

2D Geometric Surface Structure ANN Modeling After Milling of the AZ91D Magnesium Alloy

Monika Kulisz^{1*}, Ireneusz Zagórski², Jerzy Jóźwik²

¹ Department of Organisation of Enterprise, Management Faculty, Lublin University of Technology, ul. Nadbystrzycka 38, 20-618 Lublin, Poland

² Department of Production Engineering, Mechanical Engineering Faculty, Lublin University of Technology, ul. Nadbystrzycka 36, 20-618 Lublin, Poland

* Corresponding author's e-mail: m.kulisz@pollub.pl

ABSTRACT

The paper presents the results of modeling 2D surface roughness parameters in milling by means of an artificial neural network (ANN). The AZ91D magnesium alloy was used. A HSS milling cutter was employed in the research. The main aim of the study was to obtain the lowest possible surface roughness (good quality) using a commonly available HSS cutter. The results of the research work were presented in the form of bar charts, surface charts and graphs depicting the quality of artificial neural networks. The conducted research shows that it is possible to carry out the machining processes that enable obtaining an average surface quality (defined by roughness parameters Ra, Rz, RSm, Rsk). The Ra, Rz, RSm parameters increase along with the machining parameters (f_z , a_p), as expected. The Rsk parameter takes (in most cases) negative values, which may indicate a surface with more intense friction and indicative of flat-topped distribution. On the other hand, the results of modeling the selected parameters – Ra, Rz, RSm – with the use of artificial neural networks allow concluding that the obtained network models show satisfactory predictive ability ($R = 0.99$), and thus are an appropriate tool for the prediction of surface roughness parameters.

Keywords: magnesium alloys, milling, roughness, artificial neural networks, simulations.

INTRODUCTION

Surface roughness is an important manufacturing factor for the production of various types of elements from diverse materials in different industries (machinery, automotive and aerospace). These requirements are increasing especially when the mutual cooperation of two or more elements is crucial. It is also an interesting scientific aspect during the implementation of machining processes on workpieces. In the case of magnesium alloys, the roughness achieved and the manufacturing accuracy (with relatively small dispersion of dimensional values and high-performance accuracy classes) can be successfully comparable, or even better, than after various finishing processes ($Ra \leq 0.16 \mu\text{m}$ [1], accuracy class IT2 - IT5 [2]).

During dry machining of the Mg-Ca0.8 alloy with the use of a milling head with PCD blades [3], the greatest impact on the Ra parameter was the feed (mm/rev), where Ra was obtained in the range of approx. $0.2\text{--}0.8 \mu\text{m}$. The results of Ra variability with the change of v_c (up to 2800 m/min) and a_p were within the range of approx. $0.4\text{--}0.6 \mu\text{m}$. In a similar study by the authors [4], the roughness level of approx. $0.4 \mu\text{m}$ was obtained after dry milling and low plasticity burnishing. The research with the use of biodegradable MgCa0.8 magnesium alloys was also carried out in [5]. A milling head with uncoated carbide inserts was used for machining. Regardless of the change in technological parameters, the lower values of the roughness parameter $Ra = \text{approx. } 0.09\text{--}0.8 \mu\text{m}$, were obtained in inverse milling, while in milling the roughness was $Ra = \text{approx.}$

0.9–1.4 μm . The feed per tooth had the greatest impact on the obtained roughness.

Similar relationships were found during the machining of the Mg-Ca1.0 alloy. Milling was carried out using a milling head with plates of the so-called diamond-like coating (DLC) [6]. The used machining parameters: $v_c = 300\text{--}600$ m/min, $f_z = 0.0125\text{--}0.125$ mm/tooth and $a_p = 0.05\text{--}0.50$ mm made it possible to obtain the lowest values of the roughness parameter $R_a = \text{approx. } 0.08\text{--}0.16$ μm . Increasing v_c decreased the roughness, while increasing f_z resulted in its increase. Despite this fact, the mean value of the surface roughness was kept at a very low level. The optimal combination of cutting parameters (the lowest surface roughness) was also sought in [7], who conducted research on the AM60 alloy. The parameters $n = 2000$ rev/min, $f = 0.1$ mm/rev and $a_p = 1.0$ mm, where $R_a = \text{approx. } 0.3$ μm . According to the research conducted on surface roughness parameters, technological parameters, the kinematic relations between these parameters and the geometry of the tool tip influence the shape and form of the chips [8].

In scientific research, carbide cutters without coating [9], cutters with protective coatings such as TiN [7], TiAlN [10], TiB₂ [2] or TiAlCN as well as cutters with high-quality polycrystalline diamond blades [1] are often used. For example, it is possible to mill with the machining parameters defined as effective, rough ($v_c = 1200$ m/min, $f_z = 0.15$ mm/tooth, $a_p = 6$ mm) reaching the roughness parameter R_a (measured on the sample face) at the level of approx. 0.5 μm (for $\gamma = 5^\circ$) and approx. 2 μm (for $\gamma = 30^\circ$). The mean value of the R_a parameter (this time measured on the side wall of the sample) was lower and amounted to approx. 0.3 μm for the given conditions [9].

Experimental research in the field of machining process analysis is more and more often supported by the use of machine learning methods, including artificial neural networks. This is due to the fact that in connection with the development of new technologies and the emerging modern machines and devices, the efficiency of processes as well as the appropriate quality of the treated surfaces, are highly important. In the face of such challenges, numerical models representing given phenomena, based on experimental models, are used.

The use of artificial neural networks has been the subject of numerous studies, which can be seen in the works of, among others, Sangwan et al. [11], Kaviarasan et al. [12], Zerti et al.

[13], Zagórski et al. [14], Karkalos et al. [15], and Chen et al. [16]. Artificial neural networks were used for various processes, including turning [11, 13, 17, 18], milling [15, 16, 19–22] or Abrasive WaterJet Machining [23, 24]. In addition, in the literature on modeling and simulation of SNN in the area of machining, studies concern various materials, including steel [19], titanium alloys [15], aluminum alloys [13, 18, 22, 24] or magnesium alloys [17, 23]. Moreover, different scopes of research can be noticed; they concern, inter alia, optimization of machining parameters in order to obtain the appropriate surface quality [11], cutting forces [25], vibrations [14] or machining efficiency [13].

On the basis of literature analysis, it can be noticed that researchers in the field of milling machining primarily deal with modeling one surface roughness parameter, i.e. R_a , which can be seen in the works of, among others, Karkalos et al. [15], Wu et al. [19], Chen et al. [16] or Santhakumar et al. [20]. Taking into account the practical application of the modeling results, it seems insufficient to be able to perform a detailed analysis of the surface conditions. There are few works concerning a wider range of surface roughness parameters, e.g., the work of Zerti et al. [13] where the R_a , R_z , R_t parameters were analyzed or the studies by Kulisz et al. [26], where the R_a , R_z , R_{Sm} parameters were predicted. Zerti et al. [13] conducted the research related to dry turning simulations, while Kulisz et al. [26] analyzed the milling process using a PCD tool. Therefore, it is justified to expand the scope of research in the field of process modeling regarding the increase of the number of parameters as well as the change of machining conditions.

Taking into account the above-mentioned analysis, it can be concluded that the so-called basic parameters of surface roughness, while a much broader approach is required for a comprehensive assessment, taking into account, for example, a surface roughness parameter such as kurtosis. Additionally, it should be noted that for the machining of magnesium alloys, most researchers use carbide milling cutters with or without coatings. In addition, the use of, i.a. artificial neural networks may contribute to reducing the number of necessary research tests, for example, for the selection and optimization of technological processing parameters in order to obtain the appropriate surface roughness and maintain adequate process efficiency.

Therefore, the aim of the work was to conduct tests in order to obtain the possible surface roughness (defined by the roughness parameters, i.e. Ra, Rz, RSm, Rsk) using a commonly available HSS cutter. Another goal was to model 2D surface roughness parameters (Ra, Rz, RSm) in milling the AZ91D magnesium alloy with the use of the HSS tool in order to predict these parameters. This is due to the fact that Rz is the second, after Ra, most frequently used surface roughness parameter in many production companies. Due to the partial consideration of individual elevations and depressions, the parameter should be mainly analyzed for bearing or sliding surfaces and measuring surfaces. The Rsk parameter, on the other hand, can play an important role in monitoring the technological process, e.g. to detect surface defects, as well as in conductivity monitoring, and lubricant maintenance. A surface with negative skewness is characterized by a greater frequency of deep valleys; it is defined by the shape of a plateau and assumed to be optimal. On the other hand, the RSm parameter can be used to analyze contact deformations (or contact stiffness) and thermal conductivity.

The main research contribution is the extension of modeling with additional Rz and RSm parameters, and not focusing only on the Ra parameter, which will allow for a detailed analysis of the surface conditions of surface roughness. Modeling of the above-mentioned roughness parameters can constitute the basis for creating tools helpful in the work of the technologist when determining the conditions of the machining process in order to obtain the assumed surface roughness.

RESEARCH METHODOLOGY

The AZ91D magnesium alloy was used for the research. A schematic diagram of the research is shown in Figure 1. Machining was carried out on a DMU 65 MonoBlock vertical milling center, which can perform machining up to the maximum rotational speed of 12.000 rev/min. HSS Co steel by PRECITOOL 161701, mounted in the ER sleeve, was employed. It is a two-edge cutter with a diameter of $d = 20$ mm, made of steel. HSS cutters are widely available tools with lower unit costs, compared to expensive carbide tools and very expensive cutters with PCD blades. During the research, the cutting conditions were constant as: radial depth of cut $a_e = 15$ [mm] and cutting speed $v_c = 750$ m/min. The range of variable technological parameters included: feed per tooth $f_z = 0.01-0.05$ mm/tooth and axial depth of cut $a_p = 0.1-0.4$ mm.

Flat geometric and surface parameters were estimated using the Mahr's MarSurf system with the PS10 Drive measuring head. The high-class measurement systems used allowed for a wide and comprehensive analysis of both the AZ91D magnesium alloy milling process, as well as evaluating the machining effects (surface morphology and 2D roughness parameters). The research analyzed roughness parameters, i.e. Ra, Rz, RSm, Rsk. Figure 2 shows a graphical interpretation of the Rsk (kurtosis) parameter, helpful for the evaluation of the so-called exploitation characteristics of the treated surface (e.g., friction and wear).

The results of experimental studies were used to model surface roughness parameters – maximum height of profile (Rz), the arithmetical mean roughness parameter (Ra) and mean width of profile elements (RSm). Artificial neural networks

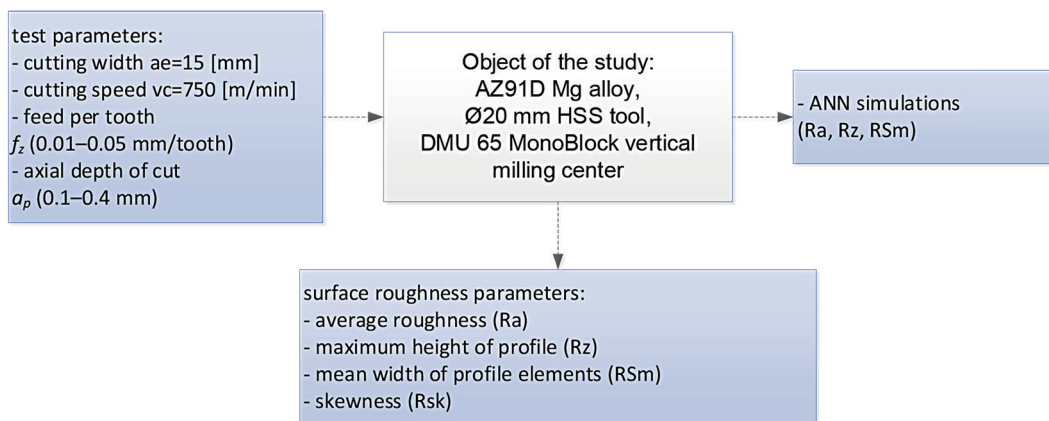
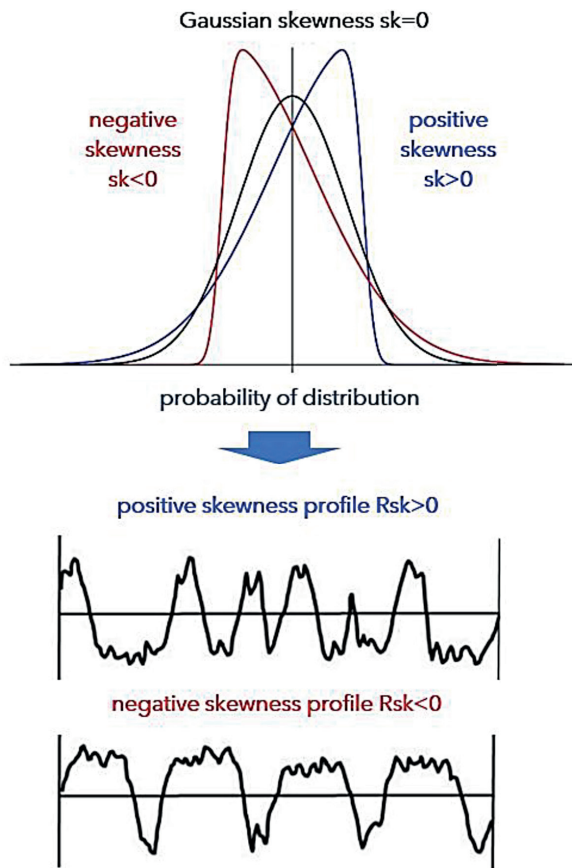


Fig. 1. Schematic diagram of the research



Rsk - represent the symmetry of profile about mean line
 Fig. 2. Interpretation of the Rsk (kurtosis) parameter

were employed for modeling. The input neurons were the variable f_z and a_p technological parameters, and the output neuron was the analyzed roughness parameter. In connection with the modeling of three roughness parameters, three models were analyzed, an example of which is shown in Figure 3.

The Statistica Neural Networks software was used for modeling and prediction of roughness

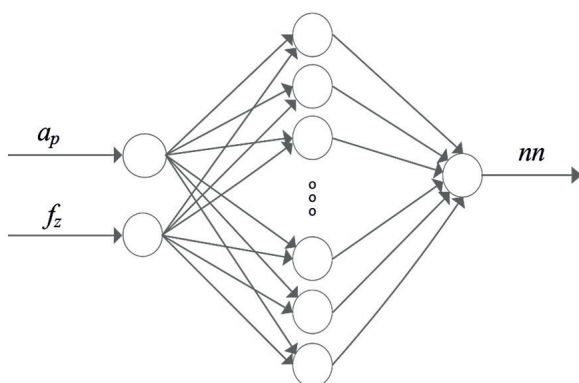


Fig. 3. Schematics of the artificial neural network with the analyzed process parameters, where nn –Ra, Rz and RSm

parameters. During the research, the MLP (multi-layer Perceptron) neural network was used to test various neuron activation functions: linear, exponential, logistic, tanh and sinus activation functions, and various learning algorithms: BFGS gradient (Broyden-Fletcher-Goldfarb-Shanno), the steepest descent training algorithm and conjugate gradient. The second type of network used to model the roughness parameters was the RBF (Radial Basis Function) network, for which the learning algorithm is RBFT, with a Gaussian hidden neuron activation function and a linear function for the output layer. A network with one hidden layer was used. The networks were modeled by changing the number of neurons in the hidden layer from two to ten and the number of training epochs from 150 to 300. The experimental data set (20 items) was divided in the proportion of 75–25%, where the first value indicates the share of training data, and the second corresponds to validation data. Due to the small set of data, the testing data was omitted [14]. The analysis of the obtained modeling results and the selection of the most appropriate network were carried out on the basis of such indicators as: quality of learning and validation as well as learning and validation errors. The quality of learning and validation is defined as the correlation coefficient for these sets, calculated in accordance with formula (1):

$$R(y', y^*) = \frac{cov(y', y^*)}{\sigma_{y'} \sigma_{y^*}} \quad R \in < 0, 1 > \quad (1)$$

where: $\sigma_{y'}$ – standard deviation of reference values,
 σ_{y^*} – standard deviation of predicted values,
 $cov(y', y^*)$ – covariance.

The errors are defined as the sum of the squared differences between the set values and the values obtained at the outputs of each output neuron, according to the formula (2):

$$SS = \sum_{i=1}^n (y'_i - y^*_i)^2 \quad (2)$$

where: n – number of cases in a given set;
 y'_i – actual value of the roughness parameter for the given set for the i-th observation;
 y^*_i – predicted value of the roughness parameter for the given set for the i-th observation.

For each roughness parameter, i.e. Ra, Rz, RSm, 200 networks were learned, from which one network was selected on the basis of the above-mentioned indicators.

EXPERIMENTAL RESULTS

Figure 4 shows an exemplary roughness 2D profile curve obtained with the processing parameters $a_e = 15$ mm, $v_c = 750$ m/min, $a_p = 0.1$ mm, $f_z = 0.01$ mm/tooth.

Figures 5 and 6 show the results obtained from 2D roughness measurements. The impact of changing the axial depth of cut a_p and feed per tooth f_z change on roughness parameters, i.e. Ra, Rz, RSm and Rsk. The Ra, Rz parameters belong to the group of vertical parameters of the roughness profile, they are quite well-known to researchers and the machine industry, hence their

choice. The RSm parameter belongs to the horizontal parameters of the roughness profile, while the Rsk (skewness) parameter is helpful in the description of the operational features of the surface. This parameter may be useful in determining the following physical or functional properties of surfaces: friction and wear, lubrication, mechanical tightness (significant influence). It can also be taken into account as an additional indicator in the case of fatigue corrosion analysis, contact deformation or contact stiffness.

Changing the parameters (f_z, a_p) increases the surface roughness parameters (Ra, Rz, RSm). Figure 5 shows the test results for the roughness

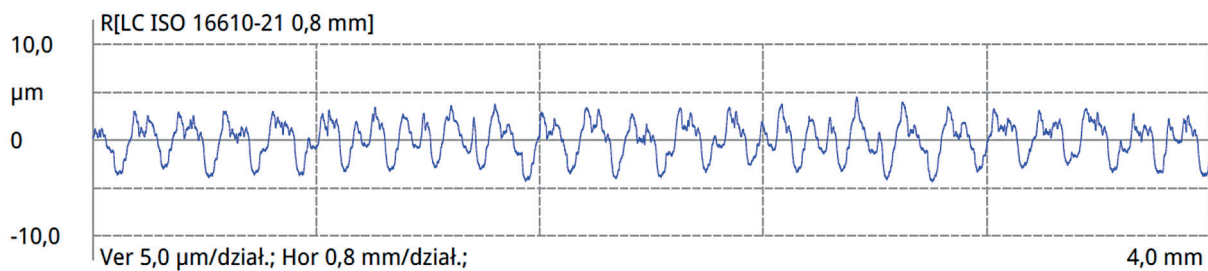


Fig. 4. Surface roughness profile ($a_e = 15$ mm, $v_c = 750$ m/min, $a_p = 0.1$ mm, $f_z = 0.01$ mm/tooth)

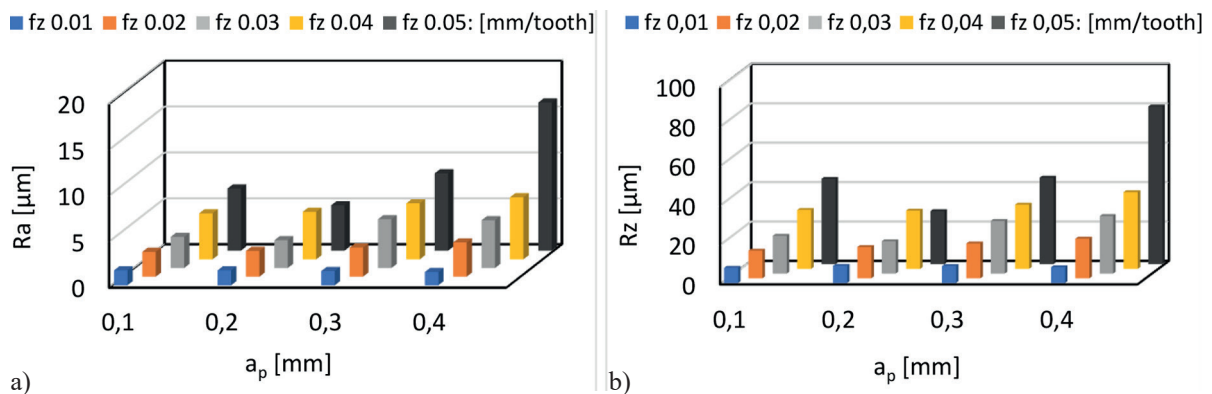


Fig. 5. Effect of axial depth of cut a_p and feed per tooth f_z change on roughness parameters: a) Ra and b) Rz ($a_e = 15$ mm, $v_c = 750$ m/min)

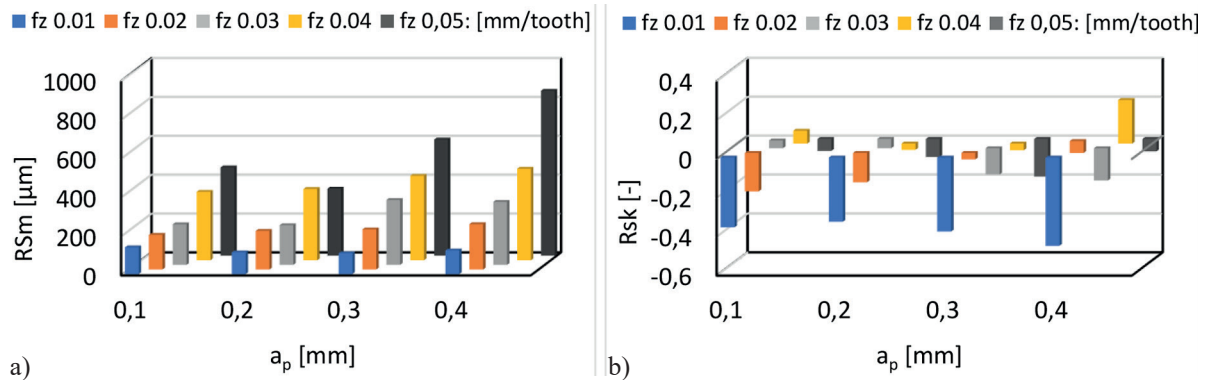


Fig. 6. Effect of axial depth of cut a_p and feed per tooth f_z change on roughness parameters: a) RSm and b) Rsk ($a_e = 15$ mm, $v_c = 750$ m/min)

parameters Ra (Fig. 5a) and Rz (Fig. 5b). In contrast, Figure 6 shows the influence of f_z and a_p on the RSm (Fig. 6a) and Rsk (skewness – Fig. 6b) roughness parameters. As it can be easily observed, the values of the surface roughness parameters increase: Ra from the value of approx. 1.5 μm to the average value of approx. 7 μm (and even at $a_p = 0.4$ mm and $f_z = 0.05$ mm/tooth – Ra = 16.125 μm), Rz from the value approx. 8 μm to the value of even approx. 80 μm , RSm from the value 110 – 120 μm to the value of approx. 344 – 598 μm (and even at $a_p = 0.4$ mm and $f_z = 0.05$ mm/tooth – RSm = approx. 848 μm). The values of the Rsk parameter are in most cases negative, which may indicate a surface with more intense friction and indicative of flat-topped distribution. Such conditions of the Rsk parameter may indicate the surface desired in operating conditions (blunted peaks of unevenness, Rsk negative).

MODELING RESULTS

As a result of the modeling, one network of each type (RBG, MLP) was selected for the

analyzed roughness parameters, selected on the basis of network errors and the quality of learning and validation. The results of the obtained modeling with the parameters of the obtained networks are presented in Table 1. The best parameters for all surface roughness parameters were obtained for the RBF networks. In any case, the quality of learning and validation is higher for the RBF network, compared to MLP. Moreover, the errors for the RBF network are smaller than for the MLP network. For the Ra parameter, the best network has six neurons in the hidden layer, Rz – five, and RSm – eight. The quality of both learning and validation for these networks exceeds 0.99. Additionally, Table 1 shows the correlation coefficients R (for the entire data set) between the data obtained as a result of the conducted tests and those obtained as a result of modeling for individual roughness parameters Ra, Rz, RSm. While analyzing R correlation, it can be concluded that the mutual correlation between the experimental data and the data predicted for the RBF network is at a very high level (above 0.99).

For a more detailed comparison of the surface roughness parameters of the RBF and MLP

Table 1. Network parameters obtained as a result of Ra, Rz, RSm modeling

Modeled surface roughness parameters	Ra		Rz		RSm	
Network name	RBF 2-6-1	MLP 2-8-1	RBF 2-5-1	MLP 2-7-1	RBF 2-8-1	MLP 2-8-1
Quality (Training)	0.9986	0.8674	0.9973	0.8851	0.9984	0.9882
Quality (Validation)	0.9931	0.9267	0.9925	0.9143	0.9932	0.9854
SS (Training)	0.0167	1.5566	0.8704	35.9328	59.7927	384.4812
SS (Validation)	0.0850	0.3032	3.4093	7.3036	197.5763	490.3510
Learning algorithm	RBFT	BFGS 72	RBFT	BFGS 33	RBFT	BFGS 651
R_{θ} correlation	0.9966	0.8776	0.9969	0.8924	0.9947	0.9863

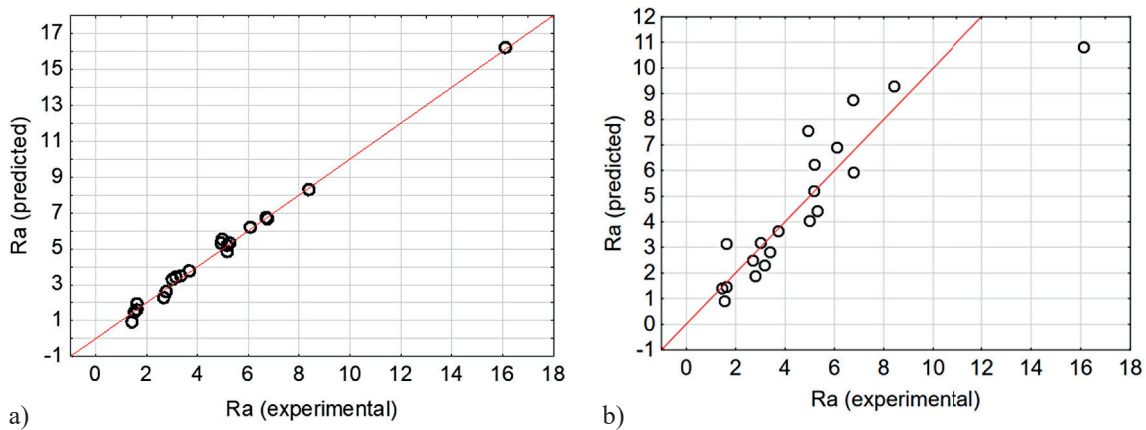


Fig. 7. Correlation graph of comparison between the modeling and experimental results of the Ra parameter for a) RBF, b) MPL networks

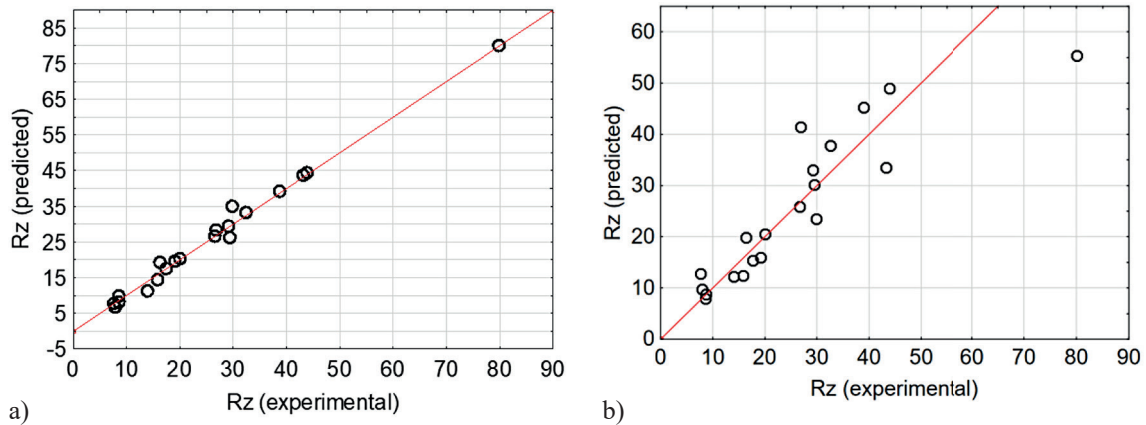


Fig. 8. Correlation graph of comparison between the modeling and experimental results of the Rz parameter for a) RBF, b) MPL networks

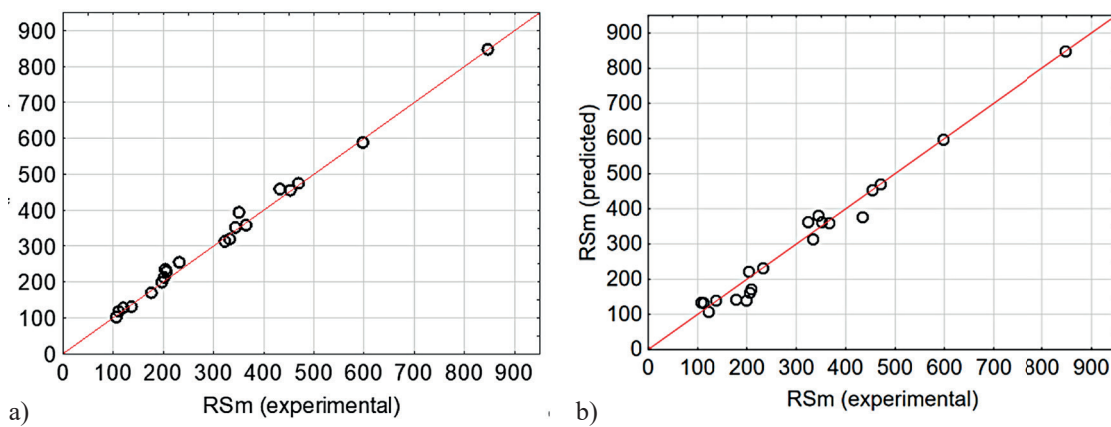


Fig. 9. Correlation graph of comparison between the modeling and experimental results of the RSm parameter for a) RBF, b) MPL networks

networks, the figures below show the correlation graphs of the dependence of individual roughness parameters obtained experimentally and as a result of modeling with RBF and MPL networks – for Ra (Fig. 7), Rz (Fig. 8), RSm (Fig. 9).

The analysis of the graphs above confirms that more suited results for each surface roughness parameters were obtained for the RBF network. Additionally, it can be concluded that artificial neural networks are a suitable tool to predict the surface roughness parameters obtained after milling the AZ91D magnesium alloy with the use of the HSS tool.

As a result of the modeling, it was possible to predict the analyzed roughness parameters, i.e. Ra, Rz, RSm. Trained RBF networks were used for this purpose. By introducing new data into the Statistica program (input data in the form of machining parameters: feed per tooth and axial depth of cut), the generated networks resulted in the predicted Ra, Rz and RSm parameters. The results of the network operation are presented for the RBF 2-6-1 network (Ra parameter) – Fig. 10a, for the RBF 2-5-1

network (Rz parameter) – Fig. 10b, and for the RBF 2-8-1 network (RSm parameter) – in Fig. 10c.

As a result of the modeling of the surface roughness parameters – Ra, Rz, RSm – and the prediction made, it can be concluded that the obtained RBF networks are characterized by a satisfactory ability to predict these parameters. This is confirmed by, among others, R correlation value at 0.99, high quality of network learning and validation at 0.99, as well as learning and validation errors. Comparing the experimental and simulation data of the values of the individual surface roughness parameters, it can be concluded that the value of the relative error does not exceed 15%, which proves that the net is well-trained.

CONCLUSIONS

The main aim of the research – and a certain novelty – was to obtaining the lowest possible surface roughness (high quality of surface) using

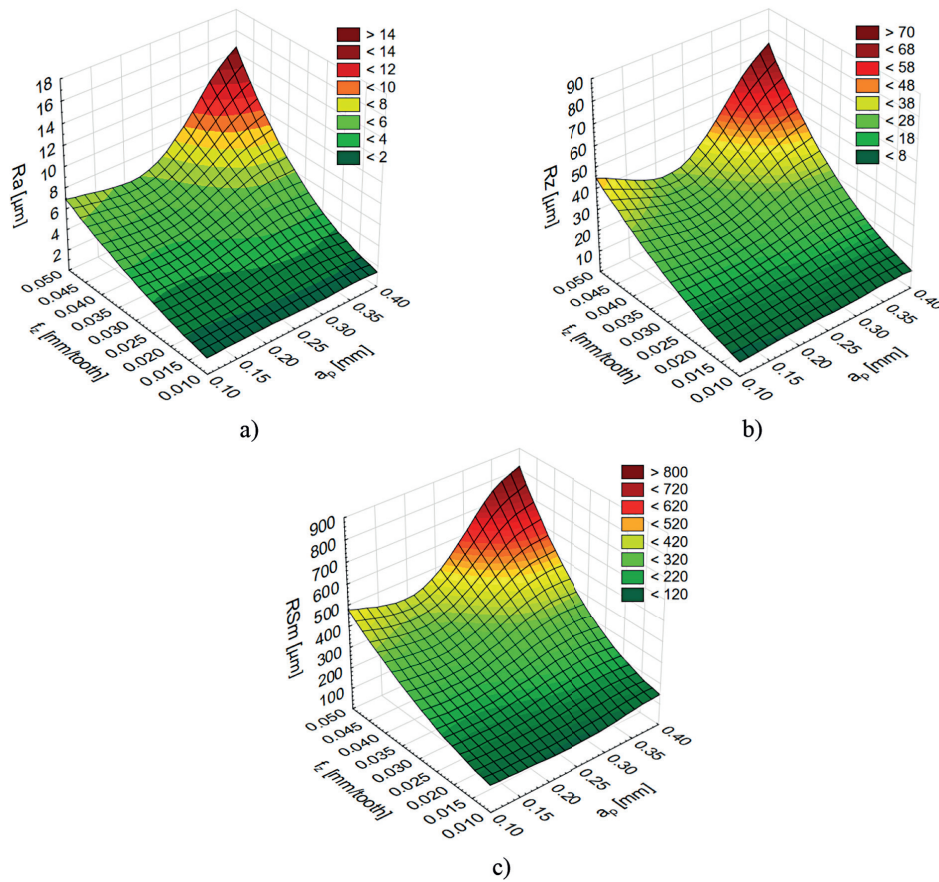


Fig. 10. The network performance results for the parameter: a) Ra – RBF 2-6-1, b) Rz – RBF 2-5-1, c) RSm – RBF 2-8-1

a commonly available HSS cutter. The conducted research shows that it is possible to carry out the machining processes that enable obtaining an average surface quality (defined by roughness parameters, i.e. Ra, Rz, RSm, Rsk). This broadened the current understanding of roughness after milling of magnesium alloys. Another novelty is the high versatility of the created models and the possibility of extrapolating the results with an acceptable error rate for the input variables outside the tested area. However, the limitation of the models is the assumption that the tool and the material of the workpiece are stable, which, despite the advantages shown above, significantly limits their use for predicting 2D surface roughness when machining other materials and using other tools.

In connection with the conducted experimental research and training of artificial neural networks, the following conclusions can be drawn. The change of machining parameters (f_z , a_p) influences the increase of the surface roughness parameters defined by the parameters: Ra, Rz, RSm. In most cases, the Rsk parameter takes negative

values; this is characteristic for the surfaces with more intense friction and indicative of flat-topped distribution. For modeling surface roughness parameters obtained after milling the AZ91D magnesium alloy with the use of the HSS tool, the RBF neural network turned out to be superior to MLP. For the RBF network, compared to MLP, the quality of learning and validation is higher, and the errors are smaller. The network for the Ra parameter (RBF 2-6-1) reached the learning quality at the level of 0.9986, and the validation – 0.9931, for the Rz parameter (RBF 2-5-1) the learning quality – 0.9973, validation – 0.9925, and for the RSm parameter (RBF 2-8-1) the learning quality – 0.9984, and the validation – 0.9932. In the case of errors, they are as follows: for Ra SS (Training) – 0.0167, SS (Validation) – 0.0850, for Rz SS (Training) – 0.8704, SS (Validation) – 3.4093, and for RSm SS (Training) – 59.7927, SS (Validation) – 197.5763. The network obtained as a result of the surface roughness parameters modeling shows a satisfactory predictive ability, as evidenced by the obtained R correlation values. They are $R_{(Ra)} = 0.9966$, $R_{(Rz)} = 0.9969$ and $R_{(RSm)} = 0.9947$. It can therefore be

concluded that artificial neural networks are an effective tool that can be used to predict surface roughness parameters. Trained networks show the relationships between the input data (f_z and a_p) and the output data (Ra, Rz, RSm parameters), enabling the determination of the appropriate values of the analyzed surface roughness parameters after entering the set machining parameters into the network. Modeling of processes can be the basis for creating the tools helpful in the work of a technologist when determining the conditions of the machining process in order to obtain the assumed surface roughness. In addition, it can save time and effort as well as eliminate the costs that would have to be incurred in the case of further machining trials.

In the broadly understood workshop practice, it may be most useful to define such machining conditions for which milling can be machining as finishing, and constitute a very effective, efficient and safe process (risk of chip ignition). Industrial companies are not able (due to the production process relied on) to perform tests on workpieces. Therefore, the presented research papers may be valuable due to the possibility of their application in the industrial practice.

Acknowledgments

This work was financed from the funds of the Ministry of Education and Science by Agreement No. DNK/SP/513880/2021 of 22 December 2021, the project “14th School of Machining and the 43rd Scientific School of Abrasive Machining”, under the programme “Perfect Science”.

REFERENCES

- Zagórski I., Korpysa J. Surface Quality Assessment after Milling AZ91D Magnesium Alloy Using PCD Tool. *Materials*. 2020; 13: 617.
- Korpysa J., Kuczmaszewski J., Zagórski I. Dimensional Accuracy and Surface Quality of AZ91D Magnesium Alloy Components after Precision Milling. *Materials*. 2021; 14: 6446.
- Guo Y.B., Salahshoor M. Process mechanics and surface integrity by high-speed dry milling of biodegradable magnesium–calcium implant alloys. *CIRP Annals - Manufacturing Technology*. 2010; 59: 151–154.
- Salahshoor M., Guo Y.B. Surface integrity of magnesium-calcium implants processed by synergistic dry cutting-finish burnishing. *Procedia Eng*. 2011; 19: 288–293.
- Qiao Y., Wang S., Guo P., Yang X., Wang Y. Experimental research on surface roughness of milling medical magnesium alloy. *IOP Conference Series: Materials Science and Engineering*. 2018; 397: 1–7.
- Desai S., Malvade N., Pawade R., Warhatkar H. Effect of High Speed Dry Machining on Surface integrity and Biodegradability of Mg-Ca1.0 Biodegradable Alloy. *Materials Today Proceedings*. 2017; 4: 6817–6727.
- Sathyamoorthy V., Deepan, S., Sathya Prasanth S.P., Prabhu L. Optimization of Machining Parameters for Surface Roughness in End Milling of Magnesium AM60 Alloy. *Indian Journal of Science and Technology*. 2017; 10: 1–7.
- Kuczmaszewski J., Zagórski I., Gziut O., Legutko S., Królczyk G.M. Chip fragmentation in the milling of AZ91HP magnesium alloy. *Strojnicki Vestnik. Journal of Mechanical Engineering*. 2017; 63(11): 628–642.
- Gziut O., Kuczmaszewski J., Zagórski I. Surface quality assessment following high performance cutting of AZ91HP magnesium alloy. *Management and Production Engineering Review*. 2015; 6(1): 4–9.
- Zagórski I., Korpysa J. Surface quality in milling of AZ91D magnesium alloy. *Advances in Science and Technology Research Journal*. 2019; 13(2): 119–129.
- Sangwan K.S., Saxena S., Kant G. Optimization of machining parameters to minimize surface roughness using integrated ANN-GA approach. *Proc. CIRP*. 2015; 29: 305–310.
- Kaviarasan V., Venkatesan R., Natarajan E. Prediction of surface quality and optimization of process parameters in drilling of Delrin using neural network. *Progress in Rubber, Plastics and Recycling Technology*. 2019; 35(3): 149–169.
- Zerti A., Yallese M.A., Zerti O., Nouioua M., Khettabi R. Prediction of machining performance using RSM and ANN models in hard turning of martensitic stainless steel AISI 420. *Proceedings of the Institution of Mechanical Engineers*. 2019; C233(13): 4439–4462.
- Zagórski I., Kulisz M., Kłonica M., Matuszak J. Trochoidal Milling and Neural Networks Simulation of Magnesium Alloys. *Materials*. 2019; 12(13): 2070.
- Karkalos N.E., Galanis N.I., Markopoulos A.P. Surface roughness prediction for the milling of Ti-6Al-4V ELI alloy with the use of statistical and soft computing techniques. *Measurement*. 2016; 90: 25–35.
- Chen Y., Sun Y., Lin H., Zhang B. Prediction Model of Milling Surface Roughness Based on Genetic Al-

- gorithms. In: Xu Z., Choo K.K., Dehghantanha A., Parizi R., Hammoudeh M. (Eds.) *Cyber Security Intelligence and Analytics*. CSIA 2019. *Advances in Intelligent Systems and Computing*, Springer, Cham; 2020: 928.
17. Abbas A.T., Pimenov D.Y., Erdakov I.N., Taha M.A., Soliman M.S., El Rayes M.M. ANN Surface Roughness Optimization of AZ61 Magnesium Alloy Finish Turning: Minimum Machining Times at Prime Machining Costs. *Materials*. 2018; 11: 808.
 18. Acayaba G.M.A., Escalona P.M.D. Prediction of surface roughness in low speed turning of AISI316 austenitic stainless steel. *CIRP Journal of Manufacturing Science and Technology*. 2015; 11: 62–67.
 19. Wu T.Y., Lei K.W. Prediction of surface roughness in milling process using vibration signal analysis and artificial neural network. *The International Journal of Advanced Manufacturing Technology*. 2019; 102: 305–314.
 20. Santhakumar J., Iqbal U.M. Role of trochoidal machining process parameter and chip morphology studies during end milling of AISI D3 steel. *Journal of Intelligent Manufacturing*. 2019; 32: 649–665.
 21. Dijmărescu M.R., Abaza B.F., Voiculescu I., Dijmărescu M.C., Ciocan I. Surface Roughness Analysis and Prediction with an Artificial Neural Network Model for Dry Milling of Co–Cr Biomedical Alloys. *Materials*. 2021; 14(21): 6361.
 22. Eser A., Ayyıldız E.A., Ayyıldız M., Kara F. Artificial Intelligence-Based Surface Roughness Estimation Modelling for Milling of AA6061 Alloy. *Advances in Materials Science and Engineering*. 2021; 2021: 5576600.
 23. Zagórski I., Kłonica M., Kulisz M., Łoza K. Effect of the AWJM method on the machined surface layer of AZ91D magnesium alloy and simulation of roughness parameters using neural networks. *Materials*. 2018; 11(11): E2111.
 24. Cojbasic Z., Petkovic D., Shamshirband S., Chong W.T., Sudheer Ch., Jankovic P., Ducic N., Baralic J. Surface roughness prediction by extreme learning machine constructed with abrasive water jet. *Precision Engineering*. 2016; 43: 86–92.
 25. Al-Ahmari A.M.A. Prediction and optimisation models for turning operations. *International Journal of Production Research*. 2008; 46: 4061–4081.
 26. Kulisz M., Zagórski I., Korpysa J. Surface quality simulation with statistical analysis after milling AZ91D magnesium alloy using PCD tool. *Journal of Physics: Conference Series*. 2021; 1736: 012034.