Multi-Response Optimization of an Automated Grass-Flower Beating Machine Using Taguchi and WASPAS in Broom Production

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ABSTRACT

Manual grass-flower beating in traditional broom production often results in inconsistent efficiency and material damage, limiting the productivity in rural communities. This study proposes a novel hybrid optimization framework combining the Taguchi L9 orthogonal array with the Weighted Aggregated Sum Product Assessment (WASPAS) method to enhance the performance of an automated grass-flower beating machine. Three key parameters: the rotational speed, beating time, and feedstock weight, were optimized to maximize the efficiency and minimize the damage. The experimental results identified optimal settings of 100 rpm, 120 s, 120 g, yielding an average efficiency of 95.50% and a low damage score of 1.23. The novelty of this work lies in the first application of Taguchi–WASPAS to optimize the community-scale broom production equipment. The proposed approach provides a cost-effective, replicable solution for improving the product quality and reducing the labor dependency. Future studies should incorporate additional variables and predictive modeling to support a broader implementation in sustainable manufacturing systems.

Keywords-broom production; multi-response optimization; weighted aggregated sum product assessment; Taguchi method; grass-flower beating machine

I. INTRODUCTION

Multi-Response Optimization (MRO) is a comprehensive statistical methodology employed within the framework of Design of Experiments (DOE) to systematically plan experiments and identify the optimal set of input parameters, using a variety of analytical tools [1]. MRO is designed to simultaneously optimize multiple, often conflicting, responses or objectives within a system, a critical capability in complex, real-world scenarios, where goals, such as minimizing costs, enhancing the product quality, and reducing the production times must be balanced effectively [2]. The essence of MRO lies in its capacity to determine the parameter settings that optimize the performance across multiple criteria while clearly highlighting the trade-offs between these competing objectives. Central to this approach is the concept of the Pareto front, a graphical representation of the set of optimal, non-dominated solutions where no objective can be improved without compromising another [3-5].

The MRO problem-solving process typically begins with the identification of the key factors and desired responses, followed by the systematic DOE that defines the factor levels [6]. Once the experimental data are collected and the responses are measured, simultaneous optimization is conducted using various advanced approaches. These include Pareto optimization [7], constraint methods [8], goal programming [9], and evolutionary algorithms [10-12], each addressing the trade-offs in complex design spaces. Multi-Criteria Decision Making (MCDM) techniques, such as TOPSIS [13], Data Envelopment Analysis Ranking (DEAR) [14], and Grey Relational Analysis (GRA) [15] have been widely used to convert multiple responses into a single aggregated measure. These are often further optimized via the Response Surface Methodology (RSM) [16], metaheuristics, or other hybrid modeling techniques [17-18].

MRO has shown broad applicability in the engineering and manufacturing domains [19-21], enabling effective resource planning and performance optimization across conflicting objectives. By combining statistical rigor with decision-making frameworks, MRO not only enhances the product and process quality, but also aids decision-makers in evaluating the trade-offs and uncertainties.

Among the DOE-based techniques, the Taguchi method stands out for its efficiency in parameter screening and robustness in small experimental designs. When integrated with MCDM approaches, it provides a practical framework for solving MRO problems. For instance, authors in [22] combined the Taguchi design with a TOPSIS-LP model to optimize he rubber sheet rolling parameters, achieving measurable gains in product thickness and processing time. Similarly, authors in [23] introduced a hybrid DEAV–Taguchi framework to improve the efficiency scores in multi-response problems, validated through case studies in fish scale scraping and CNC turning operations.

Authors in [24] implemented a hybrid Taguchi–WASPAS approach to optimize the turning parameters for X210Cr12 tool steel. Their study reported notable improvements, including substantial reductions in surface roughness, cutting force, and tool wear. While such Taguchi–MCDM integrations have been widely explored in precision-driven industrial applications, their adoption in rural or community-based production systems remains limited and under-researched. Authors in [25] combined the Taguchi method with the Delphi technique to optimize the key parameters in the extrusion vacuum-forming process for Polypropylene cup lids. Utilizing an L_{18} orthogonal array, the study identified five critical factors—material ratio, T-die thickness, wheel temperature stability, vacuum pressure time, and mold area—that led to a 2.6% reduction in material usage, decreased weight variation, and enhanced process efficiency. Authors in [26] applied a Taguchi–GRA hybrid method to determine the optimal laser cladding parameters for 316L stainless steel using an L25 orthogonal array. Laser power emerged as the most influential factor affecting the cladding quality. The optimized parameters yielded defect-free coatings with balanced layer width, height, and dilution, improving the overall multi-objective performance. In a different context, authors in [27] adopted a hybrid Taguchi–entropy–COPRAS framework to optimize the wire-cut EDM parameters for machining CRT glass powder–reinforced magnesium composites. Among the evaluated factors, the pulse-on time had the most significant effect. The optimized settings improved the Material Removal Rate (MRR), surface roughness, and kerf width, reflecting a balanced trade-off between precision and productivity.

There is limited research applying the Taguchi–WASPAS framework to optimize the production processes in small-scale, labor-intensive sectors, such as broom manufacturing. This represents a significant gap in the literature. Addressing this, the present study introduces a Taguchi–WASPAS optimization model for an automated grass-flower beating machine, aiming to reduce the raw material damage while improving the operational efficiency within the context of community-scale broom production.

Kalasin province in Thailand is a major center for the production of grass-broom heads, which serve as the core component of traditional Thai brooms. These brooms are widely used across the northeastern region and throughout the country due to their durability, lightweight structure, and low cost. They are commonly utilized in households, schools, government offices, and service industries. The increasing demand for grass brooms has made their production a key source of income for many households in Kalasin. However, the production process remains largely manual, especially during the grass-flower beating stage, where the fibers are separated from the inflorescences for broom assembly. This process, known locally as "grass-flower beating," involves striking the flower heads of the broom grass to loosen and separate the usable fibers, which are later bundled into broom heads. This manual operation is labor-intensive, time-consuming, and often results in inconsistent fiber quality, thereby reducing the productivity and scalability.

Despite these challenges, limited research has focused on the automation and systematic optimization of this process. In particular, there is a clear lack of studies applying hybrid MRO techniques to community-level broom production systems. To address this gap, the present study proposes the design and implementation of an automated grass-flower beating machine to reduce the labor dependence, enhance the processing speed, and improve the fiber consistency. Key operational parameters—speed, time, and feedstock weight—are adjusted to maintain both the product quality and production efficiency. Beyond process improvement, this automation is expected to support the local economic development, create new employment opportunities, and foster sustainable industrial transformation in rural communities. While the Taguchi method has been widely used in combination with various MCDM techniques to solve MRO problems [13], its integration with the WASPAS method has not yet been explored in the context of broom manufacturing. To bridge this gap, the present study proposes a novel hybrid optimization framework combining the Taguchi DOE with the WASPAS technique. The main contributions of this research are:

- Development of a Taguchi–WASPAS experimental framework for identifying the optimal operating parameters of an automated grass-flower beating machine, targeting both the efficiency maximization and damage minimization.
- Introduction of a flexible weighting mechanism to adjust the importance of each performance metric, facilitating the trade-offs between the beating efficiency and material preservation.
- Development of an MRO framework tailored for small-scale manufacturing, demonstrating the potential of the hybrid Taguchi–WASPAS methodology in promoting the practical automation in local and rural production settings [17-18, 22].

II. METHODOLOGY

The present research adopts a hybrid method that integrates the Taguchi method with the WASPAS method to solve an MRO problem in broom production. The goal is to identify the optimal combination of parameters that results in the maximum efficiency and minimum damage score.

A. *Experimental Design Using Taguchi L9 Array*

The experimental dataset was obtained via the Taguchi approach employing an L9 orthogonal array to investigate the influence of three operational factors, speed (*S*), Time (*T*), and feedstock weight (*F*), of the automated grass-flower beating machine, as presented in see Figure 1. Each factor was examined at three discrete levels, yielding only nine experimental runs and thereby reducing the research costs while still providing a comprehensive parameter space coverage. In each trial, two performance metrics were recorded: efficiency (*E*), which is to be maximized, and damage score (*D*), which is to be minimized. The selected parameters and corresponding responses were then utilized to design the experiments based on the Taguchi method using an L9 orthogonal array. The efficiency response (*E*) can be determined by:

$$E = \frac{w_0 - w_l}{w_0} \times 100 \quad (1)$$

where w_0 is the weight of the grass flower before entering the beating machine, and w_l is the weight of the grass flower remaining after the beating process.

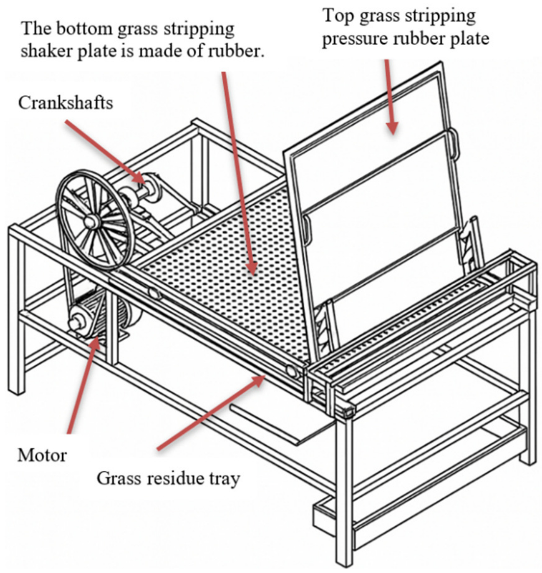

Fig. 1. Automated grass-flower beating machine.

TABLE I. FIVE-POINT DAMAGE SEVERITY SCALE

Damage score	Description
1	No damage or minor damage; the material is slightly bruised with no effect on product usability.
2	Slight damage; some parts of the material are affected but the product can still be used normally.
3	Moderate damage; begins to affect the efficiency or suitability of the grass-flower beating process, requiring corrective action.
4	Severe damage; the product's quality is significantly reduced, making it unsuitable for further processing in the grass-flower beating operation.
5	Very severe damage; the material is completely unusable.

Ten decision-makers evaluated the grass-flower beating machine using a five-point damage severity scale, as detailed in Table I. The damage severity rating scale, or damage score (*D*), was evaluated utilizing a five-point scale, as summarized in Table II. After designing the experiments deploying the Taguchi method, the experiments were conducted according to the experimental plan. Since this problem involves two response variables, *R* and *D*, it is classified as an MRO problem. The complexity lies in determining the optimal parameters, as one response needs to be minimized while the other needs to be maximized. Therefore, the WASPAS method was employed to calculate a single WASPAS score by integrating both responses into a unified evaluation metric.

B. *Multi-Response Integration Using the WASPAS Method*

The scores of the two response variables (*D* and *E*) are used to calculate the WASPAS score. The WASPAS method is an MCDM approach that combines the Weighted Sum Model (WSM) and Weighted Product Model (WPM) to enhance the accuracy and reliability [28-30]. The calculation of the WASPAS score involves the following six steps:

- Step 1: Construct the decision matrix.

Define the alternatives as A_i, where i = 1, 2,…, m, and the decision criteria as C_j, where j =1, 2,..., n. Subsequently, create the decision matrix Y, where each element signifies the performance score of the alternative A_i with respect to the criterion C_j. The resulting decision matrix is:

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ y_{n1} & y_{n2} & \cdots & y_{mn} \end{bmatrix} \quad (2)$$

- Step 2: Construct the normalized decision matrix.

To create the normalized decision matrix R, criteria must be classified into two types:

- For the benefit criteria (where higher values are better), normalization is performed using:

$$r_{ij} = \frac{y_{ij}}{max(y_{ij})} \quad (3)$$

- For the cost criteria (where lower values are better), normalization is performed using:

$$r_{ij} = \frac{min(y_{ij})}{y_{ij}} \quad (4)$$

As a result, the normalized decision matrix R is constructed accordingly.

- Step 3: Assign weights to each response according to their importance.

w_j represents the weight assigned to each criterion. In this research, equal weights are assigned: 0.5 for response D and 0.5 for response E.

- Step 4: Calculate the WSM score using:

$$Q_1(i) = \sum_{j=1}^{n} w_j r_{ij} \quad (5)$$

where Q_1(i) is the WSM score, and w_j is the weight assigned to each criterion.

- Step 5: Calculate the WPM score using:

$$Q_2(i) = \prod_{j=1}^{n} {r_{ij}}^{w_j} \quad (6)$$

where $Q_2(i)$ is the WPM score.

- Step 6: Combine WSM and WPM scores using λ = 0.5 by:

$$Q(i) = \lambda Q_1(i) + (1-\lambda) Q_2(i) \quad (7)$$

The WASPAS score $Q(i)$ obtained for each experiment is subsequently utilized to determine the optimal parameter settings.

C. *Determination of Optimal Parameters*

The WASPAS scores calculated from the experimental results are processed using Minitab software. Specifically, the WASPAS score for each trial is input into Minitab to analyze and identify the optimal parameter settings for the developed automated grass flower beating machine. In the final step, the most suitable parameter combination obtained from the analysis is used in a confirmation experiment to validate the results and ensure the reliability and effectiveness of the selected parameters.

III. RESULTS AND DISCUSSION

A. *Experimental Results Based on the Taguchi L9 Orthogonal Array*

The experimental results were obtained via the Taguchi approach employing an L9 orthogonal array to investigate the influence of three operational factors, speed (S), time (T), and feedstock weight (F), of the automated grass-flower beating machine. Each factor was tested at three levels.

The efficiency of the grass-flower beating process is calculated using (1). For example, in Trial 1, the weight of the grass-flower before entering the machine is w_0 = 80 g, and the weight of the grass-flower lost after processing is w_1 = 10 g. By substituting these values into (1), the efficiency (E) of the process can be calculated by:

$$E_1 = \frac{80-70}{80} \times 100 = 87.50 \quad (8)$$

Therefore, the efficiency of the grass-flower beating process in this trial is 87.50%.

The damage assessment of the grass-flower raw material was conducted by 10 SME operators using a five-level rating scale, as shown in Table I. The average damage scores (D) evaluated by the operators for each trial are summarized in Table II.

Following the Taguchi L9 experimental design, the data in Table II were used to perform ANOVA to statistically assess the influence of the three control factors—rotational speed (S), beating time (T), and feedstock amount (F)—on the two response variables: efficiency (E or Y_1) and damage score (D or Y_2). The ANOVA results for Y_1 and Y_2 are presented in Tables III and IV, respectively.

TABLE II. EXPERIMENTAL RESULTS BASED ON THE TAGUCHI L9 ORTHOGONAL ARRAY

Trial	*S*	*T*	*F*	*E*	*D*
1	80	60	80	87.50	1.7
2	80	90	100	91.67	1.5
3	80	120	120	93.00	1.4
4	100	60	100	91.50	1.5
5	100	90	120	95.00	1.3
6	100	120	80	94.00	1.4
7	120	60	120	93.00	1.4
8	120	90	80	92.00	1.5
9	120	120	100	95.00	1.3

TABLE III. ANOVA FOR EFFICIENCY (Y_1)

Source	DF	Adj SS	Adj MS	*F*-Value	*P*-Value
S	1	10.227	10.227	8.63	0.032
T	1	16.667	16.667	14.07	0.013
F	1	9.375	9.375	7.91	0.037
Error	5	5.923	1.185		
Total	8	42.191			
Model Summary	R^2=85.96				

TABLE IV. ANOVA FOR DAMAGE SCORE (Y_2)

Source	DF	Adj SS	Adj MS	*F*-Value	*P*-Value
S	1	0.02667	0.026667	10.91	0.021
T	1	0.04167	0.041667	17.05	0.009
F	1	0.04167	0.041667	17.05	0.009
Error	5	0.01222	0.002444		
Total	8	0.12222			
Model Summary	R^2=90.0%				

The ANOVA findings for Y_1 indicated that all process parameters were statistically significant (P < 0.05), with the beating time exerting the most substantial influence. The model accounted for 85.96% of the variance (R^2 = 85.96%), and the minimal residual mean square error (1.185) validated the reliability of the model. These findings underscore the necessity of meticulously regulating the processing parameters to improve the fiber separation efficiency in broom manufacturing.

In a similar vein, the ANOVA results for Y_2 revealed strong statistical significance across all three factors, with the amount of feedstock and beating time demonstrating the greatest impact (P = 0.009, F = 17.05). Additionally, the rotational speed exhibited a significant effect (P = 0.021, F = 10.91). The regression model displayed a high coefficient of determination (R^2 = 90.0%), indicating an excellent fit. The low mean square error (0.002444) reflects a high level of precision in capturing the variation in damage scores.

In order to gain a deeper insight into the impact of each process parameter on the two main performance metrics—beating efficiency and damage score—a collection of response trend charts was created. These visual representations enhance the ANOVA findings by depicting the connections between the input variables (speed, time, and feedstock quantity) and output measures.

As illustrated in Figure 2, the rotational speed has a considerable impact on both the efficiency of beating and the damage score. The peak efficiency of 95.5% and the minimal damage score of 1.23 were recorded at 100 rpm, marking it as the ideal operating point. Performance experiences a slight reduction at both 80 rpm and 120 rpm, suggesting that excessively slow or fast speeds hinder the optimal fiber separation. These results confirm that 100 rpm provides an advantageous equilibrium between the productivity and product quality.

Figure 3 displays the correlation between the beating time and output responses. The findings indicate that 120 s represents the ideal duration at which efficiency reaches its maximum and damage is kept to a minimum. In contrast, shorter durations (90 s) may result in an incomplete process, whereas longer durations (150 s) seem to marginally reduce the fiber quality. These trends emphasize that the extended processing does not inherently improve the output and may even lead to excessive wear or damage to the material.

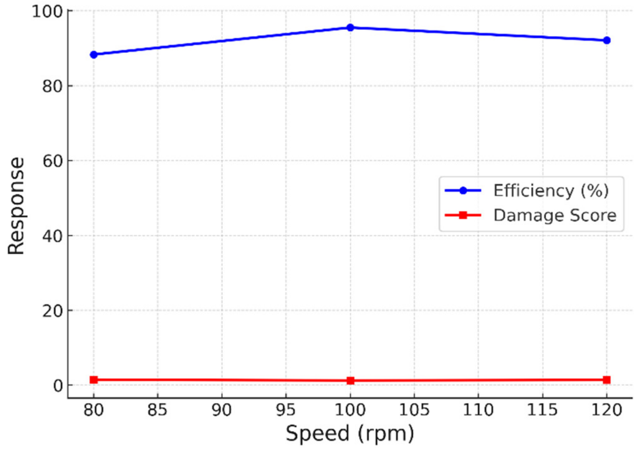

Fig. 2. Effect of speed on efficiency and damage.

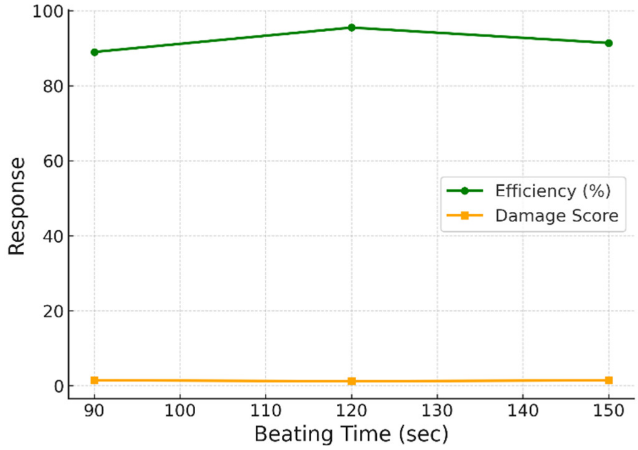

Fig. 3. Effect of beating time on efficiency and damage.

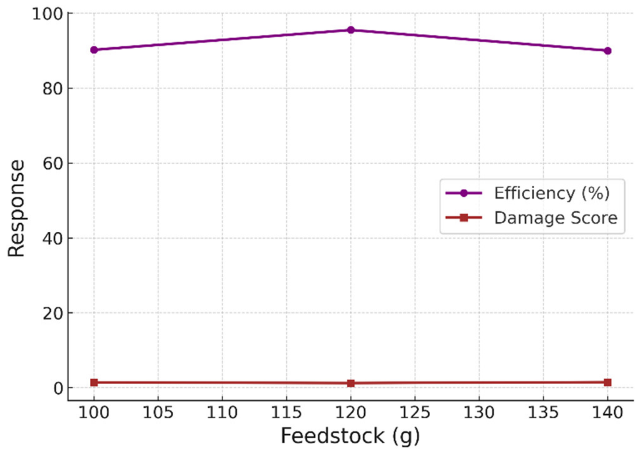

Fig. 4. Effect of feedstock on efficiency and damage.

Figure 4 portrays the effects of the feedstock input on the efficiency and damage. The 120-gram feedstock level demonstrates the highest efficiency alongside the least damage, thereby identifying it as the most favorable quantity. When utilizing 100 g, the efficiency is still satisfactory, albeit not optimal, and the damage is marginally elevated. In contrast, at

140 g, there is a decline in efficiency and an increase in damage, which are likely attributable to the material congestion within the chamber. This highlights the necessity of regulating the input volume to ensure stable operation and reduce the processing errors.

B. WASPAS Score Calculation Results

The response values Y_1 and Y_2 were used to calculate the WASPAS scores following the following steps:

- Step 1: Construct the decision matrix using (2), which results in the data shown in Table V. These values serve as the input for subsequent normalization and WASPAS score calculations.

TABLE V. DECISION MATRIX

Trial	Y_1	Y_2
1	87.50	1.7
2	91.67	1.5
3	93.00	1.4
4	91.50	1.5
5	95.00	1.3
6	94.00	1.4
7	93.00	1.4
8	92.00	1.5
9	95.00	1.3

Y_1 represents the efficiency of the grass-flower separation process (%), and Y_2 represents the damage score evaluated by SME operators.

- Step 2: Construct the normalized decision matrix, where the response variable Y_1 is normalized using (3) (for benefit criteria), and the response variable Y_2 is normalized using (4) (for cost criteria). The details of the normalization results are presented in Table VI.

TABLE VI. NORMALIZED DECISION MATRIX

Trial	Y_1	Y_2
1	0.9211	0.7647
2	0.9649	0.8667
3	0.9789	0.9286
4	0.9632	0.8667
5	0.9998	0.9998
6	0.9895	0.9286
7	0.9789	0.9286
8	0.9684	0.8667
9	1.0000	1.0000

- Step 3: This step entails allocating weights to each response according to its significance. In this study, both response variables, Y_1 (efficiency) and Y_2 (damage score), are considered equally important. Therefore, equal weights of 0.5 are assigned to each criterion.
- Steps 4–6: The WSM, WPM, and WASPAS scores are calculated following the assignment of weights to the response variables. Equation (5) was applied to calculate the WSM scores, while (6) was used to compute the WPM scores. Subsequently, (7) was employed to integrate both models and obtain the final scores. All calculated scores, WSM, WPM, and WASPAS, are summarized in Table VII.

TABLE VII. WSM, WPM, AND WASPAS SCORES FOR EACH EXPERIMENTAL TRIAL

Trial	$Q_1(i)$	$Q_2(i)$	$Q(i)$
1	0.8429	0.8392	0.8411
2	0.9158	0.9145	0.9151
3	0.9538	0.9534	0.9536
4	0.9149	0.9136	0.9143
5	0.9998	0.9998	0.9998
6	0.9590	0.9585	0.9588
7	0.9538	0.9534	0.9536
8	0.9175	0.9161	0.9168
9	1.0000	1.0000	1.0000

C. Determination of Optimal Parameters Based on WASPAS Scores

The WASPAS scores calculated/presented in Table V were imported into Minitab software to determine the optimal parameter settings for the developed automated grass-flower beating machine. The analysis began with the response table for Signal-to-Noise ratio (*S/N*), where larger values were considered better, to evaluate the influence of each factor on the process performance. This was followed by an examination of the Main Effects Plot for the *S/N* ratio to visually assess the trend and impact of each parameter level. The results of the response table analysis are presented in Table VIII, while the Main Effects Plot is illustrated in Figure 2.

TABLE VIII. RESPONSE TABLE FOR *S/N* RATIO

Level	*S*	*T*	*F*
1	-0.8954	-0.8982	-0.8744
2	-0.3814	-0.5081	-0.5162
3	-0.3890	-0.2595	-0.2752
Delta	0.5141	0.6388	0.5992
Rank	3	1	2

The analysis provided in Table VIII utilized the *S/N* ratio framework to evaluate the performance of the automated grass-flower beating machine, with the objective of maximizing the WASPAS score. The results reveal the mean *S/N* ratio corresponding to each level of the three principal input parameters. The Time (*T*) factor demonstrates the highest Delta value at 0.6388, signifying its predominant influence on the response variable. Feedstock Weight (*F*) occupies the second position in terms of impact, with a Delta of 0.5992, while Speed (*S*) exhibits the lowest Delta value at 0.5141, indicating a comparatively minimal effect.

As depicted in Figure 2, the Main Effects Plot for *S/N* ratio demonstrates the influence of speed (*S*), time (*T*), and feedstock weight (*F*) on the process performance, following the "larger is better" criterion. Among the three factors, Time (*T*) exhibits the most significant impact, with a consistent increase in the *S/N* ratio from 60 to 120 s. Feedstock weight (*F*) significantly impacts the process, while Speed (*S*) barely affects it beyond 100 rpm. These findings, consistent with the response table rankings, support the selection of optimal operating conditions. The proposed parameter settings for maximizing the WASPAS score and enhancing the machine performance are: Speed = 100 rpm, Time = 120 s, and Feedstock Weight = 120 g. This combination is proposed for implementation in future operations and validation experiments.

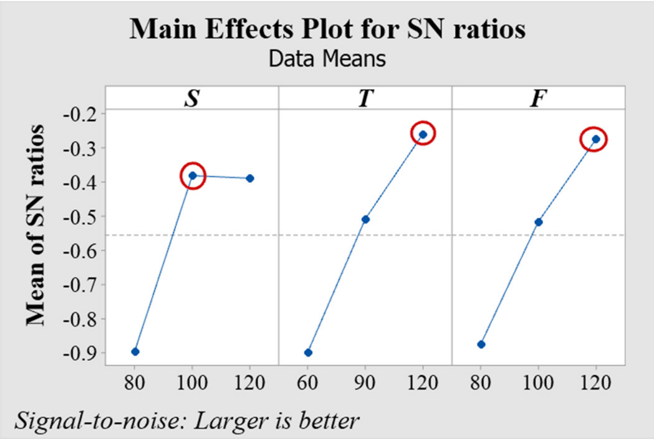

Fig. 5. Main Effects Plot for *S/N* ratio.

The comparative analysis serves as a fundamental technique for assessing the robustness and reliability of the solutions, particularly within the MCDM frameworks. By applying multiple MCDM methods, this approach enables a comprehensive evaluation of the consistency and performance stability of the proposed optimization strategy. In the present study, the results derived from the WASPAS model, based on the decision matrix presented in Table I with equal weight assignments (w_1 = 0.50, w_2 = 0.50), were used as the baseline for comparison. TABLE IX displays a detailed comparison of the WASPAS approach with alternative MCDM techniques, including TOPSIS [31], ARAS [32], and MOORA [33], offering additional insight into the comparative effectiveness of the proposed method.

TABLE IX. COMPARISON OF THE PROPOSED METHODS WITH ALTERNATIVE MCDM APPROACHES

Methods	Original parameters	Optimal parameters
TOPSIS	*S3:T3:F2* (Trial #9)	*S2:T3:F3*
ARAS	*S3:T3:F2* (Trial #9)	*S2:T3:F3*
MOORA	*S3:T3:F2* (Trial #9)	*S2:T3:F3*

The comparison reveals a strong similarity between the original and optimal parameters identified by most MCDM methods, demonstrating their robustness and consistency. This alignment confirms the reliability of these approaches in optimizing the proposed machine's settings and validates the effectiveness of the identified parameters in achieving the targeted performance outcomes, supporting their use in the optimization process.

To validate the optimal parameter settings identified through WASPAS-based analysis (Speed = 100 rpm, Time = 120 s, and Feedstock Weight = 120 g), a confirmation experiment was conducted. The experiment was repeated 10 times, and the results for the two responses, Y_1 (Efficiency) and Y_2 (Damage Score), are portrayed in Table X.

TABLE X. RESPONSE TABLE FOR *S/N* RATIO

Response	Mean	95% *CI* (lower)	95% *CI* (upper)
WASPAS score	1.0334	1.0179	1.0490
Y1	95.4975	95.0652	95.9297
Y2	1.2329	1.2038	1.2620

The average efficiency (Y_1) obtained from the trials was 95.4975%, demonstrating a high consistency and alignment with the predicted optimal value. The average damage score (Y_2) was 1.2329, indicating a minimal material damage and confirming the process's effectiveness in preserving the raw material integrity. To assess the statistical reliability of the results, 95% Confidence Intervals (CI) were calculated:

- For *Y1*, the 95% CI ranged from 95.0652 to 95.9297, confirming a narrow variability and high precision in the efficiency.
- For *Y2*, the 95% CI ranged from 1.2038 to 1.2620, suggesting consistent performance in reducing the damage.
- The WASPAS score, representing the integrated optimization metric, had a mean value of 1.0334, with a 95% *CI* of 1.0179-1.0490, reinforcing the reliability of the MRO method.

Finally, the experimental results confirm that the selected optimal parameters not only enhance the efficiency, but also minimize the raw material damage. The narrow CI for both response variables and the WASPAS score affirm the robustness and repeatability of the proposed optimization approach, validating its applicability in the real-world implementation of the automated grass-flower beating machine.

IV. CONCLUSIONS

Multi-Response Optimization (MRO) provides a powerful framework for simultaneously improving multiple conflicting objectives in complex manufacturing systems. In this study, the MRO problem is addressed in the context of optimizing an automated grass-flower beating machine developed to improve the productivity and fiber quality in broom production within the Kalasin community. The manual nature of the traditional grass-flower separation process presents significant challenges, including inconsistent quality, high labor demands, and limited scalability.

The primary objective of this research was to develop and validate a systematic methodology for determining the optimal operating parameters, namely speed, time, and feedstock weight, of the beating machine to maximize the fiber separation efficiency while minimizing the raw material damage. To achieve this, a hybrid approach combining the Taguchi Design of Experiments (DOE) (L9 orthogonal array) and the Weighted Aggregated Sum Product Assessment (WASPAS) method was proposed. This integration enables an efficient experimental design and the effective aggregation of conflicting responses into a single composite score to support data-driven decision-making.

The experimental results demonstrated that the proposed method successfully identified the optimal settings of Speed = 100 rpm, Time = 120 s, and Feedstock Weight = 120 g. The tests showed an average efficiency of 95.50% and an average damage score of 1.23, with narrow 95% Confidence Intervals (CI) ensuring reliability. The WASPAS composite score averaged 1.0334, further validating the robustness of the optimization. Qualitatively, the optimal settings significantly improved the consistency and usability of the processed fibers while reducing the operator dependency and variability in the output quality.

This study presents a promising framework for optimizing the performance of an automated grass-flower beating machine using a hybrid Taguchi-WASPAS approach. However, certain limitations must be acknowledged. Firstly, the experimental design focused solely on three process parameters—rotational speed, beating time, and feedstock amount—while excluding other potentially influential factors, such as the blade sharpness, material moisture content, and machine vibration. Additionally, the analysis did not encompass the energy consumption, operational cost estimation, or durability testing, all of which are essential for assessing the long-term sustainability and economic viability. These aspects will be addressed in future research. Moreover, while the current optimization is static, incorporating lightweight machine learning algorithms, such as Decision Trees, Random Forests, or XGBoost models, is proposed for future work to facilitate the real-time predictions, adaptability to varying material conditions, and intelligent parameter tuning. Such advancements would enhance the system's efficiency and enable its deployment in dynamic manufacturing environments.

DATA AVAILABILITY STATEMENT

The dataset supporting the findings of this study is available from the corresponding author upon reasonable request.

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REFERENCES

[1] H. Alshahrani, T. A. Sebaey, M. M. Awd Allah, and M. A. Abd El-baky, "Multi-response Optimization of Crashworthy Performance of Perforated Thin Walled Tubes," *Journal of Composite Materials*, vol. 57, no. 9, pp. 1579–1597, Apr. 2023, https://doi.org/10.1177/00219983231159508.

[2] H. Mehdi, L. Batra, A. P. Singh, and C. Malla, "Multi-response Optimization of Fsw Process Parameters of Dissimilar Aluminum Alloys of Aa2014 and Aa6061 by Response Surface Methodology (RSM)," *International Journal on Interactive Design and Manufacturing*, vol. 18, no. 3, pp. 1507–1522, Apr. 2024, https://doi.org/10.1007/s12008-023-01409-2.

[3] N. Pawaree, S. Phokha, and C. Phukapak, "Multi-response Optimization of Charcoal Briquettes Process for Green Economy Using a Novel TOPSIS Linear Programming and Genetic Algorithms Based on Response Surface Methodology," *Results in Engineering*, vol. 22, June 2024, Art. no. 102226, https://doi.org/10.1016/j.rineng.2024.102226.

[4] S. Divya and S. Praveenkumar, "An Integrated Evaluation of Graphene-based Concrete Mixture with Copper Slag and Quarry Dust Using Response Surface Methodology," *Journal of Building Engineering*, vol. 86, June 2024, Art. no. 108876, https://doi.org/10.1016/j.jobe.2024.108876.

[5] A. Sriburum, N. Wichapa, and W. Khanthirat, "A Novel TOPSIS Linear Programming Model Based on the Taguchi Method for Solving the Multi-Response Optimization Problems: A Case Study of a Fish Scale Scraping Machine," *Engineered Science*, 2023, https://doi.org/10.30919/es882.

[6] L. Selvarajan, K. Venkataramanan, A. Nair, and V. P. Srinivasan, "Simultaneous Multi-response Jaya Optimization and Pareto Front Visualization in Edm Drilling of Mosi2-sic Composites," *Expert Systems with Applications*, vol. 230, Nov. 2023, Art. no. 120669, https://doi.org/10.1016/j.eswa.2023.120669.

[7] L. Tartibu Kwanda, "Multi-objective Optimization of a Rectangular Micro-channel Heat Sink Using the Augmented ε-Constraint Method," *Engineering Optimization*, vol. 52, no. 1, pp. 22–36, Jan. 2020, https://doi.org/10.1080/0305215X.2019.1574346.

[8] Y. T. İç, F. S. Akkoç, N. Gümüşboğa, and Z. Ballı, "A New Multi-response Taguchi-Based Goal Programming Model for Sustainable Turning Process," *Arabian Journal for Science and Engineering*, vol. 47, no. 3, pp. 3915–3928, Mar. 2022, https://doi.org/10.1007/s13369-021-06312-0.

[9] T. Ghosh and K. Martinsen, "Generalized Approach for Multi-response Machining Process Optimization Using Machine Learning and Evolutionary Algorithms," *Engineering Science and Technology, an International Journal*, vol. 23, no. 3, pp. 650–663, June 2020, https://doi.org/10.1016/j.jestch.2019.09.003.

[10] S. Chakraborty and S. Diyaley, "Multi-objective Optimization of Yarn Characteristics Using Evolutionary Algorithms: A Comparative Study," *Journal of The Institution of Engineers (India): Series E*, vol. 99, no. 2, pp. 129–140, Dec. 2018, https://doi.org/10.1007/s40034-018-0121-8.

[11] M. Mia, G. Królczyk, R. Maruda, and S. Wojciechowski, "Intelligent Optimization of Hard-Turning Parameters Using Evolutionary Algorithms for Smart Manufacturing," *Materials*, vol. 12, no. 6, Mar. 2019, Art. no. 879, https://doi.org/10.3390/ma12060879.

[12] M. Singh *et al.*, "Multi Response Optimization of ECDM Process for Generating Micro Holes in CFRP Composite Using TOPSIS Methodology," *Polymers*, vol. 14, no. 23, Dec. 2022, Art. no. 5291, https://doi.org/10.3390/polym14235291.

[13] G. B. Kamath *et al.*, "Multi-Response Optimization of Milling Process Parameters for Aluminium-Titanium Diboride Metal Matrix Composite Machining Using Taguchi- Data Envelopment Analysis Ranking Approach," *Engineered Science*, vol. 18, pp. 271–277, Jan. 2022, https://doi.org/10.30919/es8d680.

[14] M. Bhaumik and K. Maity, "Multi-response Optimization of Edm Parameters Using Grey Relational Analysis (GRA) for Ti-5al-2.5sn Titanium Alloy," *World Journal of Engineering*, vol. 18, no. 1, pp. 50–57, Jan. 2021, https://doi.org/10.1108/WJE-06-2020-0210.

[15] R. Chaudhari, J. Vora, D. M. Parikh, V. Wankhede, and S. Khanna, "Multi-response Optimization of WEDM Parameters Using an Integrated Approach of RSM–GRA Analysis for Pure Titanium," *Journal of The Institution of Engineers (India): Series D*, vol. 101, no. 1, pp. 117–126, June 2020, https://doi.org/10.1007/s40033-020-00204-7.

[16] S. Thammasang, W. Thasana, B. Unpikul, P. Surin, and S. Thermsuk, "Comparison of Alumina Powder Behavior on Surface Roughness using the Surface Lapping Technique for JIS 420 and JIS 440 Stainless Steel Materials," *Engineering, Technology & Applied Science Research*, vol. 14, no. 5, pp. 16229–16236, Oct. 2024, https://doi.org/10.48084/etasr.8133.

[17] V.-L. Trinh, N.-T. Tran, and D.-T. Nguyen, "Minimum Surface Roughness Prediction of Grinding SKD11 Steel with the Response Surface Methodology," *Engineering, Technology & Applied Science Research*, vol. 15, no. 2, pp. 21469–21474, Apr. 2025, https://doi.org/10.48084/etasr.10117.

[18] S. B. Sutono, S. H. Abdul-Rashid, H. Aoyama, and Z. Taha, "Fuzzy-based Taguchi Method for Multi-response Optimization of Product Form Design in Kansei Engineering: A Case Study on Car Form Design," *Journal of Advanced Mechanical Design, Systems, and Manufacturing*, vol. 10, no. 9, pp. JAMDSM0108–JAMDSM0108, 2016, https://doi.org/10.1299/jamdsm.2016jamdsm0108.

[19] Y. Koli, S. Arora, S. Ahmad, Priya, N. Yuvaraj, and Z. A. Khan, "Investigations and Multi-response Optimization of Wire Arc Additive Manufacturing Cold Metal Transfer Process Parameters for Fabrication of SS308L Samples," *Journal of Materials Engineering and Performance*, vol. 32, no. 5, pp. 2463–2475, Mar. 2023, https://doi.org/10.1007/s11665-022-07282-6.

[20] N. A. Sristi, P. B. Zaman, and N. R. Dhar, "Multi-response Optimization of Hard Turning Parameters: A Comparison Between Different Hybrid Taguchi-based MCDM Methods," *International Journal on Interactive Design and Manufacturing*, vol. 16, no. 4, pp. 1779–1795, Dec. 2022, https://doi.org/10.1007/s12008-022-00849-6.

[21] S. Phokha, C. Sasen, P. Nasawat, and N. Kanchanaruangrong, "Optimization of Rubber Sheet Rolling Machine Parameters using a Taguchi-based TOPSIS Linear Programming Model," *Engineering, Technology & Applied Science Research*, vol. 15, no. 1, pp. 20508–20516, Feb. 2025, https://doi.org/10.48084/etasr.9718.

[22] N. Wichapa, N. Pawaree, P. Nasawat, P. Chourwong, A. Sriburum, and W. Khanthirat, "Process of Solving Multi-Response Optimization Problems Using a Novel Data Envelopment Analysis Variant-Taguchi Method," *International Journal of Technology*, vol. 15, no. 6, Dec. 2024, Art. no. 2038, https://doi.org/10.14716/ijtech.v15i6.7134.

[23] K. Safi, M. A. Yallese, S. Belhadi, T. Mabrouki, and S. Chihaoui, "Parametric Study and Multi-criteria Optimization During Turning of X210Cr12Steel Using the Desirability Function and Hybrid Taguchi-WASPAS Method," *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, vol. 236, no. 15, pp. 8401–8420, Aug. 2022, https://doi.org/10.1177/09544062221086171.

[24] D.-C. Chen, D.-F. Chen, and S.-M. Huang, "Applying the Taguchi Method to Improve Key Parameters of Extrusion Vacuum-Forming Quality," *Polymers*, vol. 16, no. 8, Apr. 2024, Art. no. 1113, https://doi.org/10.3390/polym16081113.

[25] M. Zhu, Y. Chen, Y. Chen, and K. Hu, "Application of Taguchi-grey Relational Analysis for Optimizing Process Parameters of Laser Cladding for 316L Stainless Steel," *International Journal on Interactive Design and Manufacturing*, vol. 19, no. 9, pp. 6417–6428, Sept. 2025, https://doi.org/10.1007/s12008-024-02218-x.

[26] P. M. Gopal, V. Kavimani, S. Sudhagar, T. Sonar, and S. Venkatesh, "Optimization of Wire-cut EDM Parameters Using Taguchi and Entropy Coupled COPRAS Approach for Machining of CRT Glass Powder Reinforced Magnesium Surface Composite Developed Using Friction Stir Processing," *International Journal on Interactive Design and Manufacturing*, vol. 19, no. 1, pp. 585–596, Jan. 2025, https://doi.org/10.1007/s12008-023-01705-x.

[27] R. Viswanathan, S. Ramesh, S. Maniraj, and V. Subburam, "Measurement and Multi-response Optimization of Turning Parameters for Magnesium Alloy Using Hybrid Combination of Taguchi-GRA-PCA Technique," *Measurement*, vol. 159, July 2020, Art. no. 107800, https://doi.org/10.1016/j.measurement.2020.107800.

[28] C. J. Slebi-Acevedo, I. M. Silva-Rojas, P. Lastra-González, P. Pascual-Muñoz, and D. Castro-Fresno, "Multiple-response Optimization of Open Graded Friction Course Reinforced with Fibers Through CRITIC-WASPAS Based on Taguchi Methodology," *Construction and Building Materials*, vol. 233, Feb. 2020, Art. no. 117274, https://doi.org/10.1016/j.conbuildmat.2019.117274.

[29] S. Khatai, R. Kumar, A. Panda, and A. K. Sahoo, "WASPAS Based Multi Response Optimization in Hard Turning of AISI 52100 Steel under ZnO Nanofluid Assisted Dual Nozzle Pulse-MQL Environment," *Applied Sciences*, vol. 13, no. 18, Sept. 2023, Art. no. 10062, https://doi.org/10.3390/app131810062.

[30] P. Venkateshwar Reddy, G. Suresh Kumar, and V. Satish Kumar, "Multi-response Optimization in Machining Inconel-625 by Abrasive Water Jet Machining Process Using WASPAS and MOORA," *Arabian Journal for Science and Engineering*, vol. 45, no. 11, pp. 9843–9857, Nov. 2020, https://doi.org/10.1007/s13369-020-04959-9.

[31] C.-L. Hwang and K. Yoon, "Methods for Multiple Attribute Decision Making," in *Multiple Attribute Decision Making*, vol. 186, Berlin, Heidelberg: Springer Berlin Heidelberg, 1981, pp. 58–191.

[32] E. K. Zavadskas and Z. Turskis, "A New Additive Ratio Assessment (ARAS) Method in Multicriteria Decision-making," *Technological and Economic Development of Economy*, vol. 16, no. 2, pp. 159–172, June 2010, https://doi.org/10.3846/tede.2010.10.

[33] W. Karel, W. Brauers, and E. K. Zavadskas, "The MOORA Method and Its Application to Privatization in a Transition Economy," *Control and Cybernetics*, vol. 35, no. 2, Jan. 2006.