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Optimizing Melon Seed Decortication: A Taguchi-Based Approach for Single and Multi-Objective Performance

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Abstract: This study was conducted to optimise the parameter sets for a melon seed shelling machine. The parameter sets are motor speed and moisture content with different levels were experimented and analysed to build mathematic models. The objective was to describe the relationship between the inputs parameter values and the outputs (shelling efficiency, breakage percentage and machine capacity). Single-objective and multi-objective models were constructed and studied to identify the optimal set, optimal trade-off set of parameters. Minitab software aid for analysis and decision-making. The optimisation revealed a significant trade-off between single objectives) (optimal settings for maximising shelling efficiency (96.7%), minimising seed breakage (1.41%), and maximising capacity (53.98 kg h-1) were mutually exclusive. Multi-objective analysis identified moisture content as the statistically dominant factor ($p < 0.05$), with motor speed being insignificant. The validated optimal parameter combination for balanced performance was moisture content of 26% and a motor speed of 2100 rpm, which simultaneously improved all three key performance metrics. The proposed solutions for handling single- and multi-objective optimisation through the framework are practical and can be extended to other post-harvest processing equipment.

Keywords: Design of Experiment, Melon Processing, Shelling Machine, Taguchi Optimization Method

Introduction

Agriculture remains the economic bedrock of many developing nations, constituting a primary source of rural employment and income. The agricultural value chain, encompassing activities from production, processing, packaging, storage, transport and distribution, provides significant opportunities for decent job creation and economic empowerment, particularly for women and youth in rural economies (Begho & Daubry, 2025) (Quisumbing et al, 2021). Despite agriculture's fundamental role in employment, livelihoods, and economic structure in nearly all traditional economies, many developing nations have failed to prioritize this sector as a pivotal component in achieving sustainable development (Alhassan & Ansah, 2023) (World Bank, 2023). Fostering inclusive growth and ensuring the fair distribution of wealth can enable the agricultural sector to contribute significantly to resolving unemployment challenges and promoting sustainable development in these economies.

Among diverse agricultural commodities, "Egusi" melon seeds (particularly from *Colocynthis citrillus L.*) hold substantial economic and nutritional importance in West Africa

(Mukaila et al, 2022). They are a rich source of edible oil (30-50%) and protein (25-35%), making them a valuable resource for enhancing human nutrition and formulating livestock feed (Alblooshi et al, 2023). Beyond their direct use in traditional snacks, soups, and stews, they serve as a critical raw material for value-added products like vegetable oil, potential biofuel production, margarine, and high-protein concentrate cakes (Anwar et al, 2023). The cultivation and export of these seeds represent a significant livelihood strategy, directly boosting smallholder farmers' income and contributing to regional economic stability and foreign exchange earnings.

'Egusi' is mostly grown in Nigeria, Burkina Faso, Togo, Ghana, Cote d'Ivoire, Benin, Mali, and Cameroon) (Nigeria ranks as the highest melon seed producer with an estimated 5.7 x 10^5 tons, a greater percentage being 'Egusi' seeds (FAO, 2022). Melon seeds processing is predominantly carried out manually, which is a time-consuming and tedious process that is also inefficient. Reliance on manual decortication consistently results in low output, high costs and product scarcity, exacerbating seasonal supply shortages and price volatility. However, in recent years, there has been growing interest in developing and adopting mechanical shellers to improve efficiency and reduce the drudgery of melon seed processing. These shellers automate the separation of kernels from shells, thereby increasing productivity and ensuring a consistent supply of melon seeds to meet rising demand.

To further enhance the melon seed decortication process and build on the previous studies (Tsapi et al, 2024) (Yıldız and Gencer, 2023) (Oluwabukola et al, 2021) it is necessary to explore optimisation techniques, such as single- and multi-objective frameworks. Single-objective optimisation focuses on maximising a single parameter, such as shelling efficiency, whereas multi- objective optimisation simultaneously addresses multiple objectives, which are often conflicting, such as maximising efficiency while minimising seed damage and energy consumption. Multi-objective optimisation is particularly relevant in agricultural processes, where trade-offs between different objectives (e.g. yield, environmental impact and economic cost) are common. This study employs a Taguchi-based approach to develop a framework that optimises the melon seed decortication process by considering single and multiple objectives, with the aim of improving efficiency, reducing seed damage and enhancing overall quality. The Taguchi method is a robust design methodology that can efficiently identify the optimal settings of process parameters to achieve the desired outcome, even in the presence of noise factors. By applying the Taguchi method within single- and multi-objective optimisation frameworks, this research aims to provide a comprehensive and practical approach to improving melon seed decortication.

Methodology

Shelling Machine

The seed sheller used in this study as illustrated in Figure 1 was powered by a 4.5 horsepower gasoline engine, with a production capacity of approximately 50 kilograms per hour. Its major components included the hopper, shelling chamber, separation chamber, and gasoline engine, all securely mounted on a sturdy frame.

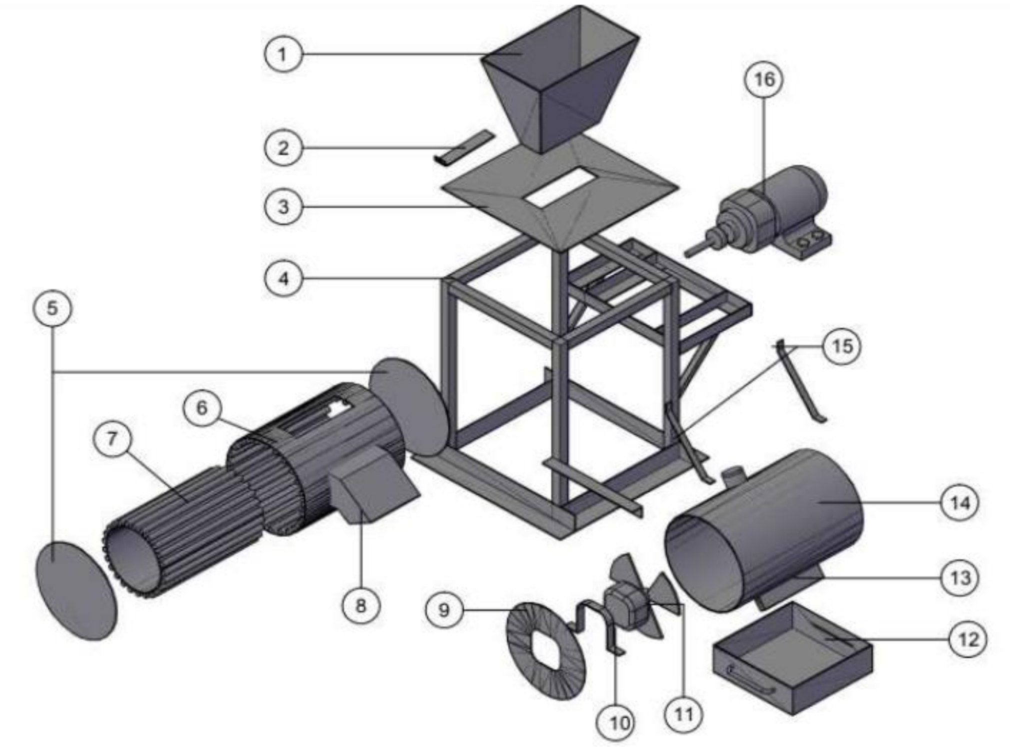


Figure 1. Fabricated melon sheller

Shelling Experiment

Experiments were designed based on the Taguchi design which requires a limited number of runs. Nine experimental runs were planned based on the L9 (3^2) Taguchi orthogonal array design for three-level two factors analysis. Experiments were carried out using a community melon seed shelling machine powered by a 4.5 horsepower gasoline engine, using a variety of white edge melon seeds commonly peeled in the community.

The selection of input shelling process parameters and levels was carried out through a literature survey and machine capabilities. Shelling features such as motor speed and seed moisture content were analysed in this research work) (the selected parameter units and levels are depicted in Table 1.

Table 1. Sellected shelling parameters and levels

Factors	***Level 1***	***Level 2***	***Level 3***
Motor speed (rpm)	900	1500	2100
Moisture content (%)	14	20	26

The predominant response quality characteristics that are considered in this research work were the shelling efficiency, the breakage percentage, and machine capacity. Performance parameters were calculated using the following relations ((Eq.1-3) (Tsapi et al, 2024) (Aturu et al, 2021).

Shelling efficiency (SE),

$$SE = \frac{M_{cbc}+M_{cuc}}{M} \times 100 \quad (1)$$

Breakage Percentage (BP),

$$BP = \frac{M_{cbc}}{M} \times 100\ . \quad (2)$$

Machine capacity (MC),

$$MC = \frac{M_{cbc}+M_{cuc}}{T} \quad (3)$$

Where, M_{cbc} = Mass of clean broken cotyledon in product collected at outlet chute (kg). M_{cuc}= Mass of clean unbroken cotyledon in product collected at outlet chute (Kg). M= Total mass of seed fed through the machine's hopper (Kg). T = Time taken to complete operation (h).

Taguchi optimization methodology

The Taguchi approach recommends a signal-to-noise (S/N) ratio for quality optimization. The higher values of the S/N present better design factor settings to make the system more robust (Nguyen et al, 2022). It is widely applied for identifying the optimal parameter settings of individual or multiple responses (Putra et al, 2025) (Nguyen, 2020). The higher values of the S/N present better design factor settings to make the system more robust.

In this research, the authors want to maximize the shelling efficiency and the machine capacity. Therefore, the type of S/N analysis is Larger-the-better and larger is better which is calculated as in Eq. (4). The goal of the research also is to minimize the seeds breakage percentage. The smaller-the-better S/N ratio is chosen for this analysis as in Eq. (5):

Larger-the-better:

$$S/N = -10 \times log_{10}\left(\frac{1}{m}\sum_{i=1}^{m}\frac{1}{Y_{ij}^{2}}\right). \quad (4)$$

Smaller-the-better:

$$S/N = -10 \times log_{10}\left(\frac{1}{m}\sum_{i=1}^{m}Y_{ij}^{2}\right). \quad (5)$$

Where Y_{ij} is the collected experimental data and m is the number of replications.

In order to balance the competing objectives of maximising shelling efficiency and machine capacity while minimising breakage breakage, it is essential to use a multi-objective optimisation framework. This approach enables the creation and analysis of models based on user-defined priorities, helping to identify the optimal set of parameters that best represent the trade-offs between these objectives.

Consequently, this study employed the Shannon entropy weighting method to optimise these quality responses simultaneously. This method determines the weights of each objective based on the inherent data dispersion of the response, thereby reducing the subjective bias in the weighting process (Hwang and Yoon, 1981). The procedure for calculating these entropy weights is as follows (Eq.6-8).

Step 1: Normalization of the response arrays. The performance indices are normalised to obtain the project outcome matrix (p_{ij}), ensuring that all values are dimensionless and comparable:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (6)$$

Where x_{ij} is the raw value of the j^{th} response for the i^{th} experiment, and m is the total number of experimental trials.

Step 2: Computation of the entropy measure. The entropy E_j for each response j is calculated as:

$$E_j = -\frac{1}{\ln(m)}\sum_{i=1}^{m} p_{ij} ln p_{ij} \tag{7}$$

This measure quantifies the degree of dispersion or uncertainty inherent in the data set for each objective.

Step 3: Determination of objective weights**.** Finally, the objective weight w_j for each response is defined based on its calculated entropy:

$$w_j = \frac{1-E_j}{\sum_{i=1}^{m}(1-E_j)} \tag{8}$$

where n is the total number of responses. A higher weight w_j is assigned to a response with lower entropy E_j, indicating that it provides more valuable information for the decision-making process.

Statistical analysis

The experimental data were analysed statistically using the Taguchi design of experiments approach in Minitab 18. Mean response values and signal-to-noise (S/N) ratios were calculated to determine the optimal parameter settings. Furthermore, analysis of variance (ANOVA) was performed and main effects, interaction and contour plots were generated to statistically quantify and visualise the significance and effects of the controlling factors.

Result and Discussion

Single objective optimization

A known initial quantity of melon seeds was fed into the melon seed shelling machine and shelling experiments were carried out. The corresponding measured data for shelling efficiency, breakage percentage and machine capacity are shown in *Table 2* for nine runs. SE represents shelling efficiency, BP represents seed breakage percentage, and MC represents machine capacity. Minitab 18 software was used to calculate the S/N ratio, means, and to generate graphs for the Taguchi method. The results of this analysis are summarised in response *Tables 3 and 4*. The main effects plots for the S/N ratios (Figures 2a–c) and means (Figures 3a–c) offer valuable insights into the impact of moisture content and motor speed on the shelling process.

Table 2. The Taguchi design matrix and experimental results

Runs			Experimental results			S/N Ratios			Means		
No.	A	B	SE (%)	BP (%)	MC (kg h^{-1})	SE	BP	MC	SE	BP	MC
1	1	1	54.10	1.82	35.27	34.664	-5.201	30.948	54.10	1.82	35.27
2	1	2	70.90	1.59	35.12	37.013	-4.028	30.911	70.90	1.59	35.12
3	1	3	73.58	1.41	34.41	37.335	-2.984	30.734	73.58	1.41	34.41
4	2	1	72.80	3.02	46.32	37.243	-9.600	33.315	72.80	3.02	46.32
5	2	2	86.52	2.30	45.30	38.742	-7.235	33.122	86.52	2.3	45.3

Runs			Experimental results			S/N Ratios			Means		
No.	A	B	SE (%)	BP (%)	MC (kg h^{-1})	SE	BP	MC	SE	BP	MC
6	2	3	92.90	2.10	42.69	39.360	-6.444	32.607	92.90	2.1	42.69
7	3	1	75.30	3.40	53.98	37.536	-10.630	34.645	75.30	3.4	53.98
8	3	2	96.7	2.61	53.47	39.709	-8.333	34.562	96.70	2.61	53.47
9	3	3	95.90	2.48	47.32	39.636	-7.889	33.501	95.90	2.48	47.32

A: Motor speed (coded value)) (B: Moisture content (coded value)

Response Table 3 (S/N Ratios) shows the average S/N ratio for each control factor at its different levels for the three responses (SE, BP and MC). For example, factor Motor speed has three levels and three measurements at each level, the average mean of S/N Ratios was calculated according to Eq. 9.

$$\overline{\frac{S}{N}_{SE\ (900)}} = \frac{34.664+37.013+37.335}{3} = 36.34 \tag{9}$$

Table 3. Response table for signal-to-noise ratios

Parameter	Factors	Level 1	Level 2	Level 3	Max-Min	Rank
SE	Motor speed (rpm)	36.34	38.45	38.96	2.62	1
	Moisture content (%)	36.48	38.49	38.78	2.30	2
BP	Motor speed (rpm)	-4.071	-7.760	-8.950	4.879	1
	Moisture content (%)	-8.477	-6.532	-5.773	2.704	2
MC	Motor speed (rpm)	30.86	33.01	34.24	3.37	1
	Moisture content (%)	32.97	32.87	32.28	0.69	2

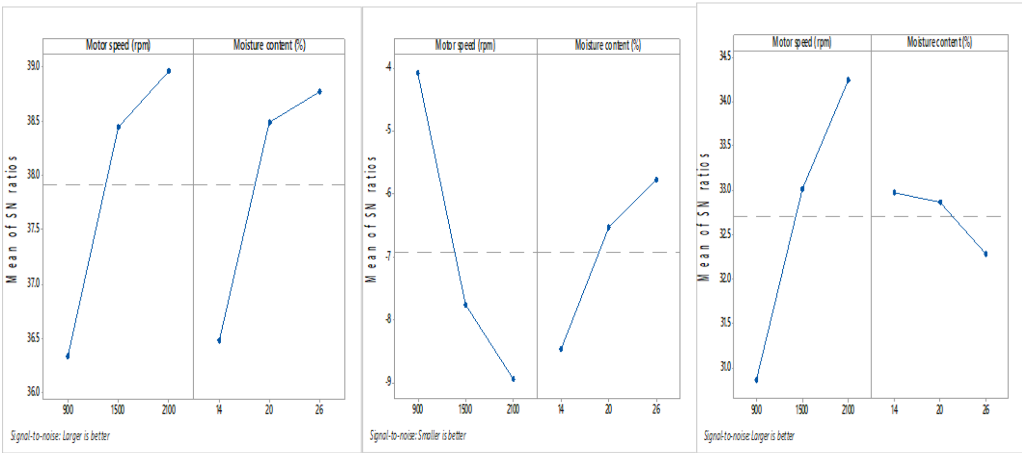
Responses in Table 3 and Table 4 were obtained for Signal to Noise Ratios Larger is better for SE) (Smaller is better for BP and Larger is better for MC. Response Table 4 (Means) shows the average raw response value for each control factor at its different levels. These averages are calculated by grouping the results for each factor level. For example, for the three-level factor 'motor speed', the average response (Eq. 10) is calculated for all runs performed at levels 1, 2 and 3 separately as

$$\overline{SE\ (900)} = \frac{54.10+70.90+73.58}{3} = 66.19 \tag{10}$$

Table 4. Response esponse table for means

Parameter	Factors	Level 1	Level 2	Level 3	Max-Min	Rank
SE	Motor speed (rpm)	66.19	84.07	89.30	23.11	1
	Moisture content (%)	67.40	84.71	87.46	20.06	2
BP	Motor speed (rpm)	1.607	2.473	2.830	1.223	1
	Moisture content (%)	2.747	2.167	1.997	0.750	2

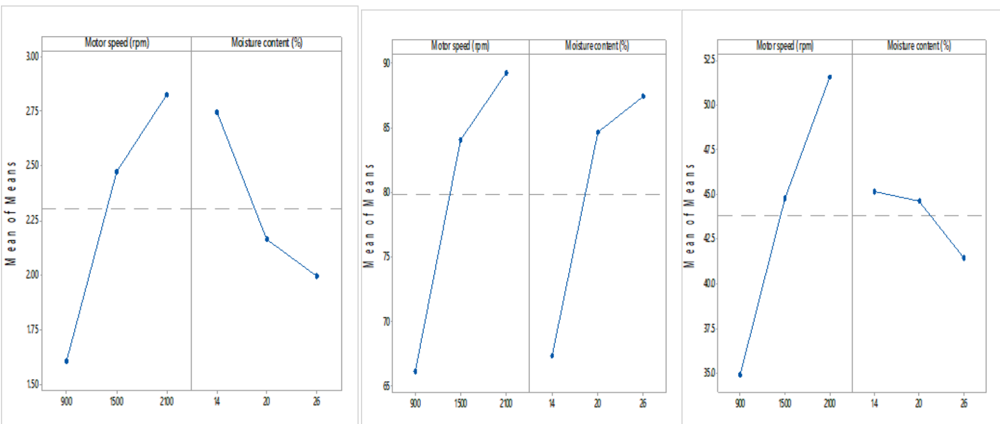
Parameter	Factors	Level 1	Level 2	Level 3	Max-Min	Rank
	Motor speed (rpm)	34.93	44.77	51.59	16.66	1
MC	Moisture content (%)	45.19	44.63	41.47	3.72	2



(a) (b) (c)

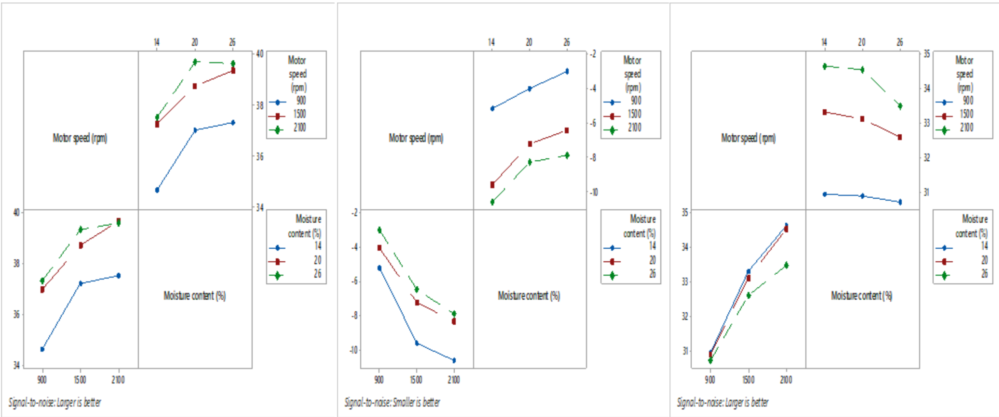
Figure 2. Mean S/N ratio versus parameters for (a: shelling efficiency, b: seed breakage percentage and , c: machine capacity)

In the response tables, the delta value (Max-Min) was calculated by subtracting the lowest average response from the highest average response value (either the mean or the S/N ratio) for levels of one factor. Based on the range value, the rank of the factor effect is defined. The delta values were used to indicate the level of the factor impact on the response. The larger order of rank represents the more significant influence on the output. A design factor with a large difference in the signal noise ratio from one factor setting to another indicates that the factor or design parameter is a significant contributor to the achievement of the performance characteristic. When there is little difference in the signal to noise ratio from one factor setting to another, this indicates that the factor is insignificant with respect to the performance characteristic.



(a) (b) (c)

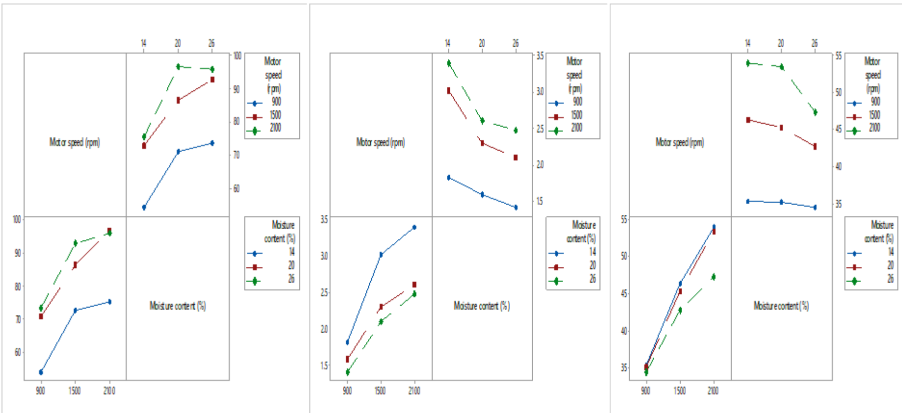
Figure 3. Main effects plots for means versus parameters for (a) shelling efficiency, (b) seed breakage percentage and (c) machine capacity



(a) (b) (c)

Figure 4. Interaction plots for SN ratios versus parameters for (a) shelling efficiency, (b) seed breakage percentage and (c) machine capacity

Interaction plots of the signal-to-noise (S/N) ratios and means (Figures 4 and 5, respectively) were analysed to assess the presence of interactions between factors.



(a) (b) (c)

Figure 5. Interaction plots for means versus parameters for (a) shelling efficiency, (b) seed breakage percentage and (c) machine capacity

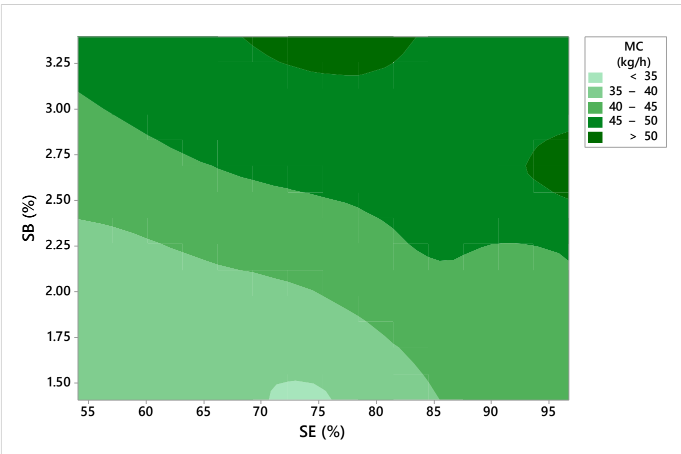


Figure 6. Contour Plot of MC (kg/h) vs SB (%), SE (%)

The development of a community-scale melon seed shelling machine represents a classic multi-objective optimisation challenge where the key performance metrics - shelling efficiency, seed breakage, and machine capacity are often in direct conflict. For end-users such as farmers and small-scale processors, the economic viability of the seeds sheller hinges on a balance of these factors) (high throughput is negated by excessive product damage, while high shelling efficiency is of limited value if the machine capacity is too low for practical use. As illustrated in Figure 6, trade-offs are evident) (maximising machine capacity often results in moderate shelling efficiency and high seed breakage. Conversely, achieving high shelling efficiency with minimal breakage typically requires operating at a reduced capacity. This inverse relationship between throughput and quality is a well-documented challenge in the design of post-harvest processing equipment. Given these competing objectives, a single "optimal" solution does not exist. Instead, the optimal parameter set is a compromise that must be determined based on weighted priorities. Therefore, an integrated multi-objective optimisation framework is essential to identify an optimal solutions, where any improvement in one objective necessitates a deterioration in another. The next section proposes results of the proposed method to simultaneously optimise shelling efficiency, breakage percentage, and machine capacity

Multiple objective optimisation

The multi-objective optimisation was initiated by determining the relative importance (weights), of each performance characteristic. For this purpose, the Shannon entropy method, a robust objective weighting technique, was employed. This method is favoured in design optimisation because it calculates the weights directly from the response data matrix, thereby eliminating subjective bias and quantifying the inherent differences between the various performance measures.

Table 6. Objective weights for combined objective

Response Variable	Contribution
SE	0.331
BP	0.338
MC	0.331

Table 7. Signal-to-noise ratios for combined objective responses

Runs No.	S/N Ratios			Combined Objective
	SE	BP	MC	(0.331 SE + 0.338SB + 0.331MC)
1	34.664	-5.201	30.948	19.960
2	37.013	-4.028	30.911	21.121
3	37.335	-2.984	30.734	21.522
4	37.243	-9.600	33.315	20.110
5	38.742	-7.235	33.122	21.342
6	39.360	-6.444	32.607	21.643
7	37.536	-10.630	34.645	20.299
8	39.709	-8.333	34.562	21.767
9	39.636	-7.889	33.501	21.542

Following the standard computational procedure (steps 1-3 and Eqs. 6 - 8), the calculated entropy weights were found to be 0.331 for shelling efficiency (S/N ratio), 0.338 for seed breakage (S/N ratio) and 0.331 for machine capacity (S/N ratio), as summarised in *Table 6*. Consequently, all three objectives - maximising shelling efficiency and capacity while minimising seed breakage, were accorded statistically equivalent importance in the subsequent analysis.

The experimental signal-to-noise (S/N) ratios for the individual responses, as well as the computed multi-objective S/N ratio, are presented in *Table 7*. The multi-objective main effects and interaction plots are presented respectively in Figures 7 and 8. The impact of the process parameters on the multi-objective response was rigorously evaluated using analysis of variance (ANOVA), and the results are presented in *Table 8*.

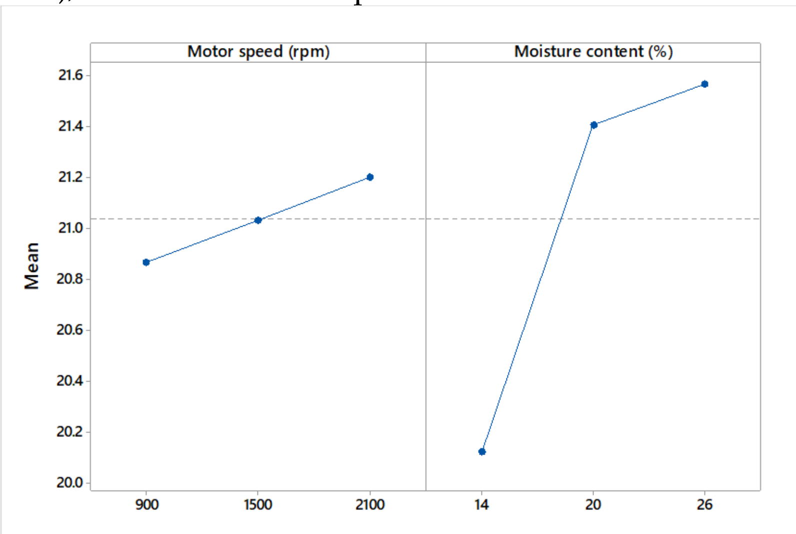


Figure 7. Main effects plots for means versus parameters for combined objective

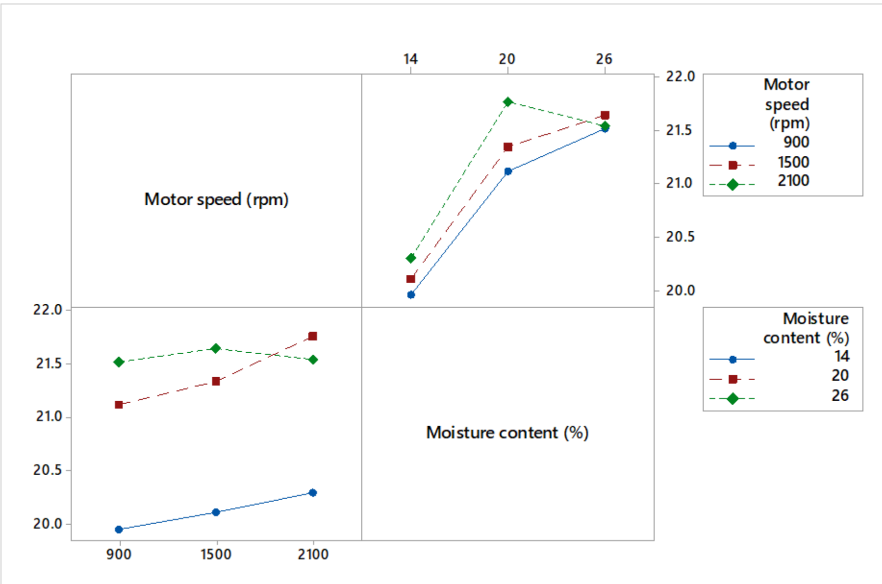


Figure 8. Interaction Plot for the SN ratios of combined objective

The model summary is presented in *Table 9*. The model exhibits an exceptionally high coefficient of determination (R^2 = 97.2%), indicating that it explains 97.2% of the observed variation in the combined objective. The adjusted R^2 value (94.20%), which accounts for the number of predictors in the model, remains high, confirming the robustness of the model and that the fit is not overstated by including non-significant terms (4). A key metric is the predicted R-squared value of 85.83%, as this estimates the model's ability to predict responses for new observations. The reasonable agreement between the adjusted and predicted R^2 values suggests that the model is not overfitted and should have good predictive capability.

Table 8. ANOVA results

Factors	DF	Adj SS	Adj MS	F-Value	P-Value
Motor speed (rpm)	2	0.1683	0.08414	2.97	0.162
Moisture content (%)	2	3.7737	1.88683	66.50	0.001
Motor speed (rpm)	4	0.1135	0.02837		
Moisture content (%)	8	4.0554			
Motor speed (rpm)	2	0.1683			
Moisture content (%)	2	3.7737			

Table 9. Model summary

Terms	Values
S	0.168444
R-sq	97.20%
R-sq(adj)	94.40%
R-sq(pred)	85.83%

The final regression equation derived by the Minitab software is as follows (Eq.11):

Combined objective = 21.0340 - 0.1662 × Motor speed_(900)- 0.0025 × Motor speed_(1500)+ 0.1687 × Motor speed_(2100)- 0.9111 × Moisture_(14)+ 0.3761 × Moisture_(20)+ 0.5351 × Moisture_(26). (11)

This equation quantifies the relationship between the factor levels and the combined response. The coefficients for the highest levels of motor speed (2,100 rpm) and moisture content (26%) are positive, which aligns with the main effects plot and confirms their positive contribution to maximising the multi-objective S/N ratio.

The residual plots shown in Figure 9 are useful in assessing the validity of the model. The normal probability plot shows that the residuals closely follow a straight line, which provides strong visual evidence that the error terms are normally distributed. This satisfies a fundamental assumption for the validity of the F-tests performed in the ANOVA. The histogram of the residuals supports this conclusion, displaying an approximately bell-shaped, symmetric distribution. The plot of residuals versus fitted values reveals no obvious pattern: the points are randomly scattered around zero within a constant bandwidth. This indicates homoscedasticity, or constant variance of the residuals, and suggests that the model's error is consistent across all levels of the predicted response. Furthermore, the absence of any severe outliers confirms that no single observation exerts undue influence on the model fit. Finally, the plot of residuals versus order of observation shows a random distribution with no discernible trends or shifts.

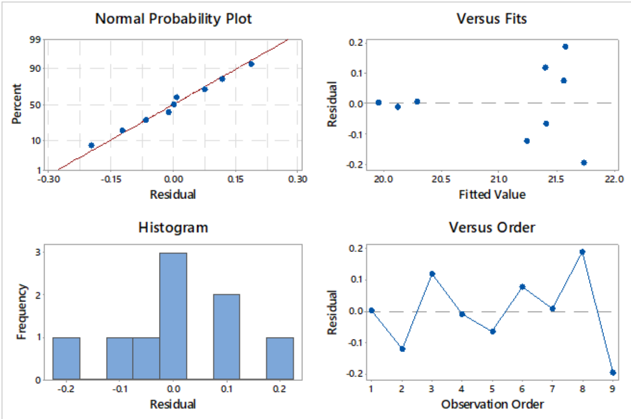


Figure 9. Residual plot for combined objective

This confirms that the data are independent of the run order and that no lurking variables, such as time-dependent effects or machine warm-up, have influenced the results systematically. Together, these diagnostic plots confirm that the underlying assumptions of normality, independence and homoscedasticity are met. This validates the model's goodness of fit and reinforces the significance tests and conclusions drawn from the ANOVA.

Discussion

Single Objective Optimization: Analyzing Results

Analysis of the means in Response Table 4 reveals that motor speed has the greatest impact on all quality characteristics (ranked 1), followed by moisture content, as indicated by their respective delta values. This conclusion is corroborated by the S/N ratio analysis presented in Table 3. The S/N ratio analysis for shelling efficiency (Figure 2a) shows that the impact of both factors is comparable. This suggests that optimising either motor speed or moisture content could be an effective strategy for maximising shelling efficiency and achieving a robust process. This finding is consistent with research on similar agricultural processing equipment, which has shown that operational speed and material properties can have a significant impact on performance (Oluwabukola et al, 2021) (Orobome et al, 2021).

In contrast, the S/N ratio for seed breakage (Figure 2b) is predominantly governed by motor speed, indicating that this is the primary factor controlling quality loss. This finding is consistent with revious research demonstrating a strong correlation between increased rotational speed and mechanical damage to seeds in post-harvest processing (Sukhanova et al, 2023) (Ali et al, 2021). Therefore, precise control of motor speed is crucial to minimize seed breakage (Sukhanova et al, 2023). Regarding machine capacity, the results demonstrate a significant main effect for motor speed, whereas moisture content has no statistically significant influence (Figure 2c). This suggests that throughput primarily depends on the machine's operational speed (El-Sharawy et al, 2017) (Adekanye et al, 2016) rather than the moisture level of the feedstock. The strong concordance between the trends in the S/N ratios (Figure 2) and the main effects plots for the means (Figure 3) further supports the reliability of these findings.

A significant interaction between motor speed and moisture content was observed for shelling efficiency (Figures 4a, 5a), which indicates that their combined effect influences performance. Several studies confirm that the interaction between moisture content and rotational speed on shelling efficiency (El-Sharawy et al, 2017). Another study on melon seed shelling found that the highest shelling efficiency was obtained from a specific combination of speed and moisture content, which highlights the interaction between the two factors (Oluwabukola et al, 2021). In contrast, breakage and capacity responses (Figures 4b-c, 5b-c) showed only minor ordinal interactions, suggesting that motor speed and moisture content can be optimised independently to minimise breakage and maximise capacity. This is consistent with separator studies, in which mechanical damage (governed by speed) and material flow (influenced by moisture) often operate through distinct mechanisms (Sudajan et al, 2002) (Borup et al, 2020).

In accordance with the Taguchi method, the optimal factor levels were identified using the main effects plots. A motor speed of 2,100 rpm and a moisture content of 26% maximised shelling efficiency. To minimise breakage, the ideal settings were found to be 900 rpm with a moisture content of 26%, whereas maximising capacity required a motor speed of 2,100 rpm with a moisture content of 14%. These results suggest that, while a high motor speed enhances efficiency and capacity, it must be balanced with moisture content to minimise seed damage. These findings are consistent with previous research showing that optimal moisture improves shelling and reduces breakage (Tan et al, 2025) (Wang et al, 2025), as well as increasing throughput capacity (Nsubuga et al, 2020).

Multiple objective optimization: Analyzing Results

The near-equality of the calculated entropy weights found to be 0.331 for shelling efficiency (S/N ratio), 0.338 for seed breakage (S/N ratio) and 0.331 for machine capacity (S/N ratio) indicates that the data for each objective provides a comparable amount of information and possesses a similar degree of dispersion within the experimental dataset. When entropy weights are nearly equal, it implies that each indicator contributes a similar amount of independent information to the analysis (Roszkowska et al, 2024).

Analysis of the multi-objective main effects plot (Figure 7) reveals that moisture content has the highest delta value, indicating that it is the most influential factor in overall shelling performance. This finding is consistent with previous research on melon seed shelling, which has shown that moisture content significantly impacts the mechanical properties and fracture behaviour of seeds during dehulling (Obi et al, 2015) (Eze et al, 2021). Specifically, moisture content influences seed dimensions, compressive strength and deformation energy, thereby impacting shelling efficiency and the extent of seed damage (Obi et al, 2015). These results are consistent with those of Tsapi et al. (2024) and Osuji et al. (2023), demonstrating the critical role of moisture content in optimising melon seed shelling processes.

Following the Taguchi methodology, the optimal combination of parameters is identified by selecting the levels that produce the highest multi-objective S/N ratio (Antony et al, 2024). Consequently, the optimal settings for maximising overall decortication process performance are a motor speed of 2100 rpm and a moisture content of 26%. The relative significance of each parameter can also be inferred from the inclination of its main effects plot: a steeper slope denotes a stronger influence on the response (4). As can be seen in Figure 7, the moisture content plot exhibits a significant slope, confirming its dominant role. In contrast, the nearly horizontal plot for motor speed suggests that its effect on the combined objective is statistically negligible within the tested range. This is a common outcome in multi-objective optimisation, where a single parameter can dominate the consolidated response (Fanya et al, 2018). The interaction plot (Figure 8) shows a strong correlation between motor speed and moisture content, especially at high levels of the parameters. This non-parallelism suggests that the effect of one factor depends on the level of the other. This interaction must be considered in robust process design, as adjustments to one parameter may require compensatory changes to the other to maintain optimal performance.

ANOVA performed on the multi-objective S/N ratio confirms the findings from the main effects plot. The p-value for moisture content is highly significant ($p < 0.05$), identifying it as the dominant factor governing combined shelling performance. Conversely, the p-value for motor speed is 0.162, exceeding the common significance level of $\alpha = 0.05$. This suggests that within the tested range, the impact of motor speed on the multi-objective response is not statistically significant. This finding aligns with studies on other seed decortication processes, where the physical properties of the feedstock, frequently influenced by moisture content, can have a greater impact on performance metrics than machine kinematics (Orobome et al, 2021).

The multi-objective optimisation, integrating three responses through a weighted Signal-to-Noise ratio, provided a balanced solution. Analysis of Variance (ANOVA) of the multi-objective model revealed that moisture content is the statistically dominant factor ($p < 0.05$), accounting for the majority of the variation in the combined response, while motor speed was found to be insignificant within the tested range. The resulting optimal parameter combination (Moisture Content: 26%, Motor Speed: 2100 rpm) provides a validated benchmark for users seeking a balanced improvement in all three quality characteristics.

Conclusion

This study successfully identified optimal parameters for melon seed decortication, emphasizing the critical roles of moisture content and motor speed in enhancing operational efficiency. The findings reveal a distinct trade-off between maximizing shelling efficiency, minimizing seed breakage, and increasing machine capacity, highlighting the complexities of achieving balanced performance in seed processing. We recommend that shelling machine operators maintain an optimal moisture content of 26% and routinely calibrate motor speed settings to 2100 rpm to ensure consistent performance. Future research could explore the impact of different seed varieties and environmental factors on processing efficiency, as well as integrating the developed Taguchi-based framework as a valuable guideline for other post-harvest processing technologies.

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