Modelling and Optimization of Surface Roughness and Material Removal Rate in Milling SKD11 Using GMDH and NSGA-II

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***Abstract*—Optimization of surface Roughness (Ra) and Material Removal Rate (MRR) to achieve higher productivity and improved quality machining is an objective in various machining processes. This study develops predictive models and optimizes the machining performance of SKD11 material during milling based on three cutting parameters: Cutting speed (Vc), Depth of cut (Dc), and Feed rate (Fr). The Taguchi Orthogonal Array (OA) design determines the appropriate number of experimental samples. Moreover, the Group Method of Data Handling (GMDH) method develops a predicting model for Ra. Then, the NSGA-II technique is employed for multi-objective optimization. The results show that the triple model (3 variables) for Ra exhibits the most accurate predictive performance among the nine types of GMDH models, with the highest R^2 of 0.981, the lowest Root Mean Square Error (RMSE) of 0.074, and Mean Absolute Percentage of Error (MAPE) of 3.6 in training, and 0.959, 0.119, and 5.864 in validation. Applying NSGA-II for multi-objective optimization generates 70 Pareto solutions, representing the trade-offs among the cutting parameters and the two conflicting objectives of Ra and MRR. Three solutions from the Pareto set are selected and machined to validate the optimal values, revealing deviations of less than 10.3% from the optimal values. This study addresses a critical challenge in milling by developing a method to optimize Ra and MRR, which are often conflicting objectives. Hence, manufacturers can improve production efficiency and product quality simultaneously.**

***Keywords*—optimization, surface roughness, material removal rate, group method of data handling, nondominated sorting genetic algorithm II**

I. INTRODUCTION

Achieving optimal surface roughness and Material Removal Rate (MRR) is fundamental in various machining processes. Surface roughness directly affects machined components' functional and aesthetic properties, while MRR is a key indicator of machining efficiency. Traditionally, surface roughness and MRR have been treated as separate objectives, with optimization efforts focused on improving one parameter while accepting compromises on the other. However, modern manufacturing has a growing demand for simultaneous optimization of surface roughness and MRR to achieve higher productivity and improved quality [1, 2].

The optimization of surface roughness and MRR is a complex task due to the inherent trade-off between these two objectives [3]. Improving surface roughness requires reducing the feed rate or increasing the cutting speed, which can decrease MRR. On the other hand, maximizing MRR may increase cutting forces and tool wear, leading to a poorer surface finish. Therefore, an effective approach is required to model the relationship between machining parameters and performance measures and identify the optimal trade-off between surface roughness and MRR. One popular modeling and optimization approach is mathematical models and evolutionary algorithms. Mathematical models can capture the complex and nonlinear relationships between machining parameters and performance measures, providing insights into the effects of different process variables on surface roughness and MRR [4–7]. Evolutionary algorithms, such as genetic algorithms, have been widely applied in multi-objective optimization problems to explore the solution space and identify Pareto-optimal solutions representing the trade-off between conflicting objectives [8, 9].

Several researchers have developed predictive models and optimized cutting parameters, studying various empirical optimization techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Response Surface Methodology (RSM). These techniques have been widely investigated and applied in the field of manufacturing and machining processes to optimize cutting parameters and improve overall performance. Osorio-Pinzon *et al.* [10] presented a multi-objective PSO algorithm to identify the optimal machining parameters, such as rake angle, velocity, and cutting feed. The algorithm utilizes finite element simulation of orthogonal cutting to assess optimality based on three objectives: minimizing the cutting force, maximizing the microstructure refinement, and maximizing the MRR during the machining process of Aluminum 6063. Xu *et al.* [11] used the Adaptive Neuro-Fuzzy Inference System (ANFIS) for tool wear estimation based on training using an improved PSO algorithm.

Manuscript received May 20, 2024; revised July 4, 2024; accepted July 23, 2024; published December 18, 2024.

doi: 10.18178/ijmerr.13.6.618-627

Furthermore, the study explored multi-objective optimization techniques focusing on minimizing cutting power, achieving desired surface roughness, and maximizing the MRR. Tran *et al.* [1] conducted a study on the multi-parameter optimization of milling aluminum alloy 7075 on a CNC machine. By utilizing multi-objective optimization with the RSM method, the study achieved optimal values for both surface roughness and MRR simultaneously. The testing results for these optimal parameters showed a deviation from reality within 5%.

Recently, evolutionary algorithms have gained significant attention for multi-objective optimization in machining processes. Genetic Algorithms (GAs) and their variants, such as NSGA-II, have been extensively applied to find the Pareto-optimal solutions between surface roughness and MRR. These algorithms iteratively evolve a population of candidate solutions by applying genetic operators such as selection, crossover, and mutation. By evaluating and comparing the fitness of candidate solutions based on the objectives evolutionary algorithms efficiently explore the solution space and identify a diverse set of solutions representing the trade-off between the conflicting objectives. Pal and Dasmahapatra [12] utilized the GA algorithm to determine the optimal cutting condition in turning operations. The pareto optimal analysis conducted in this research revealed that increasing the rake angle and cutting speed can assist the operator in minimizing the cutting forces generated during turning operations. To improve the productivity of the end milling process, Mukkoti *et al.* [13] also employed the NSGA-II multi-objective optimization technique to determine the optimal process parameters. This was achieved by combining the developed RSM model with NSGA-II in MATLAB. In addition, NSGA-II has also been combined with many other algorithms and is very useful for multi-objective optimization [14–20].

The Group Method of Data Handling (GMDH) is an algorithmic approach for modeling and prediction tasks in machine learning and data analysis [21, 22]. The GMDH is an adaptive modeling method that iteratively selects and combines input variables to build a mathematical model that can accurately predict the output variable. The algorithm autonomously determines the model's structure by evaluating different combinations of input variables and selecting the most relevant ones based on their contribution to the prediction accuracy. GMDH has been successfully applied in various fields, including pattern recognition time series analysis and predictive modeling [23–25]. The GMDH has also found applications in metal machining for prediction and optimization tasks [26–28]. However, few researchers have applied the combination of GMDH and NSGA-II to optimize machining.

The Group Method of Data Handling (GMDH) is an algorithmic approach used for modeling and prediction tasks in machine learning and data analysis [21, 22]. It is a type of adaptive modeling method that iteratively selects and combines input variables to build a mathematical model capable of accurately predicting the output variable. The algorithm autonomously determines the structure of the model by evaluating different combinations of input variables and selecting the most relevant ones based on their contribution to the prediction accuracy. GMDH has been successfully applied in various fields, including pattern recognition time series analysis, and predictive modeling [23–25]. It has also found applications in metal machining for prediction and optimization tasks [26–28]. However, the combination of GMDH and NSGA-II to optimize machining has been applied by very few researchers.

This paper aims to develop the modeling and multi-objective optimization of Ra and MRR in milling SKD11 using a combination of GMDH and NSGA-II. The GMDH method develops accurate mathematical models that capture the complex relationships between machining parameters and performance measures. Moreover, NSGA-II is used to identify a set of Pareto-optimal solutions that represent the optimal trade-off between Ra and MRR. The findings of this research will contribute to advancing the field of machining optimization, enabling manufacturers to achieve higher productivity, improved quality, and cost reduction in machining operations.

II. Materials and Methods

A. *Equipment and Materials*

The LEADWELL V20i VMC milling machine was employed in this study, as depicted in Fig. 1(a). The cutting conditions were programmed and simulated prior to the actual machining process, as shown in Fig. 1(b). The cutting tool used was a 10 mm carbide end mill with four flutes (code: SEB 1010) and an ALTiN coating, specifically designed for processing materials with a hardness of up to 60HRC. PV cutting oil was applied directly as the cutting fluid during the machining process. The roughness value of the machined surface (Ra) was measured using the TR200 instrument from Mitutoyo, Japan.

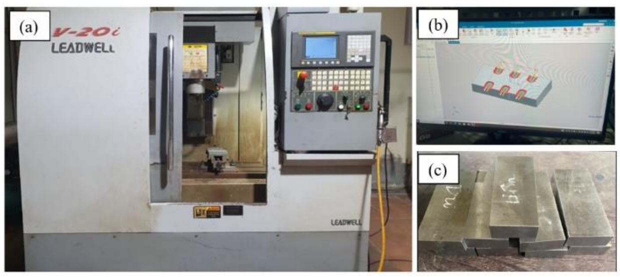

Fig. 1. LEADWELL V20i VMC (a) milling machine, (b) cutting simulation, and (c) workpieces.

JIS SKD11 steel is a tool steel alloy renowned for its high carbon and chromium content. This tool exhibits exceptional wear resistance, hardness, and strength, especially when subjected to heat treatment [20]. JIS SKD11 steel finds widespread applications in stamping dies, plastic molds, and cold work die steel. Consequently, cutting and machining SKD11 steel present significant challenges [29]. In this study, the workpiece's hardness is approximately 55HRC (Fig. 1(c)). The chemical composition, as provided by the manufacturer, is shown in Table I.

TABLE I. THE CHEMICAL COMPOSITION OF SKD11 STEEL

C (%)	Si (%)	Mn (%)	P (%)	S (%)
1.4–1.6	≤ 0.4	≤ 0.6	≤ 0.03	≤ 0.03
Ni (%)	Cr (%)	V (%)	Cu (%)	
≤ 0.5	11.0–13.0	0.2–0.5	≤ 0.25	

B. Methods

This research study is focused on developing a predictive model and optimizing Ra and MRR in milling SKD11. The study utilizes the Taguchi method to design an experimental plan and conduct the necessary trials. The machining process involves the manipulation of Vc, Dc, and Fr as input parameters. An ANOVA analysis is performed to validate the predictive model's ability to accurately represent the statistical relationships between the three objectives and the design parameters. Subsequently, predictive models are established using GMDH to correlate the design parameters with the quality characteristics. Finally, NSGA-II is employed to determine the optimal combinations of design parameters that achieve the desired outcome of minimum Ra and the highest MRR. The study methodology is visually depicted in Fig. 2 of the accompanying flowchart.

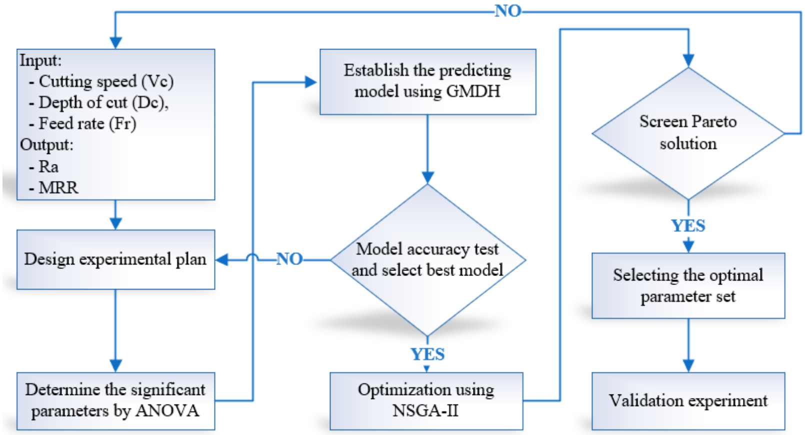

Fig. 2. Flowchart of the study methodology.

1) Design of experiments

This study utilizes the Taguchi Orthogonal Array (OA) design method to efficiently determine the number of experimental samples. The results of the Taguchi experiment are arranged in a table as an orthogonal matrix, ensuring a balanced structure. Three cutting parameters are investigated: cutting speed, feed rate, and depth of cut. Each factor is divided into five levels. The levels for these machining parameters were chosen based on previous data on SKD11 material machining using the CNC milling machine and relevant previous studies (Table II). Therefore, the study selects the orthogonal array experimental design table Taguchi OA25(5^3), which means that with three factors, each factor having five levels, a total of 25 experiments needs to be conducted. Additionally, the study includes an additional 40 cutting conditions to increase the reliability of the GMDH method (Table III).

TABLE II. INPUT PARAMETERS

Level	Vc (m/min)	Fr (mm/tooth)	Dc (mm)
1	40	0.10	0.10
2	60	0.15	0.20
3	80	0.20	0.30
4	100	0.25	0.40
5	120	0.30	0.50

TABLE III. ORTHOGONAL TABLE OA25(5^3) AND ADDITIONAL OF 40 CUTTING CONDITIONS

N. o	Input parameters			No.	Input parameters			No.	Input parameters			No.	Input parameters		
	Vc	Fr	Dc		Vc	Fr	Dc		Vc	Fr	Dc		Vc	Fr	Dc
1	1	1	1	18	4	3	1	35	2	2	4	52	4	2	4
2	1	2	2	19	4	4	2	36	2	4	2	53	4	1	3
3	1	3	3	20	4	5	3	37	2	3	1	54	4	3	5
4	1	4	4	21	5	1	5	38	2	1	3	55	4	4	3
5	1	5	5	22	5	2	1	39	2	3	5	56	4	4	1
6	2	1	2	23	5	3	2	40	2	5	3	57	4	5	2
7	2	2	3	24	5	4	3	41	2	2	5	58	5	5	1
8	2	3	4	25	5	5	4	42	3	1	5	59	5	2	4
9	2	4	5	26	1	1	5	43	3	5	1	60	5	4	2
10	2	5	1	27	1	5	1	44	3	4	2	61	5	3	1
11	3	1	3	28	1	2	4	45	3	3	1	62	5	1	3
12	3	2	4	29	1	4	2	46	3	1	2	63	5	3	5
13	3	3	5	30	1	3	1	47	3	5	3	64	5	5	3
14	3	4	1	31	1	1	3	48	3	3	4	65	5	2	5
15	3	5	2	32	1	3	5	49	3	2	5				
16	4	1	4	33	1	5	3	50	4	1	5				
17	4	2	5	34	2	1	5	51	4	5	1				

In this study, the Ra value represents the average roughness obtained from three distinct measuring points on the machined surface. The MRR was calculated using Eq. (1):

$$MRR = \frac{Dc \times Vc \times Fr \times Z \times a \times 1000}{\pi \times D}\ (mm^3/min) \quad (1)$$

where Dc is the depth of cut (mm), Vc is the cutting speed (m/min), Fr is the feed rate (mm/tooth), Z is the flute of the cutter, a is the width of cut (mm) and D is the diameter of the cutting tool (mm).

1) Group Method of Data Handling (GMDH)

In the GMDH algorithm, a network structure is designed with multiple layers, each consisting of sets of neurons. Within each layer, quadratic polynomials connect different pairs of neurons, allowing them to generate new neurons in the subsequent layer. This enables the mapping of inputs dependent on outputs [30]. The identification problem in GMDH involves approximating a function that can replace the actual function ($\hat{f}$) to estimate the output ($\hat{y}$) for a given input vector X (x_1, x_2, x_3, …, x_n) that is close to the actual output (y) [31]. Thus, for a given number (m) of multi-input and single-output data pairs:

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}) \text{ with } i = 1, 2, \dots, m \quad (2)$$

A neural network based on GMDH can be constructed to predict output values ($\hat{y}$) for any input vector X as follows:

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}) \text{ with } i = 1, 2, \dots, m \quad (3)$$

The identification of a GMDH-type neural network capable of minimizing the square of the discrepancy between the estimated output and the actual output is a crucial challenge in this procedure. By utilizing a complex discrete form of the Volterra functional series, it is possible to express the general relationships between input factors and the output as follows:

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \cdots \quad (4)$$

Fig. 3 illustrates a GMDH model with three input parameters, x_1, x_2, and x_3.

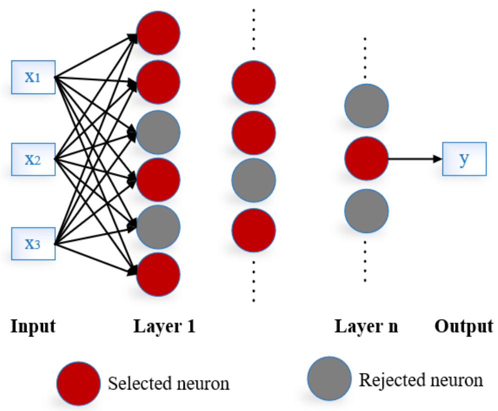

Fig. 3. GMDH model with three input parameters.

During the design of GMDH, it is important to note that the polynomials of the neurons within each layer of the network are comparable, and similar procedures are required for network design. The fundamental structure of the GMDH network is the second-order polynomial, initially proposed by Ivakhnenko [21]. Various types of polynomials, such as quadratic, tri-quadratic, bilinear, and third-order, are used to design self-organized systems. More complex networks are constructed using tri-quadratic and third-order polynomials compared to quadratic polynomials, while the bilinear polynomial produces a less complex structure. With its six weighting coefficients, the quadratic polynomial effectively solves engineering problems. The selection of a specific polynomial type depends on two parameters: the polynomial's complexity and the objective function's minimum error.

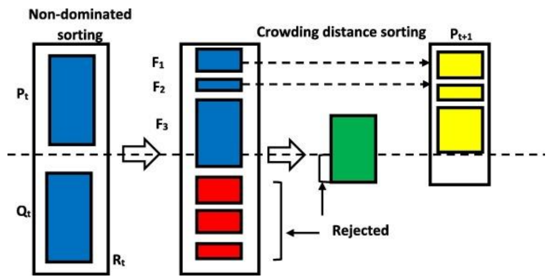

Fig. 4. NSGA-II algorithm structure.

In this study, the reliability and accuracy of the suggested polynomial models are assessed using several evaluation metrics. These metrics include the Coefficient of Determination (R^2), Mean Absolute Percentage of Error (MAPE), and Root Mean Square Error (RMSE), which are expressed by Eqs. (5)–(7):

$$R^2 = 1 - \left[\frac{\sum_{i=0}^{m}\left(y_{i(model)} - y_{i(Actual)}\right)^2}{\sum_{i=0}^{m}\left(y_{i(Actual)}\right)^2}\right] \quad (5)$$

$$MAPE = \left[\frac{\sum_{i=0}^{m}\left|y_{i(model)} - y_{i(Actual)}\right|}{m\sum_{i=0}^{m}\left(y_{i(Actual)}\right)}\right] \quad (6)$$

$$RMSE = \sqrt{\left[\frac{\sum_{i=0}^{m}\left(y_{i(model)} - y_{i(Actual)}\right)^2}{m}\right]} \quad (7)$$

2) NSGA-II algorithm

This section utilizes the NSGA-II algorithm, which is a multi-objective optimization approach widely employed to obtain the Pareto-optimal frontier. The NSGA-II algorithm distinguishes itself from the simple genetic algorithm by incorporating a stratification step before the selection operator. This stratification process is based on the dominant relationship between individuals, allowing the algorithm to identify and prioritize individuals with superior characteristics [32, 33]. The structure of the NSGA-II algorithm is provided in Fig. 4 [34]. The implementation steps of the NSGA-II algorithm involved the following steps:

(1) Initialize a random population P_t of size N. This represents the initial generation of parent solutions;
(2) Evaluate the fitness of each solution in the initial population P_t based on the objective functions;
(3) Sort the population P_t using the non-dominated sorting approach. This assigns each solution a rank based on its level of non-domination.
(4) Create an offspring population Q_t of size N by applying selection, crossover, and mutation operators to the parent population P_t.
(5) Combine the parent population P_t and the offspring population Q_t to form the combined population R_t of size 2N.
(6) Sort the combined population R_t using non-dominated sorting and identify the different non-dominated fronts F_1, F_2, etc.
(7) Select the best N solutions from the sorted fronts to create the parent population P_{t+1} for the next generation.
(8) Apply selection, crossover, and mutation operators to P_{t+1} to create the offspring population Q_{t+1} of size N.
(9) Repeat steps 5–8 until the stopping criterion is met (e.g., maximum number of generations).

Through non-dominated sorting functions, the NSGA-II algorithm ensures that individuals with the best fitness values, in terms of multiple objectives, have a higher likelihood of progressing to the next generation. This hierarchical approach organizes individuals into different tiers based on their dominance relationships, and individuals in higher tiers are favored for selection in subsequent generations.

Additionally, the NSGA-II algorithm incorporates an elitist strategy, which involves merging the parent population with sub-populations. By doing so, the algorithm allows for collaborative competition among individuals from different populations, leading to a more effective generation of the next population. This collaboration helps prevent the loss of valuable solutions and promotes the exploration of diverse regions in the search space.

In this study, the NSGA-II algorithm is combined with the GMDH method. The objective of the optimization is to enhance surface quality, specifically by minimizing the Ra value, while maximizing the MRR. The machining parameters chosen for optimization include Vc, Fr, and Dc.

III. RESULTS AND DISCUSSION

A. *ANOVA Analysis*

Table IV presents the ANOVA results for Ra, and Table V presents the MRR results. These tables provide information about the impact of three factors, Vc, Fr, and Dc, on Ra and MRR. The ANOVA results in Table IV show that all three factors (Vc, Fr, and Dc) significantly influence Ra. The p-values for these factors are all below 0.01, indicating statistical significance. The contributions of each factor to the variation in Ra are also provided. Factor Vc contributes 27.48%, Fr contributes 61.05%, and Dc contributes 3.23% to the variation in Ra. The remaining 8.24% is attributed to the error term. For MRR, the ANOVA results in Table V also indicate that all three factors significantly influence MRR. The *p*-values for these factors are all below 0.01, indicating statistical significance. The contributions of each factor to the variation in MRR are provided as percentages. Specifically, Vc contributes 28.95%, Fr contributes 9.30%, and Dc contributes 48.64% to the variation in MRR. The remaining 13.11% is attributed to the error term. However, it is worth noting that the contribution of Dc to Ra is only 3.2%, while the contribution of Fr to MRR is 9.3%.

Fig. 5(a)–(c) demonstrate the relationship between cutting parameters and the Ra value. In this study, the Ra value is most significantly influenced by the feed rate. This increase can be attributed to the formation of helical grooves on the machined surface due to the relative movement between the cutting tool and the workpiece. As the feed rate increases, these helical grooves grow in depth and width, escalating the surface roughness. Moreover, elevating the feed rate decreases the time available for heat dissipation in the machining area and promotes the accumulation of chips in the cutting zone, increasing the roughness. Ra decreases as the cutting speed increases within the range under investigation. This phenomenon may be attributed to the tendency of increasing cutting speed to eliminate the built-up edge [35]. Furthermore, higher cutting speeds can improve chip formation by generating smaller fragments that can easily exit the cutting zone. This phenomenon can reduce chip adhesion and breakage, decreasing surface defects such as wrinkles or scratches. In addition, it has been observed that increasing the depth of cut from 0.1 mm to 0.5 mm also increases Ra. This effect can be attributed to the larger chip load resulting from a greater depth of cut, increasing the cutting force [36, 37]. The elevated cutting forces can induce undesirable chatter vibrations during machining, increasing surface roughness.

According to the findings in Fig. 5(d)–(f), the MRR tends to increase with the feed rate. This relationship can be attributed to several factors. First, a higher feed rate often produces a thicker chip during machining. As the chip thickness increases, additional material is removed, increasing the MRR. In addition to the feed rate, the depth of cut also influences the MRR. Increasing the depth of cut increases the MRR. This phenomenon can be attributed to a greater depth of cut, allowing for a larger volume of material to be removed in each pass of the cutting tool. Similarly, the cutting speed, which refers to the relative velocity between the cutting tool and the workpiece, impacts the MRR. In many cases, increasing the cutting speed also increases the MRR. Higher cutting speeds often improve chip formation and evacuation, allowing for more efficient and rapid material removal.

TABLE IV. ANALYSIS OF VARIANCE FOR RA

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	*p*-Value
Vc	4	5.154	27.48%	5.7972	1.44929	48.77	0.000
Fr	4	11.4479	61.05%	11.6017	2.90043	97.61	0.000
Dc	4	0.6055	3.23%	0.6055	0.15136	5.09	0.002
Error	52	1.5452	8.24%	1.5452	0.02971		
Total	64	18.7525	100.00%				

TABLE V. ANALYSIS OF VARIANCE FOR MRR

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	*p*-Value
Vc	4	64,700,000	28.95%	63,764,793	15,941,198	28.28	0.000
Fr	4	20,800,000	9.30%	55,759,148	13,939,787	24.73	0.000
Dc	4	109,000,000	48.64%	109,000,000	27,193,760	48.24	0.000
Error	52	29,300,000	13.11%	29,312,364	563,699		
Total	64	224,000,000	100.00%				

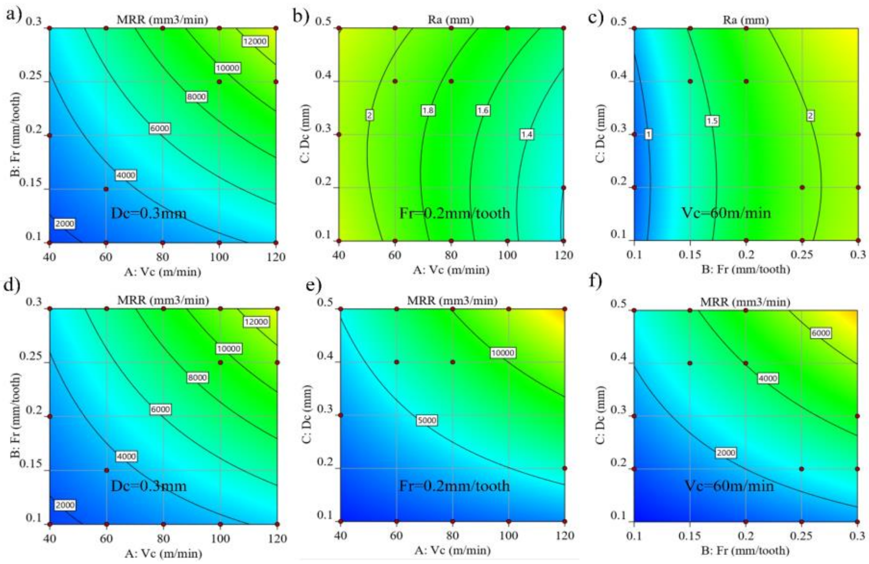

Fig. 5. The influence of cutting parameters on Ra (a, b, c) and MRR (d, e, f).

B. GMDH Predicting Model

This study analyzed the data using the GMDH polynomial network and regression analysis. The model's construction was carried out using the predictive modeling software DTREG version 10.6. Due to the limited sample size, a 10-fold cross-validation method was chosen to assess the robustness of the network's performance in the prediction model, considering sampling variation. Additionally, the maximum number of network layers was set to 30, the maximum polynomial order was set to 16, and the convergence tolerance was set to 10^{-4}. Table VI displays the target variable Ra, along with the model type, training data, and validation data. The results for the Ra target variable indicate that the triple model with three variables exhibited the best predictive performance, with the highest R^2, the lowest RMSE, and the lowest MAPE in training and validation data. Therefore, this prediction model will be selected for the subsequent optimization steps. The GMDH model equations for Ra is shown in Eq. (8):

$$\begin{aligned}Ra = {} & 0.334632+0.703492\times Dc+3.4178\times Fr+0.011385\times Vc-3.308009\times Dc2+59.12961\times Fr2-0.000283\times Vc2-\\ & 12.01444\times Dc\times Fr+0.017621\times Dc\times Vc-0.0151570\times Fr\times Vc+0.0887971\times Dc\times Fr\times Vc+3.6928532\times Dc3-\\ & 130.83393\times Fr3+0.0000024\times Vc3-7.9137545\times Dc\times Fr2-0.0001576\times Dc\times Vc2+14.487617\times Fr\times Dc2-\\ & 0.0006858\times Fr\times Vc2+0.0001819\times Dc2\times Vc+0.0905730\times Fr2\times Vc\end{aligned} \tag{8}$$

TABLE VI. THE PREDICTED MODEL FOR RA USING DIFFERENT GMDH MODEL TYPES

Model type	Training Data			Validation Data		
	R^2	RMSE	MAPE	R^2	RMSE	MAPE
Linear (1 variable)	0.539	0.364	18.475	0.535	0.366	18.767
Linear (2 variables)	0.875	0.190	10.496	0.856	0.204	11.236
Linear (3 variables)	0.873	0.191	10.455	0.852	0.207	11.762
Quadratic (1 variable)	0.566	0.354	17.173	0.554	0.359	17.534
Quadratic (2 variables)	0.971	0.092	4.357	0.933	0.139	5.871
Cubic (1 variable)	0.565	0.354	17.188	0.543	0.363	17.657
Double (2 variables)	0.976	0.082	4.163	0.948	0.122	5.963
Triple (3 variables)	0.981	0.074	3.600	0.959	0.119	5.864

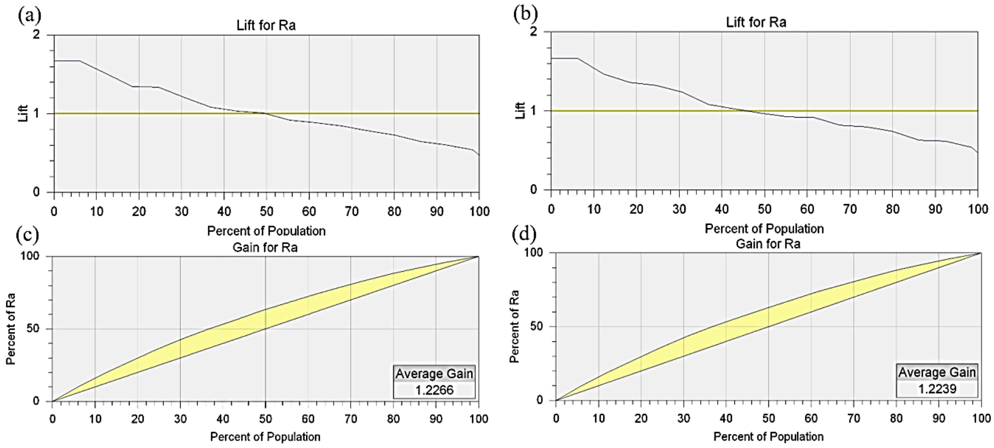

Fig. 6. Lift and gain for training (a), (c) and validation (b), (d) data.

The Ra model was evaluated using Lift and Gain charts for training and validation data. In the Lift charts (Fig. 6(a) and (b)), the lift value decreases as the population percentage increases, starting from a value higher than one, indicating the model's ability to identify target subjects higher than the total population's average. This result is consistent between the training and validation data, showing that the model retains its generalizability when applied to new data. The Gain line shows a continuous increase for the Gain charts (Fig. 6(c) and (d)), reflecting the model's capability to identify a high proportion of target cases as the percentage of the population considered increases. The average Gain values on both datasets indicate that the model provides approximately a 22% advantage over random selection methods, reinforcing the performance and reliability of the model. This result bolsters the effectiveness and applicability of the model in real-world situations with high accuracy. Fig. 7 compares the predicted values of the GMDH model and the actual values of Ra. Most predicted output values are close to the actual values, indicating that the GMDH model is highly reliable in predicting Ra.

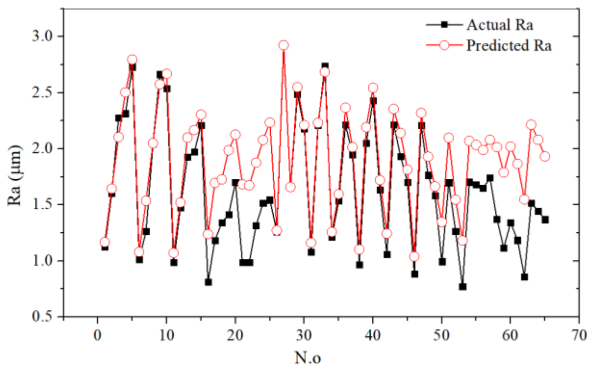

Fig. 7. Actual Ra from experiment and predicted values using GMDH.

C. *Application of the NSGA-II Algorithm for Multi-objective Optimization*

In this study, a multi-objective optimization model utilizing the NSGA-II algorithm is employed to determine the suitable input parameters, namely Vc, Fr, and Dc. The objective is to identify a set of design parameters that can concurrently achieve the smallest Ra value (indicative of improved surface quality) and the highest MRR (indicative of enhanced material removal efficiency). This optimization process aims to strike a balance between surface quality and material removal efficiency. Table VII presents the details and values associated with the input parameters and objectives.

TABLE VII. INPUT PARAMETERS AND OPTIMIZATION OBJECTIVES BY NSGA-II

Input			Output	
Parameter	**Low**	**High**	**Parameter**	**Objective**
Vc	40	120	MRR	Maximum (Eq. (1))
Fr	0.1	0.3	Ra	Minimum (Eq. (8))
Dc	0.1	0.5		

The optimization tool of MATLAB software was used. Various control parameters were selected to configure the algorithm, encompassing population size, maximum number of generations, crossover probability, and mutation probability. The "maximum generations" parameter governs the number of iterations the algorithm performs before terminating. It establishes an upper limit on the generated generations. The "crossover probability" parameter determines the frequency of crossover operations during the algorithm's execution. Higher values lead to faster convergence, while lower values result in slower convergence. Lastly, the "mutation probability" parameter influences the likelihood of random perturbations occurring in individual solutions. It controls the probability of introducing random changes to maintain diversity within the population. For this study, the following parameter values were chosen: a maximum generation number of 1,000, a crossover probability of 0.8, and a mutation probability of 0.25. In addition, a function tolerance was 10^{-5}.

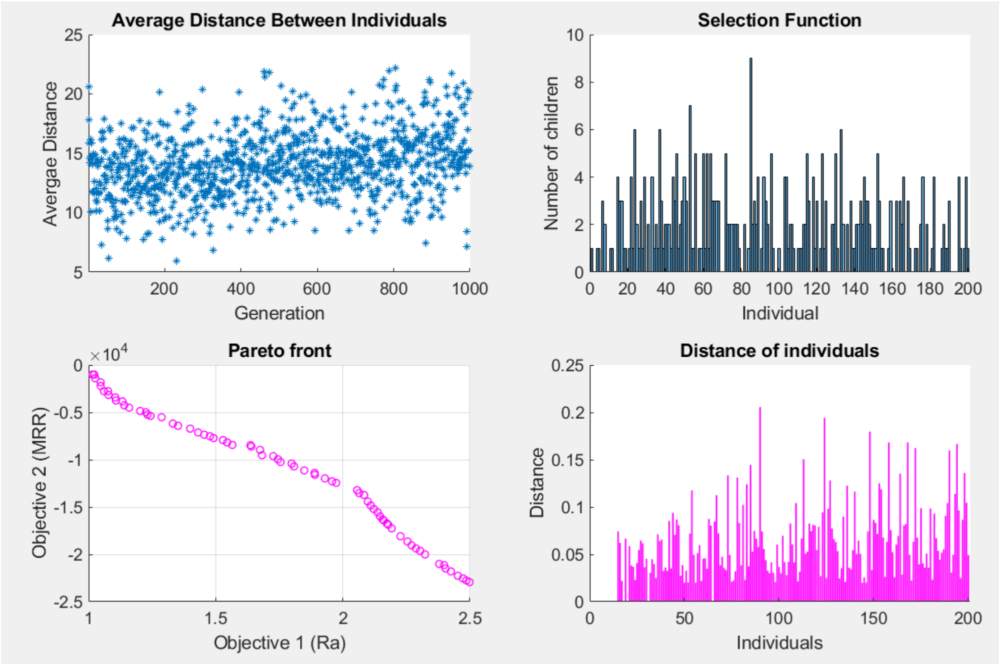

Fig. 8. Results of multi-objective optimization utilizing NSGA-II.

TABLE VIII. RESULTS OF VALIDATION RA AND MRR COMPARED TO OPTIMIZED VALUES

Solution N.o	Cutting parameter			Ra (μm)			MRR (mm^3/min)		
	Vc (m/min)	Fr (mm/rev)	Dc (mm)	NSGA-II	Actual	Deviation (%)	NSGA-II	Calculated	Deviation (%)
11	119.3	0.3	0.4	2.198	2.418	10.3	17,249.87	17,249.87	0
35	84.4	0.1	0.3	1.078	1.168	8.3	3,166.54	3,166.54	0
69	84.1	0.1	0.4	1.141	1.177	3.2	4,254.04	4,254.04	0

The optimization results are presented in Fig. 8, which visually represents the trade-offs between the two objectives. Seventy solutions were obtained after optimization, with the Ra ranging from 1.016 μm to 2.498 μm. Regarding the second objective, the MRR ranged from 998.1 mm^3/min to 22,929.1 mm^3/min. The cutting speed ranged from 78.17 m/min to 120 m/min, the depth of cut ranged from 0.1 mm to 0.3 mm, and the feed rate ranged from 0.10 mm/tooth to 0.5 mm/tooth. These Pareto-optimal solutions give the manufacturer valuable insights into the relationships and interdependencies between the machining parameters and the performance measures.

Experiments were conducted with the cutting parameters of the optimized solutions set at 11, 35, and 69 to validate the results of the Pareto solution obtained from the NSGA-II method. Table VIII shows that the deviation between the optimal value of Ra and the actual value is less than 10.3%. This deviation value is similar to some recent studies using the NSGA-II method, which also achieved good results when comparing optimized and experimental values [38, 39].

This study presents a significant advancement for industrial SKD11 milling by developing a multi-objective optimization methodology for Ra and MRR. The employed Taguchi method offers a practical and efficient approach for real-world applications due to its reduced number of experimental runs. The high accuracy of the GMDH model empowers manufacturers to tailor cutting conditions and achieve desired surface finishes. Furthermore, the NSGA-II technique identified 70 Pareto solutions, representing a spectrum of optimal cutting conditions that balance the often-conflicting goals of minimizing Ra and maximizing MRR. This versatility allows industrial managers to select parameters that best suit their priorities, such as prioritizing high-quality surfaces for critical components or maximizing production efficiency by achieving faster material removal.

IV. CONCLUSION

This study primarily focused on the modeling and optimization of surface roughness (Ra) and Material Removal Rate (MRR) in the milling of SKD11 material. The Taguchi orthogonal array experimental design approach was employed by considering three cutting parameters (Vc, Dc, and Fr) to determine the appropriate number of experimental samples. A predictive model was developed utilizing the GMDH method to establish correlations between the cutting parameters and Ra. Subsequently, the NSGA-II technique was used for multi-objective optimization. The results demonstrated that the triple model (incorporating three variables) for Ra exhibited the most accurate predictive performance. This model achieved the highest R^2 value, the lowest RMSE value, and the lowest MAPE value in training and validation datasets. Applying the NSGA-II for multi-objective optimization resulted in 70 Pareto solutions, representing the trade-offs among cutting parameters and two conflicting objectives. Three solutions from the set of 70 solutions were selected and machined to validate the optimal values obtained from the NSGA-II method. The results revealed that the deviation from the optimal values was less than 10.3%, meeting the criteria for production requirements. The findings establish that the multi-optimization methodology employed in this study identified and provided solutions for selecting cutting conditions based on diverse criteria, offering versatility for practical applications.

However, some limitations are worth considering for future research. This investigation focused on three cutting parameters. Incorporating additional factors could provide a more comprehensive understanding of the milling process. Additionally, utilizing different optimization algorithms alongside NSGA-II would enable comparative analysis and potentially identify even better solutions. Furthermore, employing real-time data during machining could allow for adaptive control strategies by dynamically adjusting cutting parameters based on actual conditions. Future research exploring these avenues can further refine the optimization process and enhance the efficiency and quality of SKD11 milling.

Conflict of Interest

The author declares no conflict of interest.

Acknowledgment

This work was conducted at the Vietnam National University of Forestry and Z119 factory. The authors would like to express their sincere gratitude to the anonymous reviewers for their meticulous review of our manuscript and their valuable comments, which greatly contributed to the improvement of the paper.

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