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Research article

Improving surface roughness in barrel finishing process using supervised machine learning

Mohammad Sajjad Mahdieh[1*], Mehdi Bakhshi Zadeh[1], Amirhossein Zare Reisabadi[2]

[1]*Department of Mechanical Engineering, Shahid Chamran University of Ahvaz, Ahvaz, Iran.*
[2]*Department of Materials Engineering, Isfahan University of Technology, Isfahan, Iran.*

[*]s.mahdieh@scu.ac.ir

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Abstract
The Barrel finishing process is a finishing method applied for cleaning, polishing, improving surface quality, Deburring, and rounding corners of both metallic and non-metallic parts. There are Several factors affect the final surface integrity of the barrel finished samples such as initial surface roughness, piece length, operation time, and different abrasive materials (i.e. aluminum oxide, steel balls, and ceramic). On the other hand, each factor has different levels, and handling this amount of data to reach desired results is approximately impossible due to the “curse of dimensionality”. Machine learning is a promising method to pave this avenue for computing huge amounts of data and predicting the future state of the system. Accordingly, in this study, it is attempted to apply a supervised machine learning algorithm, an artificial neural network- to improve surface quality in the barrel finishing process. Python is used to code the program and extract several simulations and related graphs. Results show that time has the greatest effect on surface roughness, moreover, among the different abrasive media, steel balls have the best performance to improve surface roughness and the combination of 75% steel balls and 25% aluminum oxide has the effective effect. The simulation results have an acceptable compatibility with experimental ones.

Keywords: Barrel finishing process, Machine learning, Surface roughness, ANN

1- Introduction

Surface integrity factors including surface roughness, cracks density, surface hardness, residual stresses and other tribological properties are very significant in industrial parts undergo contact stresses such as pistons and bearings [1, 2]. Conventional and modern machining processes is aimed to improve dimensional and geometric tolerances as well as surface quality [3-8]. However, in order to focus on surface quality, special finishing processes including grinding, polishing, roller burnishing, and barrel finishing should be applied to improve surface integrity [9-12]. Barrel finishing as a typical-free abrasive tool finishing methods, has advantages such as low processing cost, acceptable surface finishing, proper efficiency, and simplicity is one of the mass finishing methods which is functional for various range of parts such as cast part, plastic injected parts, metal formed parts and so forth [13-15]. There are several factors affecting the final surface roughness of barrel finished part including initial surface roughness, piece length, operation time, and different abrasive materials (i.e. aluminum oxide, steel balls and ceramic). However, according to authors' knowledge, there is no reliable formula or model to predict the final conditions of finished parts, and results have been obtained by trial and error technique that some of which are reviewed as follows [16]. Boschetto and et al. in 2009 investigated tracking trajectory of both workpiece and abrasive media in barrel finishing process. Their results indicated that the path of movements plays an important role in calculating the effective working time of the process [17]. In the ball milling process which is very similar to barrel finishing, the relative velocity between the workpiece and the abrasive materials is the influential parameters affects the shape of the workpiece. It is difficult to find a precise movement algorithm for the process [18-20]. In another survey, Boschetto et al. investigated micro-removal modeling of the specimens' surface and they were success to achieve a proper model to predict the surface roughness but only for some limited materials and abrasive media [21]. Bebosa et al. investigated the movement of small glassy balls in the ball milling process. Although they presented some predicting models for the movement of the balls, they stated that it is almost impossible to completely predict the entire dynamic model of the process [22]. According to Bushto's survey which was conducted about deburring of sheets metal by barrel finishing process, duration time of the process, has the greatest impact on the quality of the samples [23]. Some researchers such as Chiancola and Li worked on the different type media in barrel finishing process and investigated its effect on final surface quality. They conducted their surveys through several experiments and statistical analysis [16, 24].

As mentioned, obtaining a reliable formula to predict the final surface roughness of the barrel finished part is really difficult due the high volume of input data. Machine learning is a promising method to overcome this problem because of its ability for computing huge amounts of data [25-29]. Nowadays, applying machine learning is very prevailing in predicting the final circumstance of the system and many researchers used different algorithms of machine learning to evaluate the behavior of the process in the next steps [30-33]. But few studies have been conducted on applying machine learning in the barrel-finishing process [34]. In the present study, the artificial neural network algorithm (a supervised machine learning algorithm) has been applied to simulate the process and obtain the best model for predicting the surface roughness in barrel finishing. It is worth noting that the experimental data used in this survey, was extracted from our previous study [12]. The used program was coded in Python with seven libraries, two IDEs named Pycharm and Jupyter, and a total of 440 lines code. Moreover, this program applied 252 tested data (from experimental results) for learning.

2- Materials and Methods

2-1- Barrel finishing parameters

The cylindrical samples made of CK45 steel alloy, with 10mm diameter were used in this study. The process parameters are introduced in table 1. A sample before and after finishing process is demonstrated in Fig. 1.

Table 1: Process parameters

Parameters	Value			
Height of samples	10mm	15mm	20mm	
Initial roughness	6.14 µm	8.96 µm	11.90µm	
Abrasive media	Steel balls	aluminum oxide	ceramics	
Working time	1 hour	2 hours	3 hours	4 hours

Fig. 1 A sample before and after finishing process

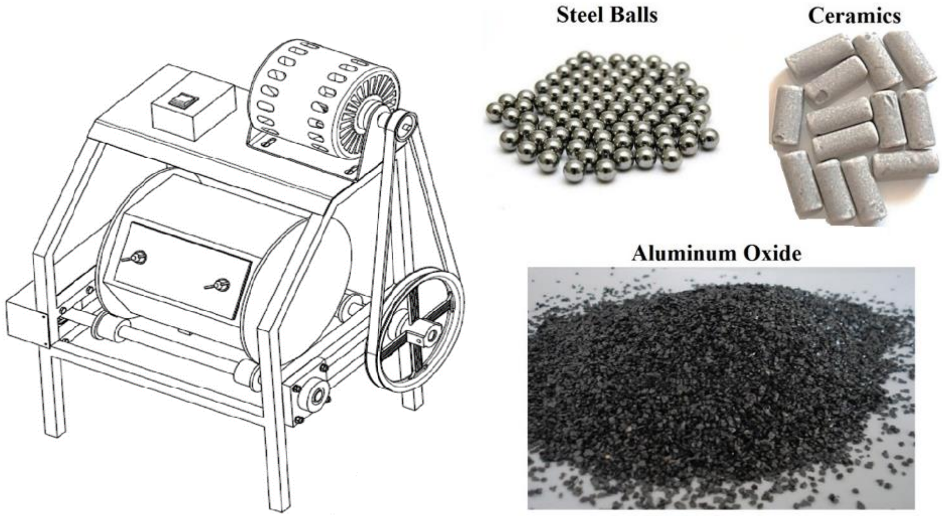

Fig. 2 Barrel finishing machine (left) – Three different media (right)

A horizontal hexagonal barrel finishing machine was used in this study. Fig. 2 shows the schematic of barrel finishing machine as well as three different abrasive media.

2-2- Machine learning parameters

Machine learning is a science that makes computers learn and make decisions about a specific subject without the need for an explicit program. Machine learning algorithms create a mathematical model based on sample data or "training data" in order to predict or make decisions without overt planning. In Supervised learning which is known as one of the subsets of machine learning, the output values are labeled and according to the received data, the machine draws a function to connect the input data to the output data, which is unique for each pair of data. linear regression is applied to analyze data that have continuous values .

In the written program in this study, simple linear regression is applied because the prediction of a dependent variable is related to several independent variables. To express the degree of dependence of an independent variable on each of the dependent variables, a parameter called "correlation coefficient" is used. The correlation coefficient has a value between 1 and -1, where 1 means a direct relationship and -1 means an inverse relationship between two variables. Data was stored in the array to minimize the processing time. In addition, the Numpy library was applied to determine Max, Min, and Mean values. Moreover, the Pandas library was used for data analysis, preprocessing, and visualization of results, and the Seaborn library to draw the correlation graph was applied as well. Matplotlib library was used to draw all kinds of diagrams as well as Scikit-learn library (Sklearn) which can be mentioned as the main library in machine learning and includes a variety of analytical algorithms such as regression, clustering of support vectors, random forests, DBSCAN, k-means, etc. Finally, the Tkinter library was applied as a GUI user interface. Also, in this program, For the training data, real 252 tests were used. All these data are stored in a file in CSV format. The reason for using the .csv format instead of .xlsx is its high-speed data reading. MSE and MAPE methods are used to calculate the error. Six independent variables in this experiment can be adjusted in different ranges. In order to train the machine, 6 variables have been tested in the following intervals: Sample length (10, 15, and 20 mm), initial surface roughness (6.14, 8.96, and 11.9 μm), time (1, 2, 3, 4 hours) and Al_2O_3, Ball, and ceramic (0 to 100% combination) .

The values of initial surface roughness variables, sample length, time, and amount of abrasive media are received from the user and the machine calculates the amount of Ball according to the values of ceramic and Al_2O_3. In addition, the entered values are controlled so that if the wrong information is entered, an error is displayed to the user and the wrong answer is prevented. For example, the user does not allow negative values for all variables. Also, the user is not allowed to enter values outside of 0 to 100 for the amount of ceramic and Al_2O_3. In order to indicate the optimal values, several libraries have been used simultaneously to demonstrate the best performance. For data entry, the machine uses the Tkinter library to get the minimum and maximum values. The received values are all of the DoubleVar types. All the information passes through several filters, such as checking whether the minimum values are smaller than the maximum values, whether all values are positive, etc. Entering the wrong information is prohibited to avoid mistaken answers. In the calculation step, the machine receives all the values and defines them in its own variables. By performing several tests in the intervals given by the user, the highest amount of surface roughness reduction is determined. For this purpose, seven nested loops are used. And the machine predicts the amount of surface roughness reduction for each test separately. The time required to receive the answer depends on the number of necessary tests and the computer's performance and finally, the results are displayed. It is worth mentioning that the program can be implemented in two different environments: CMD and Tkinter.

3- Results

3-1- Correlation

It is crystal clear that by increasing the working time, the surface roughness is reduced and it is independent of the other factors. Indeed, one solution for higher surface quality, is to increase the working time. The reason for this phenomenon is that, by increasing the working time, the more abrasive particles can collide with the specimens and consequently, the surface roughness is considerably decreased. In addition, the other parameter- initial surface roughness- plays a significant role on the final surface quality of the workpieces in the barrel machining process. A specimen with the higher initial surface roughness results in a rougher surface. It means that the reduction of surface roughness is more for a sample with the less initial surface roughness.

As shown in Fig. 3, the correlation between the data is classified between values from -1 to 1 (the lowest correlation to the highest correlation). It is also clear in the graph that ball has a direct correlation with the reduction of surface roughness (Ra), and on the other hand, Al_2O_3 has an inverse correlation with the reduction of surface roughness, which means that with the reduction of Al_2O_3, the reduction of surface roughness increases.

According to the experimental results in our previous paper [12], the two abrasive media consisting of the combination of 75% steel balls and 25% aluminum oxide as well as 100% steel balls, had the efficient effect on the surface roughness. It may because of the high density and weight of steel balls, in comparison with aluminum oxide and ceramic particles. This attribute plays a significant role when steel balls impact the surface of the samples. The high impact energy leads to best results for reducing the surface roughness. By using the steel balls, the working time can be decreased as well.

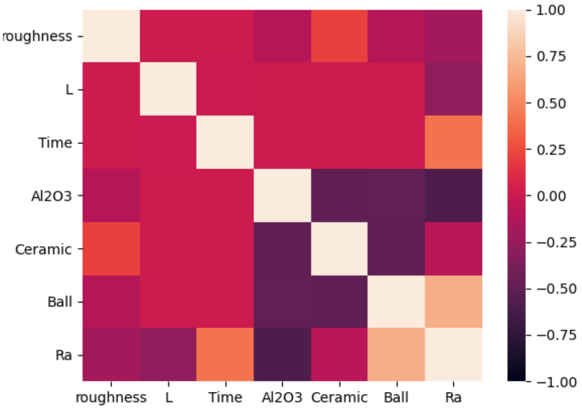

Fig. 3 Correlation diagram of data relative to each other

3-2- Error

In this section, the program calculates the amount of error in the prediction. Also, the input information of the program is used to test the error rate of the program. All input information is divided into two groups, Train and Test. The ratio of the number of information in each group is determined by a unit called alpha (α), which has a value between 0 to 1.

The Mean Square Error (MSE) method is located in the Sklearn library. In the first section, the user can get the MSE result by specifying the alpha value or Test size. Also, to get alpha, the Scale method, which is in the Tkinter library can be used. In addition, the program has the ability to calculate the lowest amount of error in both methods which is known by Mean Absolute Percentage Error (MAPE). Figs. 4 and 5 show the MSE and MAPE errors chart successively. The mathematical formula of MSE and MAPE are as follows:

$$Mean\ Square\ Error(MSE) = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

$$Mean\ Absolute\ Percentage\ Error(MAPE) = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

3-3- Finding optimal values with selected information

In Table 2, the experimental results of reducing the surface roughness are demonstrated [12], which are very close to the results of the machine in the present paper.

To show the function of the program, an example is presented in the following. As shown in Fig. 6, the machine has predicted the reduction of the surface roughness according to the input parameters (which can be observed in Fig. 6) equal to 35%.

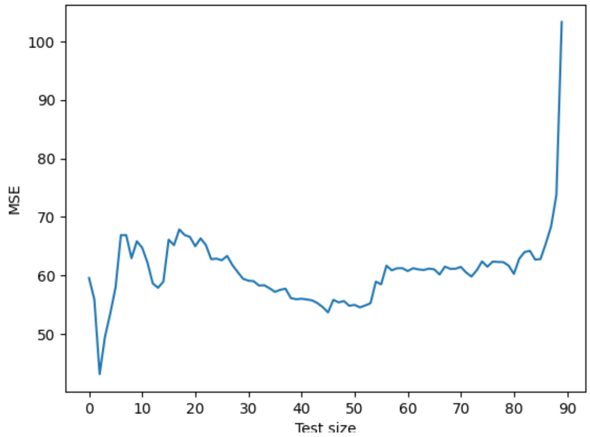

Fig. 4 MSE chart

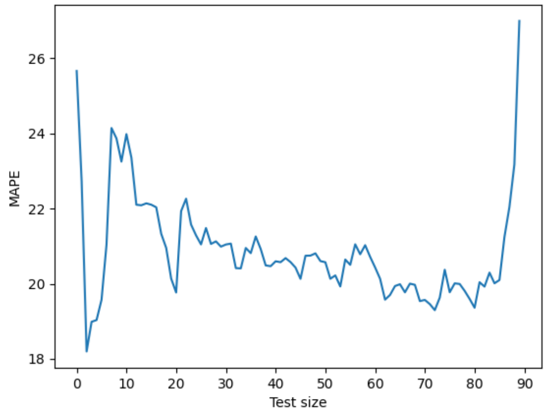

Fig. 5 MAPE chart

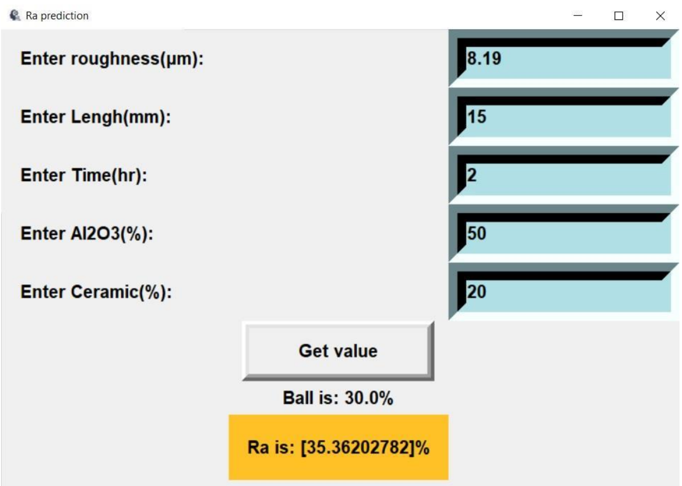

Fig. 6 Prediction of surface roughness reduction with given values

Table 2: Experimental test results

Input parameters				Al2o3	Ceramic	Ball	50% Al - 50% Cr	50% Ba - 50% Cr	75% Al - 25% Ba	50% Ba - 50% Al	75% Ba - 25% Al	33% Al- 33% Ba- 33% Ce
Workpiece number	initial surface roughness (µm)	L (mm)	Time (hr)	Ra Reduction (%)	Ra Reduction (%)	Ra Reduction (%)	Ra Reduction (%)	Ra Reduction (%)	Ra Reduction (%)	Ra Reduction (%)	Ra Reduction (%)	Ra Reduction (%)
1	6.14	10	1	-	-	-	-	-	19	44	62	-
2	6.14	10	2	-	-	-	-	-	27	52	74	-
3	6.14	10	3	-	-	-	-	-	35	61	82	-
4	6.14	10	4	-	-	-	-	-	41	69	90	-
5	6.14	15	1	-	-	-	-	-	15	31	52	-
6	6.14	15	2	-	-	-	-	-	23	43	65	-
7	6.14	15	3	-	-	-	-	-	30	48	75	-
8	6.14	15	4	-	-	-	-	-	36	56	82	-
9	6.14	20	1	-	-	-	-	-	11	21	42	-
10	6.14	20	2	-	-	-	-	-	18	33	59	-
11	6.14	20	3	-	-	-	-	-	25	40	69	-
12	6.14	20	4	-	-	-	-	-	31	48	77	-
13	8.96	10	1	17	37	60	36	42	20	38	61	38
14	8.96	10	2	23	47	69	44	49	24	47	70	46
15	8.96	10	3	27	55	76	51	57	31	54	78	54
16	8.96	10	4	29	34	80	55	65	37	62	87	57
17	8.96	15	1	13	33	53	28	34	16	28	55	30
18	8.96	15	2	18	39	59	35	41	21	39	62	36
19	8.96	15	3	23	46	65	40	48	26	45	72	44
20	8.96	15	4	25	53	70	44	57	31	52	80	49
21	8.96	20	1	9	23	46	21	25	12	21	48	23
22	8.96	20	2	15	35	56	25	36	15	30	58	31
23	8.96	20	3	18	42	62	29	43	21	35	66	36
24	8.96	20	4	22	47	66	35	49	26	43	73	43
25	11.90	10	1	14	30	42	29	35	17	40	54	33
26	11.90	10	2	18	40	48	33	43	21	46	64	37
27	11.90	10	3	22	47	65	39	51	25	52	76	42
28	11.90	10	4	25	54	72	44	58	32	47	83	49
29	11.90	15	1	12	26	38	22	31	14	33	49	27
30	11.90	15	2	16	34	53	25	36	18	36	60	33
31	11.90	15	3	20	41	59	31	45	23	45	70	37
32	11.90	15	4	22	48	65	37	51	28	49	76	44
33	11.90	20	1	9	17	33	15	24	9	25	45	23
34	11.90	20	2	12	25	48	21	31	12	28	55	27
35	11.90	20	3	15	33	57	26	38	17	36	65	32
36	11.90	20	4	18	46	61	33	47	23	41	70	38

As shown in Fig. 7, the program receives the minimum and maximum parameters from the operator and based on them determines the best possible state for each parameter individually. The program goes from minimum to maximum with a specific step for each parameter and simulates a unique test for each. Steps for each parameter: initial surface roughness (6.14µm to 11.9µm with 1µm step), sample length (10mm to 20mm with 1mm step), working time (1hr to 4hr with 1hr step), ceramic (0% to 100% with 1% step), Al_2O_3 (0% to 100% with 1% step) and ball (0% to 100% with 1% step).

In Fig. 8, the three-dimensional diagram of the reduction in surface roughness in 4 different time periods is presented. It is clear that balls have a better performance than ceramics. Moreover, the time effect is quite visible. Also, to draw this graph, 3 other variables are assumed to be fixed, initial surface roughness (8.96µm), sample length (10mm) and content of Al_2O_3 (0%).

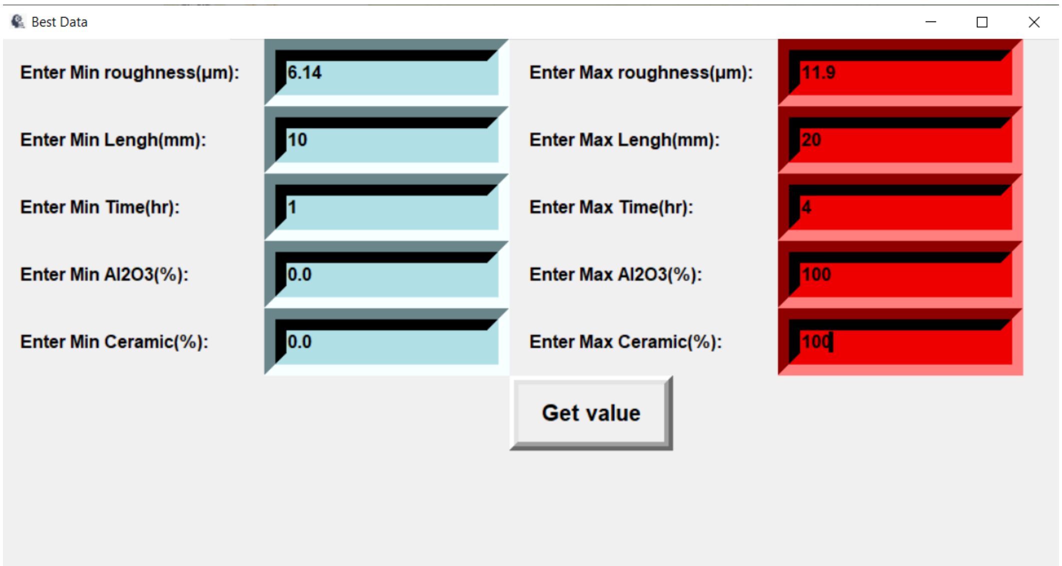

Fig. 7 Get values from the operator

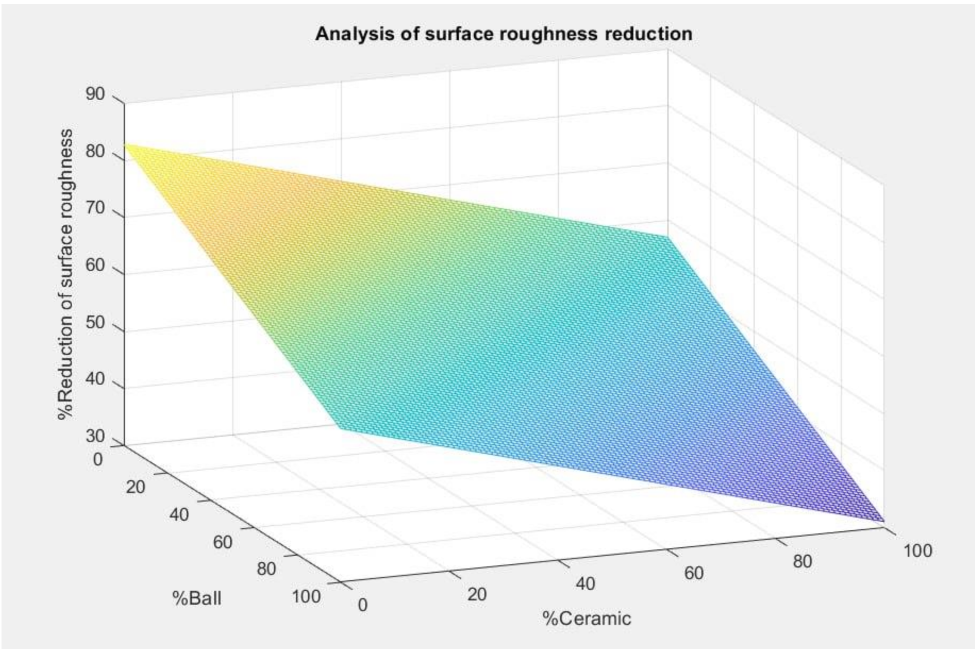

Fig. 8 Ra with different materials and work time.

As shown in Fig. 9, 2434399 tests have been performed and their results have been calculated. In the second row, the maximum reduction in surface roughness is calculated, and in the third row, the optimal values of the variables introduce which successively are: initial surface roughness, sample length, working time, ceramic%, Al_2O_3% and ball%. This result shows a good closeness with the experimental values according to table 2 (combination of 75% steel balls and 25% aluminum oxide.) All the tests were simulated separately in the program and it is possible to access the result of each test. Also, the program will answer the related results according to the input parameters of the operator, and by changing the values, the answer of the machine will definitely change.

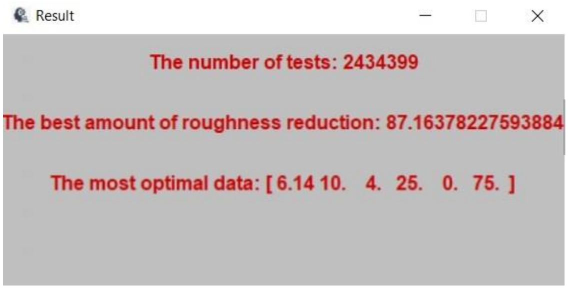

Fig. 9 Finding optimal values by machine

4- Conclusion

In this paper, improving surface roughness in barrel finishing process by means of machine learning method have been investigated. The results are as follows:

- In barrel finishing process, the time, has the greatest effect on the surface roughness of the samples.
- The shorter the height of the work piece, the greater the reduction in surface roughness of the samples were observed.
- By decreasing the initial surface roughness, the reduction in surface roughness is increased.
- Among three abrasive media, ball has the most effective influence on the reduction of surface roughness, meanwhile, ceramic has the weakest performance.

By the written program, it is possible to saving time and expense for experimental testing, and it is also possible to obtain the best performance without testing according to the available materials and available facilities. This program can improve the accuracy of its calculations by learning through the received data. It can also make decisions using artificial neural networks. This program is a comprehensive program that can be used in other subjects by a series of modifications.

References

[1] Hunsaker, J. C. (1940). Friction and surface finish. Nature, 146(3691), 138-139.

[2] Jiang, H., Browning, R., Fincher, J., Gasbarro, A., Jones, S., & Sue, H. J. (2008). Influence of surface roughness and contact load on friction coefficient and scratch behavior of thermoplastic olefins. Applied Surface Science, 254(15), 4494-4499.

[3] Mahdieh, M. S. (2020). The surface integrity of ultra-fine grain steel, Electrical discharge machined using Iso-pulse and resistance–capacitance-type generator. Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications, 234(4), 564-573.

[4] Mahdieh, M.S. (2020.) Recast layer and heat-affected zone structure of ultra-fined grained low-carbon steel machined by electrical discharge machining. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture. 234(5): 933-944.

[5] Mahdieh, M.S. and Mahdavinejad, R. (2016). Comparative study on electrical discharge machining of ultrafine-grain al, cu, and steel. Metallurgical and Materials Transactions A. 47(12): 6237-6247.

[6] Mahdieh, M.S. and Mahdavinejad, R. (2018). Recast layer and micro-cracks in electrical discharge machining of ultra-fine-grained aluminum. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture. 232(3): 428-437.

[7] Mahdieh, M.S. and Mahdavinejad, R.A. (2017). A study of stored energy in ultra-fined grained aluminum machined by electrical discharge machining. Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science. 231(23): 4470-4478.

[8] Mahdieh, M.S. and Zare-Reisabadi, S. (2019). Effects of electro-discharge machining process on ultra-fined grain copper. Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science. 233(15): 5341-5349.

[9] Mahdieh, M.S., Rafati, E. and Kargar Sichani, S. (2013). Investigation of variance of roller burnishing

parameters on surface quality by taguchi approach. ADMT Journal. 6(3):

[10] Saraeian, P., Gholami, M., Behagh, A., Behagh, O., Javadinejad, H.R. and Mahdieh, M. (2016). Influence of vibratory finishing process by incorporating abrasive ceramics and glassy materials on surface roughness of ck45 steel. ADMT Journal. 9(4): 1-6.

[11] Vakili Sohrforozani, A., Farahnakian, M., Mahdieh, M.S., Behagh, A.M. and Behagh, O. (2019). A study of abrasive media effect on deburring in barrel finishing process. Journal of Modern Processes in Manufacturing and Production. 8(3): 27-39.

[12] Vakili Sohrforozani, A., Farahnakian, M., Mahdieh, M.S., Behagh, A.M. and Behagh, O. (2020). Effects of abrasive media on surface roughness in barrel finishing process. ADMT Journal. 13(3): 75-82.

[13] Yang, S., Li, W. and Chen, H. (2018). Surface finishing theory and new technology. ed. Springer,

[14] Mahdieh, M.S. and Esteki, M.R. (2022). Feasibility investigation of hydroforming of dental drill body by fem simulation. Journal of Modern Processes in Manufacturing and Production. 11(2): 71-83.

[15] Mahdieh, M.S. and Monjezi, A. (2022). Investigation of an innovative cleaning method for the vertical oil storage tank by FEM simulation. Iranian Journal of Materials Forming.):

[16] Chiancola, M. (1995). Choosing the right media to meet mass finishing goals. Metal Finishing. 93(12): 37-39.

[17] Boschetto, A. and Veniali, F. (2009). Workpiece and media tracking in barrel finishing. International Journal of Machining and Machinability of Materials. 6(3-4): 305-321.

[18] Dong, H. and Moys, M. 2001. A technique to measure velocities of a ball moving in a tumbling mill and its applications. Minerals engineering. 14(8): 841-850.

[19] Steiner, H. 1996. Characterization of laboratory-scale tumbling mills. International Journal of Mineral Processing. 44: 373-382.

[20] Van Puyvelde, D., Young, B., Wilson, M. and Schmidt, S. (1999). Experimental determination of transverse mixing kinetics in a rolling drum by image analysis. Powder Technology. 106(3): 183-191.

[21] Boschetto, A., Bottini, L. and Veniali, F. (2013). Microremoval modeling of surface roughness in barrel finishing. The International Journal of Advanced Manufacturing Technology. 69(9): 2343-2354.

[22] Bbosa, L., Govender, I., Mainza, A. and Powell, M. (2011). Power draw estimations in experimental tumbling mills using pept. Minerals engineering. 24(3-4): 319-324.

[23] Boschetto, A., Ruggiero, A. and Veniali, F. (2007). Deburring of sheet metal by barrel finishing. Proc. Key Engineering Materials. 193-200.

[24] Li, X., Li, W., Yang, S. and Shi, H. (2018). Experimental investigation into the surface integrity and tribological property of aisi 1045 steel specimen for barrel finishing. Procedia Cirp. 71: 47-52.

[25] Fan, G., A.S, E.-S., Eftekhari, S.A., Hekmatifar, M., Toghraie, D., Mohammed, A.S. and Khan, A. (2022). A well-trained artificial neural network (ann) using the trainlm algorithm for predicting the rheological behavior of water – ethylene glycol/wo3 – mwcnts nanofluid. International Communications in Heat and Mass Transfer. 131: 105857.

[26] Xia, J.S., Khaje Khabaz, M., Patra, I., Khalid, I., Alvarez, J.R.N., Rahmanian, A., Eftekhari, S.A. and Toghraie, D. (2023). Using feed-forward perceptron artificial neural network (ann) model to determine the rolling force, power and slip of the tandem cold rolling. ISA Transactions. 132: 353-363.

[27] Esfe, M. H., Esmaily, R., Khabaz, M. K., Alizadeh, A. A., Pirmoradian, M., Rahmanian, A., & Toghraie, D. (2023). A novel integrated model to improve the dynamic viscosity of MWCNT-Al2O3 (40: 60)/Oil 5W50 hybrid nano-lubricant using artificial neural networks (ANNs). Tribology International, 178, 108086.

[28] Azimi, M., Kolahdooz, A. and Eftekhari, S.A. (2017). An optimization on the din1. 2080 alloy in the electrical discharge machining process using ann and ga. Journal of Modern Processes in Manufacturing and Production. 6(1): 33-47.

[29] Baghoolizadeh, M., Nasajpour-Esfahani, N., Pirmoradian, M., & Toghraie, D. (2023). Using different machine learning algorithms to predict the rheological behavior of oil SAE40-based nano-lubricant in the presence of MWCNT and MgO nanoparticles. Tribology International, 108759.

[30] Tian, C., Tang, Z., Zhang, H., Gao, X. and Xie, Y. (2022). Operating condition recognition based on

temporal cumulative distribution function and adaboost-extreme learning machine in zinc flotation process. Powder Technology. 395: 545-555.

[31] Li, R., Jin, M. and Paquit, V.C. (2021). Geometrical defect detection for additive manufacturing with machine learning models. Materials & Design. 206: 109726.

[32] Castro, B.M., Elbadawi, M., Ong, J.J., Pollard, T., Song, Z., Gaisford, S., Pérez, G., Basit, A.W., Cabalar, P. and Goyanes, A. (2021). Machine learning predicts 3d printing performance of over 900 drug delivery systems. Journal of Controlled Release. 337: 530-545.

[33] Ahmed, T., Sharma, P., Karmaker, C.L. and Nasir, S. (2020). Warpage prediction of injection-molded pvc part using ensemble machine learning algorithm. Materials Today: Proceedings.):

[34] Song, C.-H., Cao, J.-X. and Yang, S.-C. (2008. Quality prediction of centrifugal barrel finishing using genetic neural network.