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Experimental investigation into the performance of cutting betel nut machine via response surface methodology and desirability function

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A B S T R A C T

Cutting betel nut machines are increasingly being designed by engineers using local material. However, the performance of the cutting betel nut machine is influenced by the moisture content of the betel nut and the rotational speed of the machine. In this study, the performance of cutting a betel nut machine under moisture content of betel nut and rotational speed of the machine was studied using response surface methodology (RSM) and desirability function. Central Composite Design (CCD) coupled with RSM and desirability function was employed to evaluate the impact of moisture content of betel nut (34.68–50.54%, w.b.) and rotational speed (600–1000 rpm) on machine capacity (kg/hr), efficiency (%), and losses (%) responses. The desirability function was then used to optimize moisture content and rotational speed yielding maximum machine capacity and efficiency at lower losses. Three verification experiments were run to ensure the empirical relationships were valid. Optimum requirements of process parameters have been seen at which moisture content of 50.54% (w.b.) and rotational speed of 1000 rpm was achieved in maximum machine capacity of 44.16 kg/hr at higher efficiency (92.72%) and lower losses (6.31%). The model's conclusions were very consistent with the confirmed values. The results proved that an appropriate performance of the machine can be achieved using moisture content of betel nut and rotational speed of machine cutting betel nut.

1. Introduction

Areca nut is one of the people's plantation crops commonly cultivated in Indonesia, especially in the province of Aceh. The area of areca nut plantations in Indonesia is about 95,744 ha (Henanto, 1996). To obtain dried betel nut, several post-harvest processes must be passed by the betel nut itself. Areca nuts can be harvested when the color of the fruit is still green, orange, and brown, with a water content range of 67.66% to 33.90% (Bulan *et al*., 2020). After harvesting from the tree, the betel nut, which is still in the areca nut bunches, is threshed. After obtaining the threshed betel nut, cutting the betel nut can be done to fasten the drying process. Drying can be carried out until the moisture content reaches less than 10%. After drying, the nuts from the shell and the fibers can be separated. The mechanization technology for post-harvest handling of areca nuts until it is ready for sale is still very limited. To support efforts to develop machines that specifically handle areca nuts, Bulan *et al.* (2020) have conducted studies related to areca nut's physical and mechanical properties that support the design of these

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machines. From that, a betel nut threshing machine has been reported on its design and evaluation (Bulan *et al.,* 2021a; Bulan *et al.,* 2021b). Furthermore, the areca nut cutting machine, whose performance was compared with the manual, was also carried out by Sitorus *et al.* (2019). But unfortunately, until now, there has been no study that focuses on evaluating the performance of post-harvest handling machines, especially betel nut cutting machines internally.

Testing machine performance, especially related to post-harvest processing machines for agricultural products, is not easy. This is because many factors must be considered before testing in order to avoid under and over design. There are at least two main factors, namely the factor of the material itself and the factor of the designed machine (Hafezalkotob *et al.*, 2018; Hu *et al.*, 2019). Factors of material that must be considered are the physical and mechanical properties of the product. Factors of the machine that must be considered include the feeding mechanism, the rotating speed of the machine, the feeding speed, and so on. Therefore, the combination of these two main factors must be studied together.

Studies investigating these two factors will produce several treatment combinations that must be tested on the designed machine. In addition, repetition of each variety of treatments also needs to be done to get valid test results. In the case of the betel nut slicing machine, the internal factor of the machine, which is the main consideration, is the blade's rotational speed and the internal factor of the material is the moisture content. Each of these factors has its level of treatment.

The proposal of the response surface methodology (RSM) and the desirability function in evaluating agricultural machinery is one of the latest ways to be accomplished. Recent research conducted by Mehrijani *et al.* (2019) used RSM to evaluate tractors in plowing. In addition, Fu *et al.* (2020) assessed a frozen corn threshing machine using RSM and NSGA-II. It is used because RSM provides a treatment combination facility that can analyze the response of each treatment combination to be tested. In addition, the analysis of the variance of the responses can also be carried out simultaneously. After the response is known, the post-analysis is that RSM can provide an optimum estimation model of each treatment level being tested using a desirability function. Therefore, the objective of this study is to optimize the performance of the cutting betel nut machine via response surface methodology (RSM) and desirability function.

2. Materials and method

2.1 Design of experimental tests

The British Research Establishment was used to develop the class nine mix (BRE). In twenty-seven runs, experimental runs were generated utilizing the CCD of the response surface approach (including replication). This number of runs accurately captures the optimal settings and provides significant experimental results (Ghafari *et al.*, 2009). The design had two independent variables, moisture content and rotational speed, which were coded as A (moisture content) and B (rotational speed). The responses correspond to the machine's capacity, efficiency, and loss.

2.2 Procedure of experimental tests

RSM has produced the experimental design for testing the cutting betel nut machine's performance across all runs using the DE12 software. First, the moisture content of the betel nut samples was measured three times. The betel nut samples consisted of 3 types, i.e., 34.68±7.36%, 46.68±6.57%, and 50.54±0.34%. Second, the areca nut cutting machine that will be tested for its performance is prepared (Fig. 1) with the rotation of the cleaver at the previous 600 rpm, 800 rpm, and 1000 rpm levels. The regulation of the rotational speed of the betel nut blade was measured using a tachometer. Third, after the machine is ready to be tested, as many as 2 kg of samples of each moisture content are entered into the machine, and the operating time is recorded. Finally, the samples that have been processed are then separated between perfectly split and unsplit samples. Each test combination was performed in triplicate and presented as means ± standard deviation.

Fig. 1. Performance-tested betel nut cutting machine

2.3 Analysis by RSM

The exploratory stage of research begins by determining what things will be used as factors that can later be changed based on the ability of the object under study. The quality or quality of the final product that is expected from machine testing can be used to respond to factors that we will later change following the wishes that have been set. Determination of factors can be determined from the research team's observations and compared with previous research references. The factors that have been obtained are moisture content and rotational speed, which are then determined as the dependent factor. Moisture content is referred to as factor A and rotational speed as B. Response is a priority in determining the machine's performance, namely machine capacity, the efficiency of areca nut cutting, and losses of the machine. Data retrieval is done by recording the entire data based on predetermined factors. Statistical analysis of variance will be used to analyze each response data. The significance of the P-value on the model, lack of fit, the difference between the R-squared adj and R-squared pred values, and appropriate precision are included in the ANOVA analysis's reading findings. After analyzing the entire parameter, the machine performance is optimized depending on the identified factors and responses. The optimization process begins with determining the priority scale for each element and response. The achieved optimization is next checked to ensure that it follows the software's prediction and is appropriate for usage. Verification is done by re-monitoring the engine performance by adjusting the optimization data from the software, which shows the highest desirability value proposed by the system. After obtaining the verification data, it is then matched again to whether the results are still within the 95% prediction interval (PI) range. If the verification results are still in the field of PI, it can be concluded that the model obtained is by what is shown by the software and can be applied in the field.

3. Results and discussion

3.1 Establishment of regression model

A mathematical function was established to estimate the performance of the cutting betel nut machines, including machine capacity, efficiency, and losses at different moisture content and rotational speed conditions. The coefficients of the regression model for machine capacity, efficiency, and losses were calculated at the confidence level of 95%. The quadratic statistical model is the most recommended for predicting the response of this engine evaluation. The final regression models for machine capacity, efficiency, and losses are given in Eq. (1), Eq. (2), and Eq. (3), respectively. A favorable parameter suggests a synergetic impact in which the response extends as the number of independent variables added to the regression equation increases. On either side, a negative sign indicates an antagonistic effect, in which the response rises as the input variables are decreased. Twenty-seven investigations were conducted to optimize the two parameters (moisture content and rotational speed) and triplicate using RSM. The results show that the maximum machine capacity obtained was 52.81 kg/hr using a moisture content of 50.54%, and a rotational speed of 1000 rpm, while the minimum carbohydrate yield was 4.85 kg/hr using moisture content of 34.68%, and a rotational speed of 600 rpm. A quadratic model (Equations 1 to 3) was developed via a multiple nonlinear regression examination of the experimental data to indicate the machine capacity, efficiency, and losses obtained from the cutting betel nut machine.

3.2 Parameter effects for machine capacity model

The regression models for machine capacity in high R^2 values (0.9356) indicate an excellent fit of the data to the models. The value of R^2 should be near one for an ideal model. The residuals did not show a time-based relationship, demonstrating that the regression modelling approach was acceptable. The statistical analysis ANOVA results for the machine capacity full model are presented in Table 1.

Table 1. Machine capacity regression model statistical data

Source	Sum of squares	df	Mean square	*F* value	*p* value
Model	5514.50	5	1102.90	61.05	0.0001
A-Moisture content	5352.27	1	5352.27	296.27	0.0001
B-Rotational speed	140.56	1	140.56	7.78	0.0110
AB	1.79	1	1.79	0.0989	0.7562
A^2	378.81	1	378.81	20.97	0.0002
B^2	18.74	1	18.74	1.04	0.3201
Residual	379.38	21	18.07		
Lack of fit	33.74	3	11.25	0.5857	0.6321
Pure error	345.64	18	19.20		
Correlation total	5893.88	26			
Standard deviation	4.25		R^2	0.9356	
Mean	25.22		Adjusted R^2	0.9203	
C.V (%)	16.86		Predicted R^2	0.8962	
Press	612.04		Adequate precision	20.0574	

High F-values and low p-values show the model was statistically significant and had no significant lack of fit. Each parameter in the model was also analyzed for significance, and for the machine capacity model, all parameters were significant based on their F-values. It is crucial to mention that the interaction parameter of moisture content and rotational speed (A×B) was significant for the machine capacity model. These results imply that the models provide reasonable response surface estimates and are analyzed further. The F-value for each parameter shows the relative significance. For example, moisture content (A) of betel nut is clearly the most influential parameter in this model (F-value > 250) for the machine capacity model.

The empirical model for machine capacity (kg/hr) is shown in coded form in Eq. (1), established from the regression procedure and supported by ANOVA. The coefficients of the regression model for machine capacity were computed at a confidence level of 95%. The overview of model statistics indicated that quadratic is best suggested that it has been used for predicting the machine capacity responses. A positive value correlates with increased machine capacity when the parameters (moisture content and rotational speed) increase (vice versa). In the model, all two main parameters of the testing design are significant, as are one interaction effects and two higher-order effect. Identification of significant relations and higher-order parameters explain the experimental method's use because these parameters would not have been identified with a more straightforward experimental procedure.

$$Cm = 14.95 + 17.24A + 2.85B - 0.37AB + 11.25A^2 - 1.77B^2 \tag{1}$$

The 3D response of surface machine capacity under moisture content and rotational speed has been demonstrated in Fig. 2. This figure displays the relationship between machine capacity at the center value of the other two parameters (moisture content and rotational speed). It is clear from the graph that the maximum moisture content of betel nut parameters and increased rotational speed will produce maximum machine capacity. Utilizing Eq. (1) and Fig. 2 analyzes the response surface of machine capacity as a function of the independent variables. These surfaces were established by having two factors constant at the respective center point conditions while varying the other factors.

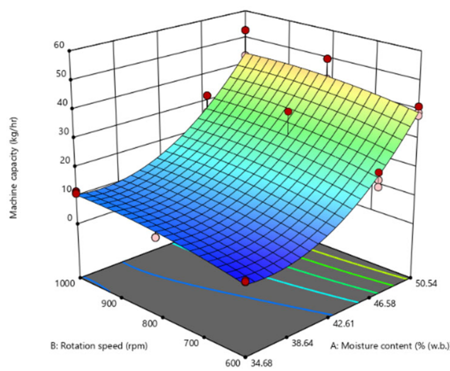
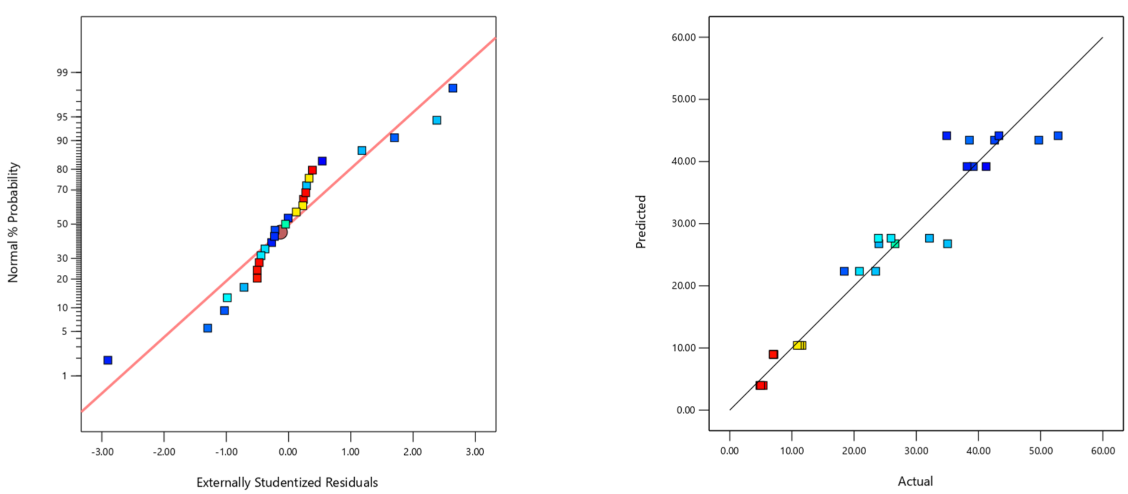


Fig. 2. 3-D surface plot machine capacity vs. moisture content and rotational speed

The normal plot of residuals and graph of actual vs. predicted values have also been drawn in Fig. 3. The normal plot of residuals is utilized to confirm the normality hypothesis, whereas the figure of indicated vs. actual values shows the forecast capability of the established model. All distribution data on the line implies the error was normally distributed. The distribution data is close to the actual values, indicating that the predicted values reasonably agree with the actual values. The regression models for expected machine capacity in high R^2 values (0.8962) show an excellent fit of the data to the models. The value of R^2 should be near one for an ideal model.



(a) Normal plot of residuals (b) Predicted vs. actual

Fig. 3. Diagnostic plots for machine capacity response

3.3 Parameter effects for cutting efficiency model

A statistical test was run on the regression model and individual model variables to determine the model's significance. The analysis of variance (ANOVA) for the data provided by Eq. (1) for cutting efficiency is shown in Table 2. A high Fisher's F and a modest P-value (Prob. > F) demonstrate the relevance of the model and its terms (Yirgu *et al.*, 2021). The model's F-value of 441.20 and p-value of 0.0001 suggested that it was significant in this investigation. The cutting efficiency of all linear terms, two quadratic terms (A^2 and B^2), and interacting terms (AB) were severely reduced. The F and P values for lack of fit were 2.26 and 0.116, respectively, indicating that the lack of fit was not significant compared to the pure error and that the model fit is satisfactory (Mendes *et al.*, 2001).

Table 2. Cutting efficiency regression model statistical data

Source	Sum of squares	df	Mean square	*F* value	*p* value
Model	13498.96	5	2699.79	441.20	0.0001
A-Moisture content	11673.92	1	11673.92	1907.77	0.0001
B-Rotational speed	32.37	1	32.37	5.29	0.0318
AB	208.94	1	208.94	34.15	0.0001
A^2	48.96	1	48.96	8.00	0.0101
B^2	62.08	1	62.08	10.15	0.0045
Residual	128.50	21	6.12		
Lack of fit	35.19	3	11.73	2.26	0.1160
Pure error	93.32	18	5.18		
Correlation total	13627.46	26			
Standard deviation	2.47		R^2	0.9906	
Mean	73.16		Adjusted R^2	0.9883	
C.V (%)	3.38		Predicted R^2	0.9852	
Press	201.57		Adequate precision	50.5398	

ANOVA was used to determine the model's adequacy. R^2 and adjusted R^2 values of 0.9906 and 0.9883 indicate congruence between experimental results and fitted regression models. The lack of fit is also negligible, which is desired given the requirement for a fitting model (Miri *et al.*, 2016). The distribution of points compatible with the regression line demonstrates the applied regression model's increased adequacy. Additionally, a random bounce of residuals establishes the reasonableness of the claimed relation. The empirical model for machine capacity (kg/hr) is shown in coded form in Eq. (2), established from the regression procedure and supported by ANOVA. A positive value correlates with increased cutting efficiency when the parameters (moisture content and rotational speed) increase (vice versa). The effect of the combination of moisture content and rotational speed is known to reduce the cutting efficiency of the machine. However, doubling both parameters' moisture content and rotational speed has the opposite effect on cutting efficiency.

$$Ef = 69.71 + 25.47A + 1.37B - 4AB - 4.04A^2 + 3.22B^2 \qquad (2)$$

The 3D response of surface cutting efficiency under moisture content and rotational speed has been demonstrated in Fig . 4. This figure displays the relationship between cutting efficiency at the center value of the other two parameters (moisture content and rotational speed). It is clear from the graph that the maximum moisture content of betel nut parameters and increased rotational speed will produce maximum cutting efficiency. Utilizing Eq. (2) and Fig. 4 analyzes the response surface of cutting efficiency as a function of the independent variables. These surfaces were created by holding two variables constant at their respective center point conditions while altering the other variables.

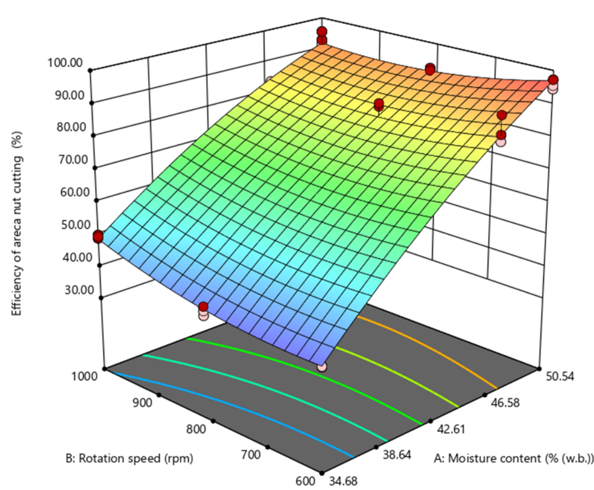
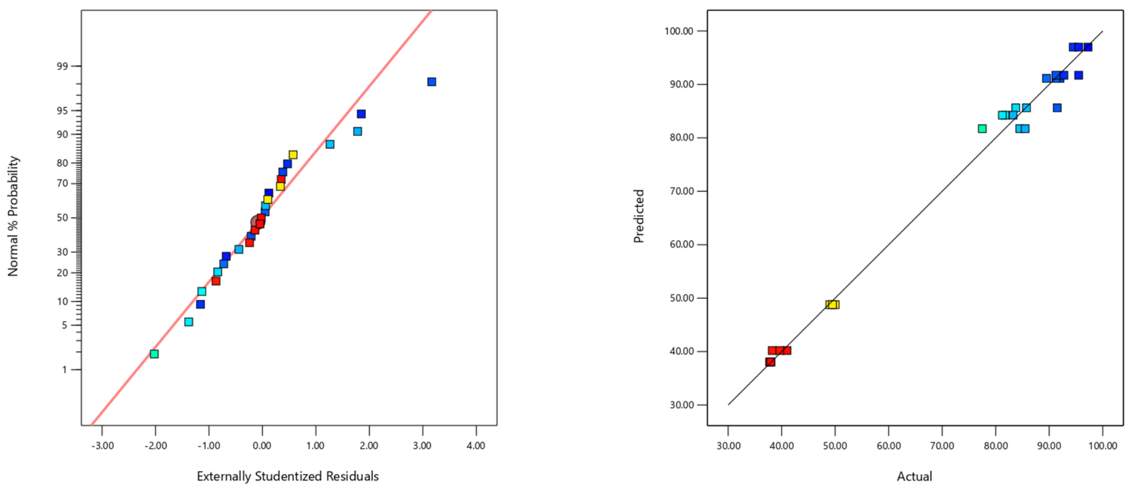


Fig. 4. 3-D surface plot cutting efficiency vs. moisture content and rotational speed

Correlation coefficients with a higher significance indicated that the model was very reliable in forecasting machine capacity; adjusted R^2 quantified the variation around a mean explained by the model (Rahim and Bharti, 2020). The R^2-value suggested that the quadratic model explained 99.06% of the variability in cutting efficiency in this investigation. The high adjusted R^2 value indicated an acceptable agreement between observed and anticipated cutting efficiency values, indicating that the proposed quadratic model equation produces desirable and accurate results. Additionally, the difference between the anticipated and adjusted R^2 values is too tiny, indicating that they are reasonably consistent with one another (Lakshminarayanan & Balasubramanian, 2009). R^2 and adjusted R^2 values are near one, suggesting a high correlation between observed and anticipated cutting efficiency values. Simultaneously, the model's low coefficient of variance (3.38%) indicated a high degree of accuracy and dependability for the experimental data (Sinha *et al.*, 2013). As a result, the constructed model could accurately predict cutting efficiency across the observed variables. The normal plot of residuals and graph of actual vs. predicted values for cutting efficiency have also been drawn in Fig. 5. The normal plot of residuals is utilized to confirm the normality hypothesis, whereas the figure of predicted vs. actual values shows the forecast capability of the established model. The regression models for predicted cutting efficiency in high R^2 values (0.9852) indicate an excellent fit of the data to the models. The value of R^2 should be near one for an ideal model.



(a) Normal plot of residuals (b) Predicted vs. actual

Fig .5. Diagnostic plots for cutting efficiency response

3.4 Parameter effects for cutting losses model

The regression models for cutting losses in high R^2 values (0.9892) indicate an excellent fit of the data to the models. The value of R^2 should be near one for an ideal model. The residuals did not show a time-based relationship, demonstrating that the regression modeling approach was acceptable. The statistical analysis ANOVA results for the full cutting losses model are presented in Table 3. High F-values and low p-values show the model was statistically significant and had no significant lack of fit. Each parameter in the model was also analyzed for significance, and for the cutting losses model, all parameters were significant based on their F-values. It is crucial to mention that the interaction parameter of moisture content and rotational speed (AB) was significant for the cutting losses model. These results imply that the models provide reasonable response surface estimates and are analyzed further. The F-value for each parameter shows the relative significance. For example, moisture content (A) of betel nut is clearly the most influential parameter in this model (F-value > 1500) for the machine capacity model.

Table 3. Cutting losses regression model statistical data

Source	Sum of squares	df	Mean square	*F* value	*p* value
Model	12576.44	5	2515.29	385.39	0.0001
A-Moisture content	10740.89	1	10740.89	1645.70	0.0001
B-Rotational speed	71.90	1	71.90	11.02	0.0033
AB	204.67	1	204.67	31.36	0.0001
A^2	62.37	1	62.37	9.56	0.0055
B^2	80.67	1	80.67	12.36	0.0021
Residual	137.06	21	6.53		
Lack of fit	38.38	3	12.79	2.33	0.1083
Pure error	98.68	18	5.48		
Correlation total	12713.50	26			
Standard deviation	2.55		R^2	0.9892	
Mean	24.74		Adjusted R^2	0.9867	
C.V (%)	10.33		Predicted R^2	0.9832	
Press	214.01		Adequate precision	47.1431	

ANOVA was used to determine the appropriateness of the created model. R^2 and adjusted R^2 values of 0.9892 and 0.9867 indicate congruence between experimental data and fitted regression models. Additionally, the lack of fit is negligible, which is desirable given the requirement for a fitting model. The distribution of points that conform to the regression line demonstrates the applied regression model's increased adequacy. Additionally, the random bounce of residuals establishes the reasonableness of the stated connection. The empirical model for cutting losses is shown in coded form in Eq. (3), established from the regression procedure and supported by ANOVA. A negative value correlates with decreased cutting losses when the parameters (moisture content and rotational speed) increase (vice versa). The effect of the combination of moisture content and rotational speed is known to increase the cutting losses of the machine. However, doubling both parameters' moisture content and rotational speed has the same effect on cutting losses.

$$Lc = 27.92 - 24.43A - 2.04B + 3.96AB - 4.57A^2 - 3.67B^2 \tag{3}$$

The 3D response of surface cutting efficiency under moisture content and rotational speed has been demonstrated in Fig. 6. This figure displays the relationship between cutting losses at the center value of the other two parameters (moisture content and rotational speed). It is clear from the graph that the maximum moisture content of betel nut parameters and increased rotational speed will produce maximum cutting losses. Utilizing Eq. (3) and Fig. 6 analyzes the response surface of cutting losses as a function of the independent variables. These surfaces were generated by maintaining two variables at their respective center point conditions while varying the other.

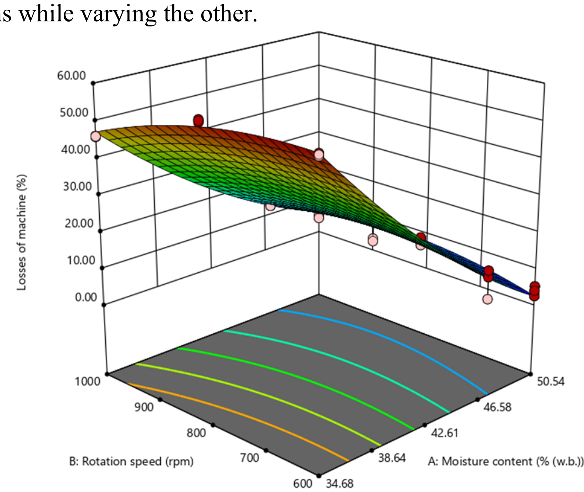
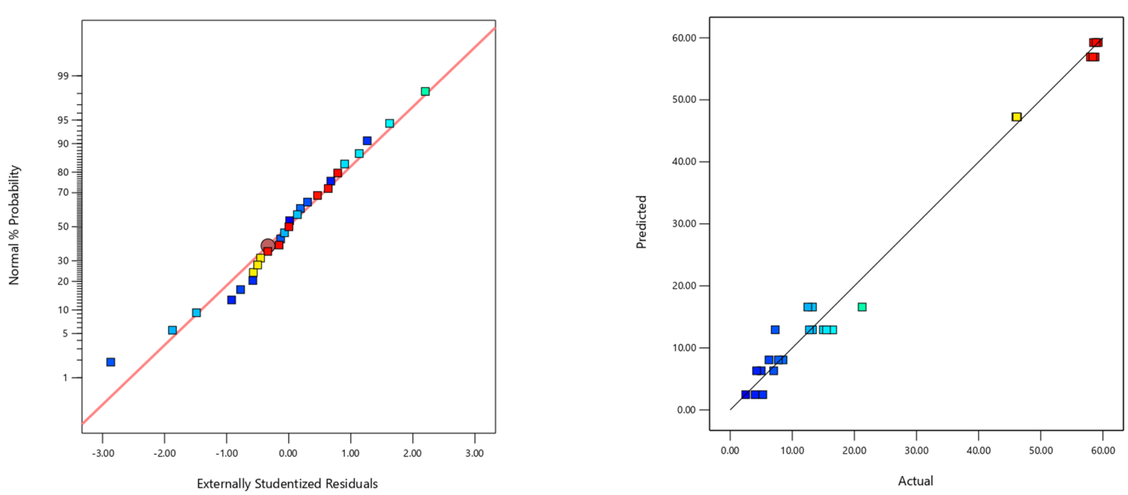


Fig. 6. 3-D surface plot cutting losses vs. moisture content and rotational speed

The normal plot of residuals and graph of actual vs. predicted values have also been drawn in Fig. 7. The normal plot of residuals is utilized to confirm the normality hypothesis, whereas the figure of expected vs. actual values shows the forecast capability of the established model. All distribution data on the line implies the error was normally distributed. The distribution data is close to the actual values, indicating that the predicted values reasonably agree with the actual values. The regression models for expected cutting losses in high R^2 values (0.9832) show an excellent fit of the data to the models. The value of R^2 should be near one for an ideal model.



(a) Normal plot of residuals (b) Predicted vs. actual

Fig. 7. Diagnostic plots for cutting losses response

3.5 Optimum of cutting betel nut machine parameter values

The model's desirability value close to one is the most desirable because it increasingly indicates the importance of optimization accuracy (Chabbi *et al.*, 2017). The desirability value indicates the level of fulfillment of the specified criteria (Fig. 8). Based on the optimization process, this method shows the prediction of the most optimal conditions in the process of testing this machine is at a moisture content of 50.54%, and a rotational speed of 1000 rpm is recommended as the most optimal formula solution because in this process condition it has the highest desirability value, namely of 0.913 or equivalent to 91.3%. So it can be concluded that the process conditions with these components will produce machine performance with the desired quality, namely machine capacity of 44.16 kg/hr, cutting efficiency of 91.72%, and cutting losses of 6.31%. Table 4 shows the criteria for each optimized response, including the target, minimum limit, the maximum limit, and level of importance at the formula optimization stage.

Table 4. Components, targets, constraints, and importance at the optimization stage

Respon	Goal	Lower	Upper	Importance
Machine capacity	Max	4.85	52.81	+++
Efficiency of areca nut cutting	Max	37.75	97.25	+++
Losses of machine	Min	2.5	59.25	+++

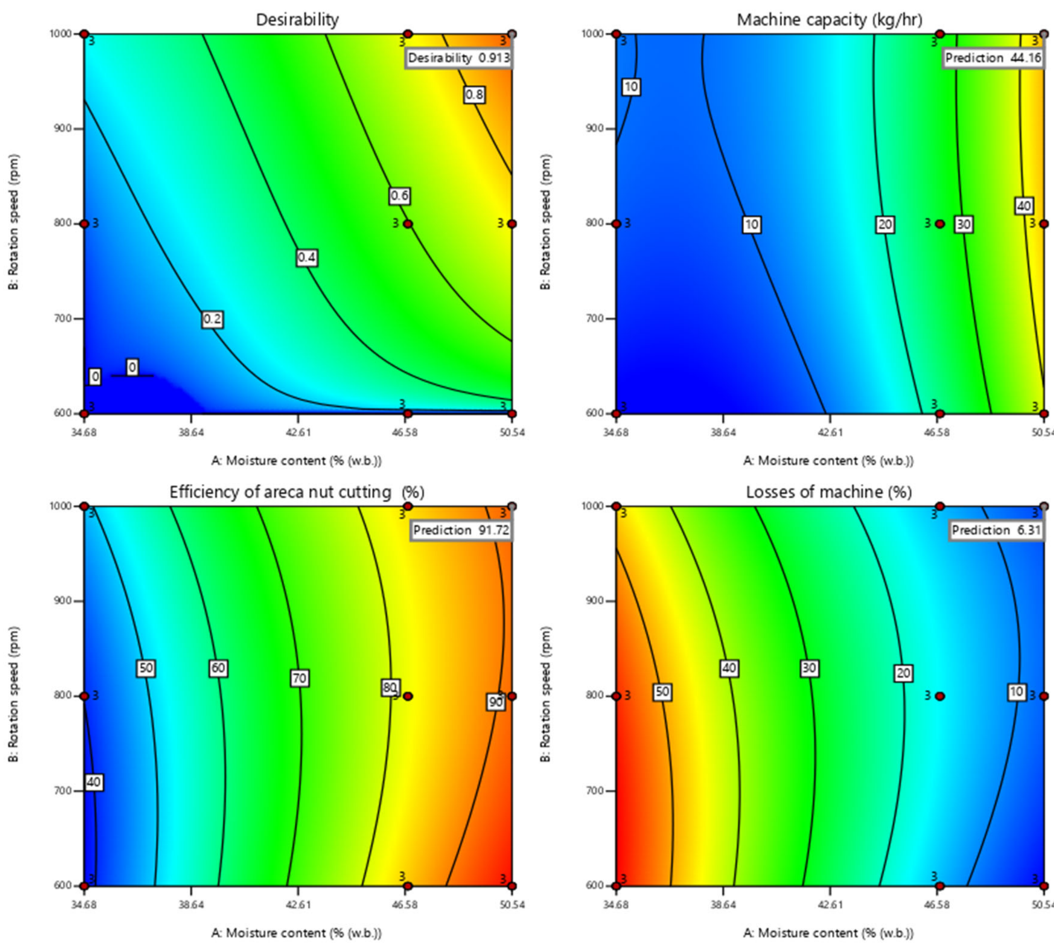


Fig. 8. Optimization of cutting betel nut machine performance using desirability function

3.6 Confirmation test

The optimization results obtained were then verified three times. The verification of optimum conditions can be seen in Table 5. Based on the verification data from the response of machine capacity, the efficiency of areca nut cutting, and losses of a machine, the values are 38.77 kg/hr, 83.17%, and 14.75%, respectively. This shows that the machine capacity response is correctly predicted in 95% CI low and 95% CI high. However, the efficiency response of areca nut cutting and losses of a machine is not in the range of 95% PI low and 95% PI high.

Table 5. Verify the optimum formula solution for cutting betel nut machines

Respon	Prediction	SD-P	SE-P	95% PI low	Verifikasi	95% PI high
Machine capacity (kg/hr)	44.16	4.25	3.21	37.48	38.77	50.84
Efficiency of areca nut cutting (%)	91.72	2.47	1.87	87.83	83.17	95.60
Losses of machine (%)	6.31	2.55	1.93	2.29	14.75	10.33

5. Conclusion

In this study, the following conclusions were established from an experimental investigation into the performance of cutting betel nut machines via response surface methodology (RSM). Source, both moisture content of areca nut and rotational speed, are known to significantly affect the performance response of this machine (machine capacity, efficiency of areca nut cutting, and losses of machine). The performance response of machine capacity, the efficiency of areca nut cutting, and losses of a machine can be predicted from the model developed with a source moisture content of areca nut and rotational speed with terminated coefficients of 89.62%, 98.52%, and 98.32%, respectively. Via RSM combined with desirability function, this research recommends a formula for moisture content of 50.54% and a rotational speed of 1000 rpm in this machine application with the highest desirability value of 91.3%. In addition, verification of machine capacity response, the efficiency of areca nut cutting, and losses of the machine showed values of 38.77 kg/hr, 83.17%, and 14.75%, respectively. RSM now has a considerable amount of information in a short period and with the fewest possible experiments.

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