A New Nelder-Mead Optimization Method for the End Milling Process's Energy Efficiency Parameters Based on Neuro-regression Modeling

Rand R. Wilcox

Izmir Katip Celebi University, Department of Mechanical Engineering, Cigli, Izmir, Turkey

Article Info

Received: 20-02-2025 ***Revised:14-03-2025*** ***Accepted:20-04-2025*** ***Published:29-05-2025***

Abstract

The fast depletion of energy sources worldwide is causing a growing number of global issues every day. One of engineering's objectives is to stop this from happening by creating creative solutions to the world's rapidly declining energy use. Reducing the energy usage of the production-related machinery might be a solution. In order to lower energy usage, a novel design method based on the neuro-regression approach and non-linear regression modeling was presented in this work as an alternative to Taguchi design. To investigate the impact of the constraint circumstances on energy consumption, a cutting parameter optimization model was developed. Cutting power, part surface roughness, and tool life were treated as objective functions (constraint conditions). Initially, design factors in end milling were used to build the multiple non-linear regression models. Spindle rotational speed, feed rate power, axial cut depth, radial cut depth, and cutting speed were identified as these design factors. This optimization modeling then brought the goal functions to the appropriate minimum optimum values. By examining

many optimization models used to improve the minimal objective functions—which are crucial in lowering energy consumption in end milling—accurate modeling was accomplished in this work due to the optimization model constructed using design variables. Following optimization, 110.791 was determined to be the maximum value. Several direct search strategy alternatives were used to maximize and reduce findings at the conclusion of the investigation.

Keywords: End milling; energy efficiency; optimization.

Introduction

Due to the depletion of natural energy supplies brought on by growing global energy crises and the ensuing climate change, the industrial sector has been forced to reduce energy use and improve energy efficiency. Since manufacturing is one of the sectors that uses the most energy, there is a lot of room to consider, evaluate, and test energy-saving solutions. In the manufacturing sector, energy resources must be utilized appropriately, and energy efficiency must be continually increased. For instance, energy may be saved in machine tools by improved machine utilization, including machining strategy and process parameter selection, or an appropriate energy-oriented machine tool component design [1]. One of the most important sectors is manufacturing, which includes machining as a major component. The broad definition of machining is the removal of material from a workpiece or item in the form of chips. Different methods may be used to manufacture a mechanical item without producing noticeably different outcomes.

However, the production and shape of components heavily relies on machining techniques like end milling. Slots, shoulders, die cavities, curves, profiles, and other milling components may be made by end milling. It is often used to make parts for automobiles, airplanes, etc. In milling operations, machine tools are the main sources of carbon dioxide emissions and power consumption End milling machines use a lot of energy because of this. Because cutting settings in end milling may improve energy efficiency, it is crucial to investigate energy parameters. Surface roughness, cutting force, cutting power, tool life, and material removal rate have all been utilized as optimization criteria in a number of published research on cutting parameter optimization [3]. Depending on the machining objective and the cutting tool selection, a variety of parameter combinations, including feed rate, spindle speed, and axial or radial depth of cut, may provide different outcomes in terms of machined surface quality and tool wear [4]. Additionally, the tool's lifespan and surface roughness will vary depending on the combination of cutting settings [5]. Increasing the machine tool's lifespan and achieving the lowest possible surface

roughness and cutting power usage are two ways to improve energy efficiency. To get at these conclusions, several investigations have been carried out. These investigations used a variety of optimization techniques. A method for optimizing cutting settings to reduce direct energy consumption during turning was described by Velchev et al. [6]. In order to minimize electrical energy consumption while turning AISI 6061 T6 using the Taguchi technique, Negrete-Compesto [7] modified the cutting parameters (cutting speed, cutting depth, and feed rate). An energy consumption model including machine setup, machining, tool change, and tool creation was developed by Mativenga and Rajemi [8] for a single pass turning operation. Under a minimal energy criteria, the energy model may choose the best tool for cutting speed and economic life. If machine stand-by power was not used to replace power consumption during the tool-changing activities in their research, their model may be improved. The presented minimal energy criteria is used to enhance and implement an approach for choosing the best cutting circumstances. The goal of Rajemi et al.'s research [9] is to enhance a unique model and method for maximizing a machined product's energy footprint. In order to minimize energy usage and, thus, lower energy costs and environmental impact, they established the crucial factors. Asilturk et al. [10] created a surface roughness model of medical alloy produced on a CNC lathe and used response surface methods to improve cutting parameters (spindle speed, feed, depth of cut, and tool radius). The improvement of turning cutting settings to reduce electrical energy consumption and increase tool life was discussed in work by Bhushan [11]. The electrical energy consumption and tool life models for the cutting parameters were established using the response surface methodology (RSM). The study's findings demonstrated that using the ideal cutting settings might result in a 13.55% decrease in electrical energy consumption and a 22.12% improvement in tool life. In order to improve energy-saving settings and assess energy efficiency, Li et al. [12] used Taguchi, the response surface approach, and multi-objective particle swarm optimization. They also chose particular energy consumption. The findings demonstrated that the most important element in reducing electrical energy use is feed rate. The least amount of electrical energy is used when the feed rate is greater. This paper's primary goal is to use a novel neuro-regression analysis to improve end milling energy efficiency by minimizing the tool's surface roughness and cutting power while maximizing its lifespan. Additionally, updated versions of the Nelder-Mead algorithm and the direct search technique have been extensively tested and shown.

1. Materials and Methods

1.1. Optimization

The notion of optimization, which is the inherent

attribute of achieving the best or most beneficial (minimum or maximum) outcome from a given situation, has enormous significance in human affairs and natural laws. Since the beginning of civilization, the human species has faced countless technological obstacles, including determining the best answer to various issues such as control technologies, power sources constructions, economic applications, mechanical engineering, and energy distribution, amongst others. Optimization problems are ubiquitous in science, and even in our daily lives, we optimize how we get to work every morning or how we should navigate to a new place. There is an objective you want to either maximize or minimize in an optimization problem, and there may be constraints within which you need to operate. This shows how design optimization may aid not just in the human activity of producing optimal designs for products, processes, and systems but also in the understanding and analysis of mathematical and physical phenomena and the solution of mathematical problems. [13]

1.1.1. Regression analysis

Regression analysis is one of the reliable tools frequently used in economics, science, and engineering. Regression analysis allows us to determine which variables have an effect on the subject we are studying. It helps us determine whether we should improve or ignore these variables. The purpose of regression analysis is to express the response variable as a function of the predictive variables. The duality of the fit and the accuracy of the result depend on the data used [14].

Regression analysis can be examined in different categories according to the number and linearity of the predictive variables: Simple and multiple regression; linear and non-linear regression. The most common form of regression analysis is linear regression, it is a model that assesses the relationship between a dependent variable and an independent variable. Multiple linear regression analysis is essentially similar to the simple linear model, except that multiple independent variables are used in the model. When the model function is not linear in the parameters, an iterative procedure must minimize the sum of squares. This introduces many complications, which are summarized in differences between linear and non-linear least squares [15].

1.1.2. Neuro-regression approach

To increase the accuracy of the predictions, a technique that combines the strengths of regression analysis and Artificial Neural Network (ANN) is utilized in the modeling step. With this approach, all the data in our table are divided into training, testing, and validation, approximately 80%, 15%, and 5%. However,

it is used by choosing an appropriate regression model. If we have only one variable, the simple regression model is used here. If there is more than one variable, a multiple regression model is used. If the variables contain non-linear terms, the non-linear regression model should be used. First, in the training part, the coefficients in the regression model are adjusted to minimize the error between the experimental and predicted values. Then, the inconsistencies of the regression model in the testing part and the validation part are minimized, and estimated results are tried to be reached. After obtaining the appropriate values, each variable's maximum and minimum values in the given ranges are calculated [14, 15].

In the Mathematica code, some terms are used. "Length" will give you the number of data sets in the experiment. The sum of squares total, denoted SST, is the squared differences between the observed dependent variable and its mean. The sum of squares error or SSE is the summation of each element's testing and prediction response data. "Ybar" is the mean of the training data [15]

1.1.3. Regression models

In this study, different models were used to reach the appropriate values. Some of them are multiple linear regression, and some are non-linear regression models. The table below contains these models.

1.1.4. Problem definition

The main problem in this study is to obtain suitable results due to optimizing the objective functions used to increase energy efficiency. Tables 2-4 give the information about the results of surface roughness and cutting power of the machine, the lifetime of the machine, and constraints of design variables of objective functions, respectively. Surface roughness and cutting power should be minimized, and the lifetime of the machine should be increased. These outputs depend on some predictive variables. As a result of controlling these predictive variables, maximum or minimum values of outputs can be reached. These constraint (predictive) variables are feed rate, spindle speed, axial and radial depth of cut, and cutting speed. Output 1 (surface roughness) and output 2 (cutting power) have the same constraint variables. These variables are feed rate, spindle speed, axial and radial depth of cut. The constraint variables of output 3 (lifetime of the machine) are feed rate, spindle speed, axial and radial depth of cut, and cutting speed. Output 1 and output 2 have 25 different data sets; Output 3 has nine different data sets. Therefore, appropriate data must be captured for these output values. For this purpose, at the end of the neuro-

regression approach, the R^2training value must be greater than 0.90, the R^2testing value must be greater than 0.85, and finally, the R^2validation value must be greater than 0.85 to fit the accurate model. If we obtain these values, the appropriate model is considered to have been reached.

Table 2. *Data table of output 1 (surface roughness) and output 2 (cutting power).* [2]

No.	n (r/min)	vf (mm/min)	ap (mm)	ae (mm)	Ra (μm)	Power (kW)
1	800	240	0.5	2	2.141	0.020
2	800	290	1	3	2.793	0.060
3	800	340	1.5	4	2.837	0.100
4	800	380	2	5	3.512	0.200
5	800	420	2.5	6	4.013	0.300
6	1200	240	1	4	2.171	0.069
7	1200	290	1.5	5	2.331	0.134
8	1200	340	2	6	2.424	0.244
9	1200	380	2.5	2	1.924	0.119
10	1200	420	0.5	3	2.187	0.047
11	1600	240	1.5	6	2.024	0.140
12	1600	290	2	2	1.897	0.086
13	1600	340	2.5	3	1.799	0.155
14	1600	380	0.5	4	2.17	0.060
15	1600	420	1	5	2.373	0.150
16	2000	240	2	3	1.533	0.143
17	2000	290	2.5	4	1.565	0.253

18	2000	340	0.5	5	1.684	0.068
19	2000	380	1	6	1.76	0.178
20	2000	420	1.5	2	1.741	0.113
21	2400	240	2.5	5	1.497	0.290
22	2400	290	0.5	6	1.728	0.115
23	2400	340	1	2	1.415	0.085
24	2400	380	1.5	3	1.321	0.185
25	800	240	0.5	2	2.141	0.020

Table 3. *Output 3 (lifetime of machine tool)Tlife.*

No.	n (r/min)	vf (mm/min)	ap (mm)	ae (mm)	Vc (m/s)	Tlife (min)
1	1300	120	2.5	3	0.816	80
2	1300	140	3	6	0.816	62
3	1300	180	3.5	9	0.816	53
4	1700	120	3	9	1.068	49
5	1700	140	3.5	3	1.068	55

6	1700	180	2.5	6	1.068	50
7	2100	120	3.5	6	1.319	20
8	2100	140	2.5	9	1.319	30
9	2100	180	3	3	1.319	25

Table 4. *Constraints of design variables.*

Constraints of Design Variables For Output 1 (Surface Roughness) and Output 3 (Cutting Power)	Constraints of Design Variables For Output 3 (Lifetime of Machine)
800 < Spindle Rotation Speed (n) < 2400 240 < Feed Rate (vf) < 420 0.5 < Radial Cut Depth (ap) < 2.5 2 < Axial Cut Depth (ae) < 6	1300 < Spindle Rotation Speed (n) < 2100 120 < Feed Rate (vf) < 180 2.5 < Radial Cut Depth (ap) < 3.5 3 < Axial Cut Depth (ae) < 9 0.816 < Cutting Speed (Vc) < 1.319

1.1.4.1. Optimization process of problem

The neuro-regression approach should be used as a first step. The data sets of the outputs should be divided into 80%, 15%, and 5% as training, testing, and validation randomly. Then the appropriate regression

models should be used respectively. In this study, non-linear regression modeling was used for three different outputs. The suitable models for outputs 1-3 are the second-order non-linear, third-order non-linear, and second-order trigonometric non-linear regression functions. Then, the regression coefficients were calculated in line with the regression analysis. Mathematica's *NonlinearModelFit* solver was applied to each model. Some values were obtained as a result of the applied neuro-regression approach. Then, the maximum or minimum desired values of the objective functions were calculated. The modified versions of the Nelder-Mead algorithm have been thoroughly tested on output 1 and output 2 to minimize their results and output 3 to maximize its result more and shown in different scenarios.

2. Result and Discussion

In this study, the neuro-regression approach was used. Different trials have been made to achieve appropriate results. Moreover, as a result of these trials, suitable models have been reached in order to reach the minimum and maximum values of the objective functions. Inputs and outputs are taken from tables as experimental data sets. It is known that constraint variables directly affect the results of the objective function. In addition to this, appropriate values were tried to be reached as a result of each model. Our first output, the second order non-linear regression model, which gives the most relevant results among the different models, was found suitable and applied for the surface roughness value. As a result of different models applied for our second output, cutting power, the third-order non-linear regression model gave appropriate results. Minimum values have been found for these two objective function values considering different scenarios.

Table 5. *Results of output 1.*

Model of Output 1	R² training	R² testing	R² validation	Maximum	Minimum
SON	0.997314	0.92675	0.883081	4.83422	-2.97059

Table 6. *Results of output 2.*

Model of Output 2	R² training	R² testing	R² validation	Maximum	Minimum
TON	1	0.90423	0.942348	0.488696	0.0275759

Table 7. *Results of output 3.*

Model of Output 3	R² training	R² testing	R² validation	Maximum	Minimum
L	1	0.1505	0.646551	80.2801	15.1206
SON	1	0.7819	-0.08065	80.6516	15.1206
TON	1	0.2675	-1.09194	92.2776	3.67565
FOLN	1	-0.3127	-0.02565	85.6958	0.225738
SOLN	1	0.6429	0.619779	88.2654	8.67709
FOTN	1	0.0351	0.708655	87.8171	-0.536101
SOTN	1	-1.4135	0.768006	102.188	9.56213
HYBRID	1	0.4996	0.996241	110.791	2.43927

Eight different models have been implemented for the third output, the lifetime of the machine. Due to the limited data set of the objective function, relevant results could not be reached. For this reason, the second-order trigonometric non-linear

regression model, which is the modeling that gives the closest results we want to obtain, was used. The following tables show the appropriate models for objective functions and their resulting values, R^2, R^2, R^2.Results are maximized and minimized for the best models. As a result of these processes, suitable design variables were determined to bring each output to appropriate values. For each model, the design variables required to achieve optimum results are given in Table 8-10.

Table 8. *Design variables values for output 1.*

Model for Output 1	Design Variables Values for Nminimize			
SON	x1 → 800.	x2 → 240.	x3 → 2.5	x4 → 2.

Table 9. *Design variables values for output 2.*

Model for Output 2	Design Variables Values for Nminimize			
TON	x1 → 800.	x2 → 240.	x3 → 2.5	x4 → 2.

Table 10. *Design variables values for output 3.*

Model for Output 3	Design Variables Values for Nminimize				
SOTLN	x1 → 1697	x2 → 180.	x3 → 3.5	x4 → 9.	x5 → 1.32

Table 11. *Results of optimization based on Modified Nelder-Mead algorithm for output 1.*

Model for	Scenario Number	Algorithm options	Outputs	Design
SON	1	Default	-2.97059	x1 → 800. x2 → 240.x3 → 2.5 , x4 → 2.
		Random Seed →	-2.97059	
		Contract Ratio	-2.97059	
		Reflect Ratio	-2.97059	
	2	Default	-1.04013	

		Random Seed	-1.04013	
		Contract Ratio	-1.04013	
		Reflect Ratio	-1.04013	$x1 \to 801, x2 \to 241, x3 \to 2, x4 \to 3$
	3	Default	-1.33004×10^{245}	$x1 \to -5.285 \times 10^{119}, x2 \to 240.$ $x3 \to 4.709 \times 10^{122}$ $x4 \to 2.121 \times 10^{121}$
	$x3 \geq 0.5 \| x3 \leq 2.5,$ $x4 \geq 2 \| x4 \leq 6$	Random Seed	$-9.988998 \times 10^{235}$	$x1 \to -1.44 \times 10^{115}$ $x2 \to -1.3 \times 10^{116}$ $x3 \to 1.290 \times 10^{118}$ $x4 \to 5.81 \times 10^{116}$
		Contract Ratio	$-9.988998 \times 10^{235}$	$x1 \to -1.5 \times 10^{115}$ $x2 \to -1.38 \times 10^{116}$ $x3 \to 1.290 \times 10^{118}$ $x4 \to 5.81 \times 10^{116}$
		Reflect Ratio	$-9.812743 \times 10^{276}$	$x1 \to -4.605 \times 10^{135}$, $x2 \to 240.$ $x3 \to 4.053 \times 10^{138}$ $x4 \to 6$

Table 12. *Results of optimization based on Modified Nelder-Mead algorithm for output 2.*

Model for Output 2	Scenario Number	Algorithm options	Outputs	Design Variables
TON	1 $800 < x1 < 2400$ $240 < x2 < 420$ $0.5 < x3 < 2.5$ $2 < x4 < 6$	Default	0.027576	$x1 \to 800. x2 \to 240. x3 \to 2.5 x4 \to 2.$
		Random Seed → 111	0.004081	$x1 \to 2400. x2 \to 420. x3 \to 0.5 x4 \to 2.$
		Contract Ratio → 0.9	0.004081	$x1 \to 2400. x2 \to 420. x3 \to 0.5 x4 \to 2.$
		Reflect Ratio → 2	0.004081	$x1 \to 2400. x2 \to 420. x3 \to 0.5 x4 \to 2.$
	2 $800 < x1 < 2400$ $240 < x2 < 420$ $0.5 < x3 < 2.5$	Default	0.060015	$x1 \to 801 x2 \to 284 x3 \to 1 x4 \to 3$
		Random Seed → 111	0.056212	$x1 \to 801 x2 \to 241 x3 \to 2 x4 \to 3$
		Contract Ratio →	0.056212	

	$2 < x4 < 6$ $\{x1, x2, x3, x4\} \in$ Integers	0.7		$x1 \to 801 x2 \to 241 x3 \to 2 x4 \to 3$
		Reflect Ratio → 2	0.056212	$x1 \to 801 x2 \to 241 x3 \to 2 x4 \to 3$
	3 $x1 \geq 800 \| \| x1 \leq 2400$, $x2 \geq 240 \| \| x2 \leq 420$, $x3 \geq 0.5 \| \| x3 \leq 2.5$, $x4 \geq 2 \| \| x4 \leq 6$	Default	-1.22984×10^{620}	$x1 \to 2400 x2 \to 3.3142 \times 10^{206}$ $x3 \to 0.5 x4 \to 4.72 \times 10^{207}$
		Random Seed → 50	-1.22984×10^{620}	$x1 \to 2400 x2 \to 3.3142 \times 10^{206}$ $x3 \to 0.5 x4 \to 4.72 \times 10^{207}$
		Contract Ratio → 0.5	-1.22984×10^{620}	$x1 \to 2400 x2 \to 3.3142 \times 10^{206}$ $x3 \to 0.5 x4 \to 4.72 \times 10^{207}$
		Reflect Ratio → 1	-1.22984×10^{620}	$x1 \to 2400 x2 \to 3.3142 \times 10^{206}$ $x3 \to 0.5 \quad x4 \to 4.72 \times 10^{207}$

Table 13. *Results of optimization based on Modified Nelder-Mead algorithm for output 3.*

Model for Output 3	Scenario Number	Algorithm options	Outputs	Design Variables
	1 $1300 < x1 < 2100$ $120 < x2 < 180$ $2.5 < x3 < 3.5$ $3 < x4 < 9$ $0.816 < x5 < 1.319$	Default	110.791	$x1 \to 1709.03 x2 \to 120.$ $x3 \to 3.5 x4 \to 3 x5 \to 1.319.$
		Random Seed → 111	110.791	$x1 \to 1709.03 x2 \to 120.$ $x3 \to 3.5 x4 \to 3 x5 \to 1.319.$
		Shrink Ratio → 1	110.791	$x1 \to 1709.03 x2 \to 120.$ $x3 \to 3.5 x4 \to 3 x5 \to 1.319.$
		Expand Ratio → 3	110.791	$x1 \to 1709.03 x2 \to 120.$ $x3 \to 3.5 x4 \to 3 x5 \to 1.319.$

2 $1300 < x1 < 2100$ $120 < x2 < 180$ $2.5 < x3 < 3.5$ $3 < x4 < 9$ $0.816 < x5 < 1.319$ $\{x1, x2, x3, x4, x5\} \in$ Integers	Default	98.3408	x1 → 1332x2 → 139. x3 → 3x4 → 5x5 → 1
	Random Seed → 300	98.3534	x1 → 1464x2 → 140 x3 → 3x4 → 5x5 → 1
	Shrink Ratio → 3	98.3534	x1 → 1464x2 → 140 x3 → 3x4 → 5x5 → 1
	Expand Ratio → 3	98.3534	x1 → 1464x2 → 140 x3 → 3x4 → 5x5 → 1

Conclusion

The goal of this research was to extend the machine's lifespan while reducing cutting power and surface roughness. For cutting power and surface roughness, there were twenty-five data sets and four distinct variables. There were nine data sets and five distinct variables during the life span. Finding an appropriate regression model that can provide us with the required optimal output values based on the variables was the goal here. In order for the R2 value to be larger than 0.90, the R2 value to be greater than 0.85, and the R2 value to be greater than 0.85, the neuro-regression technique produced an adequate regression model. Conveniently, these values for output 1 (surface roughness) were 0.997314, 0.927675, and 0.883081 for R2, R2, and R2, respectively. The second-order non-linear regression model was used because the target values were determined to be appropriate. Following optimization, a minimum value of -2.97059 was discovered.

These results were found for output 2 (cutting power): R2 = 1, R2 = 0.90423, and R2 = 0.94235. The third-order non-linear regression model was used because the intended values were determined to be appropriate. Following optimization, 0.0275759 was determined to be the lowest value. These results were obtained for output 3 (the machine's lifespan), when R2 is equal to 1, R2 is equal to 0.4996, and R2 is equivalent to 0.996241. The lack of many data sets for output 3 prevented the development of an appropriate model. Rather, a model that provides values that are closer to the intended values was used. The second-

order trigonometric non-linear regression model was used since the intended values were found to be closer. Following optimization, 110.791 was determined to be the maximum value. Several direct search strategy alternatives were used to maximize and reduce findings at the conclusion of the investigation. After applying a few situations, it was discovered that the first scenario was more suited for output 3, while the third scenario was better suited for outputs 1 and 2.

References

[1] "Energy oriented multi cutting parameter optimization in face milling," by P. Albertellia, A. Kesharia, and A. Matta Journal of Cleaner Production, volume 137, pages 1602–1618, 2016

[2] L. Zhoua, J. Lia, F. Lia, G. Mendisb, and J. W. Sutherlandb, "Optimization parameters for energy efficiency in end milling," PROCEDIA CIRP, vol. 69, pp. 312-317, Copenhagen, Denmark, 2018.

[3] R. Kumar, P. S. Bilga, and S. Singh, "Multi-objective optimization using different methods of assigning weights to energy consumption responses, surface roughness and material removal rate during rough turning operation," Journal of Cleaner Production, vol.164, pp.45-57, 2017

[4] B. A. Khidhir, and B. Mohamed, "Analyzing the effect of cutting parameters on surface roughness and tool wear when machining nickel-based Hastelloy – 276.Materials Science and Engineering Conference Series, Volume 17, pages 012043, 2011.

[5] J. Ribeiro, H. Lopes, L. Queijo, and D. Figueiredo, "Taguchi method optimization of cutting parameters to reduce surface roughness in the end milling process."Periodica Polytechnica. Engineering. Mechanical Engineering; Budapest, vol. 61, pp. 30-35, 2017.

[6] S. Velchev, I. Kolev, K. Ivanov, and S. Gechevski, "Empirical models for specific energy consumption and optimization of cutting parameters for minimizing energy consumption during turning," J. Clean. Prod, vol. 80, pp. 139-149, 2014.

[7] C. C. Negrete, "Optimization of cutting parameters for minimizing energy consumption in turning of AISI 6061 T6 using Taguchi methodology and ANOVA," Journal of Cleaner Production, vol. 53, pp. 195-203, 2013.

[8] "Calculation of optimal cutting parameters based on minimum energy footprint," CIRP Ann Manuf Technol, vol. 60, pp. 149-152, 2011; P. T. Mativenga and M. F. Rajemi.

[9] "Sustainable machining: selection of optimal

turning conditions based on minimum energy considerations," M. F. Rajemi, P. T. Mativenga, and A. Aramcharoen, J Clean Prod, vol. 18, pp. 1059-1065, 2010.

[10] I. Asilturk, S. Neseli, and M.A. Ince, "Optimisation of parameters affecting surface roughness of Co28Cr6Mo medical material during CNC lathe machining by using the Taguchi and RSM methods," Measurement, vol. 78, pp. 120-128, 2016.

[11] R. K. Bhushan, “Optimization of cutting parameters for minimizing power consumption and maximizing tool life during machining of Al alloy SiC particle composites,” Journal of Cleaner Production, vol. 39, pp. 242-254, 2013.

[12] C. Li, Q. Xiao, Y. Tang, and L. Li, “A method integrating Taguchi, RSM and MOPSO to CNC machining parameters optimization for energy saving,” J. Clean. Prod., vol. 135, pp. 263-275, 2016.

[13] A. J. Kulkarni, K. Tai, and A. Abraham, “Probability collectives: a distributed multi-agent system approach for optimization,” In: Intelligent Systems Reference Library, pp. 86, 2015.

[14] I. Polatoğlu, L. Aydın, B.C. Nevruz, and S. Ozer, "A Novel Approach for the Optimal Design of a Biosensor," Analytical Letters, pp. 1–18, 2020.

[15] I. Polatoglu and L. Aydin, "A new design strategy with stochastic optimization on the preparation of magnetite cross-linked tyrosinase aggregates (MCLTA)," Process Biochemistry, vol. 99, pp. 131–138, 2020.