one side and force and velocity of the abrasive stones used on the other side is a two-layer log-sigmoid back propagation ANN with seven hidden neurons ( $S1=7$ ) and one output neuron ( $S2=1$ ). The accuracy reached in training is  $10^{-5}$  and the training algorithm with adaptive learning rate is the Levenberg-Marquardt optimization (a modification for speeding up the steepest descent method). The default criterion (stop condition) is MSE.

The ANN model is depicted in Fig.8. Here  $R=2$  for normalized in the range (0, 1) force and velocity over their maximal values 2 and 39 respectively,  $Q=27$  measurements.

The target is the measured roughness, which is also normalized in the range (0, 1) over the maximal value of 1.8. The results for target and actual output after training are shown in Fig.9.

The generalization test uses more input values – Fig.10 and allows to determine the optimal parameters for velocity  $V=32$  and force  $F_s=2$  that ensure minimal roughness  $R_{amin}=0.2018$  microns.

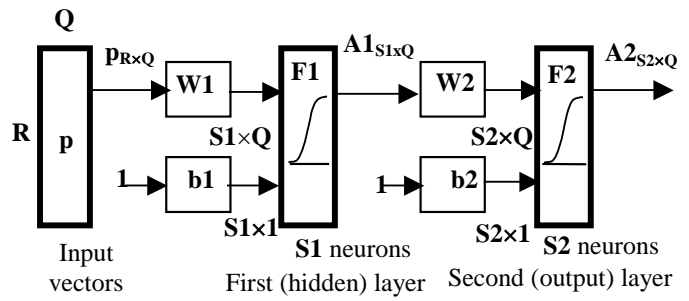


Fig. 7 Back propagation two-layers ANN

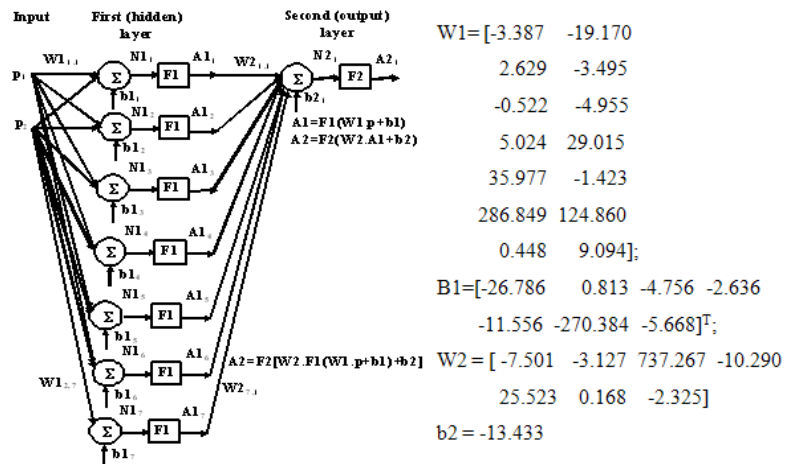


Fig. 8 Back propagation ANN model of roughness

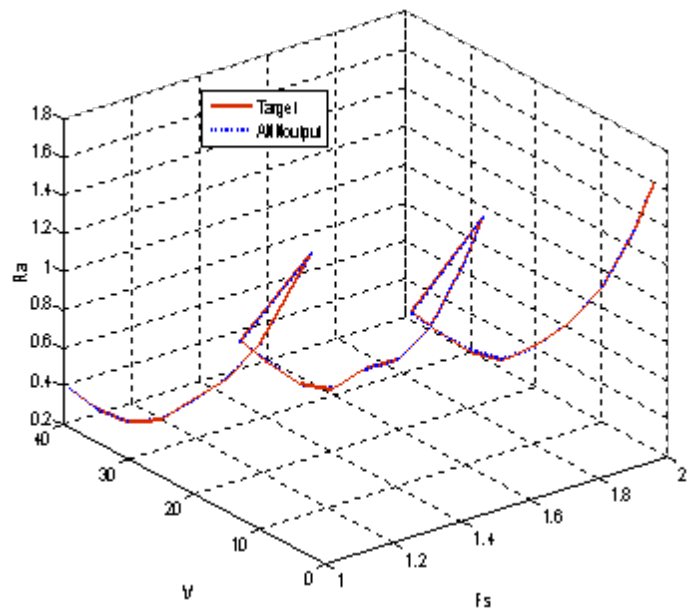


Fig. 9 Back propagation ANN model of roughness

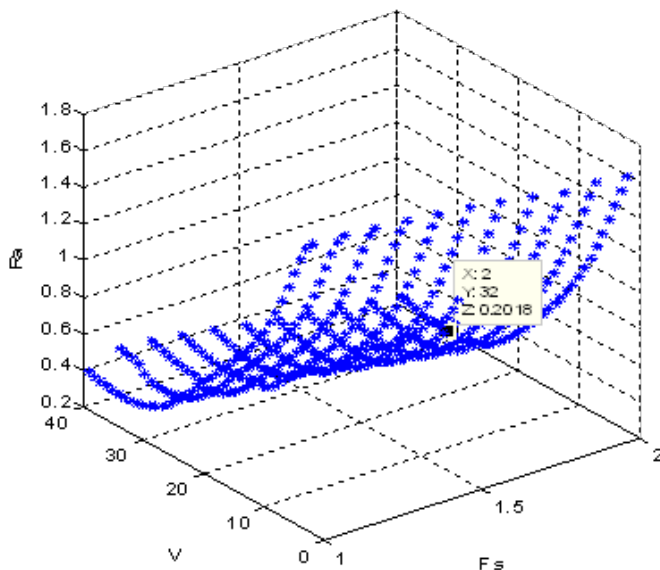


Fig. 10 ANN model of roughness in generalization

The model is generated in Simulink of MATLABM and is used to perform simulation investigations for all combinations of values for the two inputs as shown in Fig.11, where the Step block starts from 1 and by adding 0.2 covers the whole range for the force  $F_s$ , the range for  $V$  is simulated by the block Repeating Sequence – reset integrator with output from 0-40. The Gain blocks are the normalizing and denormalising gains. The results from simulation are recorded by the Graph Scope  $y\{1\}$  and given in Fig.12.

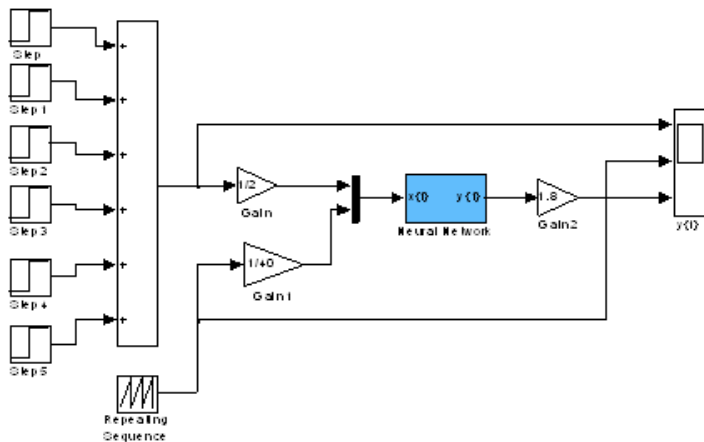


Fig. 11 Simulink model for investigation of the derived ANN model of roughness

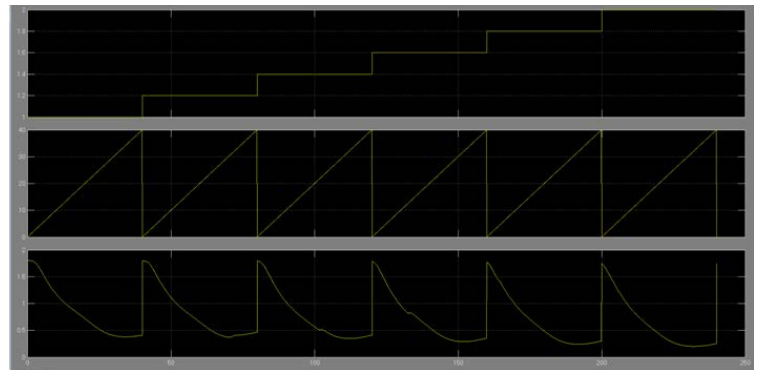


Fig. 12 Simulating ANN model output for all possible combinations of inputs

## VI. CONCLUSIONS

By using superfinishing process the roughness average ( $R_a$ ) is improved to a value of 0, 02 microns and the bearing area curve characteristics are significantly improved, while surface geometry remains unchanged.

The superfinishing process meets new market demands both in superior results and in competitive cost-performance, compared with other finishing processes. In addition, the superfinishing process reduces friction, wear, and energy consumption, and leads to savings in service and maintenance costs.

Using application of artificial neuron network for modeling and analysis, we can predict and obtain the best process parameters of superfinishing technology for each type of workpiece material.

## REFERENCES

- [1] Yordanova S., Assenov V. and Z. Nedlic. Application of Artificial Neural Networks for Linearising Control of a Non-Linear Plant, Proceedings of the 3rd Japan-Australia-New Zealand Joint Seminar JANZS'2004, Auckland, New Zealand, Jan. 22-23, 2004, pp.165-171.
- [2] Yordanova S. and R. Tzeneva. Application of Neural Networks for Analysis in Bolted Busbar Connections of New Design, Proc. of the XLIII Int. Sc. IEEE conf. on Information, Communication and Energy Systems and Technologies ICES'T'08, Serbia, Niš, 25-27 June, 2008, ISBN: 978-86-85195-61-7, pp. 666-669.
- [3] Wasserman P.D. Neural Computing. Theory and Practice. ANZA Research, Inc. Van Nosrand Reinold, N.Y., 1992.
- [4] Demuth H., M. Beale. Neural Network Toolbox for Use with MATLAB. Users Guide. The Mathworks Inc., 1993.
- [5] Yordanova S., A. Todorov. Investigation on Some Applications of Neural Networks in Control of Plants with Variable Parameters. –In: Problems of engineering cybernetics and robotics, No47, BAS, 1998, pages 59-68.
- [6] Yordanova S. Investigations on Neural Networks Flowrate Control. Proceedings of the WSES/MIUE/HNA Int. Conf. "Mathematics & Computers in Mechanical Engineering '99" (session Computer Aided Metrology), Florida Keys, 25-29 July, 1999, 71-74. ISBN: 960-8052-04-1.
- [7] Haykin S., Neural Networks: A comprehensive foundation. 2nd Edition, Prentice Hall, 1999. ISBN 0132733501.
- [8] Farago, F. T., Abrasive Methods Engineering, Vol.1, 1976, New York: Industrial Press.
- [9] Borokowski, J., and A. Szymanski., Uses of Abrasives and Abrasive Tools. Chichester, Eng.: Ellis Horwood, 1992.
- [10] King, R. I., and R.S. Hahn., Handbook of Modern grinding Technology. New York: Chapman and hall/Methuen. 1987.

- [11] McKee, R.L., *Machining with Abrasives*. New York: Van Nostrand Reinhold, 1982.
- [12] Lepadatescu, B, Dumitrascu, A.E., Enescu, I., Nedelcu, A. – Research regarding the improvement of workpieces surface finish by machining through superfinishing process. In : *Proceedings of the 4th International Conference on Manufacturing Engineering Quality and Production Systems*, Barcelona, Spania, 15-17 Septembrie 2011., pag 190-195, ISBN: 978-1-61804-031-2.