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Metrological evaluation of heterogeneous surfaces obtained by water jet cutting technology using artificial intelligence elements

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Metrological evaluation of heterogeneous surfaces obtained by water jet cutting technology using artificial intelligence elements

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Abstract. This paper deals with the design and construction of a neural network for predicting the results of roughness parameters for heterogeneous surfaces. At the same time, it demonstrates that other statistical methods, especially regression analysis, fail in this respect, and their results cannot be used reliably. The samples produced using waterjet cutting were used to obtain the necessary data for constructing the neural network. Its heterogeneity characterizes this surface. This paper describes these samples, the parameters of their creation, the laboratory measurements, the complete construction of the neural network and the subsequent comparison of the results with regression functions. This paper aims to design a functional neural network that will best describe the roughness pattern of the surface under study. This neural network will predict this waveform based on the input variables and prove that this advanced statistical method completely exceeds the capabilities and predictive value of conventional regression analyses.

1. Introduction

Over time, the development of science and technology has contributed to placing ever greater demands on the resulting quality of machine parts. The importance of these developments has been to reduce weight, extend service life and increase the reliability of manufactured components. The new concept of geometric specification of products, the ISO standard "Geometric Product Requirements" (GPS), has been developed as a system of assessment and 2D evaluation of surface structure. [1] The profile parameters are specified by EN ISO 4287. Conventional technologies such as turning, milling or grinding are characterized by relatively uniform surface quality over the entire product surface. Such a surface has almost identical results for the parameters Ra, Rz, Rmr and Rsm when several measurements are made at different points on its surface. However, when using non-conventional (modern) technologies, a surface is obtained, which varies significantly in its structure depending on the point on its surface to be tested [1,2].

A concise definition of unconventional (non-traditional) technologies is difficult to establish because of the very different processes that fall into this category. There is a consensus in the literature that this group includes processes that have been introduced into the industry over the last 80 years. These methods use standard forms of energy in a new way or use energy that has never been used for machining before [3].

Previously, these new machining methods were intended for specific applications and were not widely used. Today, however, things are very different. Much of the methods were developed to solve special problems in the aerospace industry between 1950 and 1960. Today, most of them find wide applications a diverse range of industries. This paper will consider the roughness of surfaces produced by waterjet abrasive cutting under various conditions [4].

Surface topography using waterjet cutting technology is an understudied area. Like other high-energy beams, this technology leaves visible grooves on the machined surface of products. This significantly affects the dimensional accuracy and quality of the finished surface. Factors affecting the quality of the final cut are mainly the amount of abrasive, the pressure of the waterjet, the shape of the cut and the thickness of the workpiece. Waterjet is characterised by the fact that the surface produced by this technology can be described as heterogeneous due to the fact that there is no constant texture and roughness along the cutting path [5,6].

The aim of this paper is to validate suitable statistical methods for the global evaluation of heterogeneous surfaces. For this purpose, five samples will be used to measure them and obtain the necessary data. The available literature shows that conventional statistical methods fail in the evaluation of heterogeneities [2,7]. Therefore, this work aims to design a functional neural network that will best describe the roughness waveform of the surface under study and will be able to predict this waveform based on the input variables. Furthermore, the aim will be to show that this advanced statistical method completely exceeds conventional regression analyses' capabilities and predictive value [8,9].

2. Materials and Methods

2.1 Preparation of the samples

Five samples (Q1 to Q5) with different surface quality characteristics of their cut surface were selected. These were circular cut-outs from a 60 mm diameter, 10 mm thick steel plate of E335 grade steel, made using an abrasive waterjet (figure 1). In addition to their circular shape, all the specimens show a protrusion that served as the ramp area and the end of the cutting beam to maintain the same cutting conditions on the circumference of the circle. Crushed garnet with the industrial designation GARNET MESH 80 was used as the abrasive, and the exit nozzle made of tungsten carbide was 0.3 mm in diameter. The individual samples Q1 to Q5 were cut under different cutting conditions. Therefore, the surface quality of the samples varies gradually from the lowest quality Q1 to the highest quality surface in the case of sample Q5. The cutting speed was the same for the production of all samples. Its value was 10 mm/s. The pressure of the output beam was different. In the case of sample Q1, the value of a was 240 MPa. For each subsequent sample, this value was not increased by 20 MPa, where in the last sample Q5, it was 320 MPa [10].

Figure 1. Q1 to Q5 samples.

Due to the measuring instrument used, it was impossible to measure the samples directly in the condition in which they were delivered. The surface to be tested was the cut surface and it was, therefore, necessary to measure the samples standing upright. However, this was not possible due to their diameter because the working area of the instrument did not allow this. All samples had to be divided into two parts for this reason.

2.2 Measurements in the cell

In order to obtain a quality sample of heterogeneous surface roughness values, the available Talysurf CLI 500 measuring instrument from Taylor Hobson was chosen (figure 2). It is a non-contact roughness meter that scans the surface under test using a laser beam. It is a confocal CLA head that works with white light decomposition using spectral aberration optics. The reflected beams from the sample surface are further evaluated according to their wavelengths, resulting in a bias in the spectrometer. Each such value corresponds to an actual spatial deviation. The instrument is equipped with a measuring pad electronically positionable in the X and Y axes, scanning the surface in 2D and 3D. It is for three-dimensional measurements that this instrument is factory designed.

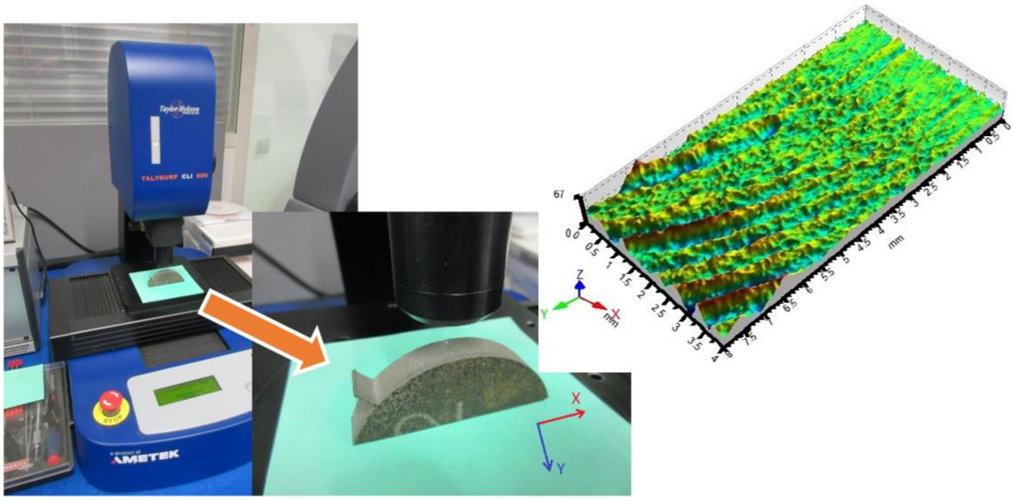

Figure 2. Measured sample coordinate system.

2.3 Measured data analysis

As is possible to recognise in figure 3 the surface is divided to characteristic parts as a result of the water jet cutting. A 3D view of the resulting scan shows that the waterjet cut samples were divided into three regions. The roughness of the parts is demonstrated the figure 4. By figure 4 and the next results is possible to find three characteristics of surface parts that are named "Primary", "Secondary", and "Tertiary" areas. In the areas is necessary to measure roughness separately.

On the graph (figure 4), it is visible that the measured values are imaginatively grouped into three parts. This aspect would confirm the theory presented in the theoretical part of this paper, where it is described that many hetero-gene surfaces are divided into primary, secondary and tertiary regions.

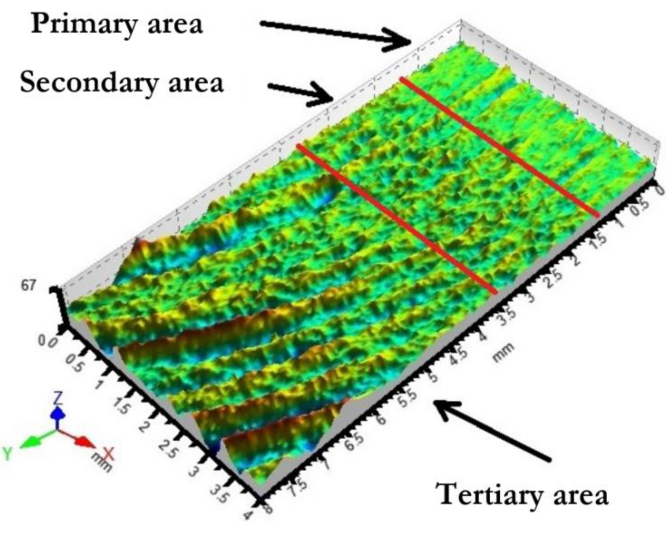

Figure 3. Surface roughness of sample Q1 in 3D with the three region theory.

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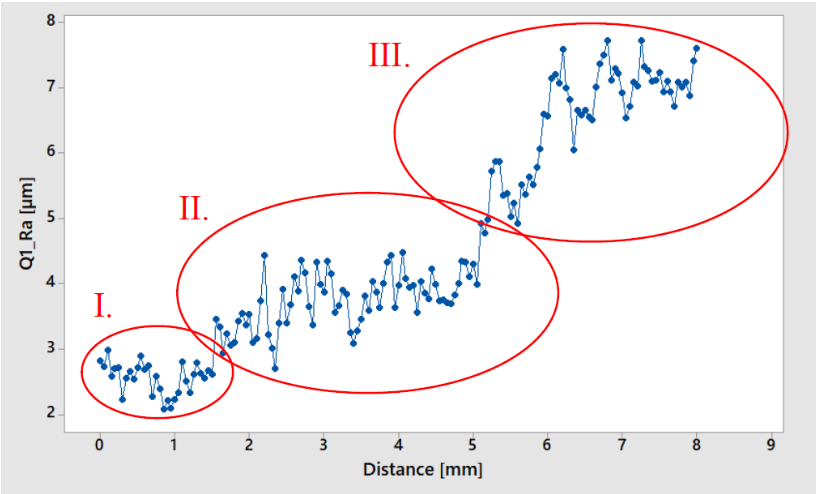

Figure 4. Dependence of Ra on the sensed path for sample Q1 with three-region theory.

The secondary region can be termed as the transition region, but the question remains whether the reasoning of the three-regioneory is correct in this case at all.

2.4 *Regression analysis*

Regression analyzes were used mainly so that we would have something at the end of the article with which to compare the results of the neural network. As an example, let us take the parameter Ra of the sample Q1. In all the following cases, a confidence interval of 95% was set. As can be seen, in figures 5A, 5B and 5C, all three regression function models fail to describe the evolution of the data under study reliably. The R-Sq values, which describe the goodness of fit of a given model, do not come out significantly better than in the previous case, even with increasing polynomials. Thus, it is evident that regression analyses are not a suitable tool for characterization and eventual prediction.

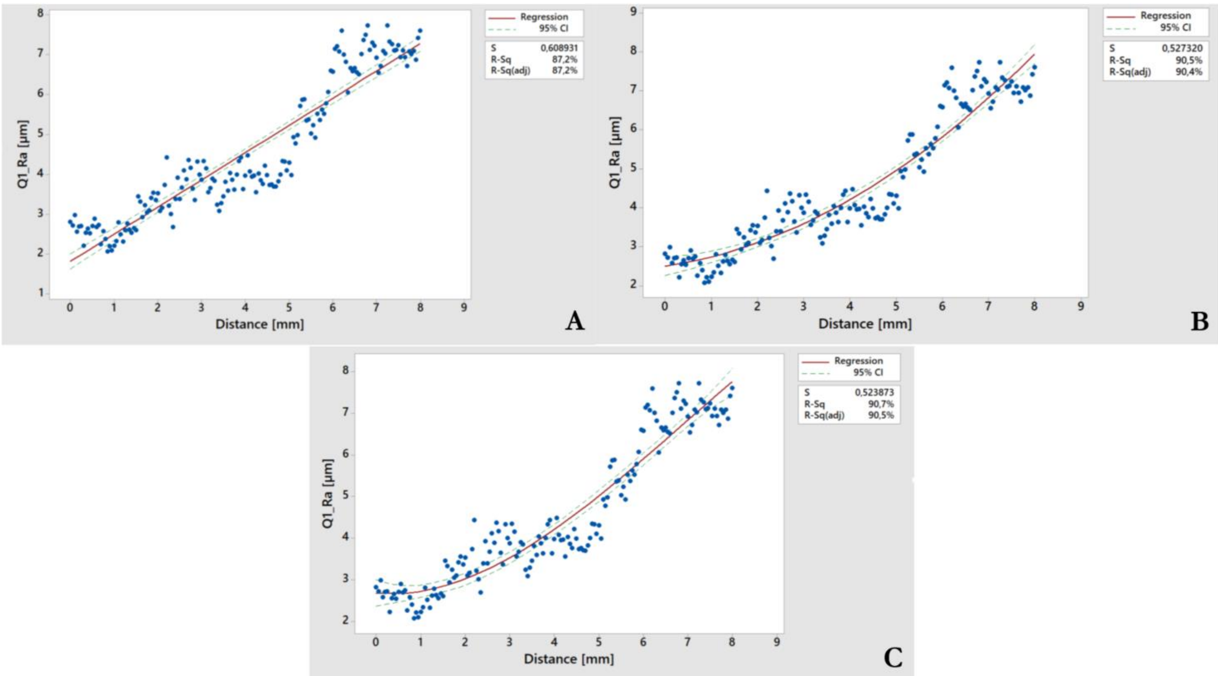

Figure 5. A) Linear regression of the Ra parameter of the Q1 sample, B) Nonlinear quadratic regression of the Ra parameter of the Q1 sample, C) Nonlinear cubic regression of the Ra parameter of the Q1 sample.

2.5 The neural network

This neural network was built in the advanced statistical program QCExpert. The neural network described here is a network with one input and four outputs, supplied as a dataset to be learned. The input is the distance on the X-axis, which was labeled as "Distance" [mm] in the dataset. The neural network's output was the predicted results of the parameters Ra, Rz, Rmr and Rsm, which the neural network learned according to the real data supplied. In order to predict these four output surface parameters, a neural network in the form of a perceptron with two hidden layers was designed. The number of neurons in these two layers was chosen in the ratio of 7:3 after several trials (figure 6). The whole proposed neural network works on the principle of Rosenblatt's backpropagation perceptron. Thus, this network can be briefly described as BP 1/7/3/4. The individual numbers represent the number of neurons in each layer. The resulting network will then look as follows for all samples Q1 to Q5 (table 1).

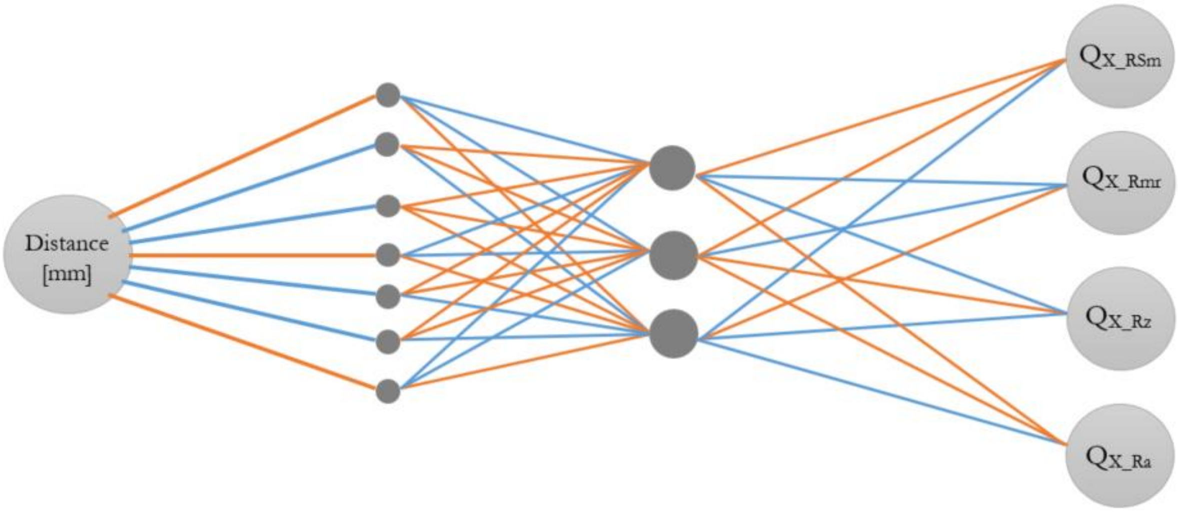

Figure 6. Perceptron network with two hidden layers.

Table 1. Comparison of neural network results and real Ra values of Q1 sample.

Distance [mm]	Q1_Ra [µm]	Q1_Ra_N [µm]	Difference [µm]	Deviation [%]
1	2.219	2.433	0.214	9.64
2	3.530	3.286	0.244	6.91
3	3.874	3.656	0.218	5.63
4	3.975	3.833	0.142	3.57
5	4.301	4.397	0.096	2.23
6	6.575	6.076	0.499	7.59
7	6.926	7.104	0.178	2.57
8	7.604	7.145	0.459	6.04

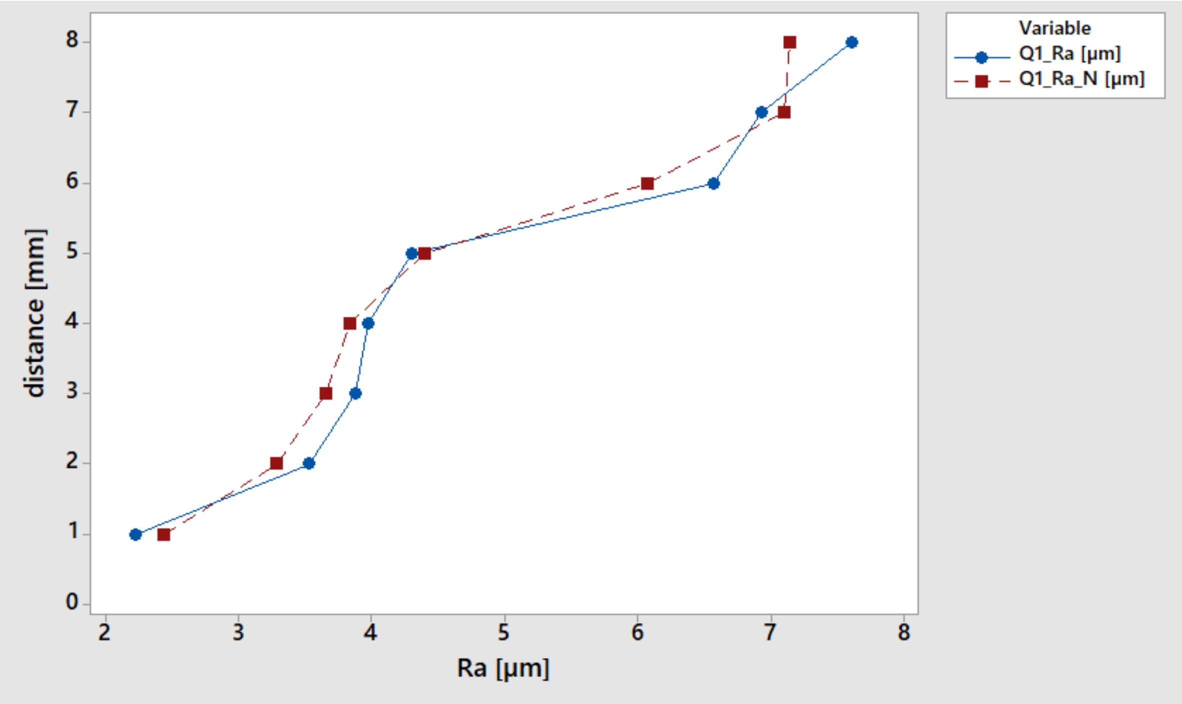

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Figure 7. Comparison of neural network results and real Ra values of Q1 sample.

A perceptron network of the SAME type (same number of layers and perceptrons) was created and learned for each surface. For all samples, the surface heterogeneity gradually decreased with increasing label number until it became almost homogeneous in sample Q5. A table comparing the average percentage deviations of the surface parameters predicted by the neural network can be seen below.

Table 2. Summary of the average percentage deviations of surface parameters predicted by the neural network compared to real data for samples Q1 to Q5.

	Deviation Ra [%]	Deviation Rz [%]	Deviation Rmr [%]	Deviation Rsm [%]
Q1	5.52	8.18	3.22	12.31
Q2	8.24	10.79	3.70	19.91
Q3	8.38	11.99	3.45	11.33
Q4	4.36	8.06	3.19	21.79
Q5	7.02	8.81	4.12	6.20

From table 2, it is well evident that the proposed neural network performed well for samples Q1 (figure 7) and Q5, with the former being without any doubt a strongly heterogeneous surface and the latter essentially a nearly homogeneous surface. Thus, it can be concluded that for samples Q2, Q3 and Q4, which are in between these two different surfaces in their surface properties, it would be advisable to design a different neural network and, above all, to do a thorough investigation to decide what can still be considered heterogeneous and what can no longer. The proposed neural network has produced very satisfactory results. However, it can be seen that its correct function is best only for significant and, conversely, negligible heterogeneity. Nevertheless, in all cases, the value of the average percentage deviation did not exceed 10% in the case of the prediction of the parameter Ra, which is an excellent result.

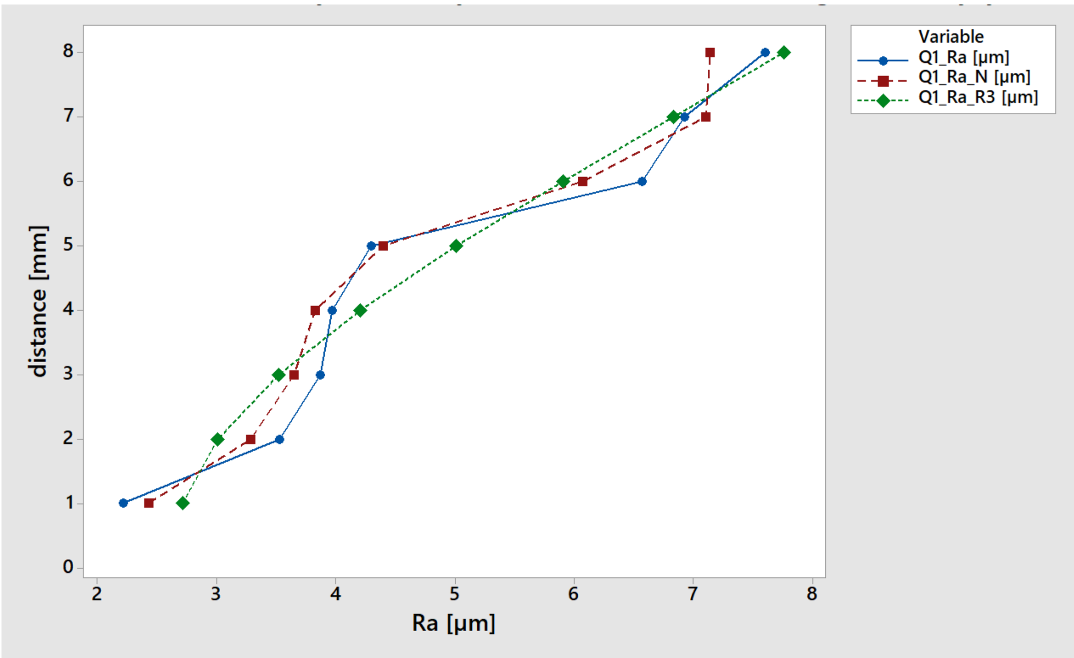

Figure 8. Comparison of the measured data and the results of the neural network and of the Ra parameter of the Q1 sample regression analysis.

The above plot is indisputable evidence of the failure of regression analyses in the case of heterogeneous surface evaluation (figure 8). The waveform of the values predicted by the neural network almost corresponds to the measured values of the actual surface. In contrast, the curve produced by fitting the regression equation has a significantly different shape from the heterogeneity under study.

3. Conclusion

After all the preparations, laboratory measurements and extraction of measured values, this work successfully constructed a neural network that can predict the resulting roughness of a heterogeneous surface based on an input parameter. In this case, the results for sample Q1 were more than satisfactory. The remaining samples are progressively closer to a homogeneous surface, where sample Q5 can hardly even be called heterogeneous anymore. This is also why the results for samples Q2, Q3 and Q4 are less successful than in the case of sample Q1, for which heterogeneity was proved beyond doubt and on which the regression functions were shown to fail when applied to this data sample.

Neural network learning is, without a doubt, a fascinating statistical tool. More comprehensive research on the same topic could result in a neural network working with several input parameters such as material type, thickness, cutting speed, working pressure, abrasive material, or abrasive jet exit nozzle diameter. A sophisticated neural network could then process these parameters into output values for the parameters of the resulting surface. Such an operator would be able to save a lot of time and expense associated with optimally setting up the workstation and achieving the most efficient production. In this direction, similar research could be taken further. However, the scope of this work would be several times more voluminous and challenging.

Acknowledgement

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