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Evaluating surface quality of heterogeneous surfaces produced by non-conventional machining technologies: methodological advances and challenges

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Abstract. This paper is focused on the evaluation of heterogeneous surface quality. In the realm of scientific practice, there exists a significant inconsistency in the methodologies employed to investigate heterogeneous surfaces produced by non-conventional machining technologies. Traditional approaches are inadequate for these types of surfaces due to the presumption of surface roughness homogeneity, which does not account for the complexities and variations inherent in heterogeneous surfaces. The utilization of unsuitable assessment methods can significantly hinder the research and development efforts related to these advanced technologies, potentially stalling innovation and the optimization of machining processes. However, through an initial investigation of roughness data obtained from heterogeneous surfaces, discernible patterns have emerged. These patterns suggest a promising opportunity for the development of a coherent and standardized approach to surface quality assessment. Such an approach would enhance the accuracy and reliability of evaluations, thereby supporting the continued advancement and refinement of non-conventional machining technologies. The findings underscore the necessity for a shift towards more sophisticated and tailored assessment methods that can accommodate the unique characteristics of heterogeneous surfaces.

1. Introduction

The development of science and technology, along with the emergence of new materials and their demanding applications across various industries, has exerted considerable pressure on the sector concerned with their machining. The demands for speed, cost-effectiveness, and machining efficiency have driven this sector towards the development of new technologies, such as laser machining, water jet cutting, plasma cutting, and many others. These technologies are continuously undergoing improvement processes. One of the tools for enhancing the aforementioned technologies is the comparison of various parameters and phenomena arising on the machined component's surface under different machining conditions. Surface roughness is a parameter often used to compare machining efficiency [1].

Due to the fundamentally different principles underlying these machining technologies compared to conventional methods, a new surface character is practically formed, for which current evaluation methods are inadequate. This newly formed surface character is referred to as a heterogeneous surface. Such a surface is characterized by variations in roughness parameters depending on the location of the measurement in the cut. Typically, there is an increase in surface roughness in the direction of the cutting depth due to the weakening of the cutting beam.

Based on a literature review of articles dealing with the development of these technologies, it can be stated that there is no consensus in practice on the methods of evaluating and comparing heterogeneous surfaces [2, 3, 4]. Inappropriately chosen methods or parameters can distort the data to such an extent that the processed results are inaccurate or misleading, thereby risking errors in statistical evaluation. In other words, there is a risk of drawing erroneous conclusions.

2. Methods

2.1. Sample preparation

Ten samples of steel plates cut by laser LVD LYNX FL-3015 (IPG Photonix), exhibiting typical heterogeneous surfaces, were selected for analysis. In the figure 1 is shown the surface of one of the samples.

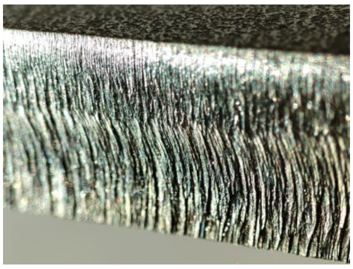

Figure 1. Heterogeneous surface.

Specifically, the material used is stainless steel DIN 1.4301, which is widely used and resistant to environmental influences with power 3000 W, cuting speed 900 mm/min and frequency 5000 Hz. The samples were measured using an optical 3D profilometer, Zygo NewView 8000, which is shown in a figure 2. Prior to each measurement, the surface was inspected for any potential contaminants and inhomogeneities that could have arisen during manufacturing and might adversely affect the measurements.

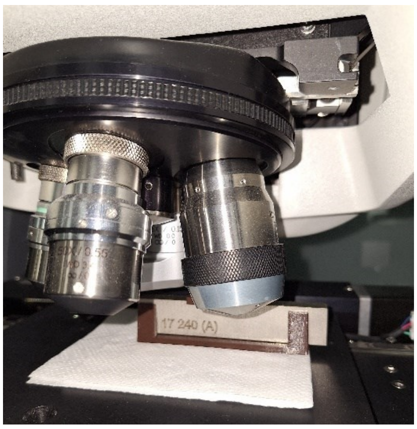

Figure 2. Zygo NewView 8000 with prepared sample.

Due to the shape characteristics of the samples and the resulting instability, it was necessary to create a fixture to ensure stability during measurement. A model of the fixture was designed in Catia software, optimized for material efficiency, and subsequently printed using a 3D printer TRILAB DeltiQ 2 3D. Special caps were 3D printed as well to precisely allocate the measurement area. The image below depicts the selected sample in the fixture with special caps applied. In the figure 3 can be seen prepared sample.

Figure 3. Sample prepared for the measurements with the special caps.

2.2. Obtaining data

The measurements of all ten samples were meticulously conducted under controlled laboratory conditions, ensuring they were completed in the shortest possible time frame. The measurement process included configuring the number of individual cuts to be measured and setting up the measurement parameters in the accompanying software. This all to ensure repeatability.

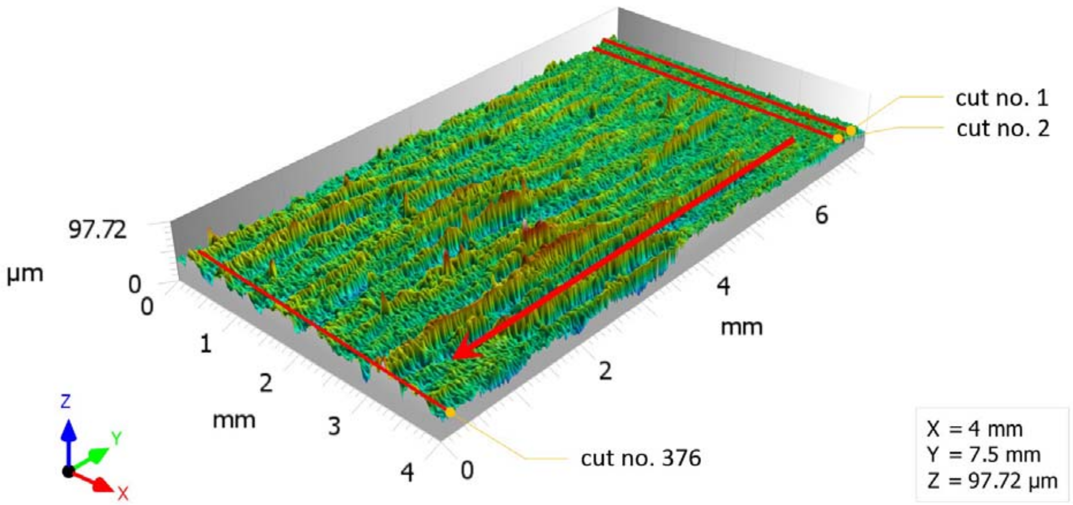

Figure 4. 3D surface scan with marked cuts and the direction of cutting.

A comprehensive total of 376 cuts of surface were taken over a surface area of 4 x 7.5 mm, with each cut spaced 20 µm apart as it it shown in a figure 4. The resultant dataset, consisting of 376 distinct values, was subsequently processed using the Exploratory Data Analysis (EDA) methodology. Following the filtration and extraction of roughness parameters, preliminary validations were performed to verify the theoretical functional relationship between the roughness parameters and the distance from the point of entry of the cutting beam. Presented below, in a figure 5, is a graph illustrating the correlation between the Ra parameter and the distance from the cutting beam entry point for sample number 1.

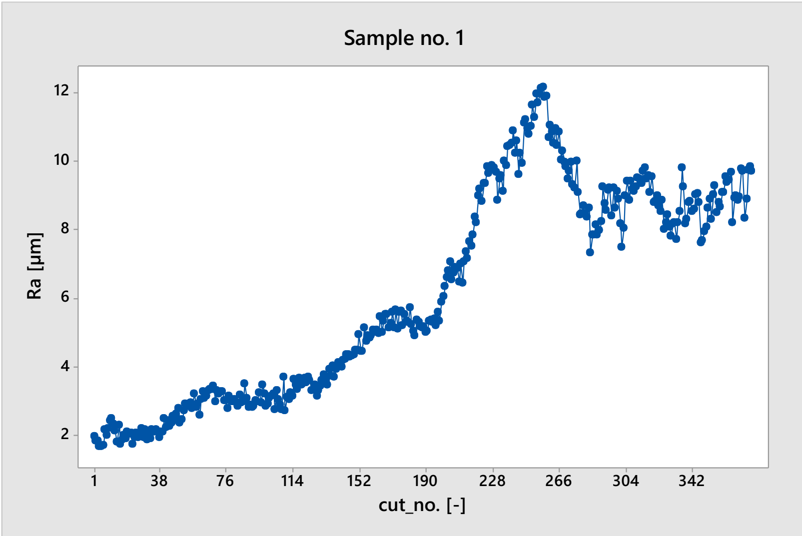

Figure 5. Graph of the dependence of cutting depth on surface roughness.

The rigorous approach ensured that the measurement process was both precise and reliable, minimizing potential errors. By maintaining a consistent measurement environment and carefully analysing the data, the study aimed to provide robust and reproducible results.

3. Results and discussion

3.1. Mechanism of heterogeneous surface formation

During laser machining, the laser beam is subjected to deflection by the material and the generated chips, and as energy is transferred into the workpiece, the beam's intensity diminishes. This process results in a gradual decline in surface quality with increasing cutting depth, as well as an increased occurrence of beam collisions with the material and droplets of molten material.

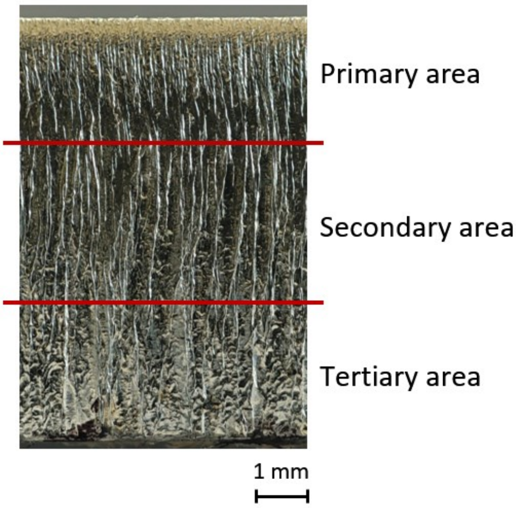

Figure 6. Heterogeneous surface divided into three areas.

This surface can be characterized as a typical heterogeneous surface because, at sufficient cutting depth to occur the phenomena, it generally consists of three distinct areas. The areas are shown in the figure 6. The primary area, exhibiting the highest possible surface quality, is located at the laser beam's entry point where the beam still retains high energy. In this area, the beam interacts with the material most effectively, creating a clean and smooth cut. As the beam transfers energy into the cutting process, it weakens, leading to the formation of a secondary area with increased surface roughness. In this area, the beam's energy is partially depleted, causing less effective cutting and a rougher surface texture [5, 6].

If the material thickness is sufficient, a tertiary area emerges where the surface roughness is the greatest, the quality is the lowest, and there is a potential for deep grooving. This area is where the beam has lost a significant portion of its energy due to continuous interactions with the material. The deflection of the beam, coupled with the re-solidification of the material melted by the laser, contributes to the poor surface quality. In some cases, this can render the workpiece unsuitable in terms of surface quality. Grooving and generally poor cut quality in the tertiary area occur due to beam deflection from its axis, combined with the re-solidification of the material melted by the laser. In the primary and secondary areas, the material is melted and transported by the particle stream of the laser beam into the tertiary area, where it resolidifies along the cut edges [7].

In the case of water jet and plasma cutting, the decrease in surface quality with increasing cutting depth is primarily due to the reduction in beam energy as it is converted into the cutting process. For water jet cutting, additional factors include turbulent flow and the resulting eddy currents caused by beam deflection from collisions with chips, as well as the potential breakup and reflections of the abrasive particles [5]. The dynamic nature of the water jet, influenced by the interactions with the cutting debris and the inherent turbulence of the high-speed jet, further exacerbates the decline in surface quality [8].

Similarly, in plasma cutting, the energy of the plasma jet decreases as it progresses through the material, leading to a deterioration in cut quality with increasing depth. The interactions between the plasma jet and the material result in complex thermal and mechanical phenomena, including localized melting, vaporization, and re-solidification, which contribute to the heterogeneous nature of the cut surface.

3.2. Classical approach of evaluation surfaces applied on heterogeneous surface

Based on the acquired data on the roughness of heterogeneous surfaces, it can be concluded that none of these datasets exhibit characteristics of a normal probability distribution. The normality of the data was tested using the Anderson-Darling test for normality, a robust statistical tool specifically designed to assess the goodness-of-fit of a given data set to a specified distribution. This test provides a more sensitive measure of deviations from normality than other normality tests, particularly in the tails of the distribution [9].

As illustrated in Figure 7, the p-value obtained from the Anderson-Darling test is lower than 0.005. This result indicates, with a high degree of confidence, that the distribution of the evaluated roughness parameter does not conform to a normal distribution. The significance of this p-value is that it falls well below the commonly accepted threshold of 0.05, thereby allowing us to reject the null hypothesis of normality for the dataset. This conclusion is further supported by the repeated application of the Anderson-Darling test across all samples. The consistency of the results, which uniformly demonstrate the absence of normal probability density distribution characteristics in the roughness parameters of all samples, reinforces the validity of the initial findings.

In summary, the comprehensive testing and analysis using the Anderson-Darling test unequivocally show that the roughness parameters of the heterogeneous surfaces do not follow a normal distribution. This finding has significant implications for the assessment and evaluation of such surfaces, necessitating the consideration of alternative statistical approaches or modifications to existing methodologies that rely on the assumption of normality.

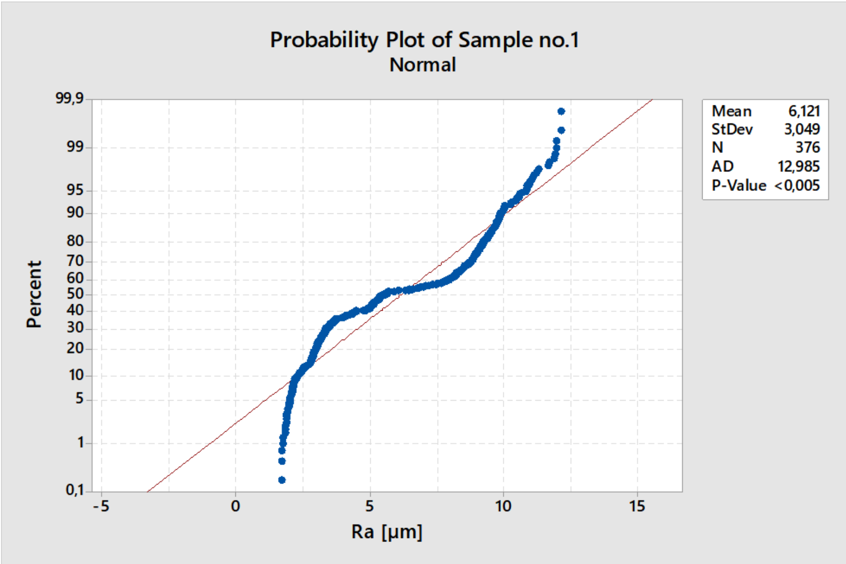

Figure 7. Anderson-Darling test of normality – Probability plot of Sample no. 1.

For surfaces that are homogeneous and created using classical conventional machining methods, it can be assumed that the probability density function of the roughness parameters follows a normal distribution [10]. This assumption is based on the premise that such surfaces exhibit consistent and predictable characteristics due to the standardized nature of conventional machining processes. Consequently, the statistical distribution of roughness parameters for these homogeneous surfaces tends to align with the normal distribution, facilitating straightforward analytical approaches.

The commonly used standard for evaluating surface roughness, EN ISO 21920-2, relies on this assumption of normal probability density distribution for the roughness parameters across the measured surface area. This standard provides a framework for assessing surface roughness, which presupposes that the parameters adhere to a normal distribution. However, when dealing with heterogeneous surfaces, where the roughness parameters do not exhibit a normal probability density distribution, the application of the procedures specified in the aforementioned standard may lead to incorrect results. Heterogeneous surfaces, due to their varied and irregular characteristics, often display non-normal distributions, rendering the assumptions of the standard inapplicable.

For instance, if the 16% rule, derived from the mentioned standard, were to be applied, it could yield nonsensical results. This rule stipulates that for a surface to be deemed acceptable, no more than 16% of all measured values of the examined roughness parameter may exceed the upper limit. This upper limit is defined as $\bar{x} + s$ and is located at the inflection point of the assumed probability density distribution of the examined parameter, which is marked by the yellow point in the diagram below. The 16% rule is predicated on the expectation that the distribution is normal, thereby situating the inflection point appropriately within the context of a normal curve. However, in the case of heterogeneous surfaces, where the distribution deviates significantly from normality, this rule becomes ineffective and potentially misleading. This highlights the necessity for alternative assessment methods or adjustments to existing standards to accurately evaluate the roughness of heterogeneous surfaces.

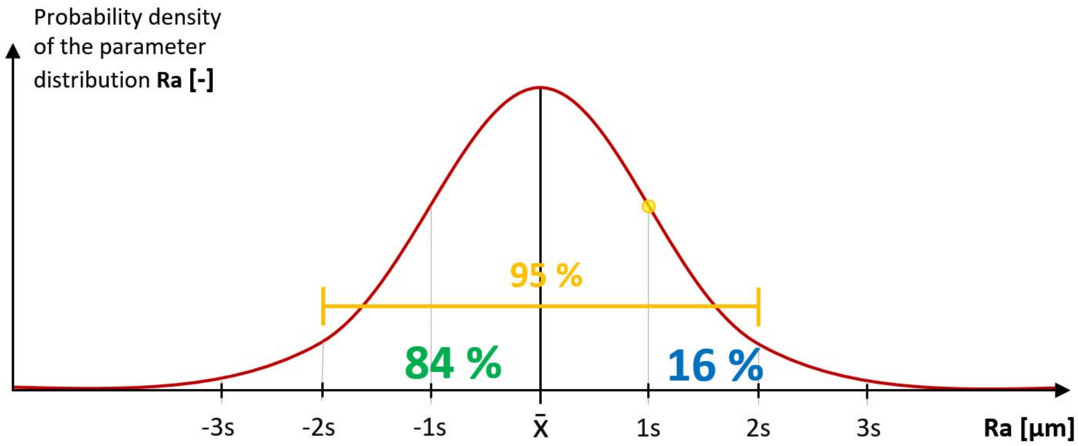

Figure 8. Probability density of the parameter Ra with marked percentages and inflection point.

From the figure 8, it is also evident that 95% of all measured data will fall within the interval $\bar{x}$ + 2s.

The table below (table 1) displays the values if this tool were practically applied to the data obtained from measuring the heterogeneous surface—specifically for the surface roughness parameter Ra.

Table 1. 16% rule applied on obtained data.

	$\bar{x}$	s	95 % Lower bound	95 % Upper bound	$\bar{x}$+s
Sample no. 1	6.121	3.049	0.023	12.219	9.17
Sample no. 2	5.399	2.018	1.363	9.435	7.417
Sample no. 3	5.97	2.557	0.856	11.084	8.527
Sample no. 4	6.517	2.802	0.913	12.121	9.319
Sample no. 5	5.961	2.283	1.395	10.527	8.244
Sample no. 6	5.81	2.843	0.124	11.496	8.653
Sample no. 7	5.953	2.795	0.363	11.543	8.748
Sample no. 8	7.701	4.349	-0.997	16.399	12.05
Sample no. 9	6.568	3.068	0.432	12.704	9.636
Sample no. 10	5.953	2.795	0.363	11.543	8.748

From the values presented in the table, it is evident that the variances of the Ra parameter are relatively high and provide limited information about the roughness of the examined surface. The 16% rule states that for a surface to be considered acceptable, maximum 16% of the values may lie above the established upper limit. The upper limit is defined as the sum of the arithmetic mean and the standard deviation. Given the width of the intervals and the absence of a normal distribution, a surface with significant roughness deviations could be deemed acceptable under this rule. In the case of sample number 8, where the variance of values is the greatest, the applied method suggests that the Ra roughness parameter values would fall within the interval from -0.0997 to 16.399 with 95% probability, which is impossible since roughness parameter values cannot be negative.

These examples indicate that conventional statistical analysis methods used for assessing surface roughness cannot be applied to heterogeneous surfaces, as they assume a normal probability density distribution of the examined parameters. Therefore, alternative methods need to be developed and employed to accurately evaluate the roughness characteristics of these surfaces.

The high variability in Ra values, as demonstrated in the table, reflects the limitations of traditional roughness assessment methods when applied to heterogeneous surfaces. For instance, the significant spread of values means that a substantial proportion of data points deviate widely from the mean, undermining the reliability of conclusions drawn from such data. The 16% rule, which permits a portion of values to exceed the upper limit defined by the mean and standard deviation, further illustrates the inadequacy of these methods in providing a precise evaluation of surface quality.

For sample number 8, the wide interval range calculated using the applied method, from -0.0997 to 16.399, highlights a critical flaw: it suggests the presence of impossible negative values for the Ra parameter. This discrepancy underscores the necessity for alternative approaches that do not rely on assumptions of normal distribution, especially for surfaces characterized by heterogeneity.

In summary, the examples clearly demonstrate that heterogeneous surfaces require distinct statistical methodologies tailored to their unique characteristics. Conventional methods, based on the assumption of normal distribution, fail to accurately capture the true nature of roughness on these surfaces. This necessitates the development and implementation of new analytical techniques that can account for the variability and complexity inherent in heterogeneous surface roughness.

3.3. 3D roughness parameters

3D roughness parameters represent an advanced and sophisticated approach to evaluating surface topography, providing significantly more detailed and accurate information compared to traditional 2D measurements. Traditional 2D parameters, such as Ra (arithmetical mean roughness) and Rz (mean roughness depth), measure surface irregularities along a single line. In contrast, 3D parameters, including Sa (arithmetical mean height) and Sp (maximum peak height), evaluate the surface topography over the entire surface area. This expanded measurement capability allows for more accurate prediction of surface properties such as wear resistance and adhesion potential, offering a more comprehensive and realistic picture of the surface's condition. These advanced parameters are standardized under ISO 25178-2, ensuring consistency and reliability in their application [11].

The methodology behind 3D roughness parameters is based on the assumption that surface irregularities follow a normal (Gaussian) distribution. This assumption is critical for the accurate functioning of various computational methods, such as random field theory, which rely on this premise. If the surface does not exhibit a normal distribution of roughness parameters, the results derived from these calculations can be flawed or misleading. The computational formulas for 3D parameters like Sa (arithmetical mean height) and Sp (maximum peak height) are specifically derived under the assumption of a normal distribution, meaning their physical significance and proper interpretation are only valid within this context.

Moreover, the correlation functions that describe the spatial properties of the surface and serve as the foundation for calculating 3D parameters are not accurate for surfaces that do not follow a normal distribution. This discrepancy can lead to erroneous descriptions of the surface topography, resulting in incorrect calculations and interpretations. The predictive power of 3D roughness parameters relies on data that adhere to a normal distribution; without this underlying assumption, predictions regarding the properties of evaluated surfaces can be imprecise, thus limiting the practical utility and reliability of these parameters.

Additionally, the use of 3D roughness parameters allows for a detailed understanding of how surface roughness evolves with increasing cutting depth, information that would be lost with traditional 2D measurements. For instance, in a figure 9, a detailed comparison of a surface photograph of sample number 1 and a corresponding graph of the Ra roughness parameter data would reveal the intricate variations in surface roughness that occur with depth. This valuable information, which includes the progressive changes in surface texture and quality, is crucial for comprehensive surface analysis and would be missing if only 2D roughness parameters were used. The extended capability of 3D measurements thus provides a richer, more nuanced understanding of surface characteristics that is essential for advanced material processing and quality control.

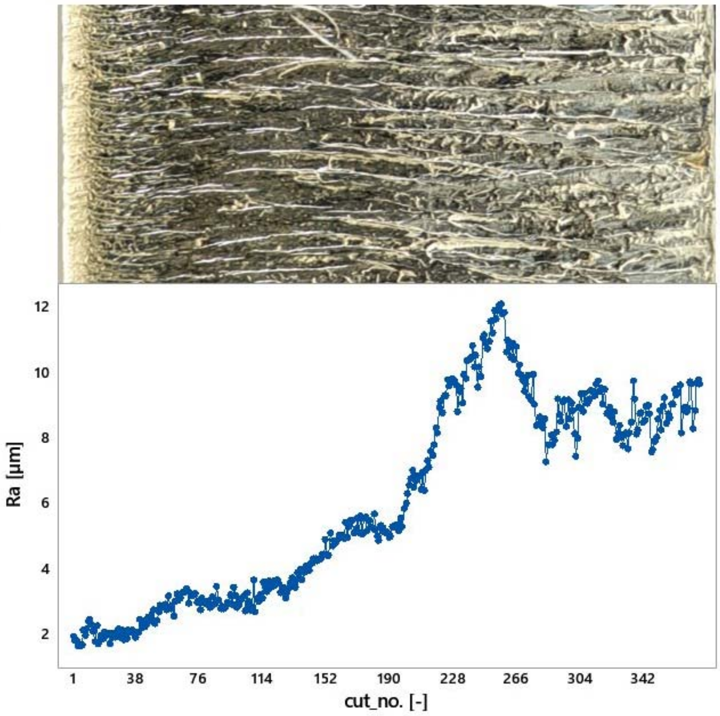

Figure 9. Surface photograph of sample no.1 and Ra roughness parameter progress comparison.

3.4. Results of Heterogeneous Surface Roughness Analysis
The obtained data were subjected to the methodology of Exploratory Data Analysis (EDA). As the initial step, the data were rigorously tested for normality. To conduct the normality testing, the Anderson-Darling test was selected, utilizing a significance level of $\alpha = 0.05$. This comprehensive testing process was carried out using the Minitab software. Upon completion of the test, it was concluded that none of the examined data sets exhibited a normal probability density distribution, indicating that the data did not conform to the normality assumption.

Following next step of exploratory data analysis, the data underwent further scrutiny to identify the presence of outliers or gross errors, which are critical to be excluded from the dataset to ensure the accuracy of subsequent analyses. For this purpose, Grubbs' test for outliers was employed. This detailed analysis was also performed using the Minitab software, maintaining the significance level at $\alpha = 0.05$. The results from Grubbs' test in the table below (table 2) revealed that none of the datasets contained any outliers, confirming the absence of anomalous data points [12].

Table 2. Resulting p-values of normality and outlier tests.

	Normality p - value	Outlier p - value
Sample no. 1	<0.005	1
Sample no. 2	<0.005	1
Sample no. 3	<0.005	1
Sample no. 4	<0.005	1
Sample no. 5	<0.005	1
Sample no. 6	<0.005	1
Sample no. 7	<0.005	1
Sample no. 8	<0.005	1
Sample no. 9	<0.005	1
Sample no. 10	<0.005	1

For further data analysis, it was necessary to select an appropriate methodology. Certain patterns were observed in the graphs showing the dependence of surface roughness on cutting depth. Surface roughness increases with cutting depth in a manner that resembles exponential growth. Subsequently, there is a reduction in roughness until a point where the roughness fluctuates, and the data in this region appear to be normally distributed.

The primary, secondary, and tertiary regions are delineated in the figure 10 below.

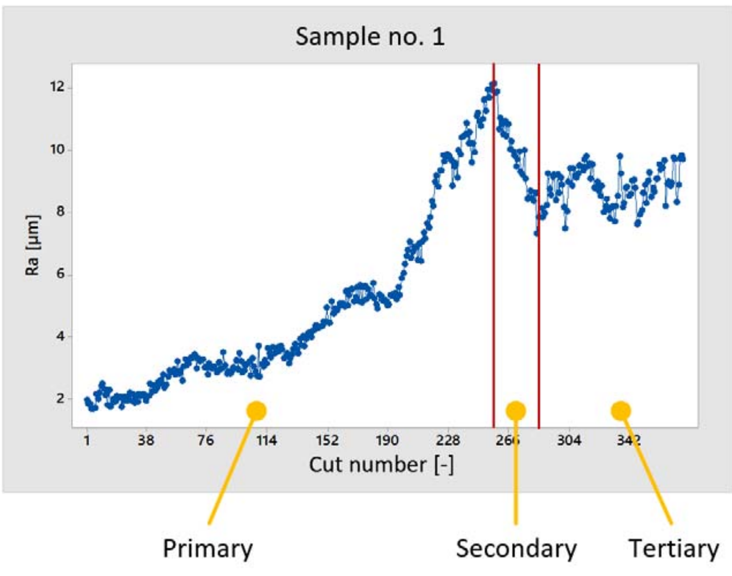

Figure 10. The dependence of roughness on cutting depth can thus be divided into three distinct regions.

3.5. Proposed Solutions for Assessing Roughness of Heterogeneous Surfaces

As previously mentioned, the classical approach to evaluating surface roughness is not suitable for heterogeneous surfaces. Therefore, an alternative solution must be found.

One potential solution involves dividing the surface into three sections and then evaluating these sections separately. Given the trends in the first two sections, regression analysis, whether linear or nonlinear, seems appropriate. If the third section demonstrates a normal distribution of probability density, then it can be assessed using the classical approach. Unfortunately, this solution is only preliminary and more suitable for practical applications due to potential inaccuracies. These inaccuracies may arise during the division of the surface into three areas, as it is not possible to determine the locations of the boundaries of each area with sufficient precision and probability. Consequently, this solution, due to the simplicity of linear regression, is recommended primarily for practical scenarios where high accuracy in the interpretation of results is not required.

Another solution involves finding a function to describe the dependency using nonlinear regression. However, given the relatively complex nature of the dependency trend, it remains uncertain whether a function can be found that accurately describes the roughness progression with sufficient precision.

At this juncture, the most suitable solution appears to be the use of a neural network. Neural networks are well-suited for describing the aforementioned surfaces due to their ability to handle complex and non-linear relationships. Unlike classical regression methods, neural networks can model intricate patterns in the data without requiring a predefined functional form. This adaptability makes them particularly effective for analyzing heterogeneous surfaces where the roughness characteristics may vary significantly across different areas.

Additionally, neural networks can improve accuracy by learning from a large set of training data, thus reducing the potential for errors that may arise from manual segmentation and regression approaches. Therefore, employing a neural network offers a more robust and precise method for evaluating surface roughness in heterogeneous materials.

4. Conclusion

This study has thoroughly examined the challenges associated with assessing the quality of heterogeneous surfaces, emphasizing the limitations of traditional evaluation methods when applied to such surfaces. The findings underscore a critical discrepancy between conventional surface roughness assessment techniques and the unique characteristics of heterogeneous surfaces produced by non-conventional machining processes.

The investigation revealed that existing methodologies, which typically rely on the assumption of surface roughness homogeneity, are fundamentally inadequate for evaluating surfaces exhibiting significant spatial variability in roughness. The analysis of roughness data from laser-cut steel samples demonstrated that the roughness parameters do not conform to a normal distribution, as validated by rigorous statistical testing using the Anderson-Darling test. This deviation from normality suggests that traditional statistical approaches, which are predicated on the assumption of normal distribution, may yield inaccurate or misleading results when applied to heterogeneous surfaces.

In light of these findings, the study advocates for the development of more sophisticated and tailored assessment methods that can effectively accommodate the inherent complexities of heterogeneous surfaces. One promising avenue for future research is the application of advanced statistical techniques, such as neural networks, which are adept at modeling complex, non-linear relationships. Neural networks offer the potential to provide a more nuanced and precise evaluation of surface roughness by learning from extensive datasets and adapting to the diverse characteristics of heterogeneous surfaces.

Additionally, the study highlights the limitations of current 3D roughness parameters, which, while providing a more comprehensive assessment compared to traditional 2D measurements, still rely on assumptions that may not hold for non-homogeneous surfaces. The validity of these parameters is contingent upon the underlying assumption of a normal distribution of surface irregularities, which is often not the case for heterogeneous surfaces. This limitation further emphasizes the need for novel analytical methods that can accurately capture the true nature of roughness on such surfaces.

The exploration of alternative methodologies, such as segmenting the surface into distinct regions and applying regression analysis or other statistical techniques, represents a practical approach to addressing the limitations of traditional methods. However, the challenges associated with defining precise boundaries and the potential inaccuracies inherent in these methods suggest that more advanced techniques may be required for optimal results.

In addition to the challenges faced in evaluating metal surfaces, the potential for non-conventional machining technologies to process a variety of materials—including plastics—has been noted [13]. This expands the relevance of these findings beyond metal cutting to other materials that also exhibit heterogeneous surface characteristics. To fully understand the applicability and effectiveness of the advanced methods developed for metal surfaces, it is imperative to extend the research to include a broader range of materials processed by laser and other non-conventional machining technologies. Future studies should investigate whether surfaces of different materials, such as plastics, exhibit similar heterogeneous characteristics and how these might influence the accuracy and reliability of surface quality assessments. Such investigations will not only validate the robustness of the proposed methods but also provide insights into their adaptability across various material types. This direction of research will be crucial for refining assessment techniques and enhancing their applicability in diverse industrial contexts.

Overall, the study underscores the urgent need for a paradigm shift in the assessment of heterogenous surface quality, moving towards more advanced and adaptable methodologies that can accurately reflect the complexities of those surfaces. Such advancements are crucial for fostering innovation and improving the precision of evaluations in the realm of non-conventional machining technologies, thereby supporting continued progress and refinement in this field.

Acknowledgments

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