

# Integrated Artificial Neural Network-Based Approach for Predicting Surface Roughness Parameters in Laser Surface Texturing of Ti6Al4V

Agata Sposato<sup>1,a\*</sup>, Giovanni Carpino<sup>2,b</sup>, Maria Rosaria Saffioti<sup>1,c</sup>,  
Giovanna Rotella<sup>2,d</sup>, Domenico Umbrello<sup>1,e</sup>

<sup>1</sup>Department of Mechanical, Energy and Management Engineering, University of Calabria, Via Ponte Pietro Bucci, Cubo 45C, 87036, Rende, CS, Italy

<sup>2</sup>Department of Engineering, University LUM Giuseppe Degennaro, Casamassima, BA 70010, Italy

<sup>a</sup>agata.sposato@unical.it, <sup>b</sup>carpino@studenti.lum.it, <sup>c</sup>mariarosaria.saffioti@unical.it, <sup>d</sup>rotella@lum.it, <sup>e</sup>domenico.umbrello@unical.it

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**Abstract.** Laser surface texturing (LST) is an effective technique for tailoring the surface properties of Ti6Al4V alloy, widely employed in biomedical applications where surface topography plays a key role in osseointegration and functional performance. Nevertheless, the strong nonlinear relationship between laser process parameters and resulting surface roughness still limits predictive control of laser-textured surfaces. This work presents an experimental study aimed at investigating the influence of laser surface texturing parameters on the surface morphology of Ti6Al4V. Key process variables, including laser power, scanning speed, pulse frequency, pulse duration and overlap percentage are systematically varied using a fiber laser system. The textured surfaces are characterized through three-dimensional surface roughness parameters, namely Sa, Sz, Sku, Svk, and Ssk, providing a detailed quantitative description of surface topography relevant for biomedical applications. The resulting experimental dataset represents a fundamental basis for the subsequent development of artificial intelligence models, based on neural networks, for predicting surface roughness parameters as a function of laser processing conditions. The proposed approach supports data-driven optimization of laser surface texturing processes within intelligent and sustainable manufacturing frameworks.

## Introduction

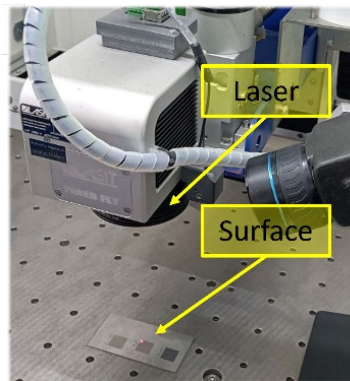
Among the most used materials in the field of medicine, titanium alloys, more specifically, Ti6Al4V stand out due to their excellent balance of high specific strength, corrosion resistance, and good biocompatibility [1]. The aforementioned characteristics of titanium make Ti6Al4V a benchmark material used in orthopedic implants, dental fixtures, and trauma devices. Nevertheless, the long-term performance of titanium-based implants cannot be described only through bulk characteristics; rather, their surface characteristics, which include topography, roughness, wettability, and microstructural integrity, play a significant role. With this idea in mind, surface engineering techniques have started to receive more attention as a potential tool to improve osseointegration, tribological performance, and biological response of titanium-based implants without altering the bulk mechanical characteristics of the component. Among the available surface modification techniques, LST has emerged as a highly flexible and controllable approach. This is because laser processing allows for the precise control of surface morphology, energy delivery, and repeatability, all while maintaining compatibility with industrial-scale production and sustainable manufacturing concepts [3]. New developments in laser technology, such as ultrafast and fiber lasers, have extended the applicability of LST to include the precise manipulation of surface features on the micro- and nano-scale without the need for a heat-affected zone [4]. The versatility of the laser processing techniques has led to the recognition of LST as a key technology in a variety of industrial fields, such as the biomedical, aerospace, and manufacturing industries. In the field of biomedicine, laser surface texturing of titanium alloys has primarily been used to modify the surface roughness in an effort to enhance the functional properties of the surface in order to improve cell adhesion, bone ingrowth, and mechanical interlocking in the surrounding tissues. Experimental investigations have shown that the surface

patterns created using laser surface texturing can significantly influence the biological responses. In particular, Rotella et al. highlighted the relevance of laser-based surface functionalization for titanium screws used in orthopaedic implants, showing that carefully designed surface textures can improve implant–bone interaction while preserving structural integrity [5]. These findings confirm that surface roughness parameters are not merely descriptive quantities, but key design variables for biomedical performance. Additionally, the laser surface treatment of Ti6Al4V has also been investigated from the point of view of the process-structure relationship. Numerical as well as experimental analyses have confirmed that the power, scanning velocity, pulse width, and hatch spacing of the laser beam strongly influence the geometry of the molten pool, as well as the cooling rate and the microstructural transformations that occur during the process. The finite element method has also been found useful for the simulation of the thermal fields as well as the molten pool during the laser surface treatment, providing useful information about the surface morphology and the microstructure that occur during the process, as reported elsewhere [6]. However, despite the significant advancements that have taken place, the highly nonlinear relationship between the surface roughness characteristics and the various parameters of the laser beam is still considered the main challenge that is faced during the surface roughness characterization process. The surface roughness characterization has shifted more towards the 3D surface characteristics, such as Sa, Sz, Sku, Svk, and Ssk, as compared to the 2D surface characteristics, such as Ra and Rz, for functional surfaces that come into contact with tissues. However, the correlation of these measures of surface roughness with the parameters of the laser process through analytical and physics-based models is extremely difficult due to the inherent complexities involved in the interaction of the laser with the material and the stochastic nature of the process involving the change of the material from the solid to the liquid phase and the subsequent ejection and solidification of the molten material. To overcome these difficulties, the application of Artificial Intelligence (AI) and Machine Learning (ML), which have gained significant attention in the area of advanced manufacturing processes, has come into prominence through several comprehensive reviews on the application of AI in the area of smart production and its ability to extract relevant patterns from complex experimental results and contribute to the decision-making process in the optimization of the process [7, 8]. AI has been reported to have strong application in the prediction of the results of the process in the area of manufacturing, including the prediction of surface roughness in the process. Batu et al. demonstrated the effectiveness of machine learning models in predicting surface roughness of additively manufactured components, showing significant improvements over traditional regression approaches when dealing with nonlinear and multivariate relationships [9]. These results are particularly relevant for laser-based processes, where multiple interacting parameters govern surface formation. Similar trends have also been reported in tool condition monitoring and predictive maintenance, where AI-based frameworks have been used to integrate the data from the sensors to improve the reliability of the processes and the quality of the products [10, 11]. Recent studies have also focused on the role of AI in the domain of laser processing. Murzin provided a comprehensive overview of AI-driven innovations in laser processing of metallic materials, underlining how neural networks and hybrid data-driven models can capture complex dependencies between laser parameters and resulting material properties [12]. Such approaches are increasingly recognized as essential tools for advancing laser surface engineering beyond empirical methodologies. While there is an increasing amount of published research on laser surface texturing and AI-based manufacturing techniques, the integration of surface roughness characterization and AI-based modeling is limited, especially for the case of biomedical-grade titanium alloy Ti6Al4V. Most published research works have focused on the qualitative nature of the surface texture and/or limited parameters of surface roughness without fully addressing the range of 3D surface parameters. Moreover, most AI-based roughness prediction models have been developed for machining or additive manufacturing processes, rather than for laser surface texturing of titanium alloys intended for biomedical use. Recent research on laser surface pre-treatment and functionalization has emphasized the significance of surface state management in the development of durable bonds and performance, thus supporting the need to implement precise and predictable surface modification techniques [13]. Moreover, the sustainability factor has also encouraged the application of laser and

AI techniques, as they can contribute to the development of efficient, waste-free, and energy-aware manufacturing processes [14, 15]. Within this framework, the present study positions itself as a foundational experimental contribution aimed at systematically correlating laser surface texturing parameters with a comprehensive set of surface roughness metrics ( $S_a$ ,  $S_z$ ,  $S_{ku}$ ,  $S_{vk}$ ,  $S_{sk}$ ) for Ti6Al4V alloy. By generating a high-quality experimental dataset, this work provides the necessary basis for the subsequent development of AI models, specifically artificial neural network (ANN), capable of predicting surface roughness outcomes as a function of laser process parameters. Such predictive capability is expected to support the design of optimized, functionally tailored titanium surfaces for biomedical applications, bridging the gap between laser processing science and intelligent manufacturing systems.

## Materials and Methods

The experimental campaign was carried out on Ti6Al4V alloy specimens in the form of flat sheets with a thickness of 1 mm. The samples were cut to suitable dimensions for laser processing and surface characterization. Before the laser treatment, the surfaces had to be cleaned to eliminate possible contaminants and ensure the repeatability of the interaction conditions during the laser treatment. Laser surface texturing was performed using an air-cooled ytterbium fiber laser system (Lasit Compact Mark G8), with a wavelength of 1065 nm. The laser treatment was provided with an F-theta lens with a focal length of 160 mm and a nominal focal spot diameter of 55  $\mu\text{m}$ . The experimental setup used for the laser treatment is schematically shown in Figure 1.



**Fig. 1.** Experimental set up of laser texturing process.

The laser surface texturing process was carried out by varying the major parameters of the process in order to observe the effect of the parameters on the surface morphology obtained by the laser surface texturing process. The parameters varied in the experiment were the laser power ( $P$ ), scanning speed ( $v$ ), frequency ( $f$ ), pulse width ( $\tau$ ), and overlap percentage ( $l$ ). The range of the parameters varied in the experiment is shown in Table 1. The selected ranges were chosen to ensure stable processing conditions while enabling the generation of a wide variety of surface topographies.

**Table 1.** Investigated laser process parameters.

Laser parameters	Range	Unit
Power ( $P$ )	20 – 100	W
Scanning speed ( $v$ )	50 – 1600	mm/s
Pulse frequency ( $f$ )	1.82 – 72.73	kHz
Pulse amplitude ( $\tau$ )	4 – 250	ns
Overlap % ( $l$ )	0 – 90	%

After laser processing, surface topography was characterized using a non-contact three-dimensional white light confocal profilometer (Rtc/UP-24). The measurement process was carried out following the ISO 25178-2:2012 standard for consistency in the obtained results. To ensure the

reliability of the obtained results, the roughness of the laser-textured surfaces was measured at five different locations for each sample. The reported roughness values correspond to the arithmetic mean of the repeated measurements. The surface morphology was quantitatively described using the following surface roughness parameters according with ISO 25178; Sa (arithmetical mean height) represents the average absolute deviation of the surface from the mean plane and provides a general indication of surface roughness amplitude; Sz (maximum height) corresponds to the sum of the maximum peak height and maximum pit depth within the sampling area, describing extreme surface features; Ssk (skewness) indicates the asymmetry of the height distribution and allows distinguishing peak-dominated from valley-dominated surfaces; Sku (kurtosis) describes the sharpness of the height distribution and provides information on the presence of sharp peaks or deep valleys; Svk (reduced valley depth) is particularly relevant for functional surfaces, as it characterizes the depth of valleys contributing to fluid retention and wear behavior. The combined evaluation of amplitude and functional parameters enables a more comprehensive understanding of the laser-induced surface morphology.

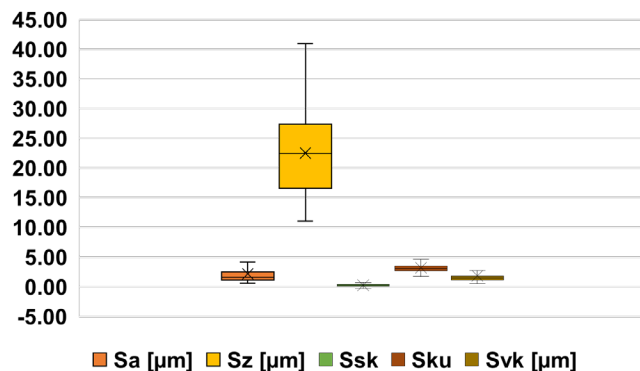
## Results

**Surface analysis.** Before developing the artificial neural network model, a preliminary statistical analysis of the experimentally measured surface roughness parameters was carried out in order to assess data dispersion, variability, and distribution. This stage is crucial to grasp the intrinsic complexity of the laser surface texturing process and to justify the use of data-driven modeling techniques. In particular, the most important descriptive statistics concerning the five surface roughness parameters (Sa, Sz, Ssk, Sku, and Svk) of the 151 laser-textured samples made of the titanium alloy Ti6Al4V are given in Table 2. For each surface roughness parameter, the minimum, maximum, average values, and standard deviations are reported.

**Table 2.** Statistical summary of surface roughness parameters.

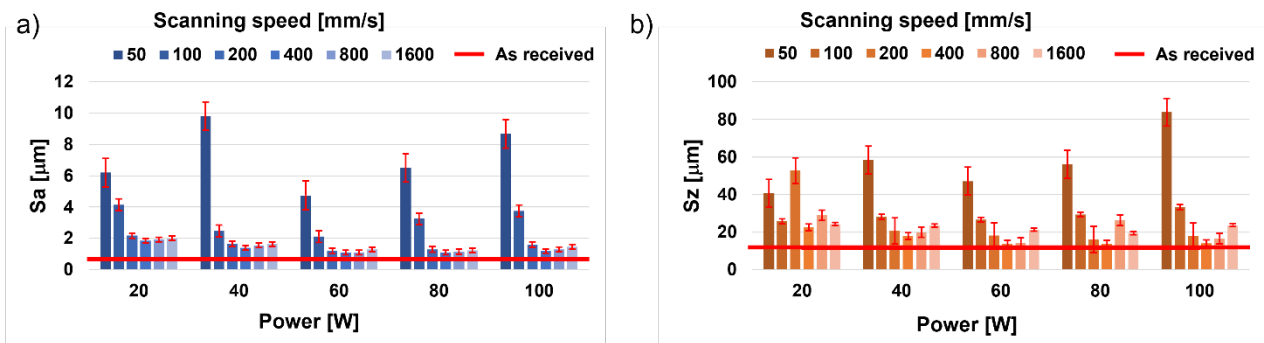
Roughness parameters	Min	Max	Mean	Std. Dev.	Unit
Sa	0.60	6.51	2.15	1.44	$\mu\text{m}$
Sz	11.04	40.96	22.39	7.22	$\mu\text{m}$
Ssk	-1.37	1.38	0.25	0.32	-
Sku	0.09	9.40	3.20	1.20	-
Svk	0.51	9.95	1.82	1.29	$\mu\text{m}$

The wide range and high standard deviation observed for the roughness parameters indicate a strong sensitivity of surface morphology to laser processing conditions, supporting the need for advanced nonlinear modeling techniques. To further investigate the variability and distribution characteristics of the measured surface roughness parameters, graphical analyses were performed. Figure 2 shows the distribution of Sa, Sz, Ssk, Sku, and Svk across the entire experimental dataset.



**Fig. 2.** Distribution of surface roughness parameters.

Boxplots were selected to highlight median values, interquartile ranges, and the presence of potential outliers, providing a concise visualization of the statistical dispersion associated with each roughness descriptor. To provide an intuitive understanding of the influence of individual laser parameters on surface roughness, selected mono-parametric scatter plots were generated.



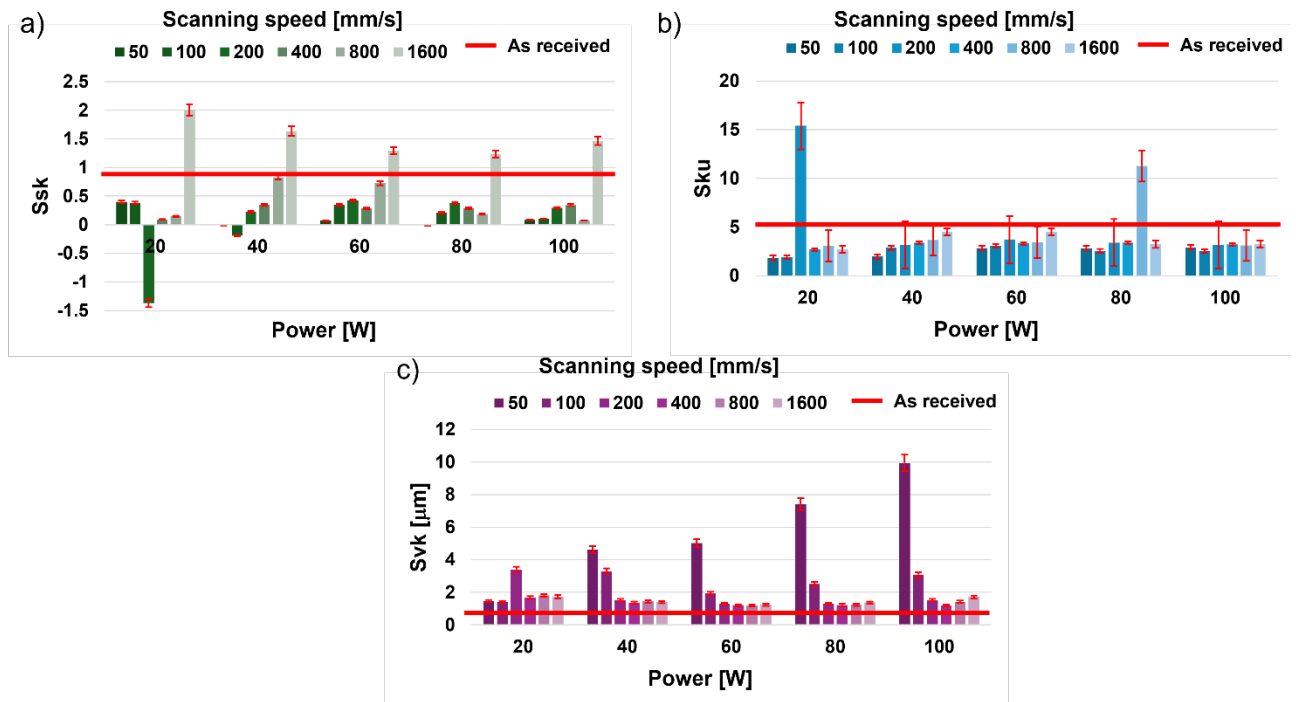
**Fig. 3.** Trend of the Sa and Sz measurements at varying scanning speed and laser power.

Figures 3 - 4 illustrate representative relationships between key laser processing parameters and selected roughness parameters. Only selected combinations (power and scanning speed) are shown to avoid redundancy and to focus on the most physically meaningful trends. For example, as shown in Figure 3 the variation of the surface roughness parameters Sa and Sz as a function of laser power for different scanning speeds. Overall, both Sa and Sz exhibit a clear sensitivity to laser power, with higher power levels generally leading to smoother surface, while lower speed lead to rougher surface. This can particularly be observed at lower and intermediate scanning speeds, where the increase in energy input results in greater melting and material redistribution, thus accentuating the surface features. However, increasing the scanning speed results in the reduction of the surface roughness values, which can be attributed to the reduced energy density provided to the surface and the corresponding reduced interaction time between the laser beam and the material.

Figure 4 shows the trends of the surface roughness parameters Ssk, Svk, and Sku as a function of laser power for different scanning speeds. The statistical parameters Ssk and Sku further highlight changes in surface morphology induced by the combined variation of power and scanning speed. Ssk values fluctuate around zero, indicating transitions between peak-dominated and valley-dominated surface profiles depending on the processing conditions. In particular, lower scanning speeds and higher power levels tend to promote more asymmetric height distributions, reflecting the formation of irregular peaks or deeper valleys. Similarly, Sku values suggest variations in the sharpness of the height distribution, with certain parameter combinations producing surfaces characterized by more pronounced localized features.

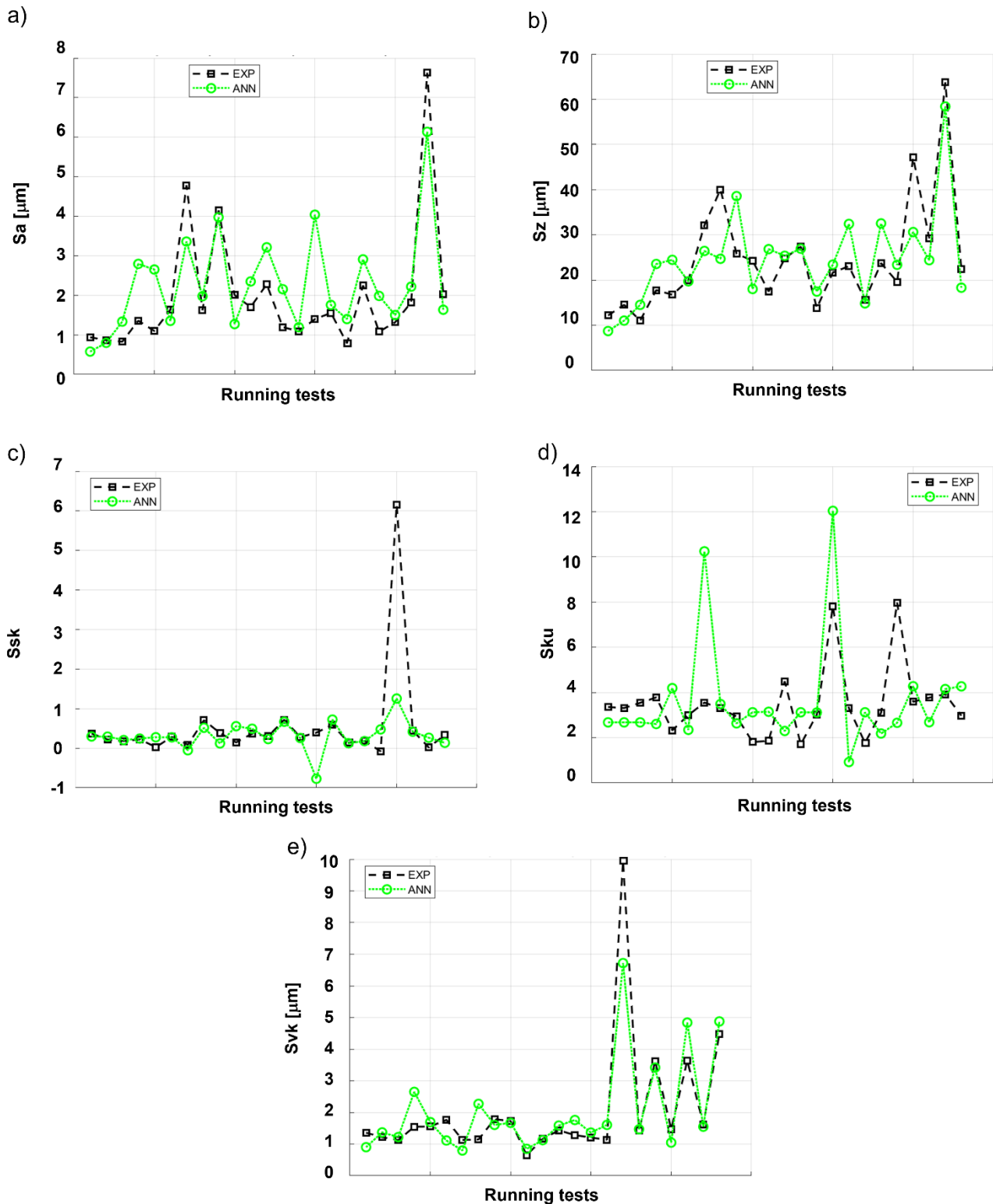
The reduced valley depth Svk follows trends broadly consistent with those observed for Sa and Sz, increasing at higher power levels and lower scanning speeds. This behavior suggests that higher energy input enhances the formation of deeper surface valleys, which may have implications for functional properties such as lubrication retention or osseointegration in biomedical applications.

Overall, the observed trends confirm that surface morphology is governed by a complex interaction between laser power and scanning speed, with nonlinear and coupled effects that justify the subsequent development of a multivariate ANN-based predictive model.



**Fig. 4.** Trend of the Ssk, Sku and Svk measurements at varying scanning speed and laser power.

**Artificial neural network.** All experimental data were collected in a structured dataset consisting of 151 cases, which was used to develop and validate the proposed ANN model. The objective of the network was to establish a quantitative relationship between laser processing parameters and the resulting surface topography descriptors. The ANN was configured as a feed-forward multi-output architecture including five input parameters (laser power, scanning speed, pulse amplitude, overlap and frequency) and five output variables corresponding to the measured roughness parameters ( $S_a$ ,  $S_z$ ,  $S_{sk}$ ,  $S_{ku}$  and  $S_{vk}$ ). This multi-output configuration enables the simultaneous prediction of correlated surface descriptors, preserving their intrinsic physical interdependence. The network consisted of one hidden layer with a number of neurons ranging between 5 and 20 in order to identify the optimal configuration balancing accuracy and generalization capability. A sigmoid activation function was adopted to capture the nonlinear interactions between process parameters and surface features. The dataset was randomly divided into training (90%) and testing (10%) subsets. During training, weights and biases were iteratively optimized through a backpropagation-based procedure aimed at minimizing the prediction error between experimental and simulated outputs. The comparison between experimental measurements and ANN predictions (Figure 5) highlights a satisfactory overall agreement. In particular,  $S_z$  and  $S_{vk}$  exhibit strong trend reproduction across different running conditions, with limited dispersion between predicted and measured values. Importantly, no systematic overestimation or underestimation is observed, confirming the absence of prediction bias and the robustness of the trained model. For  $S_a$ , slightly larger local deviations can be observed in specific tests; however, the absolute discrepancy remains moderate relative to the experimental variability, indicating that the main surface evolution mechanisms are correctly captured. In the case of  $S_{sk}$ , percentage-based metrics are inherently less representative due to the parameter's proximity to zero and sign inversion. Nevertheless, the predicted skewness values remain within the same order of magnitude as the experimental data, demonstrating the model's capability to reproduce distribution asymmetry without systematic distortion. The largest deviations are observed for  $S_{ku}$  in correspondence with isolated experimental peaks. Since kurtosis is highly sensitive to sporadic extreme asperities, these discrepancies are likely associated with limited representation of rare surface events within the dataset. This suggests that further dataset enrichment may improve prediction accuracy for higher-order statistical descriptors.



**Fig. 5.** Comparison between experimental and ANN-predicted surface roughness parameters (a) Sa, (b) Sz, (c) Ssk, (d) Sku, (e) Svk.

It is important to emphasize that the dataset consists of a limited number of experimental cases; nevertheless, the adopted network architecture and training strategy ensured good generalization capability and avoided overfitting. The ability of the ANN to simultaneously predict multiple correlated roughness descriptors highlights the robustness of the proposed modeling approach. Beyond predictive capability, the developed ANN framework represents a powerful tool for process optimization. Once the model is fully trained, the addition of more experimental data will enrich the model, which can then be employed for the determination of the optimal set of parameters for the

laser process, so as to achieve the desired surface characteristics. Additionally, the inclusion of more functional performance indicators, such as coating adhesion, tribological properties, or biocompatibility, will facilitate the implementation of an efficient data-informed, sustainable surface engineering approach, for the intelligent design of the laser process for the titanium alloy material systems.

## Conclusion

The current research has confirmed the possibility of using a multi-output Artificial Neural Network for predicting the laser-induced surface topography parameters of titanium alloys. The findings of the current research can be summarized as follows:

- Effective multi-parameter prediction: The proposed ANN model has been successfully used for establishing the nonlinear relationship between five laser process parameters and five surface roughness descriptors (Sa, Sz, Ssk, Sku, and Svk).
- Good generalization capability: despite the relatively limited dataset (151 experimental cases), the model showed satisfactory agreement between predicted and experimental values, particularly for Sz and Svk, with no evidence of systematic prediction bias.
- Robust trend reproduction with identified limitations: the ANN accurately captured the main surface evolution trends across different processing conditions. Greater discrepancies were found for higher-order statistical properties, such as Sku, in association with isolated extreme surface events, emphasizing the sensitivity of kurtosis to extreme asperities.
- Potential for data-driven process optimization: the developed modeling framework holds a promising position for intelligent laser parameter control and surface tailoring.

Future studies will aim to extend the experimental data set and incorporate additional functional performance indicators for enhanced accuracy in predicting surface properties for sustainable surface engineering strategies.

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