Optimization of Rubber Sheet Rolling Machine Parameters using a Taguchi-based TOPSIS Linear Programming Model

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ABSTRACT

The Multi-Response Optimization (MRO) problem is a critical aspect of the engineering design, particularly in improving process efficiency and product quality. This study focuses on optimizing the parameters for a rubber sheet rolling machine, a vital component of Thailand's natural rubber industry. The objective is to enhance its operational efficiency and product consistency by addressing key criteria, such as production time and rubber sheet thickness. A novel approach integrating the Taguchi method and the Technique for Order Preference by Similarity to Ideal Solution Linear Programming (TOPSIS-LP) model is proposed. The Taguchi method systematically designs experiments, while the Preference by Similarity to Ideal Solution (TOPSIS) model consolidates multiple performance indicators into a single optimal solution. Optimal roller gaps of 4.5 mm, 3.0 mm, 2.0 mm, and 0.1 mm for the first, second, third, and fourth roller pairs, were, respectively, identified. The results demonstrated a reduction in rubber sheet thickness to 2.06 mm (5.94% improvement) and production time to 9.71 seconds per sheet (1.33% improvement) compared to the original settings. The qualitative analysis confirmed the robustness and reliability of the optimized parameters, achieving consistent results across various evaluation methods. This study presents a significant advancement in the MRO problem, offering a robust framework applicable to similar challenges in industrial settings. The findings provide a foundation for future automation and optimization efforts, driving sustainable improvements in the manufacturing efficiency and product quality.

Keywords-rubber sheet rolling machine; multi-response optimization; TOPSIS; linear programming; Taugchi method

I. INTRODUCTION

The global rubber industry plays a crucial role in meeting the demand for natural and synthetic rubber products. Technically Specified Rubber (TSR) accounts for 25% of the world's export volume, highlighting its significance in the international trade. However, the domestic consumption of natural rubber remains limited, representing just 18.1% of the total global natural rubber production. Within this context, Thailand, one of the largest producers of natural rubber, consumes only 4.2% of the global supply. In contrast, China dominates the natural rubber consumption, accounting for 42.9% of the worldwide volume [1]. In recent years, the rubber industry has experienced a steady growth in both production and demand, driven by expanded cultivation areas, favorable weather conditions, and proactive farming practices supported by strong market prices. However, key producers, such as Indonesia and Malaysia, faced labor shortages, hindering a full supply recovery. On the demand side, natural rubber gained prominence as a cost-effective alternative to synthetic rubber, which saw price increases due to the rising crude oil costs amidst the Russia-Ukraine conflict. The outlook for the industry remains optimistic, with a rising demand across various sectors. The automotive industry's shift toward electric vehicles, supported by government incentives, is expected to significantly increase demand. Similarly, the medical sector is forecasted to sustain a robust consumption, particularly for rubber gloves and related supplies. Infrastructure projects are also anticipated to boost the rubber usage in construction applications. Efforts by governments to stabilize the rubber prices are likely to enhance market resilience and stability. Thailand is poised for recovery, with an increased demand from key sectors, such as automotive and healthcare. The rubber industry spans three primary sectors: upstream (rubber farming), intermediate (processing raw rubber into smoked sheets and latex), and downstream (manufacturing finished goods, such as tires, gloves, and elastic materials). These sectors collectively underpin the supply chain, driving the industry's overall performance [2-3].

The production of commercial rubber sheets—spanning filtration, coagulation, rolling, and drying—faces inefficiencies due to the labor-intensive manual rolling. Specifically, the current process, which involves multiple passes through smooth rollers before drying on patterned rollers, causes worker fatigue and inconsistent sheet quality, undermining profitability. As global demand for rubber products increases, Thailand must adopt advanced machinery to ensure a cost-effective, consistent, and precise production. These challenges were highlighted during a brainstorming session with 85 members of the Nong Pa Oi High-Quality Rubber Sheet Community Enterprise in Kalasin Province, Thailand. To address them, a semi-automatic rubber sheet press with an automated control system was developed to reduce manual labor and alleviate worker fatigue. This innovation improves the Thai agriculture by boosting productivity, enhancing energy efficiency, ensuring consistent product quality, and improving farmer well-being. The machine underwent rigorous evaluation to validate its reliability and efficiency. Optimizing the performance of these machines requires precise roller gap adjustments. Merely introducing advanced equipment is insufficient; fine-tuning is essential to achieve superior product quality and operational efficiency. This optimization must balance production efficiency, cost, and quality, which demands computational methods like the Design of Experiments (DOE). DOE provides a systematic framework for evaluating machine settings and identifying optimal parameters, streamlining the production and ensuring a consistent, high-quality output.

The literature review in Section II highlights numerous innovations addressing the MRO problems. Research shows that optimization models like the Taguchi approach minimize performance variability and improve manufacturing efficiency [4-6]. The Taguchi method's robust design framework identifies key factors influencing the production outcomes. When combined with Multi-Criteria Decision-Making (MCDM) techniques, such as TOPSIS, optimization becomes more comprehensive by considering multiple performance indicators [7-9]. The TOPSIS-LP model introduced in [10], enhances the traditional TOPSIS by reducing its computational complexity, streamlining the multi-step process, and minimizing the calculation errors. This method has demonstrated versatility across various fields [11-13]. Building on these principles, this study integrates the Taguchi method with a TOPSIS-LP model to optimize rubber sheet rolling machine parameters. By focusing on critical factors, like roller spacing, the research seeks to enhance production efficiency, improve rubber sheet quality, and promote sustainability in the rubber industry. Beyond its theoretical contributions, this study emphasizes practical applications and technology transfer to ensure a seamless implementation in real-world settings. By delivering tangible benefits to rubber farming communities, the present research bolsters economic resilience and advances the rubber sector, strengthening its impact locally and globally.

II. LITERATURE REVIEW

Optimizing parameters in machine design and engineering applications poses a multifaceted challenge, particularly in addressing MRO problems. These problems involve balancing multiple conflicting performance criteria, such as operational efficiency, energy consumption, product quality, and material usage, to ensure high performance and cost-effectiveness [14-15]. The MRO methods are essential for optimizing outcomes across diverse engineering fields, including rubber processing, which requires managing multiple factors to achieve optimal results.

A. Multi-Response Optimization Techniques in Enginnering Applications

Evolutionary algorithms [16-18] and MCDM methods [19-21] have been extensively employed to address the MRO challenges. The MCDM approaches have been integrated with principles of experimental design, which have gained a widespread acceptance for their practical applicability. Specifically, authors in [22] employed a multi-objective optimization approach using CRITIC-WASPAS and the Taguchi methodology to enhance the Open Graded Friction Course (OGFC) durability. Their findings demonstrated an improved abrasion resistance with nylon fibers over polypropylene, optimizing both functionality and mechanical properties. In [23], the BWM and TOPSIS-based Taguchi methods were deployed for optimizing ceramic waste geopolymer concrete, significantly enhancing its compressive strength, elasticity modulus, and durability while minimizing its environmental impact. Authors in [24] utilized the Principal Component Analysis and Grey Relational Analysis to optimize the Ni-based laser cladding parameters, achieving superior wear resistance, micro-hardness, and uniform microstructure.

B. Taguchi Method for Multi-Response Optimization

The Taguchi method is a widely employed experimental design framework that focuses on robustness and efficiency. By using orthogonal arrays, it minimizes the number of experiments required to evaluate multiple factors. The method also employs signal-to-noise (S/N) ratios to classify the optimization objectives as "larger-the-better," "smaller-the-better," or "nominal-the-best." Several studies have demonstrated the effectiveness of integrating the Taguchi method with MCDM techniques to solve the MRO problems.

For instance, authors in [25] applied the Taguchi-Grey Relational Analysis to optimize the geopolymer concrete properties, improving its mechanical strength and minimizing water absorption with optimal material combinations. The results indicated superior performance using 90% GGBFS, 10% FA, and an optimal alkaline solution. Additionally, authors in [26] combined the EDAS method with entropy weighting to optimize an ORC-VCR system, achieving a 30% improvement in the exergetic efficiency and reducing the environmental costs. Authors in [27] utilized the Taguchi, Analysis of Variance (ANOVA), and TOPSIS methodologies for optimizing the EN19 steel milling parameters, enhancing the surface roughness and material removal rates with optimal spindle speed and cutting conditions. Finally, authors in [28] optimized the cutting parameters for the Ti-6Al-4V titanium alloy milling under MQL using entropy-based TOPSIS and ANOVA.

C. Technique for Order Preference by Similarity to Ideal Solution and its Integration with the Taguchi Method

TOPSIS is a popular MCDM technique that evaluates alternatives by calculating their relative closeness to an ideal solution. Its simplicity and interpretability make it ideal for optimizing multiple conflicting responses across various engineering applications [29-30]. The TOPSIS-LP model introduced in [10], refines the traditional TOPSIS by reducing its computational complexity while maintaining accuracy. Based on the Relative Closeness Coefficient model [31], this approach simplifies calculations, reduces errors, and handles large datasets effectively. The original multi-step procedure is computationally complex, but this novel approach reduces its complexity, improving optimization solver efficiency and usability. It also decreases calculation errors and handles large datasets well. Combining the Taguchi method and TOPSIS-LP addresses the inherent limitations of each approach. Although the Taguchi method efficiently narrows the experimental space and optimizes the individual responses, it lacks the ability to manage trade-offs between multiple outcomes. TOPSIS-LP complements this by calculating the closeness coefficients that integrate multiple responses into a single performance index, facilitating robust decision-making. This integrated approach enhances parameter selection for maximizing machine performance while minimizing trade-offs.

D. Reasearch Gap and Study Objective

Although the integration of Taguchi and TOPSIS methods has been extensively applied in material engineering, supply chain optimization, and energy systems, limited research exists on their application to rubber sheet rolling processes. Specifically, there is a gap in addressing the trade-offs between the production efficiency and product quality in this context. Rubber sheet rolling is a critical process in Thailand's rubber industry, where inefficiencies can significantly impact product consistency and profitability. This study aims to fill this gap by employing an integrated Taguchi-TOPSIS-LP model to optimize the operational parameters for rubber sheet rolling.

III. PROPOSED METHOD

This section presents a novel methodology that integrates a Taguchi-based TOPSIS-LP model to achieve MRO. The efficacy of the proposed approach is validated through a case study focusing on the optimization of the parameters for a rubber sheet rolling machine. This investigation underscores the importance of a structured optimization strategy to address challenges, such as inconsistent sheet quality and operational inefficiencies. Figure 1 illustrates the proposed framework, which provides a systematic approach for parameter optimization, ensuring an improved efficiency and consistent product quality in the rubber sheet production.

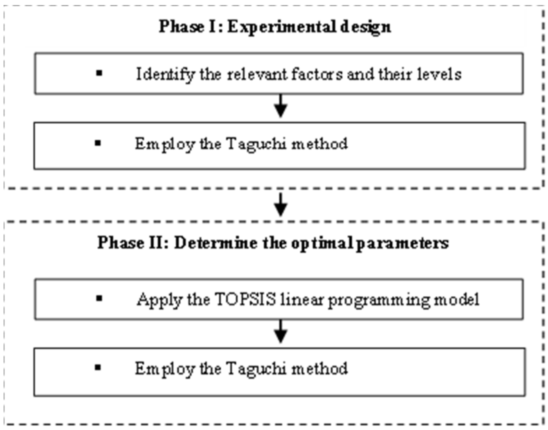

Fig. 1. Framework of the proposed methodology for rubber sheet rolling machine parameter optimization.

A. Phase I: Experimental Design

This phase presents the application of the Taguchi method to address the MRO of rubber sheet rolling machine parameters. The experimental design process is divided into two key substeps:

1) Identifying the Relevant Factors and their Levels

The identification of the relevant factors and their levels is a critical step in designing effective experiments. This involves determining the variables that significantly influence the outcome and defining the specific values or conditions, referred to as "levels", at which these variables will be assessed. By accurately identifying these factors and levels, the experimental design ensures a thorough analysis of their effects on the response variables, enabling a comprehensive understanding of the process.

2) Employing the Taugchi Method

The Taguchi method offers a systematic approach to experimental design, aiming to optimize the process conditions while minimizing variability and enhancing quality. This methodology leverages orthogonal arrays to efficiently arrange experiments, allowing the simultaneous evaluation of multiple variables with a reduced number of experimental trials. By methodically exploring the experimental domain, the Taguchi method facilitates the identification of factors that have a significant impact on process performance. This structured approach ensures an efficient and reliable analysis, contributing to the overall improvement of the rubber sheet rolling process.

B. Phase II: Determining the Optimal Parameters

Determining the optimal parameters involves selecting the most effective combination of factor levels to achieve the desired outcomes, such as improved efficiency, reduced variability, and enhanced product quality. This process requires a thorough analysis of the experimental data to identify the parameter configurations that maximize or minimize the response variables. The objective is to improve performance by understanding and leveraging the influence of each parameter on the overall process.

1) Apply the Technique for Order Preference by Similarity to Ideal Solution Linear Programming Model

Following the analysis of the response results, the TOPSIS-LP model is employed to consolidate multiple responses into a single performance metric. The calculation process for this model involves three main steps:

a) Generate the Decision Matrix

In the TOPSIS-LP model, the closeness coefficient for each experimental run is evaluated relative to specific criteria. A Decision Matrix (DM) is constructed, where each experimental run serves as an alternative (denoted as A_i), and the corresponding responses are treated as criteria (C_j). These criteria are classified into:

- Cost criteria: to be minimized.
- Beneficial criteria: to be maximized.

The DM incorporates all alternatives and the associated criteria:

$$X = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \quad (1)$$

where $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, n$. x_{ij} represents the value of the alternative i with respect to the criterion j. This structured representation forms the foundation for the decision-making process.

b) Generating the Normalized Decision Matrix

The Normalized Decision Matrix (NDM), referred to as the Y matrix, ensures that all criteria contribute equally to the analysis by adjusting their scales for a fair comparison.

$$Y = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \end{array} \quad (2)$$

The normalized performance of the alternative i with respect to the criterion j, given as y_{ij}, is calculated by:

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \quad (3)$$

$$y_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \quad (4)$$

This dual approach ensures that beneficial criteria (where higher values are preferred) and cost criteria (where lower values are preferred) are normalized appropriately, aligning with the optimization goals.

c) Calculating the Closeness Coefficient (CC)

The TOPSIS model incorporates each alternative i with a set of criteria j into the NDM y_{ij}. The weights assigned to each criterion (w_j) are determined based on the preferences of the decision-makers, ensuring that the relative importance of each criterion is appropriately reflected. The model calculates the distances of each alternative from both the positive and negative ideal solution. For each criterion j, the positive ideal value (y_j^+) represents the best performance, while the negative ideal value (y_j^-) signifies the worst performance. These values are determined as:

$$y_j^+ = \max\{y_{ij}\}, y_j^- = \min\{y_{ij}\}, for\ j = 1, 2, \dots, n$$

The relative closeness coefficient (CC_i) for each alternative i is defined by [10]:

$$\begin{aligned} & CC_i = \max \lambda_i^- \left(\sum_{j=1}^{n} \sqrt{w_j^2 (y_{ij})^2 - (y_j^-)^2} \right), \\ & \lambda_i^- \left(\sum_{j=1}^{n} \sqrt{w_j^2 (y_{ij})^2 - (y_j^-)^2} \right) + \lambda_i^+ \left(\sum_{j=1}^{n} \sqrt{w_j^2 (y_j^+)^2 - (y_{ij})^2} \right) = 1, \\ & \lambda_i^- \left(\sum_{j=1}^{n} \sqrt{w_j^2 (y_{ij})^2 - (y_j^-)^2} \right) \le \lambda_i^- \left(\sum_{j=1}^{n} \sqrt{w_j^2 (y_{ij})^2 - (y_j^-)^2} \right) \\ & + \lambda_i^+ \left(\sum_{j=1}^{n} \sqrt{w_j^2 (y_j^+)^2 - (y_{ij})^2} \right), \\ & \lambda_i^- = \lambda_i^+, \lambda_i^-, \lambda_i^+ \ge 0 \end{aligned} \quad (5)$$

A higher value of CC_i indicates that the alternative is closer to the ideal solution, signifying a better overall performance.

2) Employing the Taguchi Method

This section outlines the systematic implementation of the Taguchi method, leveraging the results derived from the TOPSIS-LP model to optimize the parameters of the rubber sheet rolling machine. The process is designed to enhance the machine's overall performance through a structured and methodical approach.

The first step involves calculating the *CC* for each experimental run using the TOPSIS-LP model. These coefficients serve as a foundation for evaluating and ranking the alternatives, providing a critical input for the subsequent optimization process. The Taguchi method is then applied using the Minitab statistical software, facilitating a robust and efficient analysis of the experimental data. The study focuses on key response types: "Larger is better" and "Smaller is better." These responses are analyzed using S/N ratios, which are a fundamental aspect of the Taguchi method by quantifying variability and guiding the determination of the optimal settings. The S/N ratio for each criterion is computed as:

- For "Larger is better":

$$S/N = -10\,log\frac{1}{n}\sum_{i=1}^{m} R^{-2} \tag{6}$$

- For "Smaller is better":

$$S/N = -10\,log\frac{1}{n}\sum_{i=1}^{m} \frac{1}{R^{-2}} \tag{7}$$

where *R* represents the response and *n* the number of replications.

IV. RESULTS AND DISCUSSION

A. Results of Experimental Design

This research developed a semi-automatic rubber sheet press featuring four pairs of rollers (eight rollers) powered by a 2-horsepower (1.49 kW) electric motor operating at 1,450 rpm. The system employs worm gear transmission and a chain drive mechanism to synchronize all rollers for an efficient operation. The rollers are divided into two smooth rollers, each with a diameter of 114 mm and a length of 610 mm, and two patterned rollers, each with a diameter of 118 mm and a length of 610 mm. An integrated control system automates the pressing process, significantly reducing the manual labor and fatigue while saving time and energy. This innovation enhances farmers' income and life quality, improving the overall quality of the Thai agricultural products. The design has been rigorously refined and tested to ensure an optimal performance and efficiency. Figures 2 provides a detailed illustration of the rubber sheet rolling machine. The roller pairs 1 and 2 are designated for smooth pressing, while the pairs 3 and 4 handle patterned pressing.

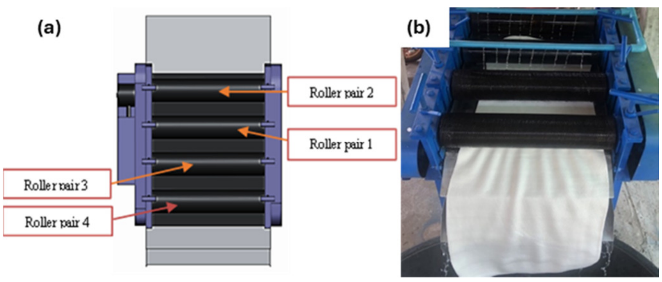

Fig. 2. The rubber sheer rolling machine: (a) schematic, (b) in operation.

Four key factors were identified for this experiment, each evaluated at three district levels. To optimize the process while minimizing costs and reducing the duration of trials, the Taguchi method was employed. This method was chosen for its efficiency and effectiveness in simultaneously optimizing multiple parameters. The factors considered in the experiment were:

- Factor *A*: The first pair of rubber sheet rollers.
- Factor *B*: The second pair of rubber sheet rollers.
- Factor *C*: The third pair of rubber sheet rollers.
- Factor *D*: The fourth pair of rubber sheet rollers

Each factor was assessed at three different levels to ensure a comprehensive evaluation. The details of these factors and their respective levels are presented in Table I.

TABLE I. FACTORS WITH THEIR LEVELS

Factors	Coded Level	Uncoded Level
A	1, 2, 3	4.5, 5.0, 5.5
B	1, 2, 3	2.0, 2.5, 3.0
C	1, 2, 3	1.0, 1.5, 2.0
D	1, 2, 3	0.1, 0.5, 1.0

During each experimental trial, two key response variables were evaluated: the thickness of the rubber sheet (*R1*) and the production time (*R2*).

- Rubber sheet thickness (*R1*): This response must meet the market requirements by staying below 3 millimeters. It is classified as a "smaller-is-better" response, signifying that minimizing this value is desirable.
- Production time (*R2*): Measured in seconds per sheet, this response is also categorized as "smaller-is-better", emphasizing the preference for shorter production times to enhance the operational efficiency.

The additional experimental results are comprehensively detailed in Table II.

TABLE II. EXPERIMENTAL RESULTS BASED ON TAGUCHI METHOD

Runs	*A*	*B*	*C*	*D*	*R1*	*R2*
1	4.5	2.0	1.0	0.1	2.14	11.43
2	4.5	2.5	1.5	0.5	2.73	10.00
3	4.5	3.0	2.0	1.0	3.24	8.57
4	5.0	2.0	1.5	1.0	3.45	9.60
5	5.0	2.5	2.0	0.1	2.19	9.80
6	5.0	3.0	1.0	0.5	2.85	9.23
7	5.5	2.0	2.0	0.5	2.94	9.60
8	5.5	2.5	1.0	1.0	3.45	8.89
9	5.5	3.0	1.5	0.1	2.35	9.23

B. Determination of the Optimal Parameters

Using the dataset of responses provided in Table II, the NDM was calculated following the procedures outlined in Section III. The results of the NDM for this case study are presented in Table III. The Lingo software was utilized to compute all the *CC* scores for the rubber sheet rolling machine optimization problem. Equation (5) was implemented in Lingo code to address the case study, as displayed in Figure 3. This approach effectively translates the mathematical model into a solvable format while incorporating the specified constraints and parameters.

TABLE III. THE NORMALIZED DECISION MATRIX RESULTS

Runs	*R1*	*R2*	*CC*
1	0.7502	0.6042	0.6984
2	0.6814	0.6537	0.5419
3	0.6219	0.7032	0.3543
4	0.5974	0.6676	0.2147
5	0.7444	0.6606	0.8396
6	0.6674	0.6803	0.5066
7	0.6569	0.6676	0.4312
8	0.5974	0.6922	0.2772
9	0.7257	0.6803	0.8270
Yn	0.5974	0.6042	
Yp	0.7502	0.7032	
w	0.60	0.40	

Lingo code

```
MODEL:
SETS:
ALTERNATIVE/1..9/:CC,SP,SN,RHO,DEL ;
FACTOR/1..2/:Yn,Yp,W;
IJ(ALTERNATIVE, FACTOR):Y ;
ENDSETS
DATA:
Y=
0.7502    0.6042
0.6814    0.6537

..........    ..........
0.7257    0.6803;
Yn=0.5974  0.6042; Yp=0.7502  0.7032; w =0.60  0.40;
ENDDATA
MAX=@SUM(ALTERNATIVE (I):CC(I));
@FOR(ALTERNATIVE(I):
CC( I)=RHO(I)*(@SQRT(@SUM(FACTOR(J):W(J)^2*(Y(I, J)-Yn(J))^2))) );
@FOR(ALTERNATIVE(I):
RHO(I)*(@SQRT(@SUM(FACTOR(J):W(J)^2*(Y(I, J)-Yn(J))^2)))          +
DEL(I)*(@SQRT(@SUM(FACTOR(J):W(J)^2*(Yp(J)-Y(I, J))^2))) =1
@FOR(ALTERNATIVE(I):
RHO(I)-DEL(I)=0 );
@FOR(ALTERNATIVE(I):
RHO(I)*(@SQRT(@SUM(FACTOR(J):W(J)^2*(Y(I, J)-Yn(J))^2))) <=
RHO(I)*(@SQRT(@SUM(FACTOR(J):W(J)^2*(Y(I, J)-Yn(J))^2))) +
DEL(I)*(@SQRT(@SUM(FACTOR(J):W(J)^2*(Yp(j)-Y(I, J))^2))) );
@FOR(FACTOR(J): W(J)>=0);
@FOR(ALTERNATIVE(I): RHO(I)>=0);
@FOR(ALTERNATIVE(I): DEL(I)>=0);
END
```

Fig. 3. The Lingo code for the rubber sheet rolling machine problem.

After calculating the *CC* values, the Minitab statistical software was utilized to determine the optimal parameters. The corresponding S/N ratios for the *CC* response are comprehensively presented in Table IV.

TABLE IV. RESPONSE TABLE FOR S/N RATIOS OF THE CC RESPONSE FOR THE RUBBER SHEET ROLLING MACHINE PROBLEM

Experiments	The pair of rubber sheet rollers			
	A	B	C	D
1	-5.818	-7.93	-6.723	-2.096
2	-6.93	-5.995	-6.779	-6.178
3	-6.7	-5.523	-5.946	-11.174
Delta	1.112	2.407	0.833	9.078
Rnak	3	2	4	1

As shown in Table IV, a higher delta value indicates that the corresponding process parameters exert a greater influence on the multi-response performance indicator. The delta statistics reveal that the *CC* response is most significantly influenced by the fourth pair of rubber sheet rollers (Factor *D*). Figure 4 portrays the main effect plot for the S/N ratios, providing a visual representation of the data. The analysis indicates that the optimal parameters for achieving the desired *CC* are as follows: Factor *A* at Level 1, with a gap between the first pair of rollers set to 4.5 mm; Factor *B* at Level 3, with a gap between the second pair of rollers set to 3.0 mm; Factor *C* at Level 3, with a gap between the third pair of rollers set to 2.0 mm; and Factor *D* at Level 1, with a gap between the fourth pair of rollers set to 0.1 mm.

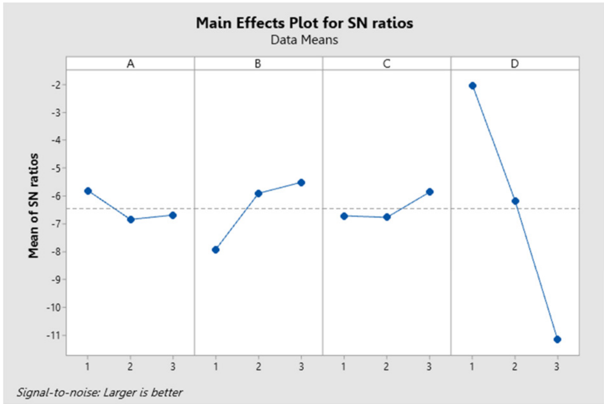

Fig. 4. Main effect plot for S/N ratios of the *CC* response for the proposed rubber sheet rolling machine.

The *CC* scores for each experimental run, obtained from the TOPSIS-LP model calculations were analyzed, using the ANOVA, as shown in Table V. The results revealed that the factors corresponding to the second pair of rubber sheet rollers (*B*) and the fourth pair of rubber sheet rollers (*D*) had a significant impact on the *CC* response. This was evidenced by P-values less than 0.05, indicating a strong statistical significance.

TABLE V. THE ANOVA RESULTS FOR THE CC RESPONSE FOR THE RUBBER SHEET ROLLING MACHINE PROBLEM

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	4	0.408115	0.102029	49.52	0.001
A	1	0.000583	0.000583	0.28	0.623
B	1	0.019684	0.019684	9.55	0.037
C	1	0.003406	0.003406	1.65	0.268
D	1	0.384442	0.384442	186.58	0.000
Error	4	0.008242	0.00206	-	-
Total	8	0.416357	-	-	-

C. *Comparative Analysis and Experimental Validation*

Comparative analysis is a widely utilized approach to evaluate the reliability and robustness of solutions, particularly in decision-making processes. By employing various MCDM methods, this analysis provides valuable insights into the consistency and stability of the proposed solutions. In this study, data from the TOPSIS-LP model were utilized, including the normalized decision matrix from Table III, with weights designated as $w_{R1} = 0.60$ and $w_{R2} = 0.40$. Table VI provides a thorough comparison of the proposed method with other MCDM approaches, such as TOPSIS [32], Weighted Aggregated Sum Product Assessment (WASPAS) [33], and the new Additive Ratio Assessment (ARAS) [34].

TABLE VI. COMPARISON RESULTS OF THE PROPOSED METHODS WITH ALTERNATIVE MCDM APPROACHES

Methods	Original Parameters	Optimal Parameters
TOPSIS	A3,B2,C3,D1	A1,B3,C3,D1
WASPAS	A3,B2,C3,D1	A1,B3,C3,D1
ARAS	A3, B2,C3,D1	A1,B3,C3,D1
Proposed	A3,B2,C3,D1	A1,B3,C3,D1

The comparison results indicate that the original parameters and the optimal parameters identified by most MCDM methods are strikingly similar. This alignment highlights the robustness and reliability of these methods in determining the optimal settings for the proposed machine. The consistency of the results across various MCDM approaches reinforces the effectiveness of the identified parameters in achieving the desired performance metrics, thereby validating their suitability for the optimization process.

In the experimental validation process, a confirmation test was performed utilizing the optimal parameters identified. The selected parameters included Factor *A* with a gap of 4.5 mm, Factor *B* with a gap of 3.0 mm, Factor *C* with a gap of 2.0 mm, and Factor *D* with a gap of 0.1 mm. Minitab software was used for the analysis, and the predicted results indicated that the values for R1 (rubber sheet thickness) and R2 (production time) were 2.09 mm and 9.64 seconds per sheet, respectively. These findings demonstrate the effectiveness of the optimized parameters in achieving the desired performance criteria. The optimal parameters were further tested with 15 replications, and the results showed close alignment with the actual experimental outcomes, within a 95% confidence interval. Comprehensive details of these findings are provided in Table VII.

TABLE VII. ACTUAL EXPERIMENTAL OUTCOMES WITH A 95% CONFIDENCE INTERVAL

Responses	95% Confidence Interval		Means	Predicted
	Low	High		
*R*1	2.04	2.08	2.06	2.08
*R*2	9.65	9.70	9.67	9.70

Additionally, the proposed method was compared against the original parameters (A3, B2, C3, D1), which yielded response values of $R1 = 2.19$ mm and $R2 = 9.80$ seconds per sheet. When comparing these results to those obtained using the optimal parameters, it was observed that *R1* decreased to 2.06 mm and *R2* decreased to 9.71 seconds per sheet, representing a 5.94% improvement in the thickness of the rubber sheet and a 1.33% improvement in production time. Figure 5 illustrates the comparison of the proposed method against the original parameters.

Although the optimized parameters demonstrate clear improvements in performance, their implementation in practical settings may face certain challenges. These include the cost of equipment upgrades, the need for operator training to ensure precise calibration, and potential variability in raw material properties that could affect consistency. Future studies could explore strategies to mitigate these challenges and assess the scalability of the proposed methodology in diverse manufacturing environments.

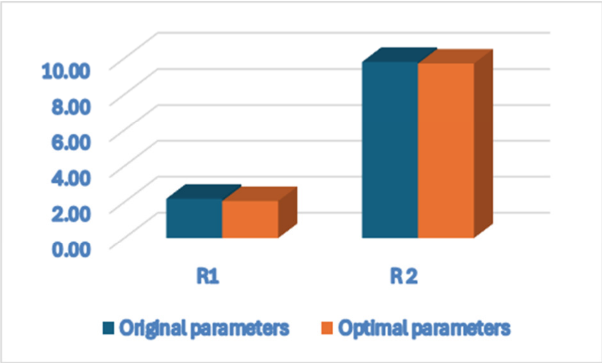

Fig. 5. Comparison of the proposed method with the original parameters.

Figure 6 depicts the characteristics of the rubber sheet produced using the optimized parameters derived from the integrated Taguchi-TOPSIS methodology. This highlights the tangible results of the optimization process, showcasing the uniformity and consistency in the thickness and quality of the rubber sheet. These results demonstrate the effectiveness of the proposed methodology in improving the production process. Specifically, it is confirmed that the optimized parameters not only enhance efficiency, but also ensure that the product meets the required industry standards.

Fig. 6. The characteristics of the rubber sheet produced under the optimal parameters.

V. CONCLUSION

Multi-Response Optimization (MRO) problems are crucial in industrial engineering, as they address the challenge of balancing conflicting objectives, such as improving production efficiency while maintaining high product quality. Effectively solving these problems is vital for advancing the manufacturing technologies and promoting sustainable practices across industries. The integration of these methodologies enabled the optimization of roller gap settings in the rubber sheet rolling machine, with a focus on reducing the production time and ensuring a consistent sheet thickness. The study's quantitative results showed significant improvements: the thickness of the rubber sheet was reduced to 2.06 mm (a 5.94% improvement), and the production time decreased to 9.71 seconds per sheet (a 1.33% improvement), compared to the original settings.

The qualitative analysis further demonstrated the robustness and reliability of the proposed methodology, as the optimized results remained consistent across different decision-making approaches. This highlights the practical utility of the method in both improving production efficiency and ensuring high product quality.

This methodology is immediately applicable to industries that require MRO, such as the automotive sector for tire manufacturing, where both quality and efficiency are paramount. Additionally, it could benefit the medical supplies industry (e.g., rubber glove production) by improving product consistency and reducing material waste. The construction industry could also benefit, especially in optimizing rubber-based materials for infrastructure projects to ensure cost-effectiveness and high-quality outcomes.

Future research should explore adapting this methodology for real-time optimization in automated manufacturing environments, particularly in sectors, like healthcare and transportation, where precision and efficiency are crucial. Additionally, integrating advanced computational techniques, such as machine learning algorithms, could further extend the applicability of this methodology to address more complex industrial challenges.

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