Surface quality simulation with neural networks in AZ91D Mg alloy milling

M Kulisz¹, I Zagórski² and J Korpysa³

¹Lublin University of Technology, Management Faculty, Department of Organisation of Enterprise, 38 Nadbystrzycka Str., 20-618 Lublin, Poland
²Lublin University of Technology, Mechanical Engineering Faculty, Department of Production Engineering, 36 Nadbystrzycka Str., 20-618 Lublin, Poland
³PhD student of Mechanical Engineering, Lublin University of Technology, 36 Nadbystrzycka Str., 20-618 Lublin, Poland

m.kulisz@pollub.pl

Abstract. The mathematical model presented in this paper describes the process of milling AZ91D Mg alloy with the TiAlN-coated tool. The experimental data from the neural network training served to determine the effect of various milling parameters on the surface roughness of the workpiece. The 2D roughness measurements were taken on the end-faces of specimens and focused on the set of three parameters – Ra, Rz and Rsm. The tests were performed at constant parameters (tool geometry, workpiece strength properties and technological machine properties), variable parameters (cutting speed, feed per tooth, depth of cut) and output variables (Ra, Rz, Rsm). The simulations were executed by means of the artificial neural networks, modelled with Statistica Neural Network software. Two types of neural networks were employed: MLP (Multilayered Perceptron) and RBF (Radial Basis Function). The comparative analysis showed that the discrepancy between the results of simulation and the results obtained from experimental tests is on an acceptable level, not exceeding 15%. The above result confirms that ANNs can be successfully used as a tool for a selection of technological parameters, enabling obtaining the desired values of surface roughness parameters without the need for time-consuming machining tests.

1. Introduction – State of the Art
Magnesium alloys are typically shaped in milling, which may also constitute a finishing operation and, therefore, the high quality of the finish is essential. The primary reason for this are the increasingly strict tolerance requirements for manufactured products, particularly in the case of mating parts. It is essential to bear in mind that the surface roughness structure of parts that are expected to achieve high performance in cooperation with other elements in a system strongly affects their functional properties. What it indicates is that extensive research on surface roughness parameters and technological factors affecting them is very much in place. These studies are conducive to the determination of the combinations of milling data the application of which will result in the improvement of the quality of machined surfaces and the efficiency of the milling process. A more accurate assessment of the impact of milling conditions on the condition of the workpiece surface requires measurements of a wider range of 2D surface roughness and 3D area roughness parameters than in standard tests.
The majority of published studies resolve to focus on one parameter. In our view, this is far from sufficient for a detailed analysis of the surface conditions [1-4]. In addition to dimensional and shape accuracy, surface roughness is among the most frequently analysed indicators of machining [5]. From the literature study, it appears that $Ra$ (average roughness) is the standard parameter to consider in tests, as exemplified by the work of Muralidharan et al. Their examination set out to determine the surface quality of Mg-SiC$_2$/B$_4$C hybrid composite following milling with nine different coated and uncoated end mill cutters [6, 7]. The results presented in their study [6] show that in the case of milling performed at a range of spindle speed, $n = 1500$–$2500$ r/min, and table feed, $v_t = 1200$–$2000$ mm/min, the surface roughness is affected to a greatest extent by the modification of table feed and Burr build-up on the cutting edge. The lowest average roughness, $Ra = 0.35$ µm, was obtained when milling with a tool with a TiN coating at spindle speed, $n = 2000$ r/min, and table feed, $v_t = 2000$ mm/min. In another study [7], carried out at a cutting speed of $v_c = 1200$ m/min, the high-quality surface finish in milling was shown to result from a suitable choice of technological parameters, among which it was feed per tooth $f_z$ that had a fundamental impact as it has relevance for both 2D surface roughness and 3D area roughness parameters. What is more, axial depth of cut $a_p$ was proven to have a negligible effect on 2D surface roughness parameters, whether considering end or lateral workpiece faces. The study concluded that due to its negligible effect on the surface roughness, axial depth of cut $a_p$ exhibits a decent capacity for increasing milling efficiency while simultaneously not compromising the quality of surface finish.

The search for the optimal combination of milling parameters in dry milling of AM60 Mg alloy with a TiN-coated carbide tool was reported in the work by Sathyamoorthy et al. [8]. It was observed that in the analysed range of spindle speed, $n = 1000$–$2000$ r/min, feed per revolution, $f_n = 0.1$–$0.2$ mm/r and cutting depth, $a_p = 0.5$–$1.5$ mm, increasing feed per revolution and depth of cut has a negative effect on the surface roughness; this can be, nevertheless, reduced by increasing the spindle speed. Machining at the top rotational speed, feed per revolution rate $f_s = 0.1$ mm/r and cutting depth $a_p = 1$ mm enabled obtaining the smallest roughness $Ra$, of approx. 0.3 µm.

Another relevant work [9] analysed the extent to which the range of machining parameters: spindle speed $n = 500$–$2000$ r/min, table feed $v_t = 50$–$200$ mm/min and cutting depth $a_p = 0.5$–$1.5$ mm, are reflected in the workpiece surface roughness. When milling AZ61 magnesium alloy with a cutting tool with carbide inserts, the $Ra$ parameter value was 0.115–0.403 µm in the entire spindle speed range. The roughness remained low regardless of the change in table feed and depth of cut. The results indicate that it is possible to increase the efficiency of the milling process while maintaining high surface quality.

A different investigation into the application of the face milling cutter was reported in the work of Kim and Lee [10]. The study set out to determine the effect of technological parameters and the number of inserts in the cutting tool ($z = 1$–$6$) in milling of AZ31B alloy with air pressure coolant. The surface roughness conditions were shown to deteriorate with the increase in feed per tooth throughout the entire range 0.04–0.25 mm/tooth and the increase in the number of cutting inserts engaged. On the other hand, the involvement of compressed air was shown to cause a slight decrease in the $Ra$ parameter value.

With respect to the workpiece material, the scientific literature tends to show preference to AZ91D/HP Mg alloys, which are widely analysed in a number of studies, including the one by Kuczmaszewski et al. [11]. In the said work, AZ91D Mg alloy was machined by means of the milling head in an attempt to test whether face milling could substitute abrasive treatment as a finishing operation. The HSM machining, performed in the range of high cutting speeds, $v_c = 900$–$1400$ m/min, low feed-rate per tooth $f_s = 0.03$–$0.09$ mm/tooth and depth of cut $a_p = 0.2$–$0.3$ mm, confirmed the tested capability as it enabled achieving low values of the $Ra$ parameter in the range 0.061–0.133 µm. The lowest surface roughness was obtained at the lowest cutting speed, feed per tooth and depth of cut settings.

The above conclusions are also confirmed by a different study [12], which ran a comparative analysis of 2D surface roughness and 3D area roughness parameters of AZ91HP magnesium alloy...
measured after it had been subjected to machining with a P320 abrasive cloth, P180 and P240 non-woven abrasive fabrics as well as a carbide milling cutter. The lowest values of the analysed roughness parameters, \( R_a = 0.124 \, \mu m \) and \( R_z = 0.952 \, \mu m \), were produced as a result of milling, while the highest roughness, \( R_a = 0.81 \, \mu m \) and \( R_z = 3.82 \, \mu m \), was observed on surfaces treated with P180 non-woven abrasive fabric. In the case of 3D area roughness parameters, the highest values were characteristic of the surface machined with P320 abrasive cloth, while the lowest values were, as previously, recorded on the surface treated with P180 non-woven abrasive fabric.

The same material was also analysed in the study by Gziut et al. [13]. In the study, the tool rake angle \( \gamma \) was shown to significantly affect the roughness of the front and side surfaces of the workpiece machined by means of carbide milling cutters with angles \( \gamma = 5^\circ \) and \( \gamma = 30^\circ \). For both surfaces, lower roughness parameters were recorded when machining with a tool rake angle \( \gamma = 5^\circ \); it was furthermore observed that on the face surfaces the differences were much more significant. In addition, the surface was reported to have a smoother finish when machined at higher cutting speeds \( (v_c = 400-1200 \, \text{m/min}) \), while the increase in feed per tooth \( (f = 0.05-0.30 \, \text{mm/tooth}) \) exhibited a counter effect.

Surface roughness is an essential data source of reference for other processes, such as plastic forming as pretreatment of semi-finished materials, which may precede e.g. AWJM [14] or brush treatment (edge deburring) [5]. It is for the given reason that there is a need for a detailed and extensive description of the workpiece surface finish. As previously remarked, current studies in the field are limited to the determination of Ra roughness parameter, which fails to provide an adequate picture of the condition of the magnesium alloy surface considering its utilitarian characteristics.

There is a distinct tendency observed nowadays towards the use of mathematical models to predict the surface roughness after milling. The primary purpose of these simulations is to ensure that the surface produced in an actual process exhibits the necessary quality. The model for the determination of Ra parameter of the surface after milling, proposed by Miko and Nowakowski [15], aid the choice of cutting data according to the desired surface roughness characteristics. Their model describes the stereometry and kinematics of the cutting tool profile on the surface, as it is the case with similar models. The findings from their study indicated that the surface roughness greatly depends on two factors in particular, namely, feed per tooth and the tool corner geometry. The key problem with these models is the inaccuracy of predictions, which results from the simplifying assumptions they employ. Therefore, there is a discrepancy between the modelled and measured surface roughness results, which may be between 1.5-5 times lower in the former case.

Other mathematical models, e.g. Zhou et al. [16] for 3D surface topography modelling upon helical milling, Urbikain et al. [17] for surface topography simulation in flank-milling by means of circle-segment end mills, or Wojciechowski et al. [18], accounted for machining parameters, the static tool run-out and dynamic effects of tool deflection. These models, as in the case of the previous paragraph, are not fully comparable with the actual results from machining, which is due to the high complexity and significant randomness factor of the modelled process.

In the face of the inaccuracy challenge, newly produced models employ AI-based techniques that derive from experimental models, which ensure higher precision in the representation of the simulated machining process. The application of neural networks for the prediction of surface roughness is presented in numerous works, e.g. by Karabulut [19], using Artificial Neural Network (ANN) modelling and Taguchi method, or by Sangwan et al. [20] for the determination of the optimum cutting data with a view to obtaining the minimum surface roughness in a joint effort from ANN and Genetic Algorithm (GA).

Neural networks have been similarly found suitable in the prediction of: dimensional errors [21], surface quality and optimisation of process parameters [22], machining performance [23], or milling chatter [24]. Although the results from simulations may not be capable of providing specific machining parameters, they do however approximate the desired range of cutting data. Therefore, neural networks prove themselves as a solid tool, which can successfully aid technologists in determining optimal machining parameters.
2. Test and simulation methodology

The experimental part of the study was performed with AVIA vertical milling centre VMC800HS, controlled by Heidenhain iTNC 530 system. The milling was performed with a VHM tool – the Ø16 two-edge TiAlN-coated carbide cutter (manufactured by Fenes), which was set in the shrink-fit holder, HSK-A63 Seco – Tools SFD 16x120, for improved stability. The entire tool system was balanced to G2.5, according to balance quality requirements specified in the International Standard ISO 21940-11:2016. The result of 0.87 g-mm, obtained from the unbalance measurement carried out with CIMAT RT 610 balancing machine, proved the tool-tool-holder system complied with the permissible residual unbalance. The workpiece material subjected to experimental testing and mathematical simulation was AZ91D Mg alloy. The variable machining parameters employed in the study were: cutting speed \( v_c = 400\text{–}1200 \text{ m/min} \), feed per tooth \( f_z = 0.05\text{–}0.30 \text{ mm/tooth} \), axial depth of cut \( a_p = 0.5\text{–}6 \text{ mm} \); whereas the constant milling parameter was radial depth of cut \( a_e = 14 \text{ mm} \). Figure 1 shows the experimental set-up for the surface roughness test plan.

![Figure 1. Schematic for surface roughness test plan.](image)

The results from experiments provided the input data fed into the ANN for the simulation of selected surface quality indicators, i.e. three surface roughness parameters – average roughness (\( Ra \)), maximum height of profile (\( Rz \)) and mean width of profile elements (\( RSm \)). Given the nonlinear character of the modelled technological process and the resulting problems for its adequate representation by means of mathematical equations, the milling process was approached as the control object and the modelled parameters, \( Rz, Ra \) and \( RSm \) become the output parameters. As previously stated, the only variable machining parameters were cutting speed \( v_c \), feed per tooth \( f_z \) and cutting depth \( a_p \). The schematic model of milling shown in Figure 2 contains the variable input parameters \( v_c, f_z \) and \( a_p \), whereas \( nn \) stands for the output parameter simulated at a given moment; therefore, as three surface roughness parameters were considered in AZ91D alloy milling – three ANNs were produced. For the reason of its performance on the training set, the black box model of ANN was employed in the study. This model is applicable in scenarios when it is difficult to determine mathematical equations describing the analysed process, as in the presented case.

![Figure 2. ANN of the analysed process parameters.](image)
The simulations performed as part of this study were executed by means of Statistica Neural Networks software package and employed two ANN types, MLP (multilayered Perceptron) and RBF (Radial Basis Function). The MLP model used linear, exponential, logistic, tanh and sinus activation functions, and was trained with BFGS gradient (Broyden–Fletcher–Goldfarb–Shanno), conjugate gradient and the steepest descent training algorithm. The RBF network model engaged the following activation functions: hidden neurons – Gaussian distribution, output neurons – linear function, and it was trained with RBFT algorithm. The training data set used 75% of data from experimental tests and 25% were used for validation. The test data set was omitted due to insufficient data from milling tests [14].

With respect to ANN structure, for simplicity considerations, one hidden layer was included in both MLP and RBF models, in addition, 3 neurons were in the input layer (cutting speed, feed per tooth and cutting depth) and one neuron in output (i.e. the predicted surface roughness parameter). The number of hidden-layer neurons (2–9) and training epochs (150-250) were determined experimentally. The chosen network types offered optimal training and validation quality and error characteristics. The least-squares algorithm was used for error identification purposes.

3. Results and analysis

3.1. Analysis of results

The results from tests and measurements are presented below as bar charts and include the standard deviation. Figures 3-5 reflect on the impact of cutting speed \( v_c \) change on the values of selected 2D surface roughness parameters. The presented values were calculated as an average of five identical measurements for a given set of cutting data. Figure 3a presents the values of \( Ra \) and \( Rz \) measured on the face surface of the Mg workpiece for variable cutting speed \( v_c \). For the parameter \( Ra \), similar values of approx. 0.3 µm were obtained in the entire range of cutting speeds; however, they did not exceed 3.12 µm, observed for \( v_c = 1200 \) m/min. Considering the \( Rz \) parameter, major changes in its values were noted in the range of 11.62-13.56 µm. The effect of cutting speed \( v_c \) on the values of the \( RSm \) parameter is shown in Figure 3b. The values ranged from 0.141 to 0.149 mm, and the change was insignificant.

![Figure 3](image1.png)

**Figure 3.** Effect of cutting speed \( v_c \) on: a) \( Ra \) and \( Rz \), b) \( RSm \) (\( f_z = 0.15 \) mm/tooth, \( a_p = 6 \) mm).

Figure 4a presents the values of \( Ra \) and \( Rz \) obtained at variable feed per tooth \( f_z \). For both parameters, the mean values exhibit a linear increase in response to the increase in feed per tooth \( f_z \), to reach the values in the range of 0.53-5.62 µm for the \( Ra \) parameter and 3.18-27.52 µm for the \( Rz \) parameter. Figure 4b shows the effect of variable feed per tooth \( f_z \) on \( RSm \). Increasing the feed-rate per tooth \( f_z \) resulted in an increase in the average value from 0.048 mm to 0.264 mm.
Figure 4. Effect of feed per tooth \( f_z \) on: a) \( Ra \) and \( Rz \), b) \( RSm \) (\( v_c = 800 \text{ m/min}, \ a_p = 6 \text{ mm} \)).

\( Ra \) and \( Rz \) parameters measured in the conditions of variable depth of cut \( a_p \) are given in Figure 5a. Significantly lower values in the 2.35-2.90 \( \mu m \) range were recorded for the \( Ra \) parameter, while for the \( Rz \) parameter the values were within 10.82-12.32 \( \mu m \). Figure 5b shows the effect of depth of cut \( a_p \) on the \( RSm \) parameter. The values obtained throughout the entire range of depth of cut \( a_p \) showed little discrepancy and amounted to 0.137-0.151 mm.

Figure 5. Effect of depth of cut \( a_p \) on: a) \( Ra \) and \( Rz \), b) \( RSm \) (\( v_c = 800 \text{ m/min}, \ f_z = 0.15 \text{ mm/tooth} \)).

From the conducted analysis, it can be seen that changes in particular technological parameters investigated in the study have been shown to exert a similar effect on 2D roughness parameters measured on the face surface of the Mg workpiece.

3.2. Simulation results
The experimental research provided data on the AZ91D alloy surface quality indicators (\( Rz, Ra, RSm \)). The data were fed into the model as the input for simulation of these quantities using ANNs. Simulations were calculated with the Statistica Neural Networks and employed MLP and RBF networks.

The suitability of a given network in a considered application is assessed by: learning quality, validation quality, learning errors and validation errors identified by means of the least-squares method, all of which are important network quality indicators. Here, 200 networks were produced for each simulation scenario. In order to select the better-suited network type, RBF or MLP, the networks were assessed with the application of the said network quality indicators. Table 1 presents characteristics of the surface roughness parameters analysed in the scope of reported investigations, i.e. \( Rz, Ra \) and \( RSm \), measured following milling of AZ91D alloy. The quality assessment indicated that, in general, the RBF network exhibits higher compatibility with \( Rz \) and \( RSm \): in particular RBF 3-
3-1 (three hidden neurons) is optimal for simulation of maximum height of profile ($R_z$), while mean width of profile elements ($R_{Sm}$) is best modelled by RBF 3-7-1 (seven hidden neurons) – in both cases the networks were trained with the RBFT algorithm. Considering average roughness parameter ($R_a$) it was the three-neuron network MLP 3-3-1 that provided the best fit with the experimental data; the Multilayered Perceptron network was trained with the BFGS algorithm over 200 iterations.

Table 1. Characteristics of multilayered perceptron (MLP) and radial basis function (RBF) networks for the simulated surface quality indicators ($R_z$, $R_a$, $R_{Sm}$) for AZ91D alloy.

| Network No. | Network Name | Quality (Training,% | Quality (Validation,% | Error (Training) | Error (Validation) | Activation (Hidden) | Activation (Output) |
|-------------|--------------|---------------------|-----------------------|-------------------|-------------------|---------------------|---------------------|
| Rz - maximum height of the profile |
| 1 | MLP 3-4-1 | 99.76 | 99.48 | 2.049 | 6.512 | Logistics | Tanh |
| 2 | RBF 3-3-1 | 98.79 | 99.99 | 1.256 | 4.478 | Gaussian | Linear |
| 3 | MLP 3-8-1 | 99.75 | 99.25 | 2.052 | 5.960 | Logistics | Exponential |
| Ra - average roughness |
| 4 | MLP 3-6-1 | 99.22 | 97.66 | 0.099 | 0.074 | Linear | Linear |
| 5 | RBF 3-7-1 | 99.79 | 97.76 | 0.082 | 0.351 | Gaussian | Linear |
| 6 | MLP 3-3-1 | 99.96 | 98.85 | 0.051 | 0.112 | Exponential | Logistics |
| RSm - mean width of profile elements |
| 7 | MLP 3-6-1 | 99.98 | 99.85 | 0.002 | 0.003 | Tanh | Exponential |
| 8 | RBF 3-4-1 | 97.62 | 99.97 | 0.002 | 0.002 | Gaussian | Linear |
| 9 | RBF 3-7-1 | 99.46 | 99.98 | 0.002 | 0.002 | Gaussian | Linear |

The graphical representation of ANN results that showed the best fit with the experimental data is given below. Since three input parameters were considered, each network was shown in two diagrams: $v_c/f_z$ and $v_c/a_p$. The results for $R_z$ surface roughness parameter produced by the RBF 3-3-1 network are shown in Figure 6, for $R_a$ (MLP 3-3-1) – Figure 7, and for $R_{Sm}$ (RBF 3-7-1) – Figure 8.

Figure 6. Numerical results from RBF 3-3-1 network for $R_z$ surface roughness parameter depending on the cutting speed $v_c$ and: (a) cutting depth $a_p=6[\text{mm}]$, (b) feed per tooth $f_z=0.15[\text{mm/tooth}]$ for AZ91D alloy.
Figure 7. Numerical results from MLP 3-3-1 network for $Ra$ surface roughness parameter depending on the cutting speed $v_c$ and: (a) cutting depth $a_p=6$[mm], (b) feed per tooth $f_z=0.15$[mm/tooth] for AZ91D alloy.

Figure 8. Numerical results from RBF 3-7-1 network for $RSm$ surface roughness parameter depending on the cutting speed $v_c$ and: (a) cutting depth $a_p=6$[mm], (b) feed per tooth $f_z=0.15$[mm/tooth] for AZ91D alloy.

The networks obtained as a result of simulations characterise the behaviour of $Ra$, $Rz$, $RSm$ surface quality parameters, obtained under variable machining parameters constraint: cutting speed, feed per tooth and cutting depth. The variable parameters ($v_c$, $f_z$, $a_p$) were subsequently fed into Statistica-developed models as network input to produce particular surface roughness parameters (depending on the type of network).
The quality of the networks is shown in Figure 9: it emerges from the comparison of $R_z$ and $R_a$ parameters for AZ91D alloy material with their simulated counterparts, depending on the cutting speed $v_c$ at $f_z = 0.15$ m/min and $a_p = 6$ mm. Figure 10 presents the identical comparison with respect to $R_{Sm}$. What is worth noting is that the discrepancy between the actual values of simulated parameters was on an acceptable level: the relative error did not exceed 15%.

Low network error indicator ($<15\%$) indicates that the ANNs implemented in this study have proven their suitability as a modelling tool.

Figure 9. Comparison of experimental and numerical results depending on the cutting speed $v_c$ for feed per tooth $f_z=0.15$[mm/tooth] and cutting depth $a_p=6$[mm] for $Ra$ and $Rz$ surface roughness parameters in milling of AZ91D alloy.

Figure 10. Comparison of experimental and numerical results depending on the cutting speed $v_c$ for feed per tooth $f_z=0.15$[mm/tooth] and cutting depth $a_p=6$[mm] for $R_{Sm}$ surface roughness parameter in milling of AZ91D alloy.

4. Conclusions
From the conducted experimental and simulation investigation, it is now possible to state that:

- Feed per tooth $f_z$ has the greatest effect on the 2D surface roughness parameters measured on the workpiece face: surface quality dropped when $f_z$ increases.
- The change in cutting speed $v_c$ does not significantly affect the 2D surface roughness parameters on the workpiece face.
• The change in depth of cut \( a_p \) has no significant effect on the 2D surface roughness of the workpiece face: therefore, the efficiency of the milling process may be increased without compromising the quality of the machined surfaces by adjusting \( a_p \).
• Considering the results from roughness parameter simulation and how they correlate with the real cutting data, it was shown that the error did not exceed 15%, thus the discrepancy is on an acceptable level. Therefore, ANNs are fully capable of providing accurate data for the preliminary determination of milling data.
• The nonlinear dependence between machining parameters and roughness parameters was successfully represented by means of ANNs. This finding suggests that neural networks are fit for the examination of milling process without the need for time-, labour- and cost-consuming machining tests.
• ANN simulation results may lay the fundamentals for designing a modelling tool to describe phenomena occurring in machining. This solution could aid the decision-making process by supplying cutting data that ensure obtaining desired surface roughness. A given set of parameters \((v_c, f_z, a_p)\) might be fed into the system as input for calculations, at the output of which surface roughness parameter values \((Ra, Rz, RSm)\) are obtained.

5. References
[1] Grzesik W 2015 Surface topography and utilitarian characteristics of machine parts Mechanik 8–9 587–93
[2] Klonica M and Kuczmaszewski J 2015 Comparative analysis of the surface energy state of az91hp alloy following abrasive treatment and milling Mechanik 8–9 212–16
[3] Sedałaček M, Vilhena L M, Podgornik B and Vižintin J 2011 Surface topography modelling for reduced friction Strojniški vestnik – Journal of Mechanical Engineering 57(9) 674–80.
[4] Sedałaček M, Gregorčič P and Podgornik B 2017 Use of the roughness parameters Skk and Sku to control friction – a method for designing surface texturing Tribol. T. 60(2) 260–66
[5] Matuszak J and Zaleski K 2018 Analysis of deburring effectiveness and surface layer properties around edges of workpieces made of 7075 aluminium alloy Aircr. Eng. Aerosp. Tec. 90(3) 515–23
[6] Muralidharan S, Karthikeyan N, Kumar A B and Aatthisugan I 2017 A study on machinability characteristic in end milling of magnesium composite International Journal of Mechanical Engineering and Technology 8(6) 455–62
[7] Zagórski I and Korypsa J 2019 Surface quality in milling of AZ91D magnesium alloy Advances in Science and Technology Research Journal 13(2) 119-29 doi:10.12913/229998624/108547
[8] Sathyamoorthy V, Deepan S, Sathy Prasanth S P and Prabhu L 2017 Optimization of machining parameters for surface roughness in end milling of magnesium AM60 alloy Indian Journal of Science and Technology 10(32) 1–7 doi:10.17485/ijst/2017/v10i32/104651
[9] Alharti N H, Bingol S, Abbas A T, Ragab A E, El-Danaf E A and Alharbi H F 2017 Optimizing cutting conditions and prediction of surface roughness in face milling of AZ61 using regression analysis and artificial neural network Adv. Mater. Sci. Eng. 2017 7560468
[10] Kim J D and Lee K B 2010 Surface roughness evaluation in dry-cutting of magnesium alloy by air pressure coolant Engineering 2 788–92
[11] Ruslan M S, Othman K, Ghani J A, Kassim M S and Haron C H C 2016 Surface roughness of magnesium alloy AZ91D in high speed milling Jurnal Teknologi 78(6–9) 115–19
[12] Kuczmaszewski J, Pieśko P and Zawada-Michałowska M 2016 Surface roughness of thin-walled components made of aluminium alloy EN AW-2024 following different milling strategies Advances in Science and Technology Research Journal 10(30) 150–58 doi:10.12913/22998624/62515
[13] Gziut O, Kuczmaszewski J and Zagórski I 2015 Surface quality assessment following high performance cutting of AZ91HP magnesium alloy Management and Production Engineering
Review 6(1) 4-9

[14] Zagórski I, Klonica M, Kulisz M and Łoza K 2018 Effect of the AWJM method on the machined surface layer of AZ91D magnesium alloy and simulation of roughness parameters using neural networks Materials 11(11) E2111 doi:10.3390/ma11112111

[15] Miko E and Nowakowski E 2015 Models for prediction of Ra roughness parameters of milled surfaces Mechanik 8-9 82-90

[16] Zhou Y, Tian Y, Jing X, Wang F and Liu Y 2018 Int. J. Adv. Manuf. Technol. 95 4561 doi:10.1007/s00170-017-1516-2

[17] Urbikain G and de Lacalle L N L 2018 Modelling of surface roughness in inclined milling operations with circle-segment end mills Simul. Model. Pract. Theory 84 161–76

[18] Wojciechowski S, Twardowski P, Pelic M, Maruda R W, Barrans S and Krolczyk G M 2016 Precision surface characterization for finish cylindrical milling with dynamic tool displacements model Precision Engineering 46 158–65 doi:10.1016/J.PRECISIONENG.2016.04.010

[19] Karabulut S 2015 Optimization of surface roughness and cutting force during AA7039/Al2O3 metal matrix composites milling using neural networks and Taguchi method Measurement 66 139-49 doi:10.1016/j.measurement.2015.01.027

[20] Sangwan K S, Saxena S and Kant G 2015 Optimization of machining parameters to minimize surface roughness using integrated ANN-GA approach Proc. CIRP 29 305-310 doi:10.1016/j.procir.2015.02.002

[21] Arnaiz-González A, Fernández-Valdivielso A, and Bustillo A. et al. 2016 Int. J. Adv. Manuf. Technol. 83 847 doi:10.1007/s00170-015-7543-y

[22] Kaviarasan V, Venkatesan R and Natarajan E 2019 Prediction of surface quality and optimization of process parameters in drilling of Delrin using neural network Prog. Rubber. Plast. Re. 35(3) 149-69 doi:10.1177/1477760619855078

[23] Zerti A, Yallese M A, Zerti O, Nouioua M and Khettabi R 2019 Prediction of machining performance using RSM and ANN models in hard turning of martensitic stainless steel AISI 420 P. I. Mech. Eng., Part C 233(13) 4439–62 doi:10.1177/0954406218820557

[24] Zagórski I, Kulisz M, Semeniuk A and Malec A 2017 Artificial neural network modelling of vibration in the milling of AZ91D alloy Advances in Science and Technology Research Journal 11(3) 261-69 doi:10.12913/22998624/76546