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Research Article

Modelling of cutting parameters for Nilo 36 superalloy with machine learning methods and developing an interactive interface

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ABSTRACT

Superalloys have become increasingly used in the machining sector due to their high strength, temperature and machinability. One of these alloys, Nilo (Invar) 36, has a low thermal expansion and its use is rapidly increasing in areas where high temperature and expansion are not required, especially in composite mould applications, such as aerospace, electronics, measuring instruments and aerospace. In this study, a mathematical model based on artificial intelligence and an interactive visual interface in MATLAB software were developed according to the test results obtained from surface roughness Ra, cutting methods, rotational speeds, cooling method and cutting speed of Nilo 36 alloy. For the mathematical analysis of the measurements, the number of experiments to be performed by using Minitab program and Taguchi method was reduced to 32. The measurement results were modelled by Response Surface Design method and the factors affecting the surface roughness were determined in order of importance. A high-performance feed-forward artificial neural network has been developed using experimental data and an interactive interface has been prepared based on the developed model. Thus, the user can easily observe the cutting forces and surface roughness values for different cutting parameters with high accuracy.

1. Introduction

Invar 36 (Nilo 36) is a 36% Nickel and 64% iron alloy and is the material with the lowest thermal expansion be-tween the metals and alloys in the temperature range of 25-230°C. Ha and Min claim that Invar 36 is an alloy that combines high strength, stiffness, thermal and dimensional stability Tae and Seok [1]. It is used in laser equipment, control devices, reference measuring devices, gas cookers and heaters with low expansion feature over a wide temperature range. It is also an important material for aerospace, telecommunications, cryogenic tanks, composite mould production Tae and Seok [1].

Maranhão and Davim showed that Invar 36 material is relatively difficult to process due to its properties. High cutting temperature, high cutting forces, rapid tool wear, chip breakage, chip adherence cause decreased surface quality Cesar et al. [2]. In the turning process, heat energy is generated in the plastic deformation process of the work-piece, mostly in the first deformation zone. Tekaslan et al. [3] have shown that the process efficiency and tool life have been directly affected by cutting length and tool geometry Tekaslan et al. [3].

It is seen that many experimental studies have been performed for investigating the effects of various parameters used on the processing of similar materials on rough-ness of surface and cutting forces. Li et al. [4]. evaluated the deviations between the theoretical and experimental results for the cutting forces in the turning process of AISI 304 austenitic stainless steel with TiC coated cutting tool and emphasized that the theoretical approach can be used with 80% accuracy. Diniz et al. [5] indicated the machinability of AISI 304 steels with coated cemented carbide cutting tools has been performed and the cutting speed is an important parameter for surface

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roughness (Ra). Kaladhar et al. [6]. Reported that when turning AISI 304 stainless steel with low feed rate and high cutting speed, it was stated that the sound pressure level during cutting decreases and thus Ra decreases. Dirviyam and Palanisamy [7] claim that the use of a cutting tool with wiper geometry during turning has a positive effect on surface quality. Basmaci et al. [8]. found out that the use of a wiper tip eliminates the second process, reducing process steps and time. However, the in-crease of the wiper surface causes the cutting forces to increase Ay [8]. In the study of parameter optimization in the process of turning AISI 304L stainless steel, the wiper tip had a positive effect on surface quality.

Basmaci and Ay [9]. Basmaci et al. [10], emphasized that production quantity, economy and time are not sufficient for a manufacturing process Dhar et al. [11]. In addition, it is directly related to the harm to the environment and its impact on human health. There are studies using different cooling techniques sensitive to human health and environmental pollution in turning operations. It has been observed that the performance of these alternative cooling techniques is superior to the general cooling technique. Dhar et al. [11] reported that MQL cutting speed, feed rate and cutting temperature have important contributions to surface integrity. Itoigawa et al. [12]. reported that MQL reduces friction between the tool and the workpiece. Sheng et al. [13]. emphasized that the main effect of MQL is to lower the cutting temperature. Marco et al. [14] reported that MQL decreased the formation of crater wear Basmaci et al. [15]. showed that the MQL technique has a positive result on the reduction of heat and wear between tool-chip and workpiece-chip and in the cutting zone, as well as on surface quality improvement Basmaci et al. [15].

In this study, the effect of cutting speed, cooling system and cutting method on surface roughness and cutting forces in turning of Nilo 36 steels were investigated. Taguchi technique has been used to determine and optimize the effect of cutting speed, cooling system and cutting method of Nilo 36 steels on turning surface roughness and cutting forces.

In addition, analysis of variance (ANOVA) was performed to figure out the effect of each parameter on the results and the optimum machinability of Nilo 36 steel. A full autonomous design of proving was formulated in this paper to study a long- term process coefficient for both materials. The bulk density, tensile mechanical attributes, fractography, material com-position, and remaining stresses of the parts produced were investigated.

An optimum process window has been pro-posed based on experimental work Yakout et al. [16]. The most significant contribution of the study to literature is the artificial intelligence supported interactive interface developed within the scope of the study. Using this interface, it is possible to predict with high accuracy what size F forces will be encountered during the process and what the sur-face roughness value will be according to various cutting parameter values and different cutting methods.

Normally, in order to know these values, very valuable and expensive materials must be consumed and repeated trials are required. In addition, there is a loss of labour, energy and time. Thanks to the implemented interface, the user can manually change the cutting parameters, cutting methods, cutting speed and type and the amount of coolant, and the result of the process of tens of combinations can be calculated instantly and displayed graphically.

2. Materials and Methods

2.1 Materials

In the present study, Nilo36 stainless steel with 150 mm length and 50 mm diameter was used as test material and its chemical characteristics are given in Table 1.

2.2 Experimental Design and RSM Analysis

In the presented study, Nilo36 alloy was processed in four different cutting speed (100, 140, 180, 220 rpm), two different cutting methods (conventional and wiper) and four different cooling methods (dry cut, MQL 20ml, MQL 40ml and CO_2). According to the experimental results, a model based on artificial neural network and also a visual interface was developed in MATLAB software environment.

In the experiments, CNMG 12 04 08 MM SUMITOMO cutting tips, Johnford TC 35 CNC Fanuc OT an x-z axis CNC and Mahr perhometer/M1 type surface roughness meter was used. In addition, Kistler 9121 dynamometer system together with a Kistler 5019 charge amplifier and DynoWare software were utilized for the force determination (Figure 1.)

Table 1. Nominal Compositions, %

Alloy	**Ni**	**Fe**	**Others**
NILO alloy 36	36.0	64.0	-
Density			
Alloy	g/cm³	lb/in³	
NILO alloy 36	8.11	0.293	
Thermal Conductivity at 20°C (68°F)			
Alloy	W/m°C	Btu in/ft²h °F	
NILO alloy 36	10.0	69.3	
Electrical Resistivity			
Temperature (Microhm cm (ohm.circ mil/ft)			
°C	°F	NILO alloy 36	
20	68	80 (481)	
Typical Mechanical Properties of NILO alloy 36			
Yield Strength (0.2% Offset)		Tensile Strength	
MPa	ksi	MPa	ksi
240	35.0	490	71.0
Elastic Modulus Data			
	Elastic Modulus		
Alloy	GPa	10^3 ksi	
NILO alloy 36	140	20.3	

Figure 1. Experimental setup

Figure 2 demonstrates the process flow performed within the scope of the study in detail. Invar alloy with an elastic modulus effect over a wide temperature range. Intensive microscopic characterizations indicate the occurrence of a prematernity transformation with formation of nano-scale domains that can be restricted by deformation Qin et al. [13].

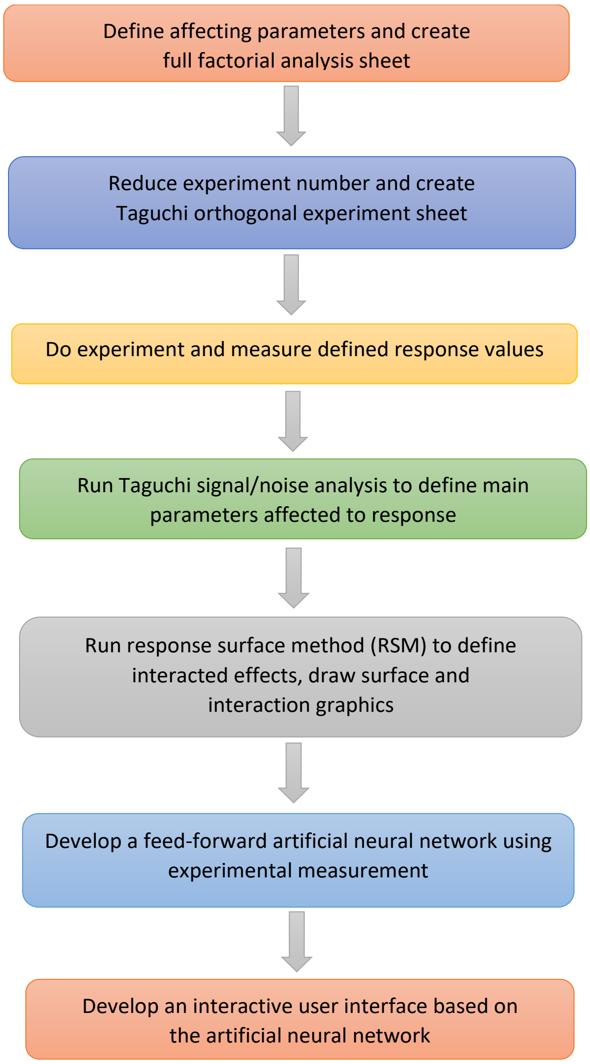

Figure 2. The process flow performed during the study

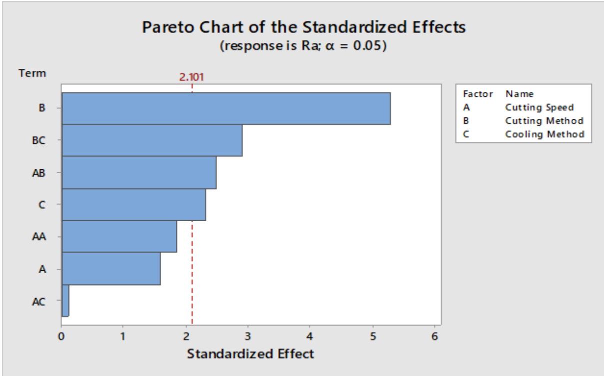

Figure 3. Pareto chart of the standardized effects on Ra

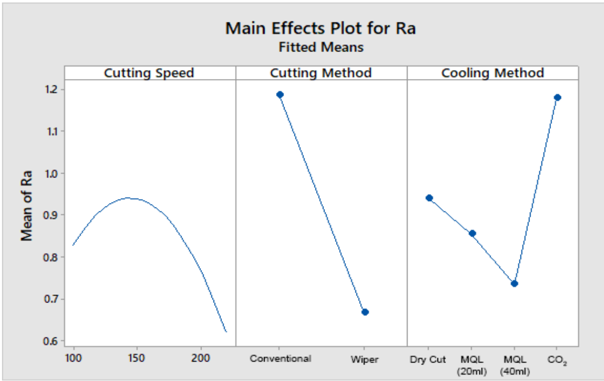

Figure 4. Main effects plot for Ra

First of all, Minitab program was used for mathematical analysis of the measurements and the number of experiments was reduced to 32 using Taguchi method. The measurement results were modelled by Response Surface Design method and the factors affecting the surface roughness were determined in order of importance. ANOVA calculation based on cutting speed, cutting method and cooling method factors is given below.

The coefficient of multiple determination for multiple regression (R squared) value was calculated as 78.88%. This value shows that the mathematical model is acceptable. Figure 3 shows the influencing parameters on the surface roughness and their degree of influence as a pareto graph. When standardized factors are compared, the most important factor affecting the surface roughness has been the cutting method. Following the method of cutting method cooling method pair, cutting speed cutting method and finally cooling method stand out as effective parameters. Figure 4 shows how the cutting speed, cutting method and cooling method parameters affect the mean Ra value.

When Figure 4 is examined, higher values for cutting speed cause lower surface roughness, wiper should be selected for cutting method and MQL 40 should be preferred for cooling method. The use of CO_2 as a cooling method gives negative results in terms of surface roughness compared to other cooling methods. There is also a difference in surface roughness between the conventional cutting method and the wiper, and the wiper method proved to be more successful.

RSM is a mathematical modelling and statistical assessment method used to optimize a cutting system's input parameters. This method is used to create multi-factor models, obtaining quantitative data from a suitable experimental design. Such models can be displayed graphically. In graphs, a response surface is used to evaluate how factors affect response, to explain the relationship between variables, and to show the combined effects of factors. Kırbaş et al. [17], Asilturk et al. [18].

RSM method consists of three stages. Firstly, physical experiments are carried out to obtain response values using experimental parameters combination. It means a decrease in costs in comparison to the number of tests performed using conventional methods with less and more efficient experiments. Searched intermediate response values could be determined in a short time. The relation between the input parameters and the reactions obtained is defined in the second stage as a quadratic or exponential polynomial. In the third stage, an analysis like ANOVA or surface graphics can determine the optimum points Abou-El-Hossein et al. [19]. Taguchi orthogonal array method provides requiring information by conducting limited experiments. Thus it, is time-energy-material saving method. The depth of cut is the heaviest coefficient that impacts the surface roughness, followed by the cutting speed and feed rate in case of milling of INVAR-36 Khanna et al. [20].

The correlation between parameters and their corresponding responses is typically given in RSM problems using the following quadratic polynomial Equation (1) Kırbas et al. [17].

$$\eta = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i} \sum_{j} \beta_{ij} X_i X_j + \varepsilon \qquad (1)$$

In the equation (1), η represents the estimated responses (Fx, Fy and Fz); β_0 is a constant; β_i and β_{ii} show the first and the second-degree encoded input parameters and β_{ij} are the coefficients of parameter interactions.

Figure 5 shows a 3-D surface plot showing the relationship between cutting method and cutting speed affecting Ra. For the cutting method on the X axis, 1 represents the conventional method and 2 represents the wiper method.

In Figure 6 and Figure 7, the cutting speed effect and cooling method factors on surface roughness are given as 3D surface graph and contour plot. For cooling method, 0 indicates dry cut and 100 indicates CO_2 cooling respectively.

During the machining of the Nilo36 alloy on the lathe, the forces Fx, Fy and Fz were also examined and a mathematical model was developed. In the ANOVA analysis given below, the factors affecting cutting speed, cutting method and cooling method were used and its effects on Fx force were calculated.

The performance of ANOVA model was 88.20%. Accordingly, the most important factor affecting Fx force emerges as cutting method. Then comes the cooling - cutting method duo and cooling method. According to the results of the analysis, the effect of cutting speed factor is much less than other factors.

The factors affecting the Fx force and their degree of influence are clearly seen in the pareto graph given in Figure 8. The factors affecting Fx force were determined as cutting speed, cutting - cooling method duo and cooling method.

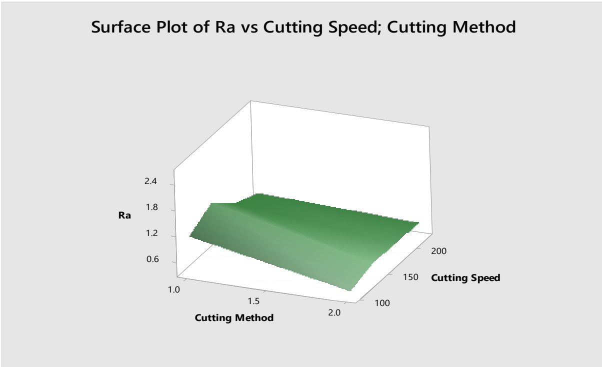

Figure 5. Surface plot of Ra vs cutting speed and cutting method

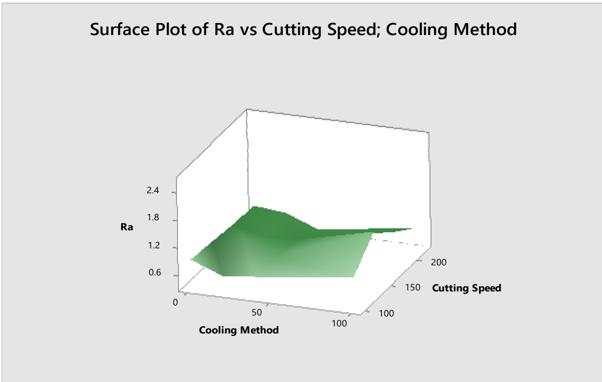

Figure 6. Surface plot of Ra vs cutting speed and cooling method

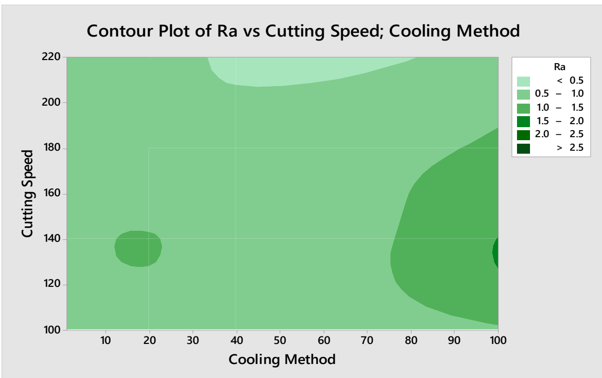

Figure 7. Contour plot of Ra vs cutting speed and cooling method

In Figure 9, factors and parameters affecting Fx force are given. It is seen that the lowest Fx values have been obtained at the lowest and highest cycles when conventional was selected as cutting method and MQL 40 ml was selected as cooling method. When using Wiper method, higher values of Fx force were measured compared to conventional method. When CO_2 was selected as cooling method, Fx force increases.

The results of ANOVA analysis to calculate the factors affecting Fy force are given below. The model performance value was found to be 77.01%, indicating that the model was acceptable.

Pareto analysis graph is given in Figure 8. The most decisive parameter for the Fy force is the cutting method. The cutting speed duo emerges as the second factor that crosses the pareto boundary.

Factors affecting Fx and Fy forces exhibit similar characteristics. The effect of the cooling method for Fy force is lower and uncertain than Fx. The effect of the cutting method is increased in the wiper method as in the Fx force and there is an obvious difference.

ANOVA analysis was performed to determine the factors affecting Fz force and 84.50% performance ratio was calculated for the developed model. This value is quite high and shows that the model is mathematically acceptable.

In the pareto graph given in Figure 11, it is obvious that the most obvious components for force Fz are the cooling method and the cutting method. However, the effect of cooling method was much higher than other effects.

It is seen that the lowest value for cooling method is obtained in MQL (40ml) process as in other force values. There is quite a difference between CO_2 and MQL method. As cutting speed value increases, Fz value decreases. Selecting conventional as cutting method leads to lower Fz force value than wiper method.

3. Artificial Neural Network Modelling and Developing an Interactive Interface

When the literature is examined, there are examples where cutting forces and cutting parameters are modelled with an artificial neural network [21-24]. However, none of these examples mention the development of the graphical user interface included in this study.

Ra, Fx, Fy and Fz values obtained by processing Nilo36 alloy were loaded into an artificial neural network consisting of 12 neurons and a total of 3 layers using MATLAB software.

The input parameters of the artificial neural network were determined as cutting speed, cutting method and cooling method. Ra, Fx, Fy and Fz values were estimated as output values. Figure 14 shows the input, output and latent layers of the trained neural network and the number of neurons in each layer.

Factors affecting the Fy force and parameter values are shown in Figure 10. The factors affecting Fz force and parameter values are given in Figure 12 and Figure 13.

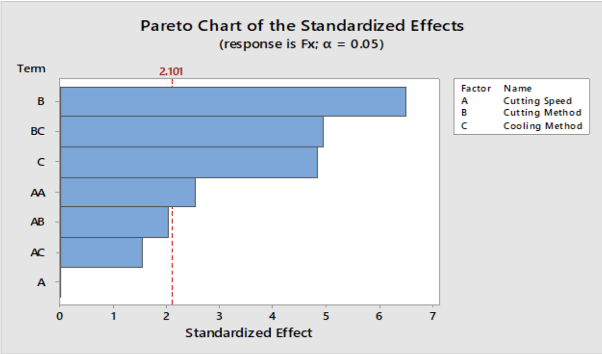

Figure 8. Pareto chart of the standardized effects on Fx force

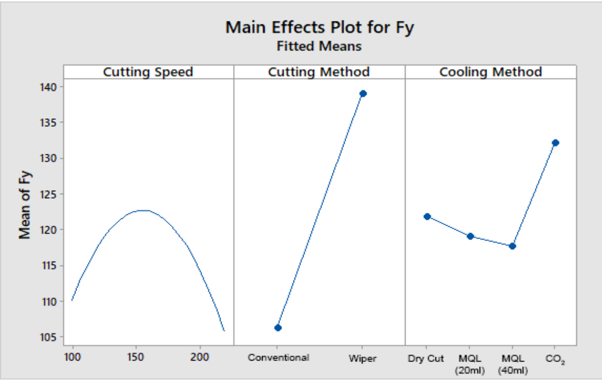

Figure 9. Main effects plot for Fx force

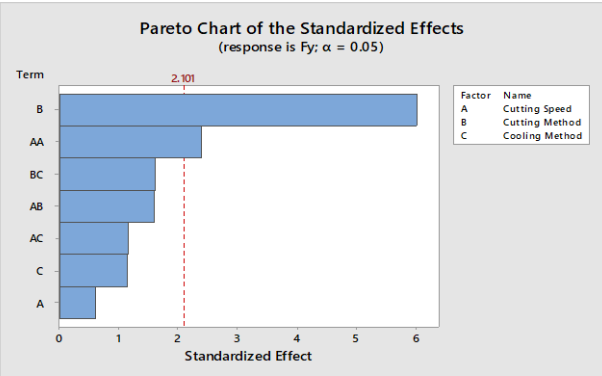

Figure 10. Pareto chart of the standardized effects on Fy force

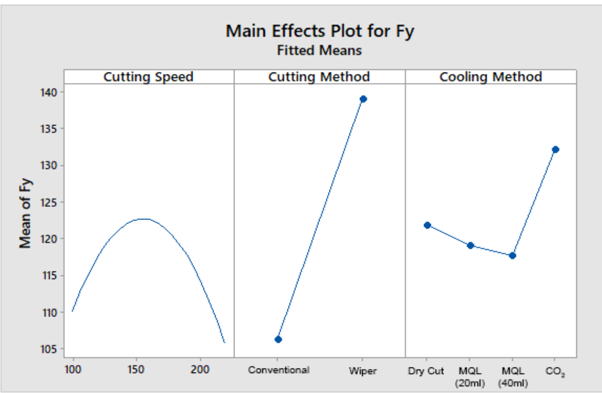

Figure 11. Main effects plot for Fy force

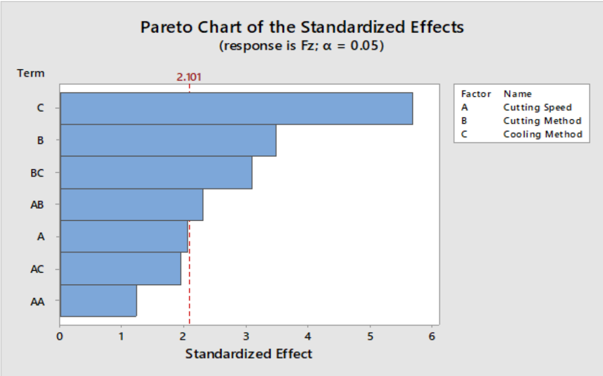

Figure 12. Pareto chart of the standardized effects on Fz force

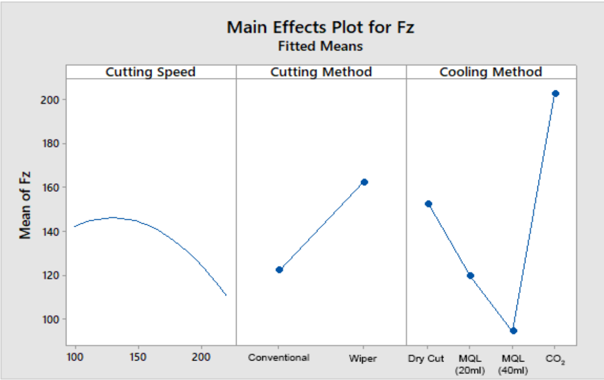

Figure 13. Main effects plot for Fz force

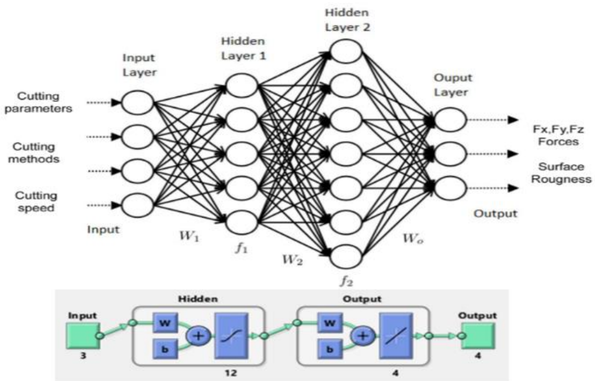

Figure 14. Structure of the trained Artificial Neural Network

To train neurons in the artificial neural network, 70% of the data were reserved for training, 15% of the data were for validation and 15% of the data were for testing. Levenberg-Marquardt method was used for the training of neurons. The Levenberg-Marquardt algorithm is generally used to solve nonlinear least squares problems [25]. Two numerical minimization algorithms are combined into the Levenberg-Marquardt algorithm: the method of gradient descent and the method of Gauss-Newton. The sum of the square errors in the gradient descent method is minimized by updating the parameters in the direction of the steepest descent. The sum of the square errors in the Gauss-Newton method is reduced by assuming that the function of the least squares is locally quadratic in the parameters and finding the minimum of that quadratic. When the parameters are far from their appropriate value, the Levenberg-Marquardt method behaves more like a gradient-descent technique and acts more like the Gauss-Newton method when the parameters are close to their optimal value. The results obtained are given in Table 2.

The R value for all training, validation and testing procedures was found to be 0.99 and above. R value close to 1 shows that the model performance is very high. The error distribution of the developed artificial neural network model has been quite smooth and is given in Figure 15.

The regression results of the artificial neural network are also given in Figure 16. The fact that the data points are located on the diagonal and not scattered shows the success of the developed model.

Cutting speed and MQL values can be set to a desired value with sliding bar components. When the calculate button is pressed, the values of Ra, Fx, Fy and Fz which the artificial neural network has predicted with high performance can be read on the interface with the input values received from the user. With the developed interface, the input parameters can be changed and the surface roughness and axial forces change as a result of machining can be easily examined.

MATLAB App Designer tool was used to develop an interactive interface for the end users. With this tool, the user can select the cooling type in the cutting parameters section and the processing method in the cutting methods section via radio buttons. The screenshot of the developed interface is given in Figure 17.

Table 2. Performance parameters for the developed ANN

Neural Network Results	MSE	R
Training	24.239	0.998
Validation	36.046	0.996
Testing	46.788	0.997

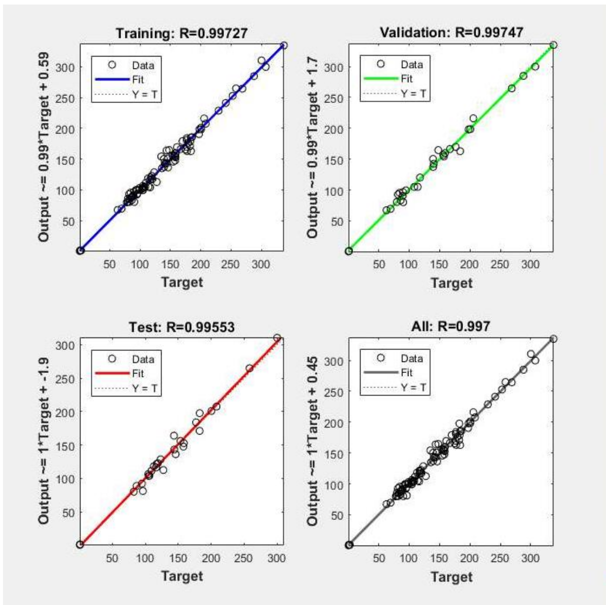

Figure 15. Error histogram for the ANN

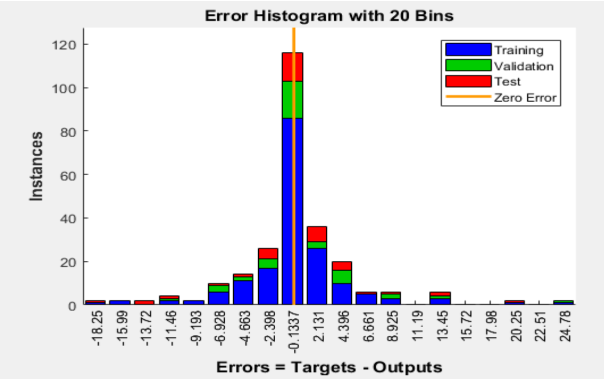

Figure 16. Regression results for the developed model.

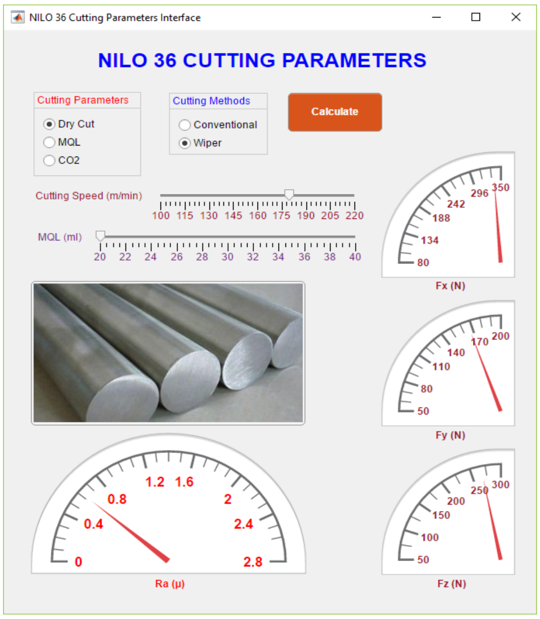

Figure 17. The interactive interface for Nilo 36 cutting parameters

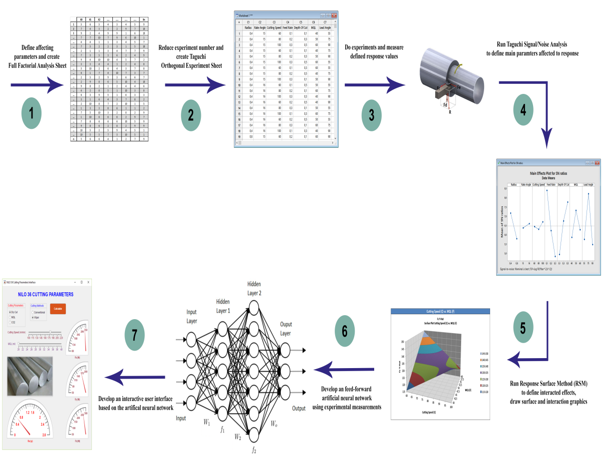

Figure 18. The graphical summary of experimental workings

4. Conclusion

In this study, Nilo 36 superalloy which is widely used in avionics sector has been processed by using 2 different methods (conventional and wiper) at different cutting speeds between 100 and 220 rpm. Dry cut, MQL (20ml and 40ml) and CO_2 cooling methods were applied during the cutting process and what effects the machining parameters have on the surface and the forces were investigated. A full factorial analysis was performed to plan the parameters to be measured before the experimental measurements were performed. Then, Taguchi method was used to reduce the number of experiments and the required number of experiments was determined as 32.

The results obtained from the measurements were examined by response surface methodology and ANOVA analysis and the effect levels of the factors affecting the results were calculated. The results are presented in graphs. After all these analyses, the results were loaded onto a feed-forward artificial neural network and it has been trained with measurement data. The performance of the trained network was calculated in terms of MSE and R parameters and the R value was found as 0.99.

After the artificial neural network developed, it is connected to an interface where the user can interact and see the interaction results instantly on the screen. The results obtained within the scope of the study, developed artificial neural network model and interface application revealed a unique and useful tool. Thus, the user can examine the effect of all cutting parameters on cutting forces and surface roughness easily.

Declaration

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The authors also declared that this article is original, was prepared in accordance with international publication and research ethics, and ethical committee permission or any special permission is not required.

Author Contributions

G. Basmacı and M. Ay both realized the experimental setup and all measurements. İ. Kırbaş also developed the artificial neural network model and the interactive user interface.

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Nomenclature

MQL	: Minimum quantit lubrication
Ra	: Surface roughness (µm)
Fx	: Force applied to “x” axis (N)
Fy	: Force applied to “y” axis (N)

Fz	: Force applied to “z” axis (N)
N	: Cutting force (N)
MSE	: Mean squared error
rpm	: Revolutions per minute

References

1. Ha, T.K. and Min, S.H., *Effect of C Content on the Microstructure and Physical Properties of Fe-36Ni Invar Alloy*, Eco-Materials Processing and Design XV, Trans Tech Publications Ltd, 2015. p. 293–296.
2. Maranhão, C. and Davim, J.P., *Finite Element Modelling of Machining of AISI 316 Steel: Numerical Simulation and Experimental Validation*, Simulation Modelling Practice and Theory, 2010. **18**(2): p. 139–156.
3. Tekaslan, Ö., Gerger, N., Günay, M. and Şeker, U., *Examination of the Cutting Forces of AISI 304 Austenitic Stainless Steel in the Turning Process with Titanium Carbide Coated Cutting Tools*, Pamukkale Uniiversitesi Muhendislik Bilim. Dergisi, 2007. **13**(2): p. 135–144.
4. Li, D.W., Chen, H.T., Xu, M.H. and Zhong,C.M., *Study on Turning Parameter Optimization of Austenitic Stainless Steel, Mechanical Engineering and Green Manufacturing*, Trans Tech Publications Ltd, 2010. p. 1829–1833.
5. Diniz, A.E., Ferreira, J.R. and Filho, F.T., *Influence of Refrigeration/Lubrication Condition on SAE 52100 Hardened Steel Turning at Several Cutting Speeds*, International Journal of Machine Tools and Manufacture, 2003. **43**(3): p. 317–326.
6. Kaladhar, M., Subbaiah, K. and Rao, Ch.S., *Optimization of Surface Roughness and Tool Flank Wear in Turning of AISI 304 Austenitic Stainless Steel with CVD Coated Tool*, Journal of Enginering Science Technology, 2013. **8**: p 165–176.
7. Dirviyam, P.S. and Palanisamy, C., *Optimization of Surface Roughness of AISI 304 Austenitic Stainless Steel in Dry Turning Operation Using Taguchi Design Method*, Journal of Enginering Science Technology 2010. **5**: p 1-9.
8. Basmaci, G., Ay, M. and Kırbaş, İ., *Optimisation of Machining Parameters ın Turning 17-4 Ph Stainless Steel Using the Grey-Based Taguchi Method*, Erzincan Üniversitesi Fen Bilimleri Enstitüsü Dergisi 2017. **10**(2): p. 243–254.
9. Ay, M., *Optimisation of Machining Parameters in Turning AISI 304L Stainless Steel by the Grey-Based Taguchi Method*, Acta Physica Polonica A, 2017. **131**: p. 349–354.
10. Basmaci, G., Ay, M., *Optimization of Cutting Parameters, Condition and Geometry in Turning AISI 316L Stainless Steel Using the Grey-Based Taguchi Method*, Acta Physica Polonica A, 2017. **131**: p. 354–359.
11. Dhar, N.R., Kamruzzaman, M. and Ahmed, M., *Effect of Minimum Quantity Lubrication (MQL) on Tool Wear and Surface Roughness in Turning AISI-4340 Steel*, Journal of Matereials Processing Technoogy, 2006. **172**(2): p. 299–304.
12. Itoigawa, F., Childs, T.H.C., Nakamura, T. and Belluco, W., *Effects and Mechanisms in Minimal Quantity Lubrication Machining of an Aluminum Alloy*, Wear., 2006. **260**(3): p. 339–344.
13. Qin, S., Li, Z., Guo, G., An, Q., Chen, M. and Ming, W., *Analysis of Minimum Quantity Lubrication (MQL) for Different Coating Tools during Turning of TC11 Titanium Alloy*, Materials, 2016. **9**(10): p. 1-13.
14. Sampaio, M.A., Machado, Á.R., Laurindo, C.A.H., Torres, R.D. and Amorim, F.L., *Influence of Minimum Quantity of Lubrication (MQL) When Turning Hardened SAE 1045 Steel: A Comparison with Dry Machining*, International Journal of Advanced Manufacturing Technology, 2018. **98**(1):p. 959–968.
15. Basmaci, G., Kurt, M., Ay, M. and Bakir, B., *Optimization of the Effects of Machining Parameters in Turning on Hastelloy C22 Composition through Taguchi Response Surface Methodology*, Acta Physica Polonica A, 2018. **134**, p. 28–31.
16. Mostafa, Y., Elbestawi, M.A., Veldhuis, S. C., *Density and mechanical properties in selective laser melting of Invar 36 and stainless steel 316L*, Journal of Materials Processing Technology, 2019. **266**: p. 397-420.
17. Kırbaş, İ., Peker, M., Basmaci, G. and Ay, M., *Predictive Modeling and Optimization of Cutting Forces Through RSM and Taguchi Techniques in the Turning of ASTM B574 (Hastelloy C-22), Handbook of Research on Predictive Modeling and Optimization Methods in Science and Engineering*, IGI Global, 2018. p. 398–417,
18. Asiltürk, İ., Neşeli, S. and İnce, M.A., *Optimisation of Parameters Affecting Surface Roughness of Co28Cr6Mo Medical Material during CNC Lathe Machining by Using the Taguchi and RSM Methods*, Measurement, 2016. **78**:p. 120–128.
19. Abou-El-Hossein, K.A., Kadirgama, K., Hamdi, M. and Benyounis, K.Y., *Prediction of Cutting Force in End-Milling Operation of Modified AISI P20 Tool Steel*, Journal of Materials Processing Technology, 2007. **182**(1–3): p. 241–247.
20. Navneet, K., Gandhi, A., Nakum, B., Anil, S., *Optimization And Analysis of Surface Roughness for Invar-36 End Milling Operations*, Materials Today, 2018. **5**: p. 5281-5288.
21. Dahbi, S., Ezzine, L., Moussami, H.E., *Modeling of cutting performances in turning process using artificial neural networks*, International Journal of Engineering Business Management, 2017. **9**: p. 184-196.
22. Çakiroğlu, R., Yağmur, S., Acir, A., Şeker, U., *Modelling of Drill Bit Temperature and Cutting Force in Drilling Process Using Artificial Neural Networks*, 2017. **20**(2): p. 333-340.
23. Kılıç, F., *Effects of three drying methods on kinetics and energy consumption of carrot drying process and modeling with artificial neural networks*, Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 2020. p. 1-18.
24. Filippis, L.A.C.D., Serio, L.M., Facchini, F., Mummolo, G., *ANN Modelling to Optimize Manufacturing Process*, InTech, 2018. p. 32-38.
25. Gavin, H.P., *The Levenberg-Marquardt algorithm fornonlinear least squares curve-fitting problems*, Lecture Notes,DukeUniversity,2020.http://people.duke.edu/~hpgavin/ce281/lm.pdf.