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Key words: *upport vector regression, non-dominated sorting genetic algorithm, minimum quantity lubricant, multi-objective optimization*

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USING SUPPORT VECTOR REGRESSION AND NON-DOMINATED SORTING GENETIC ALGORITHM IN MULTI-OBJECTIVE OPTIMIZATION OF MILLING OF S50C STEEL UNDER MQL CONDITION

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The modern machining industry faces reducing manufacturing cost pressure and improve product quality expectations. Due to this competition a manufacturer must continually identify cost cutting opportunities in manufacturing process. The keys technology represents cost-saving opportunities associated with reducing cutting fluid consumption, cutting energy consumption, and improves the overall performance of machining operations at the same time. Hence, multiple response optimization techniques have recently become the focus of research to improve product quality by increasing surface quality and reduce costs by reducing cutting force, cutting fluids, and energy consumption of the cutting process recently. Among various optimization methods, few Taguchi-based likes as TOPSIS, COPRAS, MOORA, VIKOR... were chosen to solve complex multiple criteria problems. However, the limitation of these techniques is that it was helped to rank and select the best parameters set for the implemented experiments only. In this work, an attempt was made to streamline the milling and coolant condition parameters of S50C carbon steel under MQL condition. Experiments were performed based on Taguchi's L27 orthogonal array. Five input factors includes machining parameters including cutting speed (Vc), feed (fz), and depth of the cut (ap) combined with two coolant parameters such as coolant air pressure (P), flow rate of lubricant (Q) were considered the variants, while specific cutting energy (Ec), material removed rate (MRR) and surface roughness were response variables. Particle swarm optimization Support Vector Machines (SVM) was used to generate the regression model, then Non-dominated Sorting Genetic Algorithm (NSGA) was used to optimize surface roughness (Ra), specific cutting energy (Ec), and production rate (MRR).

Key words: support vector regression, non-dominated sorting genetic algorithm, minimum quantity lubricant, multi-objective optimization

INTRODUCTION

Metal cutting fluid and energy consumption are important factors of sustainable development because of the scarcity of resources and environmental disruption. The related energy usage results in about 90 percent of the environmental impacts of machining machinery, based on preliminary studies of machining processes such as milling and turning... Hence, It is necessary to reduce energy consumption and to minimize the usage of cutting fluid in the machining process to reach sustainable production and environmental protection.

a. Minimizing the usage of cutting fluid

The method of applying a very limited volume of high-quality lubricant directly to the cutting area instead of using conventional flood coolants is the minimum quantity lubricant (MQL). Hence, MQL or dry-machining is now considered an excellent alternative to reduce the minimizing usage of cutting fluids. Many researchers claimed [1]–[5] that Oil droplets by the MQL system reduce friction between tool and chips were removed from the cutting zone by the high compressed air. P. V. Krishna [6] carried out an experimental investigating on nano cutting fluids effect in milling process under MQL environment. The experiment shows that MQL technique with vegetable oil-based executed well to reduce temperatures at cutting zone and cutting forces, and hence, decline tool wear and improve the surface quality of a product. Singh [7] shows the suitability of MQL and NMQL with vegetable oil in face milling of Inconel 625. The author claimed the positive effects of MQL on reducing tool wear and average surface roughness value. Weinert [8] carried out the research study in effects of dry machining confirm that MQL condition is suitable with most of the different machining types, and could be applied for the great number of materials like steel, cast iron, aluminium.

b. Reducing cutting energy

According to the high competition in this industry, the manufacturers always try to reduce the cost of energy,

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machining tools and value of surface roughness simultaneously. Hence, besides the research in optimizing product quality and maximum production rate, reducing energy consumption is a considerable approach. Zhang, Xuewei [9] carried out a research study on optimising energy consumption considering cutting parameters in the milling process. The research result confirmed that energy consumption could be declined by control of the cutting parameter. However, it is complicated to optimize three or more responses at the same time. Many methods were proposed in the recent decade to solve this problem. In this field, Taguchi-Based such as TOPSIS, MOORA, COPRAS… were often selected because of the simplicity in use. Recently, because of the development of computing, artificial intelligence algorithms were becoming more and more popular. Murthy et al. [10] used an Artificial neural network (ANN) approach to guess the cutting criteria like wear-vibration-cutting forces of tool and surface roughness in a boring of titanium alloy. The ANN predicted results are almost the same as experimental results. Limited studies have used support vector regression to generate the regression model but for one response only [11]–[15]. In this paperwork, the hybrid method, including SVR combined with NSGA2, was applied to solve multiple objective optimizations of milling process considering three different responses.

RESEARCH METHODOLOGY

a. Optimization Issues

In this study work, combining of NSGA2 and SVR were performed to build the regression model then optimize three machining responses such as the arithmetical mean roughness (Ra-μm), specific cutting energy (Ec-J/cm3), and material removal rate (MRR-cm3/min) simultaneously. The average roughness value is calculated as:

$$R_a = \frac{R_{a1} + R_{a2} + R_{a3} + R_{a4} + R_{a5}}{5} \quad (1)$$

The specific cutting energy is obtained by equation (2) [16] [17]

$$E_c = \frac{F_c}{f_z a_p} = \frac{\sqrt{F_x^2 + F_y^2 + F_z^2}}{f_z a_p} \quad (2)$$

The production rate is calculated as eq. (3) [18] [19]:

$$MRR = \frac{w.a_p.v_f}{1000} \quad (3)$$

Where:

MRR (cm^3/min) – material removal rate

ap (mm) - the depth of cut

w (mm) - the width of cut

vf (m/min) - feed speed

For the finishing milling process under minimal quantity lubricant (MQL) condition, the three three-levels milling parameters such as cutting speed V_c, depth of cut ap and feed rate V_f, and two three-level lubricant parameters include coolant air pressure P, the flow rate of lubrication Q) can be considered as processing inputs. The parameter data are shown in Table 1. The parameter ranges are selected based on the specification of CNC milling, namely DMG Mori Seiki DMU 50, suggestions from the cutting tool manufacturer, and the recommendations of typical machining experts. Support Vector Machines (SVM) was used to generate the regression model, then NSGA2 was performed to optimize surface roughness (R_a), specific cutting energy (E_c), and production rate (MRR).

b. Multi-Objective Optimization Framework

Regression Model:

Support Vector Machines (SVM) are famously and broadly utilized for classification issues in machine learning. The Back Vector Machine's objective is to discover the ideal hyperplane (Hyperplane may be plane or bend) to classify information into two partitioned locales so that the removal between the closest point and the hyperplane is at most extreme. Figure 1 presents a hyperplane and a margin. Suppose that the equation for a hyperplane is w.x+b=0 (4). To maximize the margin, the goal of the SVM algorithm is to find w and b in this equation.

Table 1: Cutting parameters and lubricant parameters

No.	Prameter	Symbol	Unit	Level			DoF
				-1	0	1	
1	Cutting Speed	v_c	m/min	120	210	300	4
2	Feed	f_z	mm/tooth	0.02	0.06	0.10	4
3	Depth of cut	a_p	mm	0.1	0.5	0.9	4
4	MQL Pressure	P	MPa	1	2	3	4
5	MQL Flow Rate	Q	ml/h	50	100	150	4

The SVM algorithm applies to solving classification issues and finds solutions to regression subjects named Support Vector Regression (SVR). The SVR calculation depends on a Los function was proposed by Vapnik [14], [15], Which is error-tolerant for points within a small epsilon that is far from the true value. This implies that this function gives zero error for all points in the training set in the epsilon range. Fig. 1 and Fig. 2 present linear/nonlinear regression model under the epsilon range [13] For SVR, the input x is mapped into m dimension feature space by a nonlinear mapping function first, and then the linear model is built, which is based on this dimension feature space by Eq (4):

$$f(x,w) = \sum_{i=1}^{m} w_i . g_i(x) + b \tag{4}$$

where: g_i (x)i=1,2...,m is a set of nonlinear mapping functions.

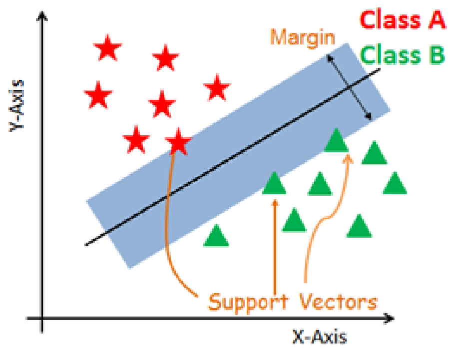

Figure 1: The presence of the hyperplane corresponding to the margin

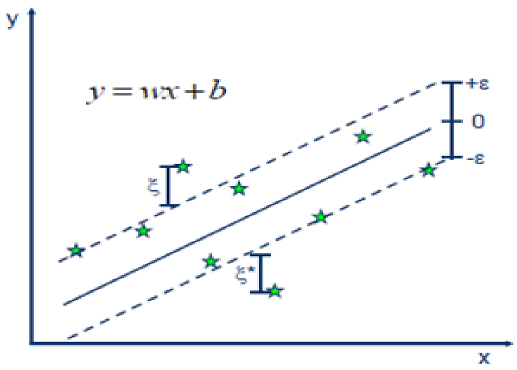

Figure 2: Linear regression under epsilon limitation range

The accuracy of the estimate is evaluated by loss function L(y,f(x,w)). Support Vector Regression uses a loss function which proposed by Vapnik [14], [15]:

$$L = \begin{cases} 0 \ if \ |y - f(x,w)| \le \varepsilon \\ |y - f(x,w)| \ otherwise \end{cases} \tag{5}$$

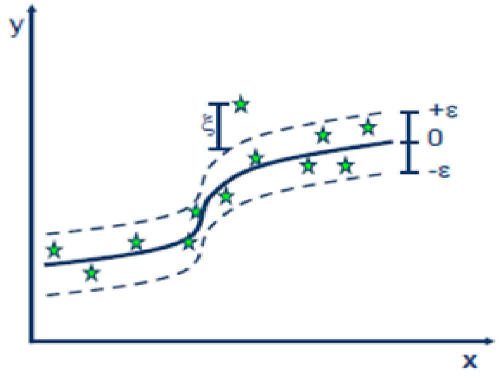

Figure 3: Nonlinear Linear regression under epsilon limitation range

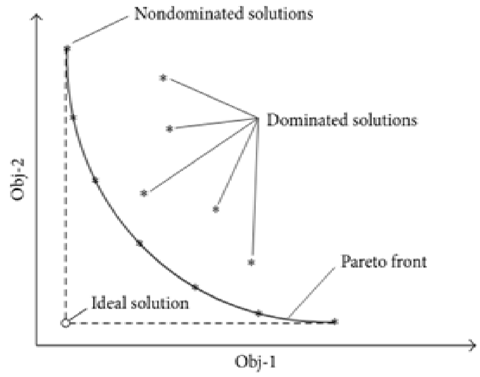

Figure 4: SVM model

Thus, SVM is performed linear regression in multiple dimension feature space using function L and minimizing |(|W|)|^2for diminishing complexity of the model. This problem can be solved by introducing slug variables $\zeta_i$and $\zeta_i^*$with i = 1, 2, … n to measure the deviation of the training samples outside the epsilon range. Subsequently, SVR is minimized by the equation underneath:

$$min \frac{1}{2} ||w||^2 + C. \sum_{i=1}^{n} (\zeta_i + \zeta_i^*) \tag{6}$$

with constraints:

$$\begin{Bmatrix} y_i - f(x_i,w) \le \varepsilon + \zeta_i^* \\ f(x_i,w) - y_i \le \varepsilon + \zeta_i \\ \zeta_i \zeta_i^* > 0 \forall i = 1,\dots,n \end{Bmatrix} \tag{7}$$

The final function f(x) could be found by applying the duality hypothesis for minimizing issues:

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*). K. (x_i, x) + b \tag{8}$$

where: nSV is the number of support vector, and $K(x_i,x)$ is the kernel function which can be defined as

$$K(x_i, x) = \sum_{j=1}^{m} g_j(x_i) \cdot g_j(x) \tag{9}$$

c. Multi-objective optimization

Typically, multiple objective optimizations have a few criteria regarding disparity and balance imperatives to optimize [12]. The objective is to discover a set of arrangements that don't have any limitation infringement and are as great as conceivable with respect to all its objectives values. Consequently, the ultimate outcome of such a multiple criteria optimization issue may be a set of trade-off arrangements among diverse destinations. These trade-off focuses are named as Pareto ideal arrangements, which are not overwhelmed by any other arrangement and cannot be progressed within the case of at slightest one other objective without declining. The set of all these doable nondominated arrangements is named as Pareto ideal arrangement set, and the comparing objective values are named the Pareto front [11]. Figure 5 outlines the Pareto front for the optimization of two objectives, namely Obj-1 and Obj-2.

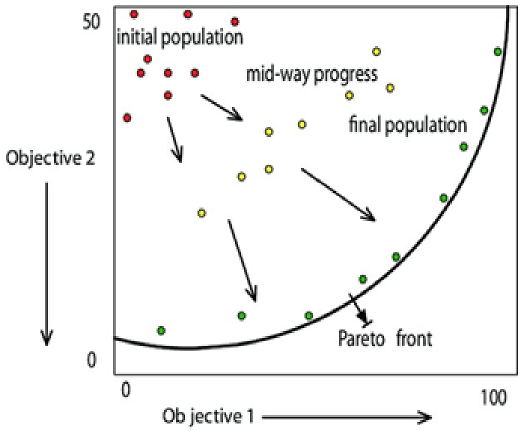

Figure 5: Pareto front for Objective 1 and Objective 2

EXPERIMENTAL PROCEDURE

a. Workpiece

In this present study, S50C grade carbon steel is applied as the workpiece material to research. The chemical composition of S50C steel has appeared in Table 2. This carbon steel is broadly utilized in apparatus fabricating since of the great mechanical properties of this steel. S50C carbon steel is, for the most part, utilized to form mechanical parts, like spring, gear, pressure bar, the roller.

Table 2: Chemical Composition of S50C Carbon Steel

Standard	Grade	C	Mn	P	S	Si
JIS G4051	S50C	0.47 - 0.53	0.60 - 0.90	0.030	0.035	0.15 - 0.35

The machining workpiece was prepared with the dimension of 250x350x15mm.

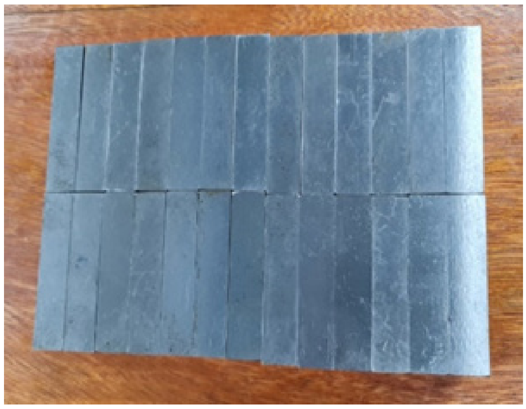

Figure 6: Workpiece specimens

b. Cutting tool:

The 390R-070202M-PM 4340 carbide inserts from Sandvik with TICN+AL2O3+TIN chemical vapour deposition (CVD) (fig.1) and the R390-020A20-07M square shoulder milling cutter (fig.2) are used to performed milling runs. The insert, holder were chosen according

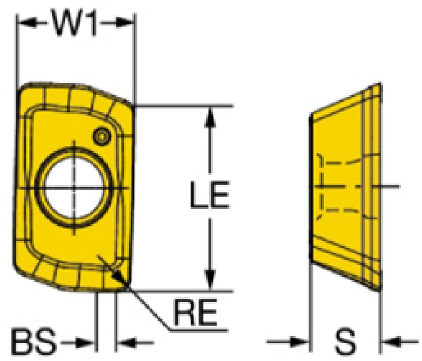

Figure 7: Cutting tool

to reduce the vibration in the milling process.

c. Measurement Equipment

The surface roughness of each experimental run was measured by Mitutoyo Surftest JS-210, the cutting force was obtained by Kisler dynamometer, specific cutting energy was determined by equation (2). The results were fill in Table 3.

Table 3: Experimental Results and Performance of SVR models

Variant				Response				SVR model's			
Exp.	P	Q	V_c	f_z	a_p	R_a	E_c	MRR	R_a	E_c	MRR
1	1	50	120	0.02	0.1	1.446	3.640	0.229	1.457	3.650	0.239
2	1	50	120	0.02	0.5	1.050	3.639	1.147	1.040	3.629	1.137
3	1	50	120	0.02	0.9	0.420	3.444	2.064	0.430	3.455	2.075
4	1	100	210	0.06	0.1	0.504	2.853	1.204	0.494	2.843	1.214
5	1	100	210	0.06	0.5	0.302	2.359	6.019	0.312	2.369	6.018
6	1	100	210	0.06	0.9	0.302	2.172	10.835	0.292	2.162	10.825
7	1	150	300	0.1	0.1	0.236	2.469	2.866	0.226	2.479	2.876
8	1	150	300	0.1	0.5	0.377	2.251	14.331	0.387	2.241	14.341
9	1	150	300	0.1	0.9	0.593	1.808	25.796	0.583	1.819	25.786
10	2	50	210	0.1	0.1	0.357	2.171	2.006	0.347	2.172	2.016
11	2	50	210	0.1	0.5	0.331	1.995	10.032	0.341	1.985	10.042
12	2	50	210	0.1	0.9	0.364	1.881	18.058	0.354	1.891	18.048
13	2	100	300	0.02	0.1	0.151	5.737	0.573	0.141	5.727	0.583
14	2	100	300	0.02	0.5	0.176	4.304	2.866	0.174	4.314	2.856
15	2	100	300	0.02	0.9	0.169	3.776	5.159	0.159	3.766	5.159
16	2	150	120	0.06	0.1	1.416	2.869	0.688	1.426	2.859	0.698
17	2	150	120	0.06	0.5	1.428	2.309	3.440	1.418	2.319	3.430
18	2	150	120	0.06	0.9	1.002	2.175	6.192	1.013	2.165	6.183
19	3	50	300	0.06	0.1	0.229	3.041	1.720	0.239	3.034	1.730
20	3	50	300	0.06	0.5	0.312	2.568	8.599	0.302	2.558	8.609
21	3	50	300	0.06	0.9	0.311	2.138	15.477	0.311	2.148	15.467
22	3	100	120	0.1	0.1	1.279	1.973	1.147	1.290	1.983	1.157
23	3	100	120	0.1	0.5	1.653	1.939	5.733	1.643	1.929	5.727
24	3	100	120	0.1	0.9	0.789	1.855	10.319	0.799	1.866	10.309
25	3	150	210	0.02	0.1	0.184	4.323	0.401	0.174	4.313	0.411
26	3	150	210	0.02	0.5	0.152	3.495	2.006	0.162	3.505	1.996
27	3	150	210	0.02	0.9	0.143	3.330	3.612	0.133	3.320	3.623
								R score	0.9996	0.9999	1.0000

RESULTS AND DISCUSSION

In this work, the Minitab was chosen to analyze the effect of cutting and lubrication variants on the average value of surface roughness (Ra,μm), specific cutting energy (Ec) and production rate (MRR, cm3/min). First, the regression model was performed by the Support Vector Regression method, and then the NSGA2 was applied to find the optimum set of cutting and lubricant parameters.

a. Effect of cutting parameters and lubricant condition on surface roughness. Fig. 8, 9 show that cut's depth exhibited a considerable effect on surface roughness is the most, followed by feed rate then cutting speed. By contrast, the influence of the lubricant flow rate and air pressure is insignificant.

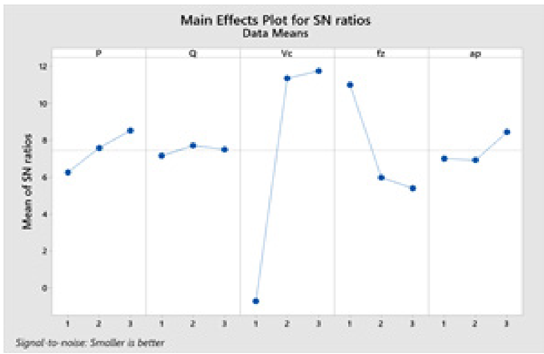

Figure 8: Main Effects Plot for Means of R_a

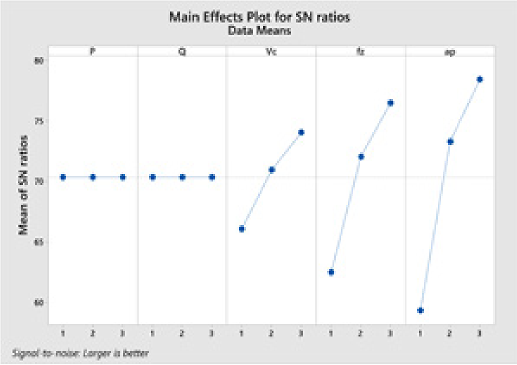

Figure 9: Main Effects Plot for Means of MRR

b. Effects of cutting parameters and lubricant condition on production rate MRR

Response Table for Signal to Noise Ratios

Larger is better

Level	P	Q	Vc	fz	ap
1	70.34	70.34	66.07	62.50	59.32
2	70.34	70.34	70.93	72.05	73.30
3	70.34	70.34	74.03	76.48	78.41
Delta	0.00	0.00	7.96	13.98	19.08
Rank	4.5	4.5	3	2	1

Figure 10: Response table for the signal to Noise Ratios of MRR

In comparing cutting and lubricant parameters, cutting parameters greatly influence material removal rate MRR, while the flow rate of lubricant Q and air pressure P does not affect MRR. This is in accordance with formula (3). Graphs 10 and 11 clearly illustrate the effect of cutting and lubricant parameters on material removal rate MRR. Where the depth of cut (a_p) affects significant on the MRR, followed by cutting speed (V_c) and feed rate (fz). The MRR value is proportional to cutting speed V_c), depth of cut (a_p) and feed rate (f_z).

c. Influence of cutting parameters and lubricant condition on specific cutting energy Ec. According to Fig. 12 and 13, the feed rate has the most significant impact on specific cutting energy (E_c), followed by the depth of cut (ap) and cutting speed (V_c). In this case, the effects of lubricant (Q) flow rate and air pressure (P) are significant. These research results are inconsistent with previous publications. The MQL condition particles the lubrication film between the cutting tool and workpiece, leading to reduced friction, thereby declining the cutting force, leading to a decrease in specific cutting energy E_c.

d. Support vector regression

Support Vector Regression (SVR) is applied to build regression models for prediction surface roughness (Ra), specific cutting energy (Ec), Material Removal Rate (MRR) with the C = 10e5 and the ε = 0.01. Table 3 presents the performance of SVR models.

Figures 14, 15, and 16 show SVR predicted output vs

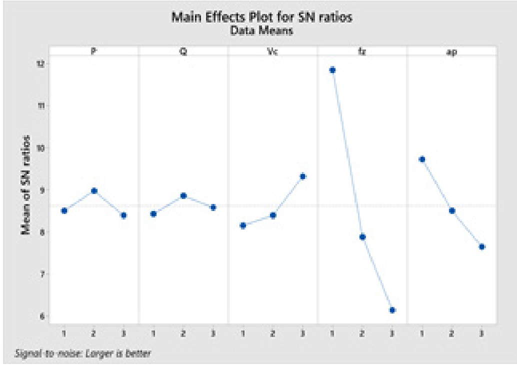

Figure 11: Main Effects Plot for Means of E_c

Response Table for Signal to Noise Ratios

Larger is better

Level	P	Q	Vc	fz	ap
1	8.503	8.428	8.153	11.845	9.724
2	8.975	8.857	8.394	7.880	8.498
3	8.390	8.583	9.321	6.143	7.646
Delta	0.585	0.429	1.167	5.702	2.079
Rank	4	5	3	1	2

Figure 12: Response table for the signal to Noise Ratios of E_c

expected output for Ra, Ec, MRR corresponding. Fig. 14, 15, 16 and the data in Table 3 show that the errors of predicted output with expected output for Ra, Ec, MRR are nearly 100%, at 99,96%, 99,99% and 100%, respectively.

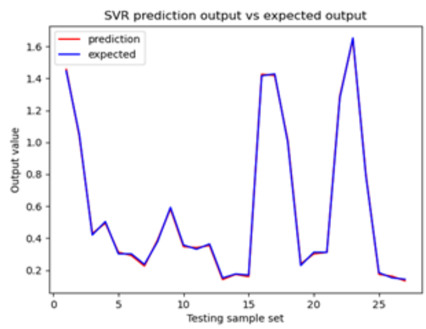

Figure 13. SVR prediction output vs expected value for R_a

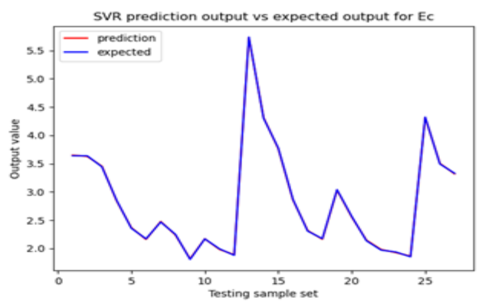

Figure 14: SVR prediction output vs expected value for E_c

e. Multi-Objective Optimization

In this case, SVR was used the first to build regression models for the surface roughness (Ra), Specific cutting energy (Ec), and Material Remove Rate (MRR). Let,

$$R_a = f_1(P, Q, V_c, f_z, a_p) \quad (10)$$

$$E_c = f_2(P, Q, V_c, f_z, a_p) \quad (11)$$

$$MRR = f_3(P, Q, V_c, f_z, a_p) \quad (12)$$

Next, the Non-dominated Sorting Genetic Algorithm (NSGA2) was applied to perform multi-object optimization. In this case, The approach of this work is to minimize f1, f2 and maximize f3. The Sklearn and Pymoo framework in Python was used to implement SVR and multi-object optimization. Pymoo method considers minimization problems only. Therefore, f3 should be multiplied by -1 and be minimized. NSGA2 was performed with a population size is 50, and the number of generations is 1000, and the optimal result is shown in table 4.

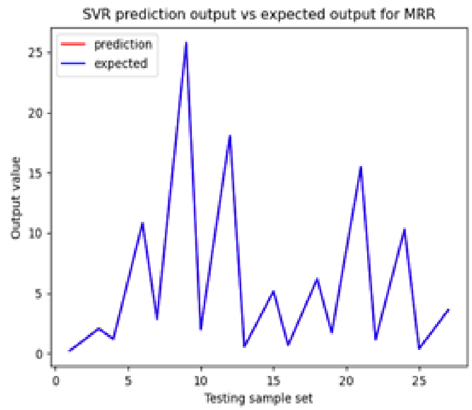

Figure 15: SVR prediction output vs expected value for MRR

Table 4: The optimal result

P	Q	V_c	f^z	a^p	R_a	E_c	MRR
2.0077	149.122	298.735	0.094	0.899	0.0275	2.7511	20.1299

CONCLUSION

Though a lot of previous techniques for multiple response optimization in cutting processes are reported, a new hybrid model was proposed in this paperwork. A multiple response optimization methodologies, by using genetic algorithm based Non-dominated Sorting Genetic Algorithm (NSGA2) combined with Support Vector Regression (SVR) was also proposed to build the regression model and optimize the cutting and lubrication parameters under MQL condition. The following conclusions are made: The optimum lubrication and cutting parameters for minimum specific cutting energy and surface roughness, and maximum material removal rate are depth of cut of 0.899 mm, cutting speed of 298.735 m/min, a feed rate of 0.094 mm/tooth, and lubricant flow rate, air pressure of 149.122 ml/h, 2.0077 MPa, respectively.

Among the lubricant parameters: flow rate of lubrication (Q), air pressure (P) and milling parameters: cutting speed (Vc), feed rate (fz) and depth of cut (ap), cutting parameters effects significant on all of the response. By contrast, the lubrication parameters have a significant effect on specific cutting energy (Ec) only, while the influence on surface roughness is insignificant and don't have an effect on production rate. SVR Model was applied successfully to build the regression model of responses in the cutting process due to the high accuracy. The errors between predicted and expected results for surface roughness Ra, specific cutting energy Ec and material removal rate MRR are 99.96%, 99.99%, 100%, respectively.

The hybrid method combining the SVR model and the Non-dominated Sorting Genetic Algorithm (NSGA2) could be used to find the optimum parameters in the milling process.

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REFERENCE

1. N. R. Dhar, M. Kamruzzaman, and M. Ahmed, "Effect of minimum quantity lubrication (MQL) on tool wear and surface roughness in turning AISI-4340 steel," J. Mater. Process. Technol., vol. 172, no. 2, pp. 299–304, 2006, doi: https://doi.org/10.1016/j.jmatprotec.2005.09.022.
2. H. P. Elma Ekinović, Edin Begović, "Effect of Minimum Quantity Lubrication (MQL) on Surface Roughness of Mild Steel of 15HRC on Universal Milling Machine," Procedia Mater. Sci., vol. 6, pp. 150–153, 2014, doi: 10.1016/j.mspro.2014.07.018.
3. R. N., "An experimental investigation on oil mist characterization used in MQL milling process," Int. J. Adv. Manuf. Technol., vol. 66, p. 1003, 2012.

4. L. R. Silva, Corrêa, J. R. Brandão, and R. F. de Ávila, "Environmentally friendly manufacturing: Behavior analysis of minimum quantity of lubricant - MQL in grinding process," J. Clean. Prod., vol. 256, p. 103287, 2020, doi: https://doi.org/10.1016/j.jclepro.2013.01.033.
5. S. K. Tamang, M. Chandrasekaran, and A. K. Sahoo, "Sustainable machining: an experimental investigation and optimization of machining Inconel 825 with dry and MQL approach," J. Brazilian Soc. Mech. Sci. Eng., vol. 40, no. 8, p. 374, 2018, doi: 10.1007/s40430-018-1294-2.
6. N. Krishna, P. V., Srikant, R. R., & Parimala, "Suspended Vegetable oil Nanofluids," Int. J. Automot. Mech. Eng., vol. 15, no. 4, pp. 5957–5975, 2018, doi: https://doi.org/10.15282/ijame.15.4.2018.17.0454.
7. P. Singh, J. S. Dureja, H. Singh, and M. S. Bhatti, "Nanofluid-based Minimum Quantity Lubrication (MQL) Face Milling of Inconel 625," Int. J. Automot. Mech. Eng., vol. 16, no. 3 SE-Articles, Oct. 2019, doi: 10.15282/ijame.16.3.2019.04.0516.
8. K. Weinert, I. Inasaki, J. W. Sutherland, and T. Wakabayashi, "Dry Machining and Minimum Quantity Lubrication," CIRP Ann., vol. 53, no. 2, pp. 511–537, 2004, doi: https://doi.org/10.1016/S0007-8506(07)60027-4.
9. X. Zhang, T. Yu, Y. Dai, S. Qu, and J. Zhao, "Energy consumption considering tool wear and optimization of cutting parameters in micro milling process," Int. J. Mech. Sci., vol. 178, p. 105628, 2020, doi: https://doi.org/10.1016/j.ijmecsci.2020.105628.
10. Murthy, Rao, and Rao, "Experimental and 3D-ANN based Analysis and Prediction of Cutting Forces, Tool Vibration and Tool Wear in Boring of Ti-6Al-4V Alloy," Int. J. Automot. Mech. Eng., vol. 16, no. 1 SE-Articles, Mar. 2019, doi: 10.15282/ijame.16.1.2019.5.0467.
11. A. E. S. A. Konak, D. W. Coit, "Multi-objective optimization using genetic algorithms: a tutorial," Reliab. Eng. Syst. Saf., vol. 9, no. 91, pp. 992–1007, 2006.
12. K. Deb, Multi-Objective Optimization Using Evolutionary Algorithms. John Wiley & Sons, Inc, 2001.
13. "Support Vector Regression - Data Mining Map." https://www.saedsayad.com/support_vector_machine_reg.htm.
14. V. Vapnik, Statistical Learning Theory. Wiley, 1998.
15. V. Vapnik, The Nature of Statistical Learning Theory, 2nd ed. Springer-Verlag New York, 2000.
16. T. T. Nguyen, "Prediction and optimization of machining energy, surface roughness, and production rate in SKD61 milling," Meas. J. Int. Meas. Confed., vol. 136, pp. 525–544, 2019, doi: 10.1016/j.measurement.2019.01.009.
17. A. Shokrani, V. Dhokia, and S. T. Newman, "Comparative investigation on using cryogenic machining in CNC milling of Ti-6Al-4V titanium alloy," Mach. Sci. Technol., vol. 20, no. 3, pp. 475–494, 2016, doi: 10.1080/10910344.2016.1191953.
18. L. Norberto López de Lacalle, F. J. Campa, and A. Lamikiz, "3 - Milling," in Modern Machining Technology, J. Paulo Davim, Ed. Woodhead Publishing, 2011, pp. 213–303.
19. Sandvik, "Milling formulas and definitions." https://www.sandvik.coromant.com/en-gb/knowledge/machining-formulas-definitions/pages/milling.aspx.

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