Identification of the Most Important 3D Roughness Parameters for Surface Characterization for Enhanced Process Optimiztion in Mechanical Blasting

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***Abstract*—To achieve desired surface properties, various mechanical processes are used, including mechanical blasting, a technique involving the high-pressure projection of grains onto a surface. This study focuses on surfaces treated through mechanical blasting, specifically analyzing stainless steel components. The influence of key manufacturing parameters, such as grain shape and rotational speed, is systematically investigated across different stages. A comprehensive methodology for feature selection is presented, aiming to identify crucial roughness parameters and analyze their impact on the manufacturing process. The objective is to determine the most significant roughness parameters to establish a tailored quality control system aligned with the outcomes of mechanical blasting. This system provides targeted feedback on the manufacturing parameters, enabling precise adjustment and achieving the desired surface roughness. This approach contributes to sustainable process optimization by minimizing rework and reducing rejects 32 3D roughness parameters, defined by ISO standards, are calculated and analyzed. Based on a data set with 300 measured values, a statistical analysis was performed, which includes a correlation analysis and a regression analysis using Lasso regression for parameter selection. The results of the correlation analysis suggest that feature, functional and volume parameters seems to be important role for surface characterization. However, in further analysis by Lasso regression, the volume parameters were found to be irrelavant. In this context, the roughness parameters Spc, which represent the arithmetic mean peak curvature of surface features, and Spd, which signifies the number of peaks per unit area, stand out as notably significant and have been emphasized as the most crucial parameters.**

***Keywords*—lasso regression, mechanical blasting, surface integrity, surface treatment**

I. Introduction

Due to increasing demands for functionality and aesthetics of a product [1], many components produced by additive or conventional manufacturing undergo finishing processes for material and surface enhancement. One such process is mechanical blasting, a manufacturing technique where an abrasive medium is accelerated and brought into contact with the component surface using blasting systems [2]. In this study, an innovative blasting technology is being investigated, primarily focused on surface cleaning and optical modification. This technology involves a blasting system developed by company BMF, where the abrasive medium is distributed using a centrally located, horizontally operating impeller wheel with a curved blade geometry. The components are mounted on a satellite holder and move in a conical path around the rotating impeller wheel. A schematic illustration of the blast wheel is shown in Fig. 1. The blasting system generates a homogeneous surface structure by combining rotational and oscillatory movements, enabling the components to traverse the impeller blast at different angles with each revolution. However, to achieve an optimal blasting process, precise definition of its parameters is imperative, particularly in accurately describing the desired surface. A comprehensive overview of the key parameters is presented in Fig. 1:

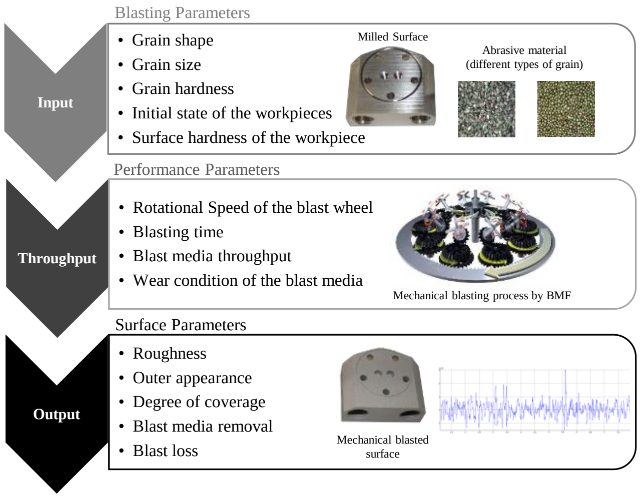

Fig. 1. Input-throughput-output diagram of the mechanical blasting process [3].

As shown in Fig. 1, main factors influencing the blasting result or the surface roughness are the grain shape and the rotational speed of the blast wheel. This study aims to demonstrate the functional relationships between these two influencing factors and surface roughness. The objective is to identify the optimal roughness parameters that effectively characterize a mechanically blasted surface from an optical perspective.

Traditionally, 2D parameters have been predominantly used for surface roughness characterization. These parameters are derived from surface scanning within a defined plane, resulting in a one-dimensional representation of surface elevations. One widely utilized 2D parameter for describing surface roughness is Ra, which provides a general indication of the average roughness by considering overall height deviations from the centerline [1, 4]. Due to its simplicity and rapid quantification, Ra has become an established parameter in various fields for surface roughness description [5]. However, 2D parameters like Ra have

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limitations in capturing all aspects of surface roughness, including texture and structural features, due to limited information depth [6]. In the case of mechanically blasted surfaces, visual differences cannot be reliably represented by 2D parameters like Ra. Surfaces with similar Ra values may exhibit significant visual disparities due to differing structures. This effect is illustrated in Figs. 2 and 3.

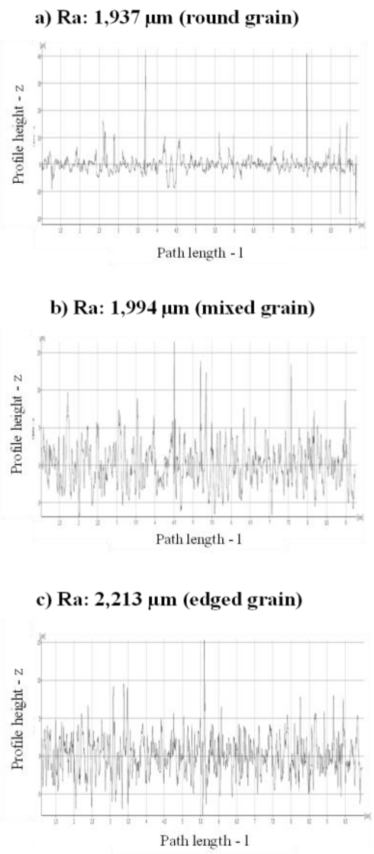

Fig. 2. A Qualitative comparison between different profiles of the surface roughness of components manufactured with different grain shapes a) blasted with round grain, b) blasted with mixed (round/edged) grain, c) blasted with edged grain.

Fig. 2 presents images of three mechanically blasted components, where differences in the profile are evident but are not reflected in the Ra value. The differences are also visually apparent, as shown in Fig. 3 with further illustrations of the components:

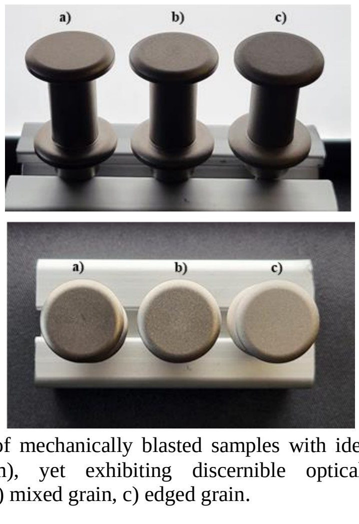

Fig. 3. Images of mechanically blasted samples with identical Ra values (approx. 2 µm), yet exhibiting discernible optical discrepancies, a) round grain, b) mixed grain, c) edged grain.

The components were illuminated uniformly across their surfaces and captured from two different perspectives. The utilization of different grain shapes is reflected not only in the surface structure but also in color, which can be attributed to the glossiness and reflection properties of the surfaces. As illustrated by Fig. 2 and Fig. 3, it becomes evident that 2D parameters, such as Ra, are insufficient for characterizing surface roughness when structural differences in the surface are perceptible optically. Consequently, the importance of 3D parameters is increasingly recognized, as they enable a more precise and comprehensive characterization of surface roughness by including the spatial distribution and texture of surface features. This enables a more detailed analysis of surface roughness, allowing better fulfilling the quality requirements in terms of functionality and aesthetics [5–7]. In this study, a total of 32 3D parameters were determined, and their relevance with regard to the manufacturing parameters of abrasive particle shape and rotational speed was analyzed. The findings of this analysis will be presented in the subsequent sections.

II. Statistical Analysis

A. Data Set and Experimental Procedure

To conduct the analysis, a representative dataset of mechanically blasted surfaces was utilized. For this study the conducted samples were plates made of stainless steel (X5CrNi18-10) with a size of 10×10 cm and were fabricated with varying manufacturing parameters. In the present case, the manufacturing parameters differ in terms of grain shape and rotational speed. The grain is made of stainless steel with a size of 0.1 mm. Specifically, two variations of grain shape (round and mixed) and three variations of rotational speed of the blast wheel (4,000, 7,000, 9,000 rpm) were considered. Consequently, a total of six distinct combinations of grain shape and rotational speed were generated, and their relationships with the 3D parameters were analyzed. The examined combinations are presented in Table 1.

Table 1. Combination for the manufacturing parameters analyzed in this study

No.	Grain shape	Rotational speed [in rpm]
1.	Round (S)	4,000
2.	Round (S)	7,000
3.	Round (S)	9,000
4.	Mixed (SGM)	4,000
5.	Mixed (SGM)	7,000
6.	Mixed (SGM)	9,000

For each parameter combination listed in Table I, two samples were prepared. In total, the measurements were thus performed on 12 samples. For each sample 50 measurements were taken, so the study is based on a data set of 300 measurements. To capture a surface image that closely approximates reality, measurement points were randomly selected across the surface. A confocal microscope CONSIGNO by twip was used for the measurements. The measuring tip has a size of 180×110×55 mm³. Furthermore, it uses a 450 nm laser diode as the light source with a camera resolution of 1280×1024 pixels.

B. Correlation Analysis

A correlation analysis was conducted to gain insights into the data structure and the relationships between the manufacturing parameters and the 3D parameters. The Bravais/Pearson correlation coefficient was used for this purpose. The Pearson correlation coefficient, denoted as r, is calculated as the ratio of the covariance (cov) between variables x and y and their respective standard deviations s [8]:

$$Pearson\, r = \frac{\operatorname{cov}(x,y)}{s_x \cdot s_y} \tag{1}$$

The correlation coefficient can assume values between 1 and −1, with the sign indicating the direction of the correlation. For instance, a coefficient of $r = 1$ implies that when variable x changes by one unit, variable y will change positively by one unit. Accordingly, a value of $r = 0$ indicates no correlation between the variables. Fig. 4 illustrates the correlations between the examined 3D roughness parameters and the manufacturing parameters (grain shape, rotational speed).

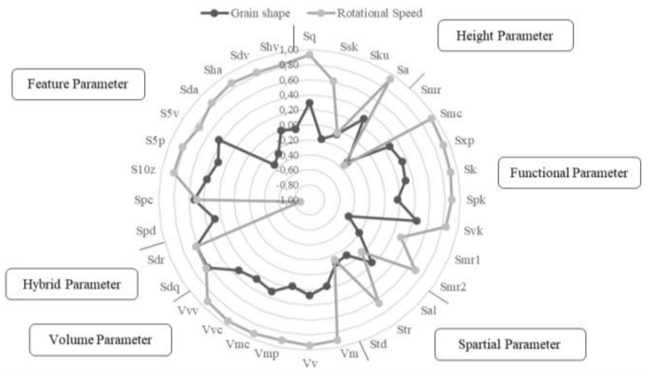

Fig. 4. Correlations between the 3D roughness parameters and the manufacturing parameters (grain shape, rotational speed).

As shown in Fig. 4, the correlations predominantly exhibit a positive direction. Generally, both manufacturing parameters show correlations with the same parameters, although the correlations with rotational speed are slightly more pronounced. Furthermore, it becomes evident that there are particularly connections between the functional, volumetric, and feature parameters.

C. Lasso Regression

Regression models are often used for statistical analysis and are also a popular method for predicting results. The selection of an appropriate regression model depends on the model's ability to provide the best predictions of the outcome [9]. Various studies have shown that standard regression methods contain certain drawbacks, making their use unsuitable for some applications. For example, one major disadvantage is the tendency to overfitting. Overfitting occurs when the model becomes excessively tailored to the underlying training data, compromising its ability to make accurate predictions on new, independent data. For example, random variations in the training dataset may be erroneously interpreted as genuine relationships, despite their lack of applicability to new data. In particular, overfitting is more likely to occur in models that incorporate numerous variables or parameters, as well as those with high complexity [10]. Accordingly, to address this concern, the present study utilized Lasso regression to analyze key metrics, ensuring a more robust approach.

In order to conduct Lasso regression, the independent variables consisted of the 3D parameters, while the dependent variable was represented by manufacturing parameters within the model. Through Lasso regression, the coefficients associated with insignificant 3D parameters were automatically shrunk, effectively eliminating those parameters that made an insignificant contribution to the prediction of surface roughness. The Lasso regression technique incorporates L1 regularization, wherein a penalty equal to the absolute value of the coefficients' magnitude is added. This form of regularization promotes sparsity in the models, with a subset of coefficients potentially being driven to zero and thus excluded from the model. By increasing the penalty parameter, the coefficient values tend towards zero, thereby facilitating the creation of parsimonious models with reduced complexity [11]. Lasso solutions involve quadratic programming problems that are typically solved using specialized software, such as Matlab. The primary objective of the algorithm is to minimize a specific objective function Eq. (2):

$$\sum_{i=1}^{n}\Big(y_i - \sum_j x_{ij}\beta_j\Big)^2 + \lambda \sum_{j=1}^{p}\left|\beta_j\right| \tag{2}$$

This objective function (Eq. (2)) can be understood as minimizing the sum of squares subject to the constraint that the sum of the absolute values of the coefficients (denoted by $\Sigma\, |\beta_j|$) is less than or equal to a predetermined threshold value (represented by "s"). Through this optimization process, certain coefficients, β_s, may be shrunk precisely to zero, leading to a regression model that is easier to interpret [10, 12–14]. The strength of the L1 penalty is controlled by a tuning parameter, λ. This parameter serves as a measure of shrinkage:

- When λ is set to zero, no coefficients are eliminated, and the estimate corresponds to that obtained through linear regression.
- As λ increases, more coefficients are progressively set to zero and eliminated from the model, potentially resulting in a scenario where, theoretically, all coefficients are eliminated when λ approaches infinity.
- As λ increases, the bias of the model increases.
- Conversely, as λ decreases, the variance of the model increases.

It is worth noting that when an intercept term is included in the model, it is typically left unchanged during the Lasso regularization process [3, 10].

Following Lasso regression, the metrics that exhibit longer non-zero lines are considered to have a greater influence on the prediction. Accordingly, these metrics can be regarded as important predictors as they retain significant coefficients despite the shrinkage process.

Fig. 5 shows the results of the Lasso regression, narrowing down only to the nine most importantly identified:

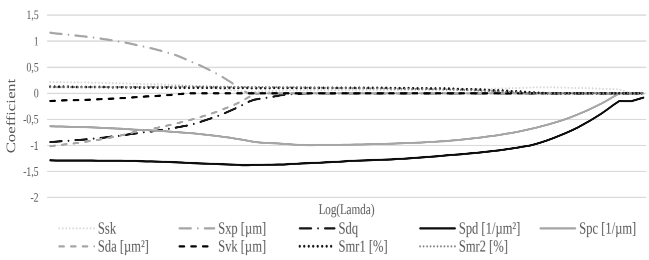

Fig. 5. Feature selection and most important 3D roughness parameters.

Based on the results shown in Fig. 5, notably the metrics Spc and Spd were identified as key metrics. Among them, the metric Spd stands out notably. According to DIN ISO 25178 [15], the Spd metric represents the peak density, which measures the number of peaks per unit area of 1 mm² (Fig. 6) while the Spc metric quantifies the average curvature radius of peaks in surface features [15, 16].

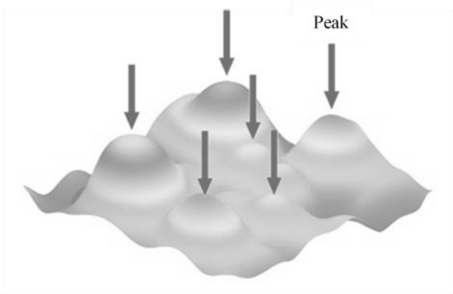

Fig. 6. Density of peaks (Spd) [17].

III. Conclusion

In this work, the methods of correlation analysis and lasso regression were used to identify the most important roughness parameters. According to the results of the correlation analysis, most roughness parameters show strong correlations with the rotational speed, whereas there are no strong correlations with the grain shape. Based on these results, it is only possible to narrow down the roughness parameters to a limited extent, which is why a feature selection method was used. The feature selection was implemented using lasso regression. Using this method, the roughness parameters Spd and Spc were identified as particularly important. Fig. 7 illustrates the results of Spd and Spc.

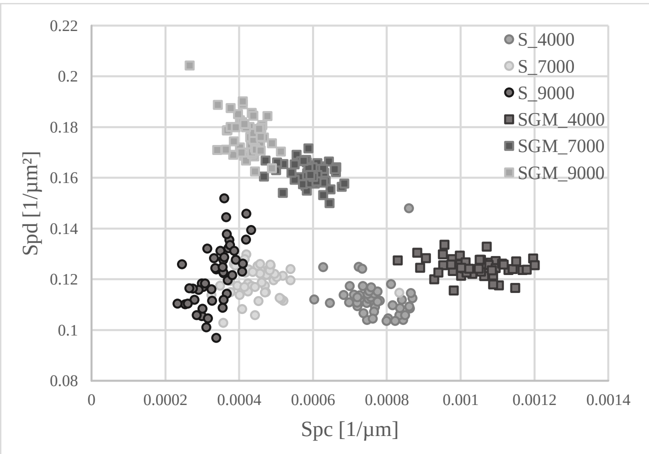

Fig. 7. Classification of the manufacturing parameters using Spd and Spc.

As can be seen from Fig. 7, the parameters Spd and Spc are suitable for an initial classification of the production parameters. A distinction between the grain shapes is thus evident. However, the clear delimitation of the rotational speeds is more difficult, particularly in the higher range between 7,000 and 9,000 rpm. Further analyses are therefore required to determine whether additional parameters need to be included or whether the Spd and Spc parameters are sufficient.

IV. Summary

This study introduces a methodology for selecting appropriate 3D roughness parameters to characterize mechanically blasted surfaces. Initially, a correlation analysis was conducted to explore the relationships between manufacturing parameters and roughness parameters. Subsequently, a Lasso regression was performed to identify key parameters that effectively characterize mechanically blasted surfaces. Interestingly, the Lasso regression results highlight a small number of 3D parameters as particularly important, with the Spc and Spd parameters standing out significantly. These parameters maintain notable correlations with the manufacturing parameters, even after considering the correlation analysis. However, other parameter classes, such as volume and functional parameters, display strong correlations but are deemed insignificant in the context of Lasso regression. These findings underscore the selective significance of specific parameters in accurately characterizing mechanically blasted surfaces. The identified parameters offer valuable insights for implementing a targeted feedback mechanism to control manufacturing parameters and produce surfaces with desired optical properties. The feasibility and statistical validation of implementing a precise feedback loop using these parameters will be explored in further research.

The results of this study offer preliminary findings for characterizing mechanically blasted surfaces. Notably, previous studies have also recognized Spd as a critical parameter in Electrical Discharge Machining (EDM) [18]. Given the similarities between eroded surfaces and mechanically blasted surfaces, such as their irregular structures without preferential orientation, it is reasonable to hypothesize that both processes share common parameters for effective roughness characterization, with Spd playing a crucial role in both cases. Fig. 3 illustrates the impact of grain shape on the visual perception of components, resulting in varying levels of surface glossiness based on the grain shape. This glossiness could be associated with the curvature behavior of the peaks, as different curvatures influence reflection properties. Further complementary analyses are necessary to validate the identified parameters and research findings. The findings of this study provide crucial insights and contribute to a targeted research effort for the further investigation for feature selection.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Mei Yun Liu conducted the research and measurement series, analyzed the data and wrote the paper with the support of Holger Schlegel and Martin Dix; all authors had approved the final version.

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