Surface quality simulation with statistical analysis after milling AZ91D magnesium alloy using PCD tool

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Abstract. Machined surface quality is one of the key indicators of a correctly conducted milling process. This paper reports on the results from numerical and statistical analysis of the condition of AZ91D Magnesium Alloy after milling using the PCD Tool. Three surface roughness indicators were of interest – average roughness (Ra), maximum height of profile (Rz) and mean width of profile elements (RSm). The surface quality, described by Ra/Rz, shows negligible deterioration at higher speeds vₙ. Two artificial neural networks, MLP (Multilayer Perceptron) and RBF (Radial Basis Function), modelled with Statistica package, were employed to simulate the effects that individual process variables have on the 2D surface roughness parameters. The statistical significance of the results was assessed using the one-way ANOVA technique. Given the successful validation of the numerical and empirical data (R² > 0.85), it may be inferred that our ANNs are an accurate predicting tool that models milling parameters ensuring that the surface is of suitable quality. The surface roughness indicators are generated from the corresponding technological parameters. Simulations save time, effort and costs that would be incurred by additional machining tests.

1. Introduction – state of the art

Modern machining is a complex process that is executed in strictly-controlled conditions so as to ensure exceptional quality and accuracy of the workpiece. The overall quality of the product is often judged through the prism of the surface finish. The state of the workpiece surface can be easily assessed by means of surface roughness parameters. Given the rapid developments in the field of numerical modelling, it has been found that the exploration of relationships and phenomena occurring during machining must not necessarily be limited to actual machine cutting tests. Various models enable predicting the surface roughness of the workpiece from the input data, and recently artificial intelligence has become more widely employed due to its capacity to provide good quality of predictions verified by experimental models.

There is a wide range of scientific publications describing mathematical modelling of machining processes, including Zhou et.al. [1], Urbikain et al. [2], Miko & Nowakowski [3], Kong et al. [4] and Yeganefar et al. [5]. Machine-learning has been used in a similar scope of research by Lu et al. [6], whereas Artificial Neural Networks (ANN) by e.g. Abbas et al. [7], Acayaba et al. [8], Zerti et al. [9],...
Karkalos et al. [10], Wu et al. [11] or Zagórski et al. [12]. The implementation of Genetic Algorithm-Artificial Neural Networks (GA-ANN) can be found in the works of Cojbasic et al. [13], Sangwan et al. [14], Chen et al. [15] as well as Santhakumar et al. [16]. For reference, the studies in question are presented in Table 1, which additionally specifies the type of modelling, processes and materials under analysis as well as the parameter(s) that the investigations attempted to establish.

From Table 1, it can be seen that mathematical modelling can be applied to simulate numerous processes, which may employ ANN techniques, e.g. milling [1-6,10,11,15,16], turning [7-9,14] or Abrasive WaterJet Machining (AWJM) [12-13] of different materials, such as steel or light metals. The synopsis of studies in machining indicates that the vast majority of research papers limits the surface-roughness-oriented considerations to one parameter, Ra – average roughness. It should seem that such a narrow scope is insufficient to provide a detailed analysis of surface conditions [17-19], therefore, it is justified that the simulation tests should encompass a wider range of surface roughness parameters.

Table 1. Synopsis of surface roughness parameter modelling methods.

| Method                  | Machining          | Research object: surface roughness parameters | Materials       | Reference |
|-------------------------|--------------------|----------------------------------------------|----------------|-----------|
| mathematical model      | helical milling    | Ra                                           | Ti6Al4V/TC4     | [1]       |
| mathematical model      | flank-milling, circle-segment end mills | Ra, Rz                                      | Al7075T         | [2]       |
| mathematical model      | shoulder/face milling | Ra                                     | -              | [3]       |
| mathematical model      | milling            | Ra                                           | AI 6061         | [4]       |
| ANN/mathematical model  | milling            | Ra                                           | Al 7075-T6      | [5]       |
| machine-learning method | micro-milling      | Ra                                           | single-crystal copper | [6]       |
| ANN                     | turning            | Ra                                           | AZ61            | [7]       |
| ANN                     | low speed turning  | Ra                                           | AISI1316        | [8]       |
| ANN                     | dry turning        | Ra, Rz, Rt                                  | AISI 420        | [9]       |
| ANN                     | milling            | Ra                                           | Ti-6Al-4V       | [10]      |
| ANN                     | milling            | Ra                                           | S45C steel      | [11]      |
| ANN                     | AWJM               | Ra, Rz, RSm                                 | AZ91D           | [12]      |
| ANN-GA                  | AWJM               | Ra                                           | Al 6060         | [13]      |
| ANN-GA                  | turning            | Ra                                           | Ti-6Al-4V       | [14]      |
| ANN-GA                  | milling            | Ra                                           | P1.2738         | [15]      |
| ANN-GA                  | milling            | Ra                                           | AISI D3         | [16]      |

Although the simulations may not suffice for the purpose of providing specific machining data, however, their value consists in approximating the range of cutting parameters that produce predicted results of machining. Considering the contribution from the surface roughness prediction and modelling solution presented in this work, the developed method could become an element of a ready-to-use tool for the selection of machining parameters for a given surface roughness effect.
2. Methodology
This study is a continuation of the works conducted by I. Zagorski & J. Korpysa. The results obtained from the team’s former experimental research, described in the paper "Surface Quality Assessment after Milling AZ91D Magnesium Alloy Using PCD Tool" [20] were used as the input for the ANOVA analysis and ANN simulation. The study concerns three surface roughness parameters (average roughness (Ra), maximum height of profile (Rz) and mean width of profile elements (RSm)) that were determined on the surface of AZ91D workpieces after milling. The design of the neural networks was based on three variable machining parameters: cutting velocity \( v_c \) (400–1200 m/min), feed per tooth \( f_z \) (0.05–0.30 mm/tooth) and axial depth of cut \( a_p \) (0.5–6 mm), which served as three neurons in the input layer. The output layer contained one neuron, i.e. one of the surface roughness parameters (Ra, Rz, RSm). Therefore, three neural network models were obtained.

The numerical simulations were performed using Statistica Neural Networks and two ANNs, MLP (Multilayer Perceptron) and RBF (Radial Basis Function). Table 2 specifies the network learning parameters.

| ANN types | Activation function | Learning algorithm | Hidden layer | Hidden-layer neurons | Training epochs |
|-----------|---------------------|--------------------|--------------|----------------------|----------------|
| MLP       | linear, logistic, exponential, tanh, sinus | BFGS               | 1            | 2+9                  | 150-200        |
| RBF       | Gaussian (hidden neurons) Linear (output neurons) | RBFT              |              |                      |                |

The results from the experimental tests were employed for training and validation purposes in the 75%-25% share respectively. Owing to the limited amount of data from milling [21], the test dataset was not included in the analysis. The specific network types were selected as they offered the best quality of training and validation as well as good robustness to error. With respect to error detection, the least-squares method was employed.

3. Results and analysis

3.1. Statistical analysis
The impact of the machining parameters (cutting speed, feed per tooth, axial depth of cut) on the surface roughness parameters (Ra, Rz, RSm) was analysed statistically using the one-way ANOVA at the confidence level \( \alpha = 0.05 \). The procedure consisted of 3 steps. In the first step, the Shapiro-Wilk test verified the normal distribution of the data. Secondly, Levene’s test was employed to compare variances in the study groups. Following the positive confirmation of the homogeneity of variance, the ANOVA analysis was performed. The results obtained for the variable cutting speed are shown in Table 3.

| Source   | DF | Ra       |       |       | Rz       |       |       | RSm     |       |
|----------|----|----------|-------|-------|----------|-------|-------|---------|-------|
|          |    | SS       | MS    | F     | p        | SS    | MS    | F       | p     |
| Between  | 4  | 0.0032   | 0.0008| 1.0051| 0.4282   | 0.3464| 0.0866| 1.9954  | 0.1341| 0.0002| 0.0000| 3.5886| 0.0232|
| Within   | 20 | 0.0158   | 0.0008| 0.8680| 0.0434   | 0.0003| 0.0000|         |       |
| Total    | 24 | 0.0190   | 1.2144|       |          |       |       |         |       |

Regarding Ra and Rz, no legitimate reasons arise for rejecting the null hypothesis (equality of means), which supports the inference that the change in the cutting speed has no statistically significant effect on the values of these parameters; however, it also emerges that the cutting speed is a relevant factor for RSm. To facilitate the interpretation of the tabular data, the scatter of the surface roughness parameters is shown in Figure 1 as box-and-whisker plots. Several tendencies emerge from the
numerical values obtained from the measurements relative to the increase in $v_c$ (in extremes): while the maximum Ra is observed to rise from the nominal 0.38 $\mu$m to 0.42 $\mu$m, Rz is relatively unaffected and the maximum $R_{Sm}$ is correlated negatively.

Figure 1. The effect of the cutting speed change on the values of the surface roughness parameters: a) Ra, b) Rz and c) $R_{Sm}$.

Figure 2. The effect of the feed per tooth change on the values of the roughness parameters: a) Ra, b) Rz and c) $R_{Sm}$. 
Table 4. ANOVA results for Ra, Rz and RSm following milling with a variable feed per tooth $f_z$.

| Source  | DF  | SS  | MS  | F     | p     | SS  | MS  | F     | p     | SS  | MS  | F     | p     |
|---------|-----|-----|-----|-------|-------|-----|-----|-------|-------|-----|-----|-------|-------|
| Between | 5   | 0.1429 | 0.0286 | 29.2041 | 0.0000 | 4.8857 | 0.9771 | 27.0175 | 0.0000 | 0.0006 | 0.0001 | 2.0820 | 0.1029 |
| Within  | 24  | 0.0235 | 0.0010 | 0.8680 | 0.3632 | 0.0014 | 0.0000 | 0.0006 | 0.0001 | 2.0820 | 0.1029 |
| Total   | 29  | 0.1664 | 0.0257 | 0.7653 | 0.0020 | 0.0020 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

The results from the analysis of variance for the variable feed per tooth are shown in Table 4. It is shown that as for the Ra and Rz parameters, the hypothesis about the equality of groups’ means should be rejected. Overall, this indicates that the feed per tooth has a statistically significant impact on the values of Ra and Rz. On the other hand, considering the tabular data, the hypothesis concerning the equality of means is not to be rejected for the RSm parameter, therefore, there is no statistically significant correlation between RSm and the feed per tooth. Figure 2 summarises the scatter of Ra, Rz and RSm values. The behaviour of the surface quality descriptors is in close proximity to the theoretical assumptions. In specific terms, the rise in $f_z$ (for maximum values) exerts a two-fold increase in Ra, from approx. 0.3 $\mu$m to 0.5 $\mu$m, an increase in Rz from approx. 2.1 $\mu$m to 3.2 $\mu$m, and a slight change in RSm (from 0.04 $\mu$m to 0.05 $\mu$m).

Table 5. ANOVA results for Ra, Rz and RSm following milling with a variable axial depth of cut $a_p$.

| Source  | DF  | SS  | MS  | F     | p     | SS  | MS  | F     | p     | SS  | MS  | F     | p     |
|---------|-----|-----|-----|-------|-------|-----|-----|-------|-------|-----|-----|-------|-------|
| Between | 4   | 0.0008 | 0.0002 | 0.2596 | 0.9003 | 0.1016 | 0.0254 | 0.7651 | 0.5604 | 0.0004 | 0.0001 | 2.4345 | 0.0809 |
| Within  | 20  | 0.0146 | 0.0007 | 0.6640 | 0.0332 | 0.0008 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Total   | 24  | 0.0154 | 0.0257 | 0.7656 | 0.0020 | 0.0020 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Figure 3. The effect of the axial depth of cut change on the values of the roughness parameters: a) Ra, b) Rz and c) RSm.
The ANOVA results for the variable axial depth of cut can be compared in Table 5. From the data for the three surface roughness parameters shown here, it emerges that there are no grounds for rejecting the null hypothesis of equality of means, which concludes that within the tested range of axial depths of cut, the modification of this machining parameter will not result in statistically significant differences in the values of the workpiece surface roughness under scrutiny. The variation of results for the Ra, Rz and RSm parameters is shown in detail in Figure 3 below. The analysis of the response of the surface roughness quality indicators to the increase in \( a_p \) shows the following tendencies: the Ra parameter is most notably affected, its value reaches the level of 0.425 \( \mu m \), whereas the other two indicators in question, Rz and RSm are not affected to a relevant degree.

### 3.2. Simulation results

The simulation of the surface quality indicators (Rz, Ra, RSm) was performed using the Statistica Neural Networks’ MLP and RBF models. For each surface parameter, 200 networks were formed, of which one was selected for each surface quality indicator, based on learning and validation quality, as well as learning and validation errors. The most accurate results of simulations were obtained from networks of 7-8 neurons. Table 6 summarises the characteristics of the networks. The RBF model was shown to exhibit higher compatibility with Rz and RSm; in specific terms, network no. 1, RBF 3-8-1 (eight hidden neurons), was found to be the optimal model considering the height of profile (Rz) and mean width of profile element (RSm) simulations should be performed with the use of network no. 2, RBF 3-7-1 (seven hidden neurons). Both networks were trained with the RBFT algorithm. In terms of average roughness (Ra), the best performance considering the experimental data was provided by the network with seven neurons (network no. 3 MLP 3-7-1); the Multilayer Perceptron network was trained with the BFGS algorithm in 55 iterations.

### Table 6. Detailed information regarding Artificial Neural Networks simulating surface roughness parameters (Rz, Ra, RSm).

| Network No. | Network Name | Quality (Training,%) | Quality (Validation,%) | Error (Training) | Error (Validation) | Activation (Hidden) | Activation (Output) |
|-------------|--------------|----------------------|------------------------|-----------------|-------------------|---------------------|---------------------|
| 1           | RBF 3-8-1    | 90.59                | 99.41                  | 0.0025          | 0.0052            | Gaussian            | Linear              |
| 2           | MLP 3-7-1    | 9655.                | 99.81                  | 0.0001          | 0.0001            | Sinus               | Linear              |
| 3           | RBF 3-7-1    | 87.75                | 76.36                  | 0.0001          | 0.0001            | Gaussian            | Linear              |

The surface roughness data obtained from the numerical models for the investigated alloys are presented below. Due to the fact that three input parameters were considered in the study, the changes in the values of each respective quality indicator are presented twice under the impact of a pair of cutting parameters: \( v_c/f_z \), and \( v_c/a_p \). The results from the RBF 3-8-1 network for Rz are illustrated in Figure 4a and 4b), for Ra (MLP 3-7-1) – Figure 4c and 4d), and for RSm (RBF 3-7-1) – Figure 4e) and 4f). The simulations were run once the input data (i.e. milling parameters \( v_c, a_p, f_z \)) had been entered into the Statistica modelling tool for each network.

### Table 7. \( R^2 \) correlation for surface roughness parameters Ra, Rz, and RSm.

| Surface roughness parameters | Ra   | Rz   | RSm  |
|-----------------------------|------|------|------|
| Network                     | RBF 3-8-1 | MLP 3-7-1 | RBF 3-7-1 |
| \( R^2 \) correlation       | 0.9813 | 0.9566 | 0.8731 |
Figure 4. Surface roughness parameters obtained from the numerical model. The 3D surface plots illustrate changes in Ra, Rz and RSm depending on the cutting speed $v_c$ / the feed per tooth $f_z$ for the constant axial depth of cut $a_p = 6$ [mm] (a, c, e); and the cutting speed $v_c$ / the axial depth of cut $a_p$ for the constant feed per tooth $f_z = 0.15$ [mm/tooth] (b, d, f).
Table 7 presents coefficients of determination of the surface roughness parameters $Ra$, $Rz$, and $RSm$. The results confirm that neural networks provide sufficient predictive strength for modelling surface roughness parameters. The correlation between the simulated and experimental data is further displayed in the graphs in Figure 5.

![Graphs showing Ra, Rz, and RSm](image)

Figure 5. Comparison of experimental and numerical results of surface roughness parameters $Ra$ (a), $Rz$ (b) and $RSm$ (c).

From the data above, it can be seen that the obtained networks exhibit satisfactory predictive capacity, evidenced by R-squared values of more than 0.85. Hence, artificial neural network modelling has been shown to be an effective simulation tool, capable of closely approximating surface quality parameters after milling. Given their reliability, the network models could in future become a key component in an elaborate system for numerical modelling of machining processes.

4. Conclusions
Several conclusions emerge from the reported statistical analysis and simulations using artificial neural network models:

- The condition of the surface, described by $Ra$ and $Rz$ parameters, does not show signs of substantial deterioration under the effect of variable cutting speed $v_c$ and axial depth of cut $a_p$; the change in the feed per tooth $f_z$ does cause statistically significant changes in the surface quality.
• The width of profile elements, RSm, is strongly correlated with the change in the cutting speed
\( v_c \) – it is not with the feed per tooth \( f_z \) or the axial depth of cut \( a_p \).
• ANN modelling tools accurately predict surface roughness parameters: the R-squared
  correlation levels were 0.9813 for Ra, 0.9566 for Rz and 0.8731 for RSm; hence, the trained
  networks exhibit the necessary capacity to successfully model surface quality parameters of the
tested alloys.
• The formed neural networks correlate the input data \((v_c, f_z, a_p)\) and the output data \((Ra, Rz, RSm)\)
  thereby enabling to determine the end quality of the machined surface – defined by respective
  surface roughness parameters – from the set of input milling data entered into the network.
• The presented findings might help to solve surface quality issues encountered in machining
  either as a stand-alone feature or an element of a more complex tool. Both the simulations and
  the networks that computed the results emerge as an agile tool for use in workshop applications,
  providing the necessary aid to the technologists faced with surface quality problems.

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