DOI:10.25092/baunfbed. 1864040 ***J. BAUN Inst. Sci. Technol., 28(2), 573-587, (2026)***

Investigation of the effect of sanding parameters on surface roughness of S235 steel and PP plastic by response surface method and artificial neural networks

Yunus Emre NEHRİ[1,*] , Melih SARILIGİL[2] , Ali ORAL[1,3]

[1] Balıkesir University Faculty of Engineering,
Department of Mechanical Engineeering, Cagis Campus, Balikesir.
[2] Kemal Başaran Industry Inc., Altıeylül, Balikesir.
[3]ArgeoN Technology Balıkesir University Technopark Inc., Cagis Campus, Balikesir.

Geliş Tarihi (Received Date): 15.01.2026
Kabul Tarihi (Accepted Date):10.03.2026

Abstract

In this study, the surface roughness values obtained as a result of sanding the surfaces of S235 and polypropylene (PP) materials with different sanding parameters were investigated. Sanding size (P60, P100, P180, and P320) and sanding time (15, 30, 45, and 60 seconds) were used as sanding parameters. The effect ratios on material roughness were determined by analysis of variance. It was concluded that sanding size was the most effective parameter on surface roughness. Mathematical models and artificial neural networks were created for prediction. Surface roughness decreased with increasing sanding size number and sanding time. In the applied parameters, it was measured that there was a decrease in surface roughness of over 80% for both materials. Optimum parameters were determined based on the criterion of minimizing the surface roughness (Ra) value. As a result of the optimisation with Response Surface Method (RSM), a 60-second sanding process with P320 sandpaper was determined as the optimum condition for achieving the minimum Ra value.

Keywords: *Sanding, surface roughness, RSM, prediction.*

[*]Yunus Emre NEHRİ, yunusnehri@balikesir.edu.tr, https://orcid.org/0000-0003-2119-9031
Melih SARILIGİL, melihsariligil@gmail.com, https://orcid.org/0000-0002-1402-3049
Ali ORAL, a.oral@balikesir.edu.tr, https://orcid.org/0000-0002-9144-3821

S235 Çelik ve PP Plastikte zımparalama parametrelerinin yüzey pürüzlülüğüne etkisinin yanıt yüzey metodu ve yapay sinir ağlarıyla incelenmesi

Öz

Bu çalışmada, S235 ve polipropilen (PP) malzemelerin yüzeylerinin farklı zımparalama parametreleriyle zımparalanması sonucunda elde edilen yüzey pürüzlülüğü değerleri incelenmiştir. Zımpara tane büyüklüğü (P60, P100, P180 ve P320) ile zımparalama süresi (15, 30, 45 ve 60 saniye) zımparalama parametreleri olarak kullanılmıştır. Zımpara parametrelerinin malzeme yüzey pürüzlülüğü üzerindeki etki oranları varyans analizi ile belirlenmiştir. Yüzey pürüzlülüğü üzerinde en etkili parametrenin zımpara tane büyüklüğü olduğu belirlenmiştir. Tahmin amacıyla matematiksel modeller ve yapay sinir ağları oluşturulmuştur. Zımpara tane büyüklüğüne ait numara ve zımparalama süresi arttıkça yüzey pürüzlülüğünün azaldığı görülmüştür. Uygulanan parametreler kapsamında, her iki malzeme için de yüzey pürüzlülüğünde %80'in üzerinde bir azalma ölçülmüştür. Optimum parametreler, yüzey pürüzlülüğü (Ra) değerinin minimize edilmesi kriterine göre belirlenmiştir. Yanıt Yüzey Yöntemi (RSM) ile gerçekleştirilen optimizasyon sonucunda, minimum Ra değerinin elde edilmesi için P320 zımpara ve 60 saniyelik zımparalama işlemi optimum koşul olarak belirlenmiştir.

Anahtar kelimeler: *Zımparalama, yüzey pürüzlülüğü, RSM, tahmin modeli*

1. Introduction

The high surface quality and low surface roughness of the parts produced in the industry are considered important for many applications. It is difficult to achieve high surface quality with traditional manufacturing methods such as milling and turning. For high surface quality, the roughness on the surface can be brought to the desired tolerance values with the help of various abrasives. The industry performs Sanding and grinding as surface abrasion [1]. Sanding is more advantageous because the grinding process causes surface cracks depending on the material composition and rapid (unbalanced) heating/cooling on the surface. As a final process, manual or machine sanding provides ease of control, especially on free surfaces. Sanding is used as an abrasive to increase surface quality consisting of minerals, resin, and paper [2].

The sanding process is carried out by trial and error, by estimation, or based on experience. Since there are differences in raw surface roughness, knowing the type of abrasive mineral, sandpaper support type, and size is insufficient to determine the roughness value. The most important factors affecting surface roughness are the grit size of minerals, sanding time, sanding method, and mineral and sandpaper type (Figure 1). Trial and error in the sanding process causes loss in terms of cost and time. In order to prevent these losses, prediction models, optimisation processes, and determination of parameters with artificial neural networks can be a suitable solution [3].

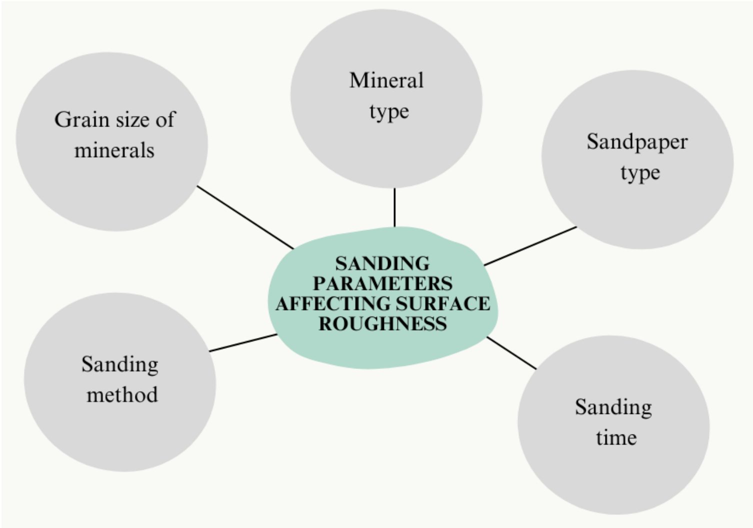

Figure 1 Sanding parameters affecting surface roughness

In addition to sanding, surface smoothing is also achieved by methods such as grinding, sandblasting, and laser processing. Although it is a traditional method, sanding is widely used in the industry. Although the sanding process has been extensively investigated, research focusing on the sanding of steel and polypropylene materials is still relatively scarce. In studies on sanding parameters (sanding time, sanding size, and type), wooden materials were generally used. In the literature, boards produced from wood fibres were processed using different speeds and sanding combinations with sands of different grain sizes, and it was seen that low sanding speed gave good results in terms of surface roughness [4]. In order to reduce high experimental costs, artificial neural networks were used for optimum roughness and positive results were obtained [5], [6]. It has been observed that sanding size, which is one of the sanding parameters to increase surface quality, has a significant effect on surface roughness [7]–[14]. Luo et al. investigated the effects of sanding size [15], and Xu et al. investigated the effects of feed rate (Xu et al. 2015) on the forces coming out during the sanding. It was concluded that the forces increased with the increase in sanding size and feed rate. Luo et al. stated the effectiveness of feed rate on sanding efficiency and sanding force [9]. Salca stated that there is an increase in power consumption with increasing feed rate and sanding depth [16]. Ratnasingam and Scholz optimised the sanding parameters of rubber materials and highlighted the importance of machine planning [17].

In this study, the surface roughness of S235 structural steel and PP-MH-418 polypropylene sheets, which are widely used in the industry, were comparatively investigated after sanding with different parameters. The effects of sanding size and sanding time on surface roughness were investigated to determine the effective parameters and their impact ratios. Another aim of the study was to create a mathematical model with RSM depending on sanding size and sanding time and to provide the prediction of surface roughness with a mathematical model and artificial neural networks.

2. Materials and methods

The study was carried out based on the flow and process flow diagrams, as shown in Figure 2. Sanding factors and levels were determined according to industrial applications, and an experimental design was made. The surfaces were sanded with sandpaper, and surface roughness was measured depending on the experimental design. The experimental results were analysed using variance analysis (ANOVA), and mathematical models and artificial neural networks were created. This study used S 235 structural steel and PP-MH-418 polypropylene sheets, which are commonly used in the industry. Sanding process was applied on the sheets with the dimensions of 150x150 mm2 at 12000 rpm and 6 bar pressure with the Kb Promach brand Ø150 mm sandpaper-based air sander given in Figure 3 and with the Kb Gold Premium Ø150 mm diameter P60, P100, P180, P320 sanding sizes shown in Figure 4 [18]. These operating conditions (12000 rpm and 6 bar) were selected based on the technical specifications of the air sander and the compressor system available in the industrial facility, as well as their common use in practical applications for processing these materials. The abrasives are named according to the number of sands passing through the 1 inch2 sieving machine. When naming, the number of sands per inch2 is next to the "P" symbol (such as P60, P100, etc.). The greater the number of sand passing through 1 inch^2, the smaller the grains of sand.

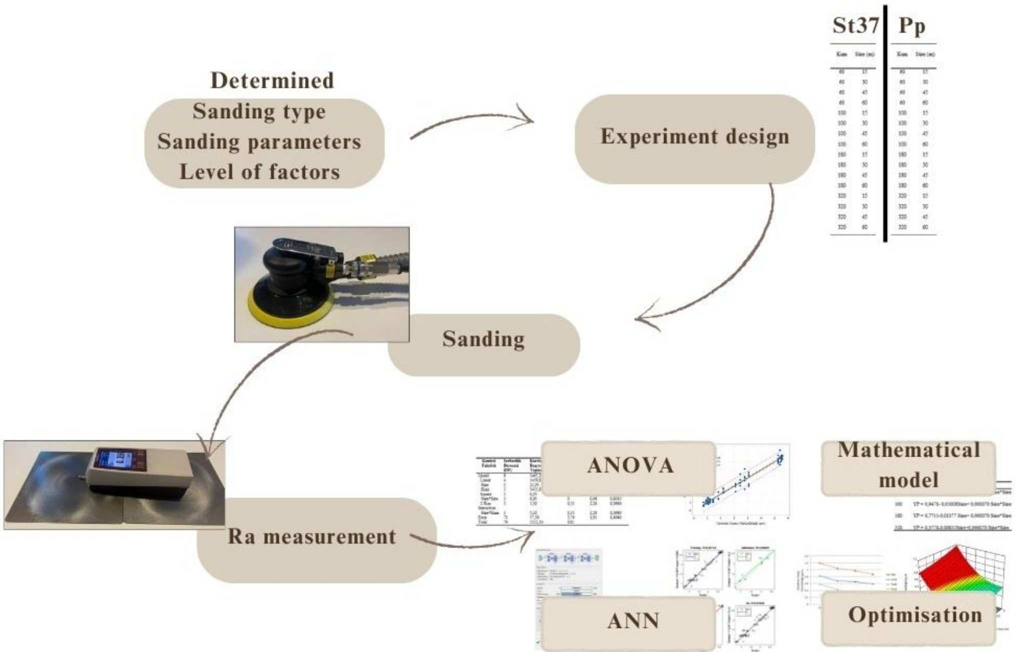

Figure 2 The flow diagram of the study

Figure 3 Kb Promach ROS6316CV air sander

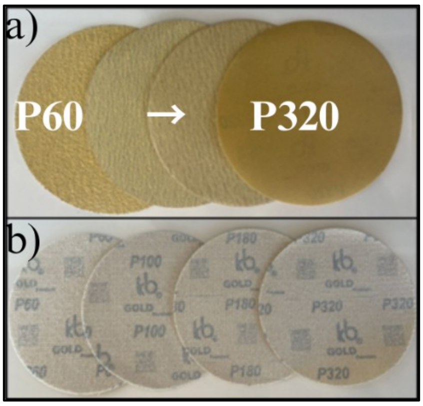

Figure 4 The sandpapers used in the study (KB Gold Premium) a) front, b) back surface

Sanding experiments were carried out on S235 and polypropylene plate surfaces with four different sanding sizes and four different sanding times (Table 1). After sanding, surface roughness measurements were taken with the Mutitoyo SJ-210 roughness measuring device shown in Figure 5. The measurements are given as the average of Ra values obtained from 5 different regions of the sample (Table 2). Analysis of variance (ANOVA) was performed to examine the effects of the sanding size and sanding time taken as variables on surface roughness.

Table 1 Experimental parameters and variables

Material	Sanding Size	Time (second)			
S235	P60	15	30	45	60
	P100	15	30	45	60
	P180	15	30	45	60
	P320	15	30	45	60
Polypropylene	P60	15	30	45	60
	P100	15	30	45	60
	P180	15	30	45	60
	P320	15	30	45	60

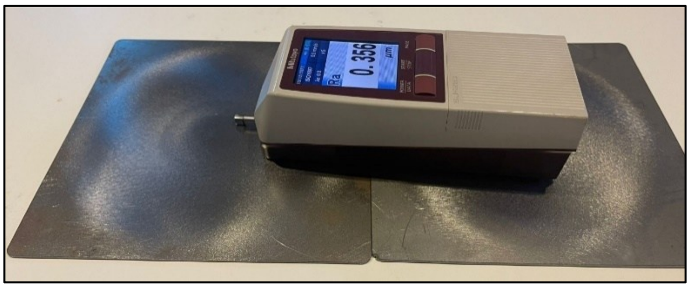
Figure 5 Surface roughness measurement

In this study, the response surface method (RSM) was used to establish a relationship between the input parameters and the output and to create a mathematical model. The model to be created between the sanding size and sanding time parameters that give the surface roughness output with RSM is given in Equation 1.

$$Ra(i) = f(P, T) + \varepsilon \quad (1)$$

P is the sanding size, T is the sanding time, and ε is the error.

Since sanding sizes P60, P100, P180, and P320 are categorical factors and sanding time is a continuous factor, Equation 1 was developed as Equation 2 for each sanding size.

P(i) $$Ra(i) = f(T) + \varepsilon \quad (2)$$

Based on regression, a second-order mathematical model is developed according to the input parameters as in Equation 3.

P(i) $$Ra = \beta_0 + \beta_1.T + \beta_2.T^2 \quad (3)$$

A model was created to predict the surface roughness values according to the sanding size used for any period of sanding time at a 95% confidence level within the given level range. For this purpose, sanding size and sanding time were taken as input parameters, and Ra roughness values were taken as the result. The relationships between these parameters were examined using the Response Surface Method (RSM), and mathematical models were created. Input parameters and stages are presented in Table 1.

In order to benefit from the recognition, perception, and prediction skills, an artificial neural network structure was created, as shown in Figure 6. The network structure was used to evaluate the experimental results conducted with S235 structural steel and polypropylene plate. The network structure consists of two input parameters (sanding size and sanding time), two hidden layers with 10 neurons in each layer, and one output neuron representing surface roughness (Ra).The parameters used in the network structure for S235 and PP sheets are given in detail in Table 2. The input layer in the network structure transfers the input data from the data set to the model with neurons. The data coming to the input layer is multiplied with certain weights, added with bias values, and processed in the sum function (Equation 4). The data going from the sum function to the activation function is processed with the Tan-Sigmoid function as given in Equation 5 and forms the output value.

$$x = \sum_i w_i.x_i + b \quad (4)$$

$$f(x) = \frac{2}{1 + e - 2x} - 1 \quad (5)$$

Where: w: weight coefficient, xi: inputs, b: bias value, x: net inputs.

The sanding size is considered a categorical variable and is defined numerically. Input values are sanding size and sanding time. When the model parameters are entered into the network structure as data, all weights and bias values are randomly assigned. The input values in the training set are linked to the model. Outputs of all neurons and errors are calculated. Weights and bias values are updated with the Levenberg-Marquardt backpropagation algorithm. This process continues until the approach is achieved. After the approach is provided, the model is verified to be reliable if the error is less than the mean square error.

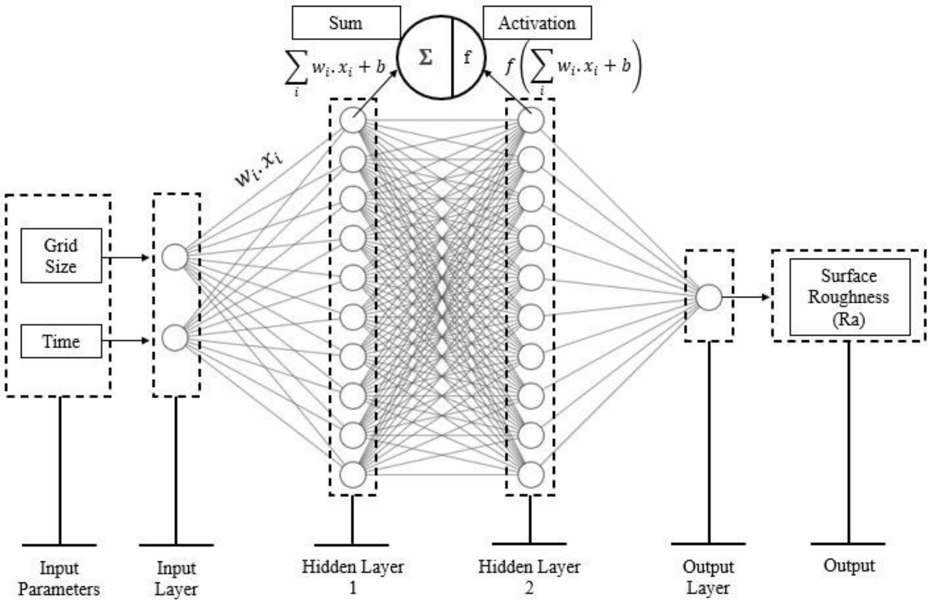

Figure 6 Artificial neural network structure

Table 2 Artificial neural network structure parameters for S235 and PP plates

Model Parameter	S235	PP
Network structure	Feedforward backpropagation	Feedforward backpropagation
Number of hidden layers	2	2
Number of neurons in the input layer	2	2
Number of neurons in hidden layer 1	10	10
Number of neurons in hidden layer 2	10	10
Number of neurons in the output layer	1	1
Activation function	Tansig (tangent sigmoid)	Tansig (tangent sigmoid)
Training algorithm	Trainlm (Levenberg–Marquardt)	Trainlm (Levenberg–Marquardt)
Epoch	500	500
Learning factor	0.001	0.001
Split rate (random) for training (%)	75	75
Split rate (random) for validation (%)	5	5
Split rate (random) for testing (%)	20	20

A feed-forward back-propagation network structure was used to control the model coefficients by changing according to the data set. The number of hidden layers was determined as two due to the analysis of the outputs and the fact that the data set was not too much. The number of neurons in each hidden layer was determined as 10 based on experimental trials and error minimization to ensure generalization capability and to avoid overfitting. The tan-sigmoid function was used as the activation function because of its successful results in multiple hidden layers and complex problems. This function gives function outputs between -1 and 1 and allows the outputs to be divided into negative and positive values. It applies non-linear transformations to the neural network. Thanks to these transformations, we can establish connections between complex relationships. Levenberg-Marquardt's training algorithm was used as the training function because it is suitable for medium-sized networks, has a good memory, and gives high-speed results. The number of epochs (periods) was determined at 500 to avoid over-learning. The learning factor was determined to be 0.001 for a more stable, sensitive, and careful learning process and to avoid local minimums. The data set was randomly divided at 75% for training, 20% for testing, and 5% for validation.

3. Results

In this study, the measurements are given as the average of Ra values obtained from 5 different regions of the sample surface (Table 3). The surface roughness results obtained by sanding the test samples with different sanding sizes and sanding times are given in Figure 7. Sanding size and sanding times are expressed categorically as values between 0 and 1. As the sanding size number and sanding time increased, the surface roughness decreased (Figure 8). Increasing the sand number by 1 inch2 (for example, from P60 to P320) made the surface smoother. It is seen that the larger grain size number and sanding for a long time increased the abrasion on the plate surface. The small number of sand grains in 1 inch2 indicates that the sand grain size is large. Large sand grains provide more abrasion on the surface than small sand grains.

Table 3 Average surface roughness results

Material	Sanding Size	Sanding Time (sn)	Meas-1 Ra (μm)	Meas-2 Ra (μm)	Meas-3 Ra (μm)	Meas-4 Ra (μm)	Meas-5 Ra (μm)	Average Surface Roughness Ra (μm)
S235	60	15	1.139	1.122	1.319	1.157	1.231	1.1936
	60	30	0.973	1.025	1.06	1.183	0.985	1.0452
	60	45	0.989	0.964	1.019	0.953	0.955	0.976
	60	60	0.918	0.825	0.85	0.83	0.923	0.8692
	100	15	0.807	0.813	0.771	0.818	0.913	0.8244
	100	30	0.829	0.654	0.627	0.637	0.641	0.6776
	100	45	0.539	0.59	0.666	0.777	0.726	0.6596
	100	60	0.622	0.62	0.648	0.498	0.549	0.5874
	180	15	0.608	0.556	0.447	0.668	0.615	0.5788
	180	30	0.468	0.356	0.585	0.251	0.46	0.424
	180	45	0.38	0.263	0.228	0.322	0.256	0.2898
	180	60	0.224	0.213	0.19	0.151	0.202	0.196
	320	15	0.229	0.338	0.188	0.306	0.331	0.2784
	320	30	0.182	0.16	0.209	0.119	0.153	0.1646
	320	45	0.201	0.204	0.145	0.131	0.133	0.1628
	320	60	0.078	0.165	0.08	0.089	0.2	0.1224
PP	60	15	12.805	13.576	12.638	13.333	13.518	13.174
	60	30	12.137	13.57	12.885	12.543	13.219	12.8708

	60	45	11.271	14.874	13.164	13.001	11.921	12.8462
	60	60	13.59	12.788	11.638	12.032	12.464	12.5024
	100	15	8.783	9.382	8.571	5.982	6.477	7.839
	100	30	7.377	10.242	8.283	8.076	5.249	7.8454
	100	45	7.554	8.985	6.813	6.037	6.86	7.2498
	100	60	6.552	4.601	5.852	5.839	6.474	5.8636
	180	15	4.518	5.423	5.233	4.585	4.362	4.8242
	180	30	4.511	2.763	2.811	2.737	2.892	3.1428
	180	45	3.944	1.986	2.629	2.105	2.235	2.5798
	180	60	2.412	3.043	1.932	2.395	2.419	2.4402
	320	15	2.398	2.778	1.911	2.092	2.557	2.3472
	320	30	1.542	2.805	3.064	2.021	1.646	2.2156
	320	45	1.79	2.542	2.305	1.61	1.624	1.9742
	320	60	1.122	2.024	1.203	0.999	1.29	1.3276

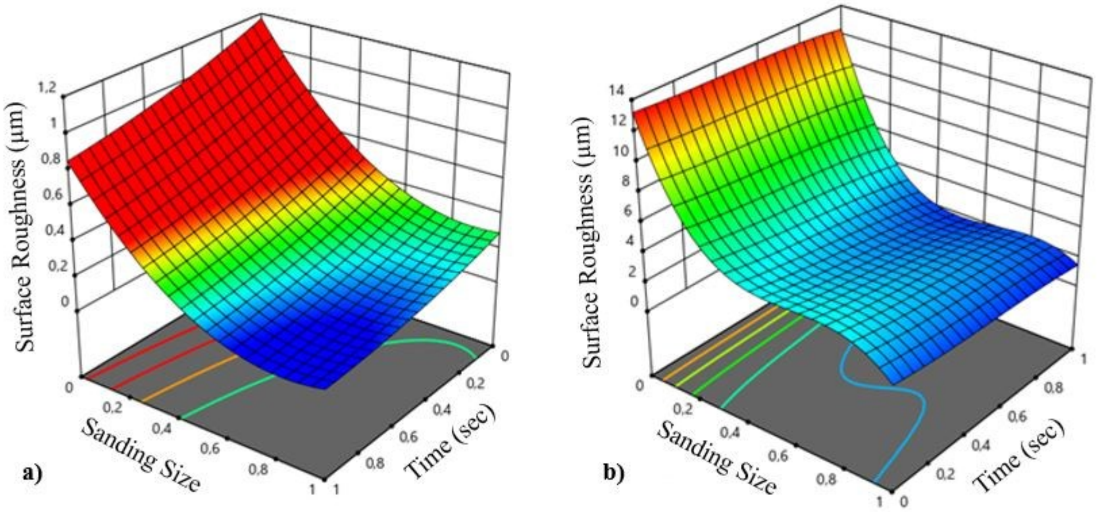

Figure 7 Graph of sanding size - sanding time - surface roughness a)S235 plate, b)polypropylene plate

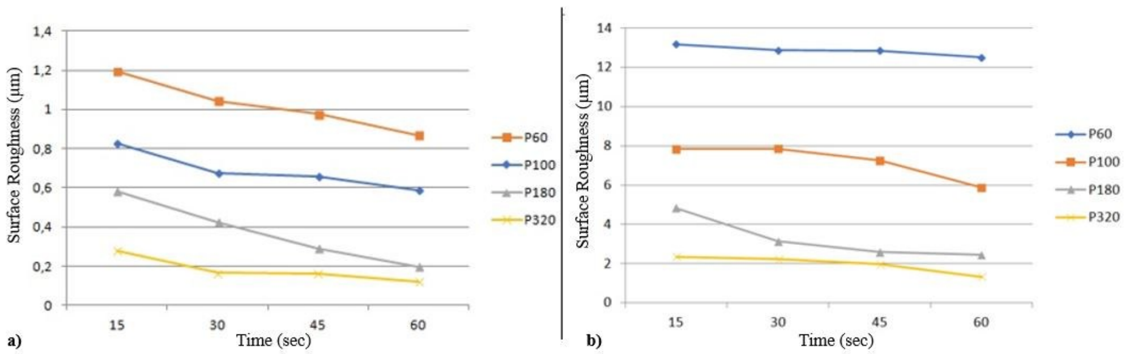

Figure 8 Average surface roughness-sanding time graph a)S235 plate, b)polypropylene plate

The surface roughness obtained from the experimental studies based on the sanding size and time was plotted as a surface on a 3-axis graph (Figure 7). The average surface roughness obtained depending on the sanding time for the categorically specified sanding size is given in Figure 8. A decrease in surface roughness was observed in both materials with the increase in sanding time and sanding size number. For the S235 plate, the increase of the sanding size number from P60 to P320 shows a reduction in surface roughness of 85.6% - 84.2% - 83.3% - 85.9% for 15, 30, 45, and 60 seconds, respectively. For the PP plate, the increase of the sanding size number from P60 to P320 shows a reduction in surface roughness of 82.2% - 82.8% - 84.6% - 89.4% for 15, 30, 45, and 60 seconds, respectively.

RSM, a suitable method for developing, improving and optimising processes for the optimisation of the obtained surface roughness, was used [19]. The relationship between independent variables and experimental results can be established with RSM. Analysis of variance (ANOVA) is used to evaluate the error variance of the result values obtained as a result of the input parameters and to determine the effect rates of the input parameters on the result values [20]. The ANOVA results for the surface roughness results for both sanded materials are given in Table 4. As a result of the study, it was observed that the most effective parameter on the surface roughness was the sanding size. It was observed that 86.96% sanding size and 8.3% sanding time were effective on the surface roughness of the S235 plate. The surface roughness of the polypropylene plate was 94.31% affected by the sanding size and 1.57% by the sanding time (Table 4). It was observed that the explanatory power of the regression model was created at a 95% confidence interval to explain the surface roughness of the S 235 plate and polypropylene plate, which was over 96% (Table 5). It was observed that the predictive power of the created model was 95%. This situation explains that the created model is highly reliable.

Table 4 ANOVA for surface roughness

	Source	**DF**	**Seq SS**	**Contribution (%)**	**F-Value**	**P-Value**
S235 plate	Model	8	9.02501	96.48	243.47	0.0000
	Linear	4	8.91050	95.26	480.76	0.0000
	Sanding Time	1	0.77607	8.30	167.49	0.0001
	Sanding Size	3	8.13443	86.96	585.19	0.0001
	Square	1	0.01963	0.21	4.24	0.0430
	Sanding Time*Sanding Time	1	0.01963	0.21	4.24	0.0430
	2-Way	3	0.09488	1.01	6.83	0.0001
	Interaction					
	Sanding Time*Sanding Size	3	0.09488	1.01	6.83	0.0001
	Error	71	0.32898	3.52	0.54	0.7990
	Total	79	9.35399	100		
Polypropylene plate	Model	8	1465.20	96.24	226.92	0.0000
	Linear	4	1459.82	95.88	452.18	0.0000
	Sanding Time	1	23.95	1.57	29.68	0.0002
	Sanding Size	3	1435.87	94.31	593.02	0.0001
	Square	1	0.05	0	0.06	0.8010
	Sanding Time*Sanding Time	1	0.05	0	0.06	0.8010
	2-Way	3	5.32	0.35	2.20	0.0960
	Interaction					
	Sanding Time*Sanding Size	3	5.32	0.35	2.20	0.0960
	Error	71	57.30	3.76	1.05	0.4040
	Total	79	1522.50	100		

When the ANOVA results were examined according to the p-value, it was seen that the sanding size and sanding time have a significant effect on the surface roughness of both materials. Sanding size has a dominant effect on surface roughness, while sanding time has a lower effect. Since the model was designed according to the 95% reliability level, the p-value mustn't exceed the 0.05 reliability level limit. The fact that the p-value is less than 0.05 in the results reveals that the input parameters significantly affect the surface roughness.

Table 5 Regression statistics for Ra

Material	**S**	**R-sq**	**R-sq(adj)**	**R-sq(pred)**
S 235	0.06807	%96.48	%96.09	%95.60
Polypropylene	0.898388	%96.24	%95.81	%95.32

Using RSM, mathematical models were created that give surface roughness results depending on the sanding time separately depending on the categorical sanding size numbers (Table 6).

Table 6 Regression equations created for surface roughness in RSM

Material	**Sanding Size**	**Equation**
S235	60	Ra = $1.3599- 0.01217*T+ 0.000070*T^2$
	100	Ra = $0.9478- 0.01008*T+ 0.000070*T^2$
	180	Ra = $0.7711-0.01377*T+ 0.000070*T^2$
	320	Ra = $0.3778-0.00835*T+0.000070*T^2$
Polypropylene	60	Ra = $13.231- 0.0051*T- 0.000113*T^2$
	100	Ra = $8.703- 0.0350*T- 0.000113*T^2$
	180	Ra = $5.049- 0.0430*T- 0.000113*T^2$
	320	Ra = $2.664- 0.0135*T- 0.000113*T^2$

The comparison of the obtained experimental results with the estimated surface roughness values given by RSM is shown in Figure 9. When the graph is examined, it is seen that there are very few values outside the 95% confidence interval dashed lines. It is seen that the prediction results of the mathematical model created with the obtained experimental results are ranked near the regression line. This situation shows that the created model is meaningful.

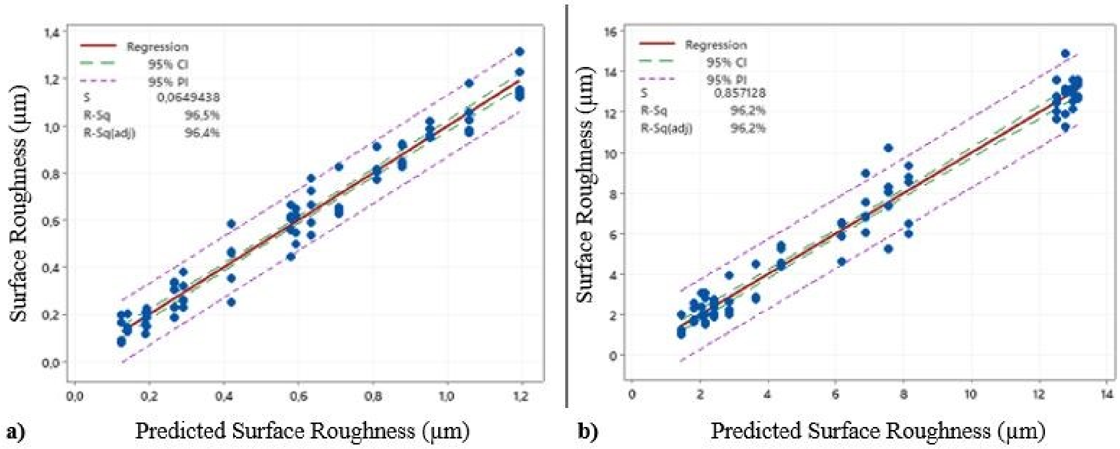

Figure 9 Regression graph for predicted surface roughness and measured surface roughness values a) S235 plate, b) PP plate

The surface roughness output values obtained from the experiments conducted with the sanding size number and time parameters defined as input parameters and the estimated surface roughness values given by the artificial neural networks in response to these input parameters are given in Figure 10. It was seen that the experiments conducted at a 95% confidence interval have an explanatory power of 98.3% for the S235 plate and 97.6% for the PP plate with the artificial neural network models created.

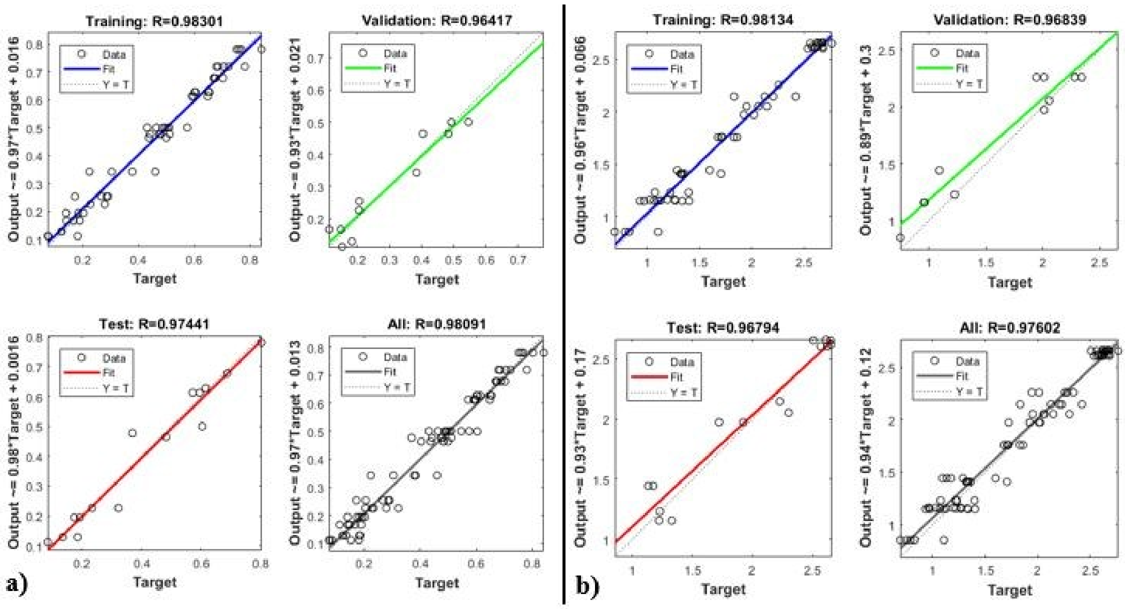

Figure 10 Regression graphs for surface roughness with artificial neural networks a) S235 plate, b) PP plate

The explanatory power being over 95% for both plate types proves the reliability of the artificial neural network created and the reliability of the data to be predicted with the artificial neural network.

4. Discussion

In the literature, sanding is generally focused on wood surfaces. Few studies have been published on sanding S235 structural steel and polypropylene material surfaces. These studies are studies carried out as a preliminary preparation process. However, there are no studies on the surface sanding parameters of these materials. The sanding process, which is widely used in the furniture industry, is also used in many areas of the industry. The sanding process is frequently performed in different applications, such as bringing the surface roughness of S235 structural steels and PP sheets to the desired tolerance range and for better paint adhesion by roughening the surface. There are no studies regarding the sanding process on the surfaces of the materials used in this study. This study contributes to the literature by examining the sanding parameters of S235 structural plates and PP plates.

Determining the parameters effective on the surface of the sheets by performing variance analysis. Determining the surface roughness without experimenting between the limit values by creating mathematical models. Making predictions with artificial neural networks. These support S235 and PP sheet users in the industry to gain time and cost.
Studying the predictability of more complex structures by entering more data and more parameters into artificial neural networks will increase the efficiency of machine learning.
External factors such as the dust remaining on the surface, filling between the sanding sands, or the abrasion of the sands will contribute to the industry and the literature.
Conducting cost and time analyses or conducting experiments with different parameters (such as sand raw material, backing paper type, sanding time, and sanding of different surfaces) will contribute to the literature.
When the experimental results are examined, it is seen that the sanding size is more effective than the sanding time due to the surface being worn in proportion to the sanding size shortly after the sandpaper first penetrates the part. Continuing the sanding time of the surface provides lower changes in the roughness due to the decrease in high roughnesses. Therefore, the sanding size is a more effective parameter for surface roughness than the sanding time.

The surfaces of S235 and polypropylene materials give different results even though they are processed under the same sanding conditions. The difference in material hardness, thermal properties, and elasticity causes different surface roughness results from the plates. The sanding process applied to the surface of the polypropylene material may have caused tearing instead of abrasion. While the heat generated due to friction during sanding is distributed in the S235 plate, it may have caused melting in a certain area in the polypropylene plate. When the metal surface undergoes plastic deformation and starts to wear, the polypropylene surface may have undergone elastic deformation.

5. Conclusion

In this study, the effects of sanding size number and sanding time on surface roughness were investigated and optimised. It was observed that surface roughness decreased with increasing sanding size number and sanding time. It was determined that sanding size was a more effective parameter than sanding time on surface roughness. As a result of the optimisation with RSM, 60 60-second sanding process with P 320 sandpaper was determined as the optimum value. With the mathematical models created, the loss of time and cost to be spent for trial and error were prevented. Before the sanding process, it can be determined which sanding size and how long to sand using mathematical models created for the desired surface roughness value. Intermediate values can be estimated without experimentation using an artificial neural network that has an explanatory power of over 97% in a 95% confidence interval. This study will help companies that will perform the sanding process in the industry in choosing the sanding size and sanding time.

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