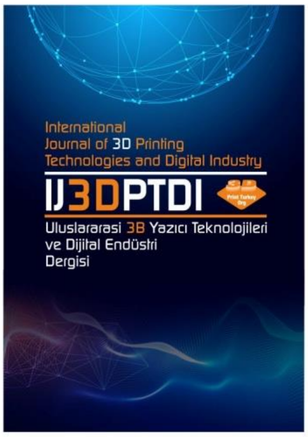

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REDUCING SOUND LEVEL BY OPTIMIZING CUTTING PARAMETERS ON CNC MILLING MACHINES

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ABSTRACT

In the cutting process with machine tools in the Machinery Manufacturing Industry; while the desired surface integrity is ensured by the optimization of the cutting parameters, the noise level must be kept at a minimum to protect the health of the workers. The noise level can be reduced by using this optimization without compromising the surface roughness through processing of EN AW 6013 material on a CNC milling machine. Experimental design was examined in three variables, three levels and two target functions. The effects of these parameters on the target function were studied by performing experimental plans determined by "Central Composite Design (CCT)" of Response Surface Method (RSM)". To assess the sound level and surface roughness, mathematical models were developed by performing regression analysis on the experimental results. These developed models have been tested with control experiments and it has been seen that the models have acceptable error rates. The obtained regression equation is highly modeled with a validity of 93.29% for sound level and 97.33% for surface roughness. Therefore, cutting parameters were found to be related to sound level and surface roughness values.

Keywords: Noise, Occupational Health, Machine Tools, Roughness, EN AW 6013.

1. INTRODUCTION

Noise is common in almost all workshops, often exceeding the health hazard threshold. Recently, Occupational Health and Safety issues (OHS) on the environment and operators have come to the fore with the developments in machine tools. Operators and those working in the same environment are faced with health problems caused by the noise originating from the benches. According to the Occupational Health and Safety directive; the precautions to be taken regarding noise in the workplaces should be eliminated or minimized at the source. For doing this; this study covers an optimization study to minimize the noise levels of noise-producing machines. On the other hand, the efficient operation of the parts manufactured with the machining method, the long mechanical life and resistance to external effects depend on the surface quality [1], [2]. These surface characteristics can be very critical for the manufacturer while producing relevant surface sections. Noise, on the other hand, is not among the issues that pay much attention to the manufacturer. Therefore, noise emissions from machining need to be enhanced by employing various technological tools. In these technological advances, the first solution is to add a silencing equipment to the machine. The second solution is based on designing new machine parts with inactive damping components or effective mechanical units to reduce noise [3]. These methods are accurate for new innovations unlike existing machine tools, which are widely available production systems. Therefore, a more competent plan is needed to develop new processing designs which confine noise emission. Between these aforementioned strategies, experimental design and statistical methods are widely used for analysis, estimation and optimization in machining [4]. Precise and dependable mathematical models are highly demanded for anticipating surface roughness as well as certain traits of a product

[5]. Recently, artificial neural networks and regression models have been extensively conducted [6]. Finite element analysis, Taguchi method, fuzzy logic (FL), genetic algorithms (GA) and ANN are widely used in different machining processes [4]. Machining processes in machining can be improved using progressive optimization procedures such as the Response Surface Method and Taguchi, which help manufacturers meet their desired needs [7], [8]. Therefore, a multi-response optimization technique can be used to estimate a set of optimum process parameters to simultaneously achieve minimum sound level and surface roughness. Therefore, the cutting parameters; without increasing the surface roughness values, it is mandatory that the sound level should be optimized within the limits in accordance with the legal regulations.

Some studies in the literature on this subject are as follows; Şahinoğlu and Rafighi [9], employed the RSN to examine the impacts of cutting parameters on roughness and sound level as lathe machining of AISI 4140 is on. Asiltürk and Akkuş [10], aimed to optimize the turning parameters based on the Taguchi method in order to minimize the surface roughness. They reported that the developed model can be used in metalworking industries to determine optimum cutting parameters for minimum surface roughness. Özel and Karpat [11], prepared regression and ANN models for finishing hard turning of AISI H13 steel for surface roughness and tool wear. Basak et al. [12], performed optimization of a finishing hard turning process for machining D2 steel with ceramic tools using neural network models to comprehend surface roughness and tool wear as functions of cutting speed, feed, and machining time, and found suitable machining parameters. Singh and Venkateswara Rao [13], developed first and second-order mathematical models. And, they found that this model showed parallelism with the experimental results. Kalidass and Palanisamy [14], by proposing a prediction model with two modeling techniques, namely mathematical regression (ANN) and artificial neural networks (ANN). investigated the surface roughness of stainless steel AISI 304 for end milling. They reported that the (ANN) method better predicts the surface roughness. Kuram and Ozcelik [15], an experimental study was conducted to investigate the effects of cutting parameters on tool wear, cutting forces and surface roughness during micro-milling of AISI 304 stainless steel and used regression and fuzzy logic methods for modeling and optimization of the process. Bagaber and Yusoff [16], used multi-objective optimization by applying the desirability function to reduce machine power consumption, surface roughness and tool wear. As a result of the study, they reported a reduction of 14.94% in power consumption, 4.71% in surface roughness and 13.98% in tool wear.Bouzid [17],applied various mathematical models to predict the cutting force and surface roughness in the turning process of AISI 420 using a chemical vapor deposition coated carbide tool. They reported that the main factor (82.51%) affecting the surface roughness (Ra) was the amount of progress. Zerti et al. [18], applied the multi-objective optimization Gray Associative Analysis (GRA) technique based on Taguchi design analysis to simultaneously optimize both surface quality and productivity, which represents an important attribute of a manufacturer. Bouzid [19], investigated the effect of machining parameters during stainless steel X20Cr13 turning operations, both individually and simultaneously, with the Taguchi and (GRA) method. They concluded that the (GRA) method can be applied for simultaneous optimization of roughness and stock removal. Karabulut [20], used artificial neural networks (ANN) and regression analysis methods to predict the surface roughness and cutting force of AA7039/Al2O3 metal matrix composite materials during milling. Campatelli et al. [21], used the response surface methodology (RSM) method to model the power consumption and optimize the cutting parameters during dry milling on a CNC machine. By optimizing the cutting parameters in the manufacturing process, the surface roughness values can be improved, and the noise levels can be reduced as a result of the optimization of the parameters. Therefore, the selection of optimized cutting parameters is extremely important as the noise generated by the machine and the surface quality and for dimensional accuracy of the fabricated pieces are determined [2], [7].

Based on the literature review, many researches have been conducted on surface roughness values, optimization of cutting parameters and bench sound level, and it has been noted that in most of the studies, surface roughness rates and

bench sound level are generally examined separately. However, no study has been found that evaluates the surface roughness values and sound level together with the optimization of the cutting parameters and minimizes both at the same time.
Within the scope of this study, it is intended to lessen the noise level in the workplace environment without compromising the roughness by optimizing the cutting parameters of the Response Surface Method with MKT while processing EN AW 6013 material on the CNC milling machine.

Response Surface Method (YYY) was used in the optimization of cutting parameters within the scope of this research. It is a useful method of mathematical and statistical techniques to improve, develop and optimize processes [22]. Unlike traditional methods, interactions between process variables can be determined by statistical techniques. There are studies in the literature showing that surface quality can be characterized by the model of experiments in metal cutting using the response surface method [23], [24]. After literature review, the cutting parameters determined within the scope of this study were taken as; cutting speed, amount of progress and depth of cut [25], [26]. The study is a multidisciplinary study between the machinery manufacturing sector and statistics disciplines. It is thought that it will provide significant contributions to the literature on the protection of the health of the manufacturing sector and employees.

2. MATERIALS AND METHOD

2.1. Test Samples

Test models were prepared in the dimensions of 100x80x70 mm (Length x Width x Thickness). Sample surfaces were cleaned of oil and oxide layers. The samples were not subjected to any heat treatment. The picture of the EN AW 6013 mold aluminum material used in the experiment was given in Figure 1 and its chemical components were given in Table 1.

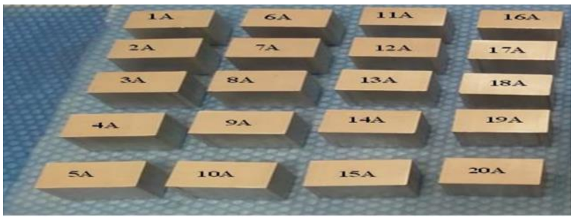


Figure 1. Samples used in the experiments

Table 1. The average chemical components of the EN AW 6013 mold aluminum material (%)

Fe	Si	Cr	Mn	Mg	Zn	Cu	Ti	Other	Al
0,5	0,6-10	0,1	0,2-0,8	0,8-1,2	0,25	0,6-1,1	0,1	0,15	Left

2.2. The Testing Apparatus

Victor Taichung/Vcenter-102 brand/model CNC milling machine was used in the experiments. YBD152 quality carbide coated inserts with ONHU08T508-PM code produced by ZCC - CT Cutting Tools company are used with tool holders containing five cutting inserts. sound level measurements were completed with the Smart Sensor Ar 844 Noise Meter Decibel Recorder. The recorded data were transferred to the computer via USB. Surface roughness measurements of the prepared samples were made from three different points with Mitutoyo SJ-201 brand surface roughness measuring device. The average roughness (Ra) values were found by taking the average of the values obtained as a result of the measurements.

2.3. Experimental Design

The experiments were carried out in accordance with the experimental plan determined in the central composite design of the Response Surface Method. The response surface method consists of 3 stages; experimental design, mathematical modeling and model validation. The equation shown in 1 was used in the experimental design, which is the first step of the response surface method.

$$Y = f(x_1, x_2 x_3, \ldots \ldots . x_n) + \varepsilon \qquad (1)$$

In this equation, Y represents the dependent variable, Xn the independent variable, and ε the error term. Considering that the cutting parameters (amount of progress, cutting speed and depth of cut) will affect the surface roughness and sound level in the experiments, they were chosen as the design parameters. These three parameters were examined for two target functions determined at 3 levels. The cutting parameters used in the experiments, the catalog values of the cutting tool company and the machine capacity were taken into account, and the variables and their levels were selected and given in Table 2. The geometric parameters are defined as progress rate (X_1), cutting speed

(X_2) and depth of cut (X_3). In Table 2, the highest level of the parameters as (1), the middle level as (0), and the lowest level as (-1) were shown. Within the scope of this study, 23 experiments were conducted in order to investigate the contribution of the parameters given in Table 2 to the target function; 3 of these experiments were carried out for the validation.

Table 2. Experimental parameters and levels

Design Variables	Levels		
	-1	**0**	**1**
X_1, Pitch (mm min^{-1})	200	400	600
X_2, Cutting Speed (m min^{-1})	200	300	400
X_3, Depth of Cut (mm)	0,5	1	2

In the analysis of the data, the quadratic polynomial model was chosen to produce the mathematical model. The validation of the model was applied to the mathematical model, and the relevant values of the parameter levels that were not in the experimental plan were verified with the results of the experimental study. YYY analysis results and graphics made with Minitab 18 program were examined separately for surface roughness and sound intensity. The correlation between both outcome targets was then investigated.

The surface roughness values and sound level of the EN AW 6013 mold aluminum material obtained as a result of the experiments were given in Table 3. Using the values in Table 3, the test measurement results were analyzed with the Minitab 18 package program.

Table 3. Experimental measurement results

Experiment Order Number	VARIABLES			RESULTS	
	X1 (mm min^{-1})	X2 (m min^{-1})	X3 (mm)	Surface Roughness Value (Ra)(µ)	Sound (dB)
1	200	200	2,0	1,15	85
2	200	400	0,5	0,55	78
3	400	300	2,0	1,43	90
4	600	200	0,5	2,50	79
5	400	300	1,0	1,40	82
6	600	400	2,0	2,01	92
7	400	300	0,5	1,30	80
8	200	200	0,5	0,82	72
9	600	400	0,5	1,35	86
10	400	300	1,0	1,45	83
11	400	300	1,0	1,40	82
12	600	300	1,0	1,62	85
13	400	300	1,0	1,41	80
14	400	300	1,0	1,38	79
15	600	200	2,0	2,90	92
16	400	200	1,0	2,10	78
17	200	300	1,0	0,54	75
18	200	400	2,0	0,52	89
19	400	300	1,0	1,39	82
20	200	200	1,0	1,00	90

2.4. Response Surface Regression for Roughness Values and Sound Level

The effects of the design parameters on the surface roughness and sound level were examined and statistical information was obtained by looking at the usability of the relationship between the parameters. The regression occurred in the 95% confidence interval. The ANOVA table for the surface roughness and sound level of the EN AW 6013 material was given in Table 4.

In Table 4, since the P-values are less than 0.05 according to the null hypothesis, the model is acceptable and effective. According to this table, "X_1", "X_2", "X_3", "$X_1.X_1$", "$X_2.X_2$" and "$X_1.X_2$" parameters for surface roughness have acceptability. and it is seen that the model is modeled with a validity rate of 97.33%. For sound level, the parameters "X_1", "X_2" and "X_3" are acceptable and seem to be effective. In addition, it is clearly seen in the table that the model for sound level is modeled with a validity of 93.29%.

X1: Amount of progress; X2: Cutting speed; X3: Depth of cut; dB: Decibel; Surface pr.: Surface roughness; Ra: The arithmetic mean of the roughness value.

Table 4. Anova table for roughness and sound level

Table of ANOVA		Roughness	Sound level
Resource	DF	P-Value	P-Value
Model	9	<0,05	<0,05
Lineer	3	<0,05	<0,05
X_1	1	<0,05	<0,05
X_2	1	<0,05	0,001
X_3	1	0,007	<0,05
Square	3	0,042	0,234
$X_1.X_1$	1	0,025	0,108
$X_2.X_2$	1	0,013	0,155
$X_3.X_3$	1	0,856	0,393
Interaction	3	0,033	0,231
$X_1.X_2$	1	0,016	0,609
$X_1.X_3$	1	0,057	0,321
$X_2.X_3$	1	0,995	0,083
Error	10		
Mismatch	5	<0,05	0,163
Total	19		
R-sq		97,33%	93,29%

The regression equation, which is an algebraic representation of the response surface, defines the relationship between the response and model terms. A quadratic model was obtained for the response variables (surface roughness and sound level). The equations in equation 2 and equation 3 obtained through the ANOVA program were defined to be used in the mathematical modeling and model validation steps.

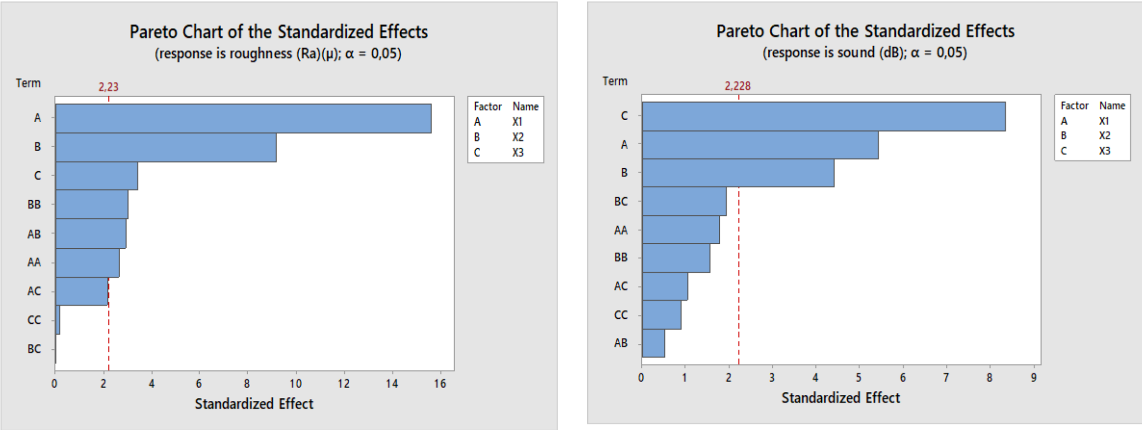
$$\boldsymbol{S}.\mathbf{Roughness}(\boldsymbol{R_a}) = 1{,}917 + 0{,}00909X_1 - 0{,}01621X_2 - 0{,}157X - 0{,}000005X_1.X_1 + 0{,}000025X_2.X_{2_3} + 0{,}032X_3.X_3 - 0{,}000007X_1.X_2 + 0{,}000696X_1X_3 - 0{,}000004X_2.X_3 \quad (2)$$

$$\boldsymbol{Sound}(\boldsymbol{dB}) = 59{,}3 + 0{,}0717x_1 - 0{,}0537x_2 + 8{,}95x_3 - 0{,}000053x_1.x_1 + 0{,}000186x_2.\ 2{,}19x_3.x_3 - 0{,}000019x_1.x_2 - 0{,}00489x_1.x_3 - 0{,}01804x_2.x_3 \quad (3)$$

2.4.1. Pareto Chart for Surface Roughness and Sound Level

A Pareto chart is used to compare the relative magnitude and statistical significance of the key, square, and interaction effects of parameters on previously determined performance characteristics. This graph shows the effect of the absolute value of the standardized effects on the result. Standardized effects are t-statistics that test the null hypothesis that the effect is zero. The chart also includes a baseline to indicate which effects are statistically significant. Any effect that crosses this reference line, called the significance line, is statistically significant. The significance line depends on the level of significance. The “A” factor represents the amount of progress, the “B” factor represents the cutting speed, and the “C” factor represents the depth of cut.

The standardized effect pareto chart is shown in Figure 2.a for surface roughness values. As it is clearly seen in the figure, it has been seen that the "A", "B", "C", "BB", "AB" and "AA" models have crossed the 2.23 significance line and reached significant values. It is seen that the most effective parameter in roughness is "A" (feed rate) in the pareto chart. In Figure 2.b, the standardized effect Pareto chart for sound level is given. Factors greater than 2.228 significance lines; it is seen that the "A", "B" and "C" factors are statistically significant and the most effective parameter for sound level is "C" depth of cut.



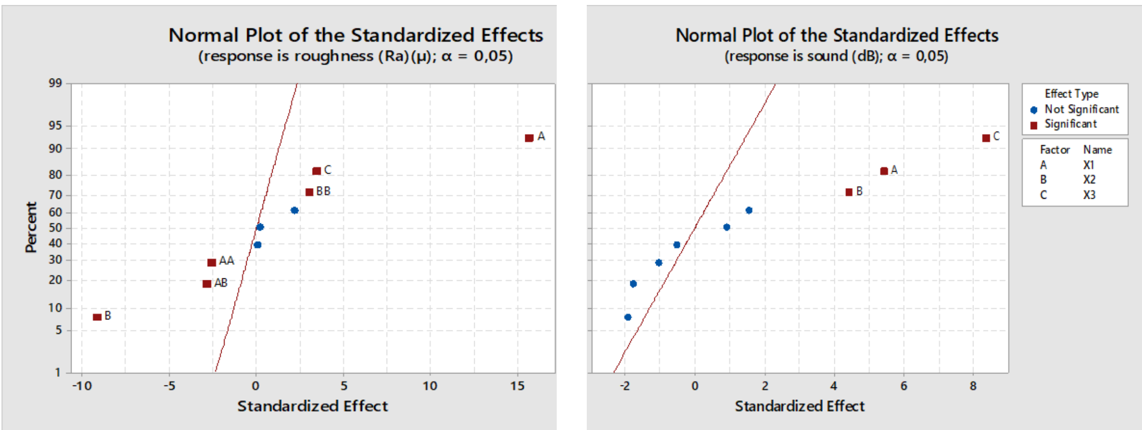
(a) Surface roughness (b) Sound level

Figure 2. Pareto graph of the standardized effect

In the graph given in Figure 2.a and Figure 2.b, information about the severity of the factor can be obtained, but there is no information about how the severity affects the result. The direction in which the factor affects the result can be seen in the normal curve of the standardized effect given in Figure 3.a and Figure 3.b.

2.4.2. Normal Curve of Standardized Effect

Line in the normal curve of the standardized effect; corresponds to the distribution for which the standard deviation is one. These values are marked with a square icon on the graph and the effect type is determined as significant. A negative value means that the interaction direction of the target function and the value is opposite, and for positive values, the interaction direction of the target function and the value is in the same direction. In Figure 3.a and Figure 3.b, the normal curve of the standardized effect for EN AW 6013 die aluminum material was given. The values on the figure represent the same values as in the pareto chart. Figure 3.a shows the effects of cutting parameters on the surface roughness. Round points close to the line are the factors that do not matter on the target function. Each point away from the line shows its effect on the target function.



(a) Surface roughness (b) Sound level

Figure 3. Normal Curve of Standardized Effect

Figure 3.a shows the effects of cutting parameters on roughness. According to this figure; The increase of ‘’AA’’, ‘’B’’ and ‘’AB’’ means a decrease in surface roughness, while an increase in ‘’A’’, ‘’BB’’ and ‘’C’’ means an increase in surface roughness carries. It is seen in the normal curve of the standardized effect, as well as in the pareto graph, where the most important effect on roughness is “A” (the amount of feed). Therefore, in order to reduce the surface roughness in the processing of EN AW 6013 mold aluminum material, the level values of “A”, “BB” and “C” parameters are decreased, while “AA”, “B” and “AB”‘’ it is seen that the level values of the parameters should be increased.

Figure 3.2.b shows the effects of cutting parameters on sound level. According to this figure; the increase in the level values of the "A", "B" and "C" parameters means that the sound level increases, and it is seen that the most effective parameter is "C" (depth of cut). Therefore, it is clearly seen that the level values of the "A", "B" and "C" parameters should be reduced in order to reduce the sound level in the processing of EN AW 6013 mold material.

2.4.3. Three-Dimensional Surface Curves for Surface Roughness Values and Sound Level

All the values kept constant while obtaining the surface curves are the optimum values of the relevant geometric parameters. In Figure 4, the surface graphs obtained for the surface roughness values of EN AW 6013 mold aluminum material are given. In these graphs, while one variable is kept constant from a total of 3 geometric parameters, it is seen how the other two variables affect the target functions and how the variable 2 parameters should be in line with the desired target function.

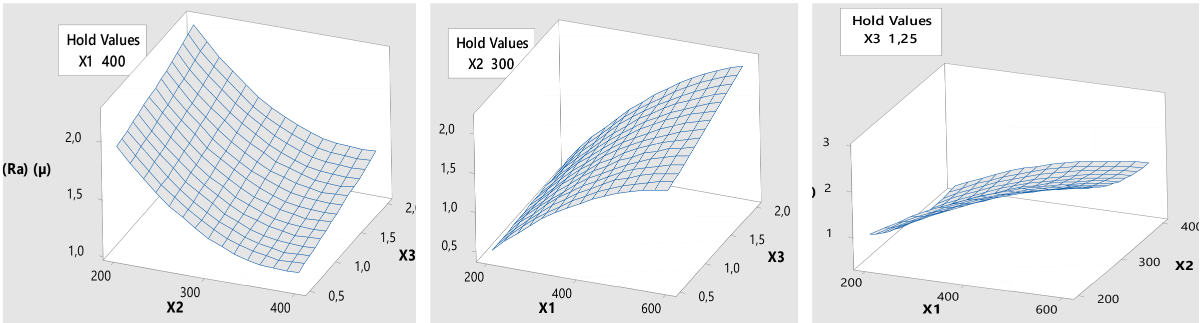


Figure 4. Three-dimensional surface curves for surface roughness values

In Figure 5, surface graphs for the sound level values of EN AW 6013 mold aluminum material were shown. One of the 3 geometric parameters is kept constant and shows the effect of the other two parameters on the target function.

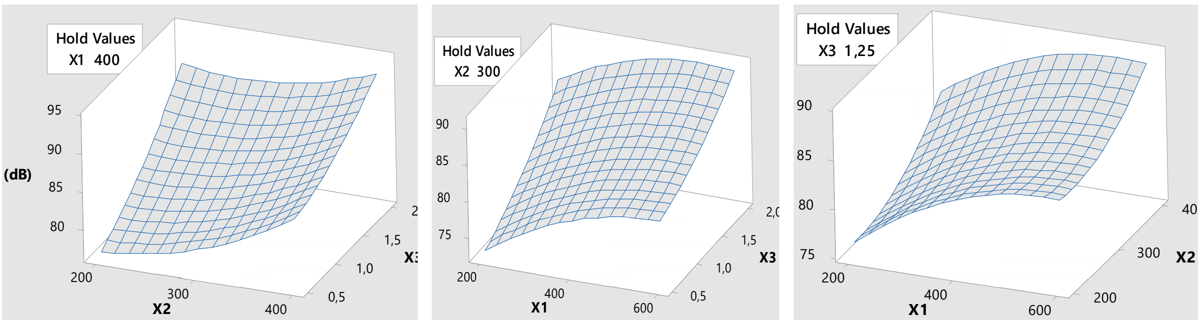


Figure 5. Three-dimensional surface curves for sound level

According to this figure; in the processing of EN AW 6013 mold aluminum material on the milling machine; it has been determined that the parameters should be compatible with each other in order to prevent the increase in sound level. It was observed that the sound level increased at the points where the harmony of the parameters with each other was impaired. Optimization of target functions was provided with optimization graphics.

2.4.4. Optimizations of Target Functions

The optimization graphic is used to determine the optimal cutting parameters settings for estimation, given the parameters we have previously specified. For surface roughness and sound level, the composite desirability value is 1. The aim is to minimize the surface roughness and sound level. Optimum parameter values, which give the lowest surface roughness values obtained as a result of the optimization made by using the response surface method in accordance with the experimental values of EN

AW 6013, are given in Figure 6 and in this chart, 200 mm min-1 cutting speed (X_2) for the feed rate (X_1) and 0.5 mm for depth of cut (X_3) and the estimated surface roughness value was found to be 0.409 µ. The given D value represents the maximum objective function value. It represents the ratio of the optimum value of the objective function to the maximum that can be obtained from the model, and also shows the intersection of the geometric parameters and the optimally calculated values.

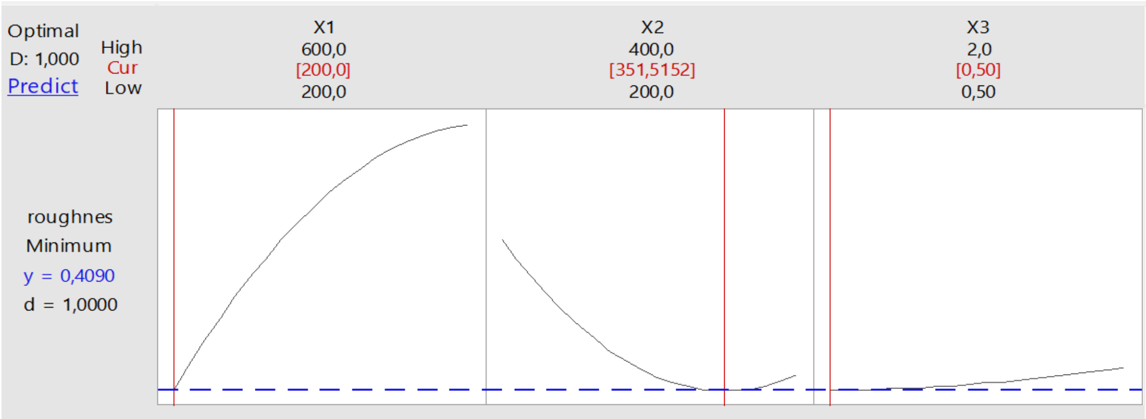


Figure 6. Surface roughness optimization

Parameter values providing the lowest sound level were shown in Figure 7. As seen in Graphic 2, the optimum levels for processing EN AW 6013 were; 200 mm min^{-1} for the amount of progress (X_1), 200 m min^{-1} for the cutting speed (X_2) and 0.5 mm for the depth of cut (X_3) and the estimated sound level value was found to be 70.22 dB.

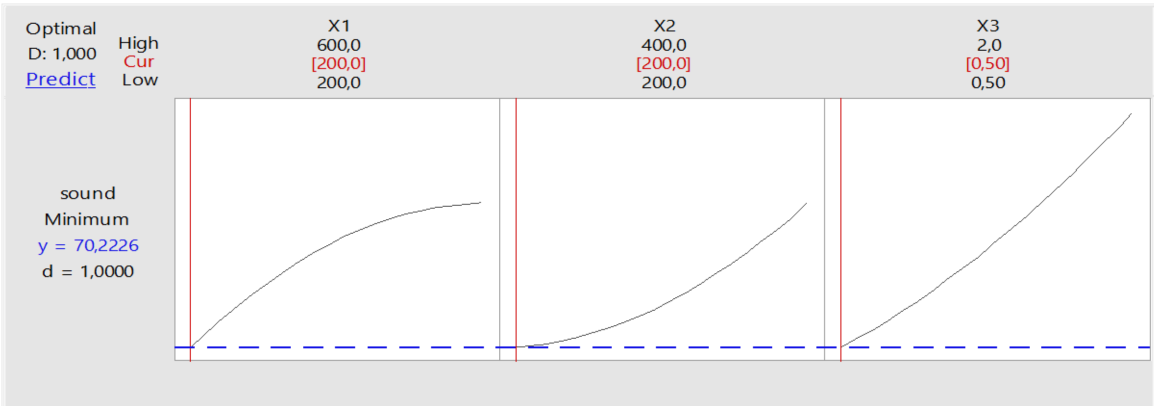


Figure 7. Sound level optimization

2.4.5. Optimization for Surface Roughness and Sound Level

In Figure 8, the intersection of the geometric parameters and the optimum calculated values were given. The "d" value given in the figure represents the optimum value of the target function for the minimum roughness value and sound level. The "D" value in the concept of mixed desirability is the average of the "d" values in the minimum target functions. The target is to minimize the surface roughness and sound level. According to figure 8, 278.78 m min^{-1} for the 200 mm min^{-1} cutting speed (X_2) for the amount of progress (X_1) and 0.5 mm for the depth of cut (X_3) and the estimated sound level is 72, 01dB, and the surface roughness value was found to be 0.543µ.

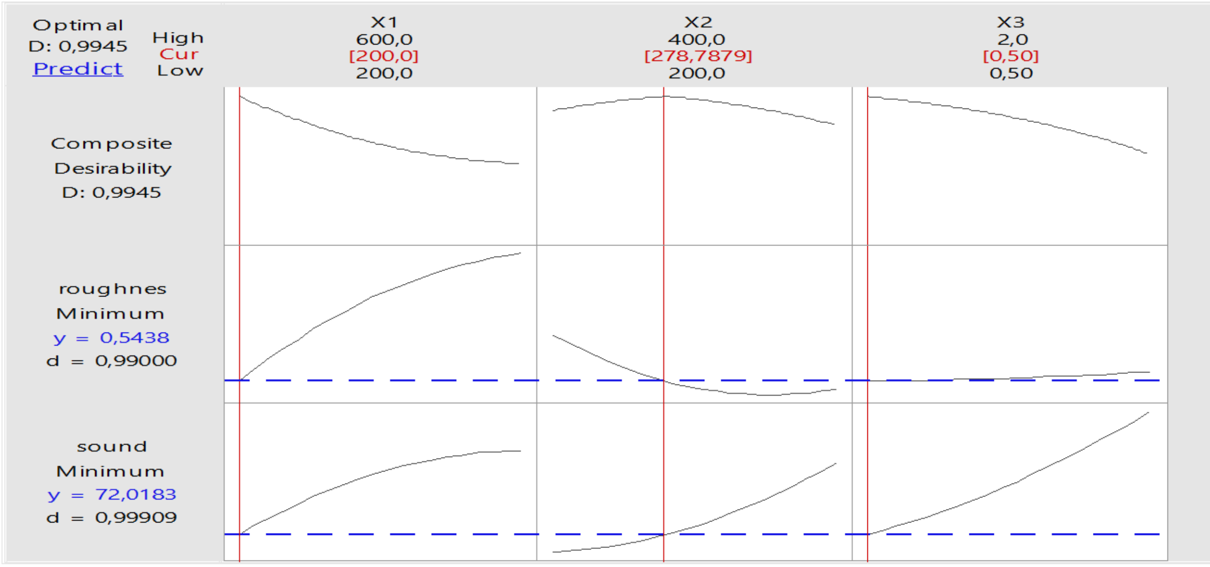


Figure 8. Optimization of surface roughness and sound level together

In Table 5, the values of the ideal cutting parameters for the minimum roughness and sound level estimated as a result of the experimental and model optimization of EN AW 6013 were given. According to this table, it is seen that the amount of feed and the depth of cut should be selected at a low level in order to minimize the roughness and noise level together, and the cutting speed should be adjusted according to the progress amount and depth of cut.

Table 5. Value of ideal cutting parameters

EN AW 6013 Mold Aluminum					
Parameters	Minimum	X_1(mm min^{-1})	X_2(m min^{-1})	X_3 (mm)	Result
Experimental Results	Roughness		400	2	0,52 µ
	Sound level		200		72 dB
Multiple Response Estimation	Roughness		351,51		0,40 µ
	Sound level	200	200	0,5	70,02dB
Multiple Response Estimation for Two Objective Functions	Roughness		278,78		0,54 µ
	Sound level				72,01dB

3. MODEL VERIFICATION FOR SURFACE ROUGHNESS AND SOUND LEVEL

The model needs to be validated to understand how accurate the generated model is and how representative it is of true values. In this study, the effective parameters were changed, and the results obtained from the mathematical model were compared with the experimental results. The geometric parameter values used in the verification experiment, which are not in the created experiment plan, were given in Table 6. The model prediction value was found by calculating the parameter values in Table 6 according to the equations in equation 2 and equation 3 obtained as a result of regression. The roughness and sound level measurements were made when the machine was operated in accordance with the parameter values given in Table 6. The obtained model and test results and error percentages were given in Table 7 and Table 8. Percentage error values occurred between 4.76µ and 7.05µ for surface roughness, and between 1.60dB and 3.76dB for sound level. This percentage of error shows that the model created according to the Multiple Response Estimation given in Table 9 and Table 10 and the experimental results were in agreement.

Table 6. Geometric parameters used in the validation experiment

Experiment Number	Design Parameters		
	X_1(mm min^{-1})	X_2(m min^{-1})	X_3(mm)
1	300	200	0,5
2	400	200	1,5
3	300	300	1

Table 7. Verification results for surface roughness

Experiment Number	Design Parameters			Surface Roughness of EN AW 6013(μ)		
	X_1(mmmin^{-1})	X_2(mmin^{-1})	X_3(mm)	Model	Experiment	%Error
1	300	200	0,5	1,56	1,45	7,05
2	400	200	1,5	2,20	2,31	4,76
3	300	300	1	1,03	1,09	5,50

Table 8. Verification results for sound level

Experiment Number	Design Parameters			Sound of EN AW 6013(dB)		
	X_1(mmmin^{-1})	X_2(mmin^{-1})	X_3(mm)	Model	Experiment	%Error
1	300	200	0,5	73,54	76	3,29
2	400	200	1,5	84,69	88	3,76
3	300	300	1	80,69	82	1,60

The multiple response estimation chart for surface roughness of EN AW 6013 is given in Table 9. As seen in this table, possible values for a value of 0.40 μ are in the range of 0.01 μ to 0.80 μ.

Table 9. Multiple response estimation chart for surface roughness

Response	Fit	95%PI
Roughness(μ)	0,40	0,01;0,80

Fit: Fitness**; PI:** Prediction Interval

In Table 10, the multiple response estimation chart for the sound level of EN AW 6013 is given. As seen in this table, possible values for a value of 70.22 dB range from 64.29 dB to 76.15 dB.

Table 10. Multiple response estimation chart for sound level

Response	Fit	95%PI
Sound(dB)	70,22	64,29;76,15

Fit: Fitness; **PI:** Prediction Interval

4. RESULTS

In this study, it was aimed to reduce the sound level and surface roughness simultaneously with the optimization of the cutting parameters during the processing of EN AW 6013 aluminum material on the CNC milling machine, and experimental studies were carried out. In the experimental studies, it has been observed that the surface roughness was brought to an acceptable level by processing in suitable cutting conditions, and the sound level decreases. Mathematical models were developed to predict sound and surface roughness by performing regression analysis of experimental results. Optimization of cutting parameters has been achieved with the developed mathematical models and control experiments for these models. Thus, while the desired surface roughness values were obtained successfully, the values, at which the sound level was reduced, were determined. The results found were shown below.

• For the target functions, the sound level was between 72 dB and 92 dB, and the surface roughness values were found to be between 0.52 μ and 2.90 μ.

• The most ideal values of cutting parameters for simultaneously minimizing sound level and surface roughness as a target function in parameter optimization of EN AW 6013 aluminum material; the amount of progress was found to be 200 mm/min., the cutting speed was 278.8 m/min., and the depth of cut was 0.5mm, and the sound level was 72 dB and the surface roughness was 0.54μ.

• In the processing of EN AW 6013 aluminum mold material on the milling machine; It has been determined that the cutting parameters should be compatible with each other in order to prevent the increase in sound level. It was observed that the sound level increased at the points where the harmony of the parameters with each other was impaired.

• In the obtained regression equations; sound level was modeled with an accuracy of 93.29% and surface roughness with an accuracy rate of 97.33%. The regression equation, ANOVA analysis, preato plot, standardized effect normal curve and surface plots show that they are consistent with each other. It is thought that this method can be used safely for other similar studies.

• As seen in this study, it has been observed that the cutting parameters should be chosen in harmony with each other for minimum sound level in terms of occupational health and safety, and the cutting parameters were related to the sound level and surface roughness values.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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