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Optimization of Microwave Treatment to Improve Adsorption Properties of Porous Rice Starch

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ABSTRACT

Porous starch (PS) is used in various foods as a flavoring, absorbent, and to protect vitamins and oils. Rice starch is processed to minimize the preparation time of PS, while simultaneously maintaining its adsorption efficiency. This study aims to optimize microwave treatment to improve the water, oil, and methylene blue adsorption capacity and PS yield of rice. This study used Response Surface Methodology (RSM) with Central Composite Design (CCD) to optimize the water, oil, and methylene blue adsorption capacity and PS yield of rice. Two factors were considered: time (X_1: 3-15 s) and power (X_2: 100-200 W/g). The statistical significance of the responses was evaluated using analysis of variance (ANOVA) at the 95% confidence level, with differences considered significant at $p<0.05$. Linear and quadratic models were the modes suggested by the software. Model analysis showed that microwave time and power significantly affected the adsorption properties. Based on the research results, the optimum conditions for making porous rice starch were obtained by using a microwave time of 15 s and a power of 171 W/g, resulting in a water absorption capacity of 96.34±2.93%, an oil absorption capacity of 142.85±0.94%, a methylene blue absorption capacity of 34.73±5.67%, and a yield of 95.26±3.23%.

1. INTRODUCTION

Porous starch (PS) is a modified form of starch characterized by numerous pores distributed both inside the core and on its surface (Guo *et al.*, 2021). Its granules have easily accessible cavities and a large surface area. PS is used in various foods as a flavoring, absorbent, or carrier for volatile substances and to protect delicate components, including probiotics, vitamins, and oils (Benavent-Gil & Rosell, 2017). PS is produced using physical, chemical, and enzymatic treatments. Enzymatic methods are commonly used to produce PS due to their efficiency, controllability, and minimal by-product output. However, enzymatic techniques are time-consuming and require further improvement of the product's absorption capacity. Researchers have combined physical treatments with enzymatic hydrolysis to produce PS and improve its absorption capacity. Su *et al.* (2025) applied microwave treatment during enzymatic hydrolysis in modifying rice starch (long-grain fragrant rice with amylose content 16.6%) to produce porous rice starch with wide pores, a large number of pores, and increased water and oil absorption capacity from 84.32% to 103.1% and 115% to 170% ($p<0.05$).

Adsorption properties are the defining characteristics of porous starch (PS). Waste materials, such as wastewater, oil, and gas, often require effective adsorption capacity. However, conventional adsorbents, including carbon, silica gel, and alumina, are usually expensive and non-biodegradable (Chen *et al.*, 2020; Guo, *et al*., 2015). Meanwhile, the adsorption

capacity of some biodegradable adsorbents (such as chitosan or sodium alginate) is quite low. PS has recently been identified as a new type of adsorbent. The preparation technique of PS is easy, versatile, and can be modified.

Adsorption properties are one of the important parameters of porous starch. Starch with high water adsorption capacity (WAC) will absorb or encapsulate hydrophilic active substances more efficiently and effectively. Microwave treatment for 2 min followed by enzymatic hydrolysis resulted in an enhance in WAC from 110.99% to 128.29%, improving the structural properties, thermal stability, and functional characteristics, thus expanding the applications of porous corn starch (Jiang *et al.*, 2023). In addition, microwave treatment for 5 min effectively increased the WAC of lotus seed starch from 105.13±5.21% to 174.93±8.43%, and the oil absorption capacity (OAC) from 92.87±4.03% to 123.93±6.23% (Nawaz *et al.*, 2018). Microwave irradiation has been shown to increase the adsorption capacity of biosynthesized iron oxide nanoparticles methylene blue (MBAC) (Shalaby *et al.*, 2022).

Response Surface Methodology (RSM) is a statistical application that functions to optimize a process through a combination of various independent variables. One of the models in RSM that is considered more efficient in modeling is Central Composite Design (CCD. Sai-Ut *et al.*, (2024) applied RSM with CCD in optimizing the extraction process of polyphenol compounds from *Careya sphaerica* Roxb flowers using Microwave assisted Extraction. The results obtained with a microwave power of 1000 W, a solid-to-solvent ratio of 1:100 g/mL, an ethanol concentration of 40% v/v, and an extraction time of 20 seconds were able to obtain optimal yield, total phenolic, extracted phenols, DPPH, and flavonoid content. In addition, Liu *et al*., (2018) also used RSM for the polyphenol extraction process from Sorghum Moench obtained 60.37% ethanol, a temperature of 59.07°C and an extraction duration of 2.97 h, capable of producing a total phenolic content of 313 mg GAE/100 g dry weight. Limited research has been conducted on optimizing microwave time and power related to adsorption capacity and porous starch yield. Therefore, this study aims to optimize microwave time and power to increase WAC, OAC, MBAC, and porous rice starch yield using RSM with CCD.

2. MATERIALS AND METHODS

2.1. Materials

The rice variety Inpari 32 was obtained from Toko Tani Berkah Nandur, Surakarta, Indonesia. Additional analytical-grade reagents were purchased from Merck and Sigma-Aldrich, Inc.

2.2. Research Method

2.2.1. Extraction of Rice Starch

Rice starch was extracted using the procedure of (Verma & Srivastav, 2022) with modifications. Sample isolation began with weighing, washing with water, and soaking with rice at a distilled water ratio of 1:2 (w/v) for about 24 h. The rice was washed 3 times and ground using a blender. The mixture was filtered through a 100-mesh screen, and was separated at 1410×g for 15 min. The precipitate was dehydrated in a cabinet dryer for 20 h at 50 °C.

2.2.2. Microwave Treatment

Rice starch was treated by microwave following with minor modification of the procedure by (Wang *et al.*, 2022). The starch was dissolved in distilled water until it reached a 25% suspension. After that, it was heated to 100 W/g, 150 W/g, 200 W/g for 3, 5, 15 s in a microwave oven (Electrolux, Sweden, 220 V, 800 W, 2450 MHz). The starch was separated for 15 min at 1410×g, and the precipitate was dehydrated for 20 h at 50 °C. The samples were then ground to 100 mesh and analyzed in triplicate.

2.2.3. Optimization Process Design

The experimental design was carried out using the Central Composite Design (CCD) from Response Surface Methodology (RSM). The first step taken was to determine the independent variables of the process conditions, namely time and microwave power. The response variables were measured based on preliminary experiments by determining the upper and lower limits on the WAC. The obtained upper and lower limit values were entered into the DX 7.0 software. The model was presented as the following:

$$Y = \beta_0 + \sum_{i=1}^{2} \beta_i X_i + \sum_{i=1}^{2} \beta_{ii} X_i^2 + \sum_{i=1}^{1} \sum_{j=i+1}^{2} \beta_{ij} X_i X_j \quad (1)$$

where Y is predicted response, β_0 is intercept, and β_i, β_{ii}, and β_{ij} is respectively linear, quadratic, and interaction coefficients. X_i, X_i^2, and X_iX_j are coded independent variables. Table 1 presents the coded and uncoded levels of the independent variables used in the experimental design.

2.2.4. Response Analysis and Process Optimization

ANOVA was used to examine each response. Polynomial models were generated using Design Expert 7.0® software that represented the response of each factor. Polynomial models can be cubic, quadratic, mean, linear, or 2FI (two-factor interaction). A 3D surface graph serves as a visual representation of the model. The software's suggestion, namely a model that can accurately represent the response by meeting the following four criteria, resulted in the adoption of the ANOVA model. Initially, the selected model must have: a *P*-value of 0.05 or less is significant; a misfit greater than 0.05 is considered insignificant.

The model's suitability for the response data is indicated by the absence of a fit value, which is not significant; the difference between the adjusted and anticipated R^2. The value of the precision of sufficiency, the basis for the final criterion, should be higher than 4. Setting the requirements in advance will optimize the response. So, we have to decide the objectives and the importance of the process to get the best process conditions. The objectives, in the range, maximize, or minimize, form the objective value. In addition, the level of relevance of each response is determined by its importance, which ranges from 1 to 5 (+) to (++++).

The greater the interest, the greater the incentive to produce the best possible product. The output of the optimization phase is the program's suggestion of a number of ideal process conditions. A high attractiveness score identifies the best process conditions. Attractiveness scores range from 0 to 1. The process conditions suggested by the program will produce the most desirable results, based on a high attractiveness score (close to 1).

2.2.5. Verification

The desirability value is used as a benchmark in determining optimum conditions. Then the verification stage is carried out through WAC measurements as a response in the laboratory. Furthermore, a comparison is made with the response predicted by the DX 7.0 software. The confidence interval (CI) and prediction interval (PI) values are used in determining the process conditions that are verified at a significance level of 5%. Verification is carried out through laboratory experiments with three repetitions. Then a comparison is made between the laboratory experiment and the response value predicted by the Design Expert 7.0 software.

2.3. Analysis Procedure

2.3.1. Water and Oil Adsorption Capacity (WAC, OAC)

Porous rice starch (PRS) (0.5 g, W_0) was added into 8 mL of aquadest or palm oil and homogenized, following the procedure reported by (Han *et al.*, 2021) with slight modifications. The material was left for 30 min to allow for water or oil absorption. Subsequently, the slurry was separated at 1410×g for 15 min. The supernatant was discarded to determine the precipitate (W_1). The equations for measuring oil and water absorption are as follows:

$$\text{WAC (\%)} = \frac{(W_1 - W_0)}{W_0} \times 100\% \quad (2)$$

where W_1 = precipitate weight (g), and W_0 = initial starch weight (g)

2.3.2. Methylene Blue Absorption Capacity (MBAC)

This analysis is based on a study, with slight modifications. 0.025 g of PRS was diluted in 11 mL of 0.01 mg/mL MB solution. The materials were then mixed for 5 hours. The sample solution was separated at 1410×g for 5 minutes, after which the absorbance of the resulting supernatant was measured at a wavelength of 665 nm. The standard curve for MB

was $y = 190.8x - 0.0177$, with $R^2 = 0.998$, where y represents absorbance, x represents concentration (mg/mL). The absorbance of MB was calculated as:

$$\text{MBAC (\%)} = \frac{(C_0 - C_1)}{C_0} \times 100\% \quad (3)$$

where C_0 = initial MB concentration, and C_1 = final MB concentration

2.3.3. Porous Starch Yield

Yield percentage was calculated as the ratio of dry porous starch mass to the initial rice starch dry mass.

3. RESULTS AND DISCUSSIONS

3.1. Model Fitting and Statistical Analysis

The response surface regression model in Design Expert 13 software was used to evaluate the data obtained from the microwave treatment, as shown in Table 1. The regression model aims to describe the relationship between microwave time and power (independent variables) and the responses (WAC, OAC, MBAC, and yield). The adequacy of the independent variables to the responses of WAC (Y_1), OAC (Y_2), MBAC (Y_3), and starch yield (Y_4) was assessed through ANOVA analysis.

Table 1. Design of the processing conditions and resulting values of the response of PRS

Treatments	Coded variables		Actual variables		Observed values			
	X_1	X_2	Microwave time (s)	Power (W/g)	WAC (%)	OAC (%)	MBAC (%)	Yield (%)
1	0	0	9	150	97.20	138.57	36.35	89.13
2	0	0	9	150	95.79	143.58	39.58	93.55
3	+1	+1	15	200	97.70	146.82	40.20	87.88
4	-1	+1	3	200	91.11	139.34	40.51	95.23
5	-1	-1	3	100	94.59	132.83	33.83	97.12
6	0	0	9	150	95.46	143.70	35.46	92.15
7	-1	0	3	150	95.04	140.89	33.07	97.06
8	+1	-1	15	100	99.63	118.61	31.04	97.99
9	0	0	9	150	93.81	139.40	34.20	98.26
10	+1	0	15	150	95.65	140.76	35.45	98.49
11	0	0	9	150	91.48	137.89	37.78	98.71
12	0	-1	9	100	95.88	126.37	30.14	98.93
13	0	+1	9	200	94.99	144.86	41.09	89.44

Table 2 shows that R^2 is 0.4952, 0.9508, 0.7673, and 0.4143 for Y_1, Y_2, Y_3, and Y_4, respectively, with insignificant lack of fit ($p>0.05$) among the responses. The R^2 is a coefficient symbol that measures how well the predicted data fits the regression line (Oktavia *et al.*, 2024). The difference between the adjusted and predicted coefficients of determination (R^2) should ideally be less than 0.2, indicating good agreement between model fit and predictive ability. A large difference may indicate overfitting or poor model generalization. Furthermore, model adequacy can be evaluated through the Adequate Precision metric, which measures the signal-to-noise ratio. A value greater than 4 is generally considered acceptable, indicating that the model has sufficient signal and can be used effectively to explore and optimize the design space (Datria *et al*., 2023). Table 2 shows that the regression models of 3 models (WAC, OAC, MBAC) are appropriate. There is one model that is not significant to be applied to the yield response.

Table 3 outlines the coefficients from the adjusted second-order polynomial regression model used to evaluate the impact of independent variables X_1 and X_2 on responses Y_1 through Y_4. The statistical significance of each coefficient is determined by its p-value, with values below 0.05 indicating a significant contribution to the model. The coefficients represent the nature and strength of the relationship between the variables. Positive values indicate that an increase in X_1 or X_2 causes an increase in WAC, OAC, MBAC, and Yield, while negative values indicate that the variable has a

decreasing effect on these responses. The size of the coefficient reflects the degree of its impact—the larger the coefficient, the more significant the impact. Figure 1 provides a visual representation of the second-order polynomial model, highlighting how the responses change with variations in X_1 and X_2.

Table 2. Statistical analysis for the response surface of PRS

Source	Df	Sum of squares	Mean squares	F-value	*P*-value
Regression linear model of WAC					
Model	2	31.60	15.80	4.91	0.0328
Residual	10	32.21	3.22		
Lack of fit	6	13.07	2.18	0.4552	0.8141
Pure error	4	19.14	4.78		
Total	12	63.80			
R^2	49.52%	R^2 adjust	39.43%	R^2 predicted	21.39%
Adeq Precision	7.1680				
Regression quadratic model of OAC					
Model	5	709.86	141.97	27.05	0.0002
Residual	7	36.74	5.25		
Lack of fit	3	5.31	1.77	0.2252	0.8746
Pure error	4	31.43	7.86		
Total	12	746.60			
R^2	95.08%	R^2 adjust	91.56%	R^2 predicted	87.23%
Adeq Precision	18.3699				
Regression linear model of MBAC					
Model	2	119.66	59.83	16.48	0.0007
Residual	10	36.29	3.63		
Lack of fit	6	18.89	3.15	0.7238	0.6560
Pure error	4	17.40	4.35		
Total	12	155.95			
R^2	76.73%		R^2 adjust	72.07%	
			R^2 predicted	63.03%	
			Adeq Precision	10.0193	
Regression linear model of Yield					
Model	2	81.18	40.59	3.54	0.0689
Residual	10	114.75	11.48		
Lack of fit	6	47.69	7.95	0.4741	0.8023
Pure error	4	67.06	16.76		
Total	12	195.93			
R^2	41.43%	R^2 adjust	29.72%	R^2 predicted	5.54%
Adeq Precision	5.4330				

Table 3. The regression coefficients of the prediction model for the response investigated from PRS and the independent effects of the factors

Variable [a)]	WAC Coefficient	OAC Coefficient	MBAC Coefficient	Yield Coefficient
β_0	+95.26*	+140.82*	+36.05*	+94.92^{ns}
β_1	+2.04*	-1.15^{ns}	-0.1206^{ns}	-0.8394^{ns}
β_2	-1.05^{ns}	+8.87*	+4.46*	-3.58*
β_{12}		+5.43*		
β_{11}		-0.4851 ^{ns}		
β_{22}		-5.69*		
R^2	49.52 %	95.08 %	76.73 %	41.43%
Adj-R^2	39.43%	91.56%	72.07%	29.72%

[a)] polynomial model $Y = \beta_0 + \sum_{i=1}^{2} \beta_i X_i + \sum_{i=1}^{2} \beta_{ii} X_i^2 + \sum_{i=1}^{1} \sum_{j=i+1}^{2} \beta_{ij} X_i X_j$ adjusted with backward elimination at the 0.05 % level with the lack of fit test, where β_0 is the constant coefficient, β_i is the linear coefficient, β_{ii} is the quadratic coefficient, and β_{ij} is the two-factor interaction coefficient.
* significant ($p< 0.05$); ^{ns} = not significant ($p>0.05$); WAC = water absorption capacity; OAC = oil absorption capacity; MBAC = methylene blue absorption capacity

The regression models developed for the response variables WAC, OAC, and MBAC were found to be statistically significant ($p< 0.05$), indicating that the models provide an accurate representation of the relationship between the independent variables and the associated responses. The statistical significance of each regression coefficient was evaluated using its associated *P*-value, with lower values indicating higher levels of significance. Coefficients with *P*-values less than 0.05 were considered to have a meaningful effect in the context of the adjusted second-order polynomial regression model. The reduced model, presented in Table 3, was used to refine the analysis by focusing on the linear and interaction effects of microwave time (X_1) and power (X_2). The analysis identified X_1 as the only variable with a statistically significant effect on WAC. Thus, the predictive model for WAC is expressed in Equation (4).

$$WAC = 95.26 + 2.04X_1 - 1.05X_2 \quad (4)$$

The quadratic coefficient is significant in the OAC. OAC implemented quadratic coefficients because peaks and curves are formed in the resulting model. The model analyzes non-linear interaction variables in determining optimal response conditions accurately. OAC describes the regression model shown in the following Equation (5).

$$OAC = 140.82 - 1.15X_1 + 8.87X_2 - 0.4851X_1^2 - 5.69X_2^2 + 5.43X_1X_2 \quad (5)$$

The linear coefficients are significant in MBAC. MBAC describes the linear regression model shown in the following Equation (6).

$$MBAC = 36.05 - 0.1206X_1 + 4.46X_2 \quad (6)$$

The linear coefficient is not significant on yield. Yield describes the linear regression model shown in the following Equation (7).

$$Yield = 94.92 - 0.8394X_1 - 3.58\,X_2 \quad (7)$$

3.2. Effect of Independent Variables on Their Responses

Figure 1A shows the effect of microwave time (X_1) and power (X_2) on WAC. The interaction between X_1 and X_2 has a significant value ($p<0.05$) in affecting WAC. The X_1 has a significant value ($p<0.05$) in affecting WAC. The longer the time, the higher the WAC value of rice starch. The same trend as the study conducted by (Rao *et al.*, 2021) that millet flour processed with microwaves for 2, 4, and 6 minutes will produce WAC of 1.33±0.041 g/g; 1.47±0.015 g/g; 1.55±0.047 g/g, respectively. In addition, microwave treatment for 3 minutes can increase WAC in alfalfa (Sahni & Sharma, 2020). The X_2 has an insignificant value in affecting WAC. The swollen starch granules are neatly grouped in the electric field. By continuously shifting the positive and negative polarity of the alternating electromagnetic field, microwaves can make starch granules vibrate at high frequencies. As a result, starch granules convert microwave energy into heat energy. Thermal energy can be formed inside the starch granules due to the impact of heat loss on the starch surface.

High pressure can be created inside the starch granules due to rapid water evaporation. The starch granules will swell and crack to form pores when the pressure is high enough. The more pores, the larger the surface area, resulting in more hydroxyl groups being exposed and increasing WAC (Chen *et al.*, 2020). The increase in WAC can be attributed to the addition of hydrophilic carboxyls, which increase the ability of starch to absorb water. The holes on the surface of the starch granules are very important because they allow water to penetrate the granules, thereby increasing the WAC of the starch (Subroto *et al.*, 2022).

Figure 1B shows the effect of X_1 and X_2 on OAC. The interaction between X_1 and X_2 has a significant value ($p<0.05$) in affecting OAC. Furthermore, the X_2 has a significant value ($p<0.05$) in affecting OAC. The higher the power, the higher the microwave heating temperature. Microwave power can convert heat energy into thermal energy, increase the temperature, which is then able to make starch porous. High microwave power will increase the hydrophobicity of the protein (Deng *et al*., 2022). This is due to the collision of water-soluble protein molecules, the emergence of free radicals, causing disulfide bonds to dissolve, and the formation of sulfhydryl groups. The high total content of sulfhydryl groups will also enhance the hydrophobicity of the protein (Lou *et al*., 2017). Hydrophobic residues can be found in the protein structure (Zheng *et al.*, 2020; Zeng *et al.*, 2013). During microwave treatment, the protein structure expands and more nonpolar amino acids are exposed on the surface, thereby increasing the hydrophobicity property (Lou *et al*., 2017).

Microwaves can accelerate protein degradation, breaking protein disulfide bonds so that hydrophobic core residues are exposed in the solvent, and proteins undergo de-polymerization. Microwave-treated rice increased amino acids glutamic acid, glycine, alanine, phenylalanine, valine, lysine, methionine, leucine, isoleucine, change little serine, and decreased aspartic acid, arginine, cysteine, histidine, and tyrosine (Deng *et al*., 2022; Meng *et al.*, 2019). Most of these amino acids are hydrophobic and thus will increase OAC. The secondary structure of proteins can shift from regular to irregular as a result of external treatment, partly due to the disruption of the stabilizing hydrogen bonds between carbonyl (C=O) and amino ($–NH_2$) groups. Among these structures, α-helices are highly ordered and contribute greatly to the conformational stability of proteins. Consequently, a larger proportion of α-helices is usually associated with increased structural stability in the protein matrix (Cao *et al.*, 2019; Li *et al.*, 2016). Microwave irradiation significantly alter the secondary structure of food proteins. In particular, an increase in the random coil content was observed, accompanied by a reduction in α-helices. In contrast, β-sheets and β-coils show an initial increase followed by a subsequent decrease, indicating a structural transition in which α-helices are partially transformed into β-sheets and β-coils, while β-structures may evolve into random coils (Cao *et al.*, 2018). These conformational changes are mainly driven by the synergistic weakening of intramolecular and intermolecular forces—such as hydrogen bonds, disulfide bridges, and hydrophobic interactions—under microwave exposure, resulting in the rearrangement of molecular interactions and the formation of new structural configurations (Zhu *et al.*, 2018).

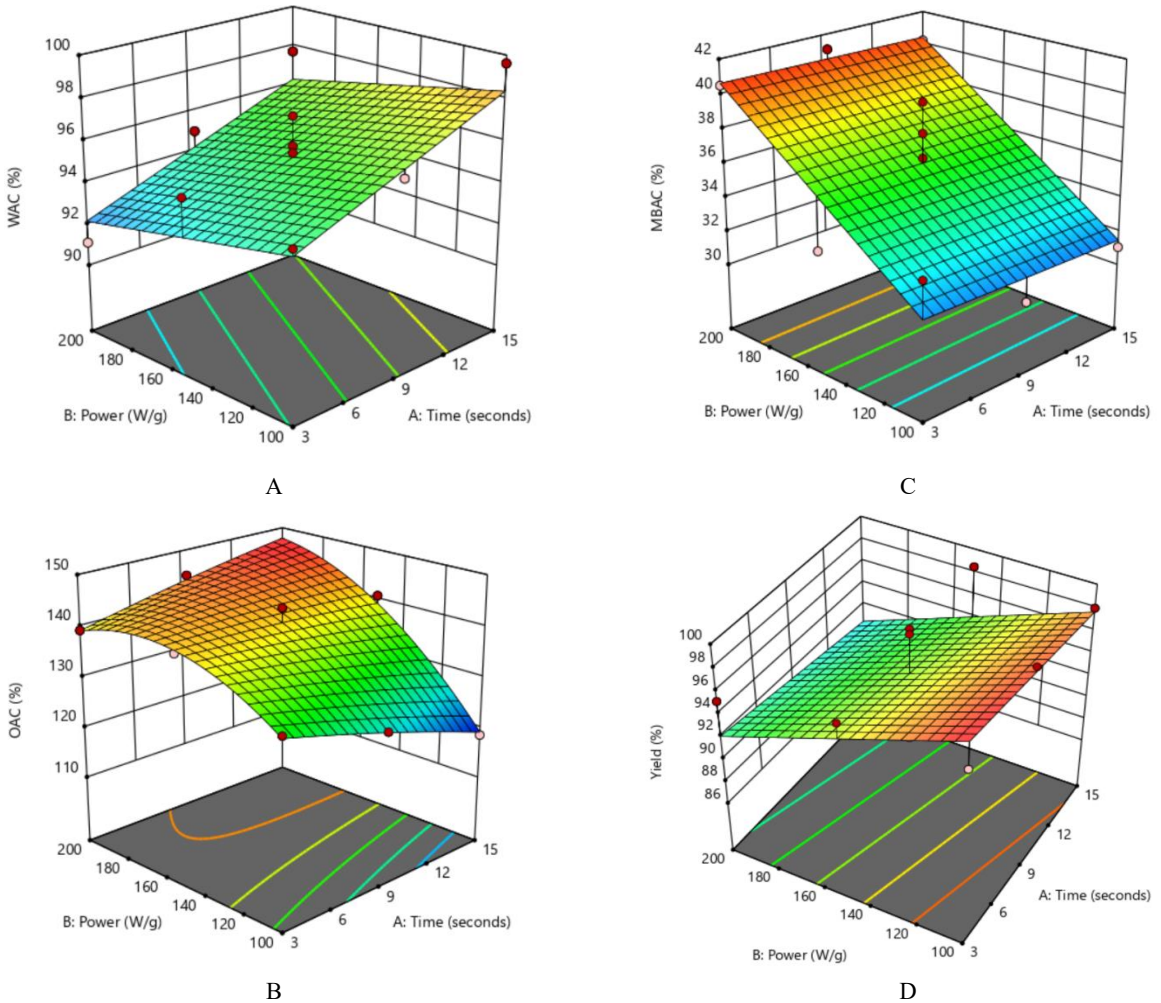

Figure 1 (A-D). Three-dimensional surface plots showing the correlation between microwave time and power on A. WAC, B. OAC, C. MBAC, and D. Yield of rice starch

In addition, microwave treatment increases the affinity of proteins for lipid molecules by exposing nonpolar side chains, thereby increasing oil absorption through interactions with lipid hydrocarbon chains (Khan *et al.*, 2011). Regarding cassava starch treated with microwaves at 600 W for 3-15 minutes, the OAC increased from 89.65% to 104.35%. Similar studies also showed an increase in the OAC of millet starch treated with microwaves at 720 W and 840 W for 2 minutes, showing OACs of 1.45±0.033 g/g and 1.58±0.035 g/g, respectively (Rao *et al.*, 2021).

Figure 1C shows the effect of X_1 and X_2 on MBAC. The interaction between X_1 and X_2 has a significant value (p<0.05) in influencing MBAC. Furthermore, X_2 has a significant value (p<0.05) in influencing MBAC. The higher the power, the higher the absorption of methylene blue by rice starch. This is in line with the research reported by Shalaby *et al.* (2022) Regarding the increase in methylene blue absorption on iron oxide nanoparticles biosynthesized by microwaves. With improving X_2 from 144 W (20%) to 800 W (100%), the sorbent capacity increased from 57.5 mg/g (86.3%) to 60.6 mg/g (90.9%). This increase in absorption performance can be attributed to the synergistic effect between interior and volumetric heating, which increases the surface area of the sorbent and configures the pores of the new surface structure (Mahmoud *et al.*, 2018). This can facilitate the flow of methylene blue into the iron oxide nanoparticle (IONP) sorbent and consequently enhance the adsorption process. Figure 1D shows the effect of X_1 and X_2 on the results. The interaction between X_1 and X_2 has an insignificant value (p>0.05) in affecting the results. This result was obtained from non-gelatinized starch from microwave treatment.

3.3. Process Optimization of Microwave Treatment and Experimental Validation

The objective of this step is to obtain process conditions that can produce ideal responses with the desired criteria. Table 4 shows that the criteria values of 4 (++++) and 5 (+++++) were set for microwave time and power. The WAC response was targeted in the range of 5 (+++++) because the starch is expected to have the optimum levels of WAC, OAC, MBAC, and Yield observed in the experiment.

The verification stage aims to compare the experimental response value with the software response value. Based on these criteria, the optimization results obtained are X_1 of 15 seconds and X_2 of 171 W/g with a desirability value of 0.653 as shown in Table 5.

Table 4. Determining the optimum process-based factor, response, and condition criteria

Factor/ response	Goal	Importance
Microwave time (s)	In range	++++
Power (W/g)	In range	++++
WAC (%)	Maximize	+++++
OAC (%)	Maximize	+++++
MBAC (%)	Maximize	+++++
Yield (%)	Maximize	+++++

Table 5. Optimal microwave treatment for PRS

Factor	Unit	Value
Time	sec	15
Power	W/g	171

Table 6. The predicted and experimental results for PRS

Condition	Response values			
	WAC	OAC	MBAC	Yield
Predicted	96.85 %	144.24 %	37.83 %	92.56 %
Experimental	96.34 ± 2.93 %	142.85 ± 0.94 %	34.73 ± 5.67 %	95.26 ± 3.23 %
Desirability	0.653	0.653	0.653	0.653

Table 6 compares the prediction results of the software and the experimental values. Based on the program prediction results, rice starch made under optimum conditions will have a WAC of 96.85%, OAC of 144.24%, MBAC of 37.83%,

and Yield of 92.56%. Meanwhile, the experimental verification data showed a WAC of 96.34±2.93%, OAC of 142.85±0.94%, MBAC of 34.73±5.67%, and yield of 95.26±3.23%. The verification results are in accordance with the predictions of the DX 7.0 software. Therefore, the mathematical equation of the response is suitable for predicting the response value in process optimization.

4. CONCLUSION

Microwave time of 15 s and power of 171 W/g were optimal to increase the water, oil, and methylene blue absorption capacity of rice starch. The optimized process resulted in WAC of 96.34±2.93%, OAC of 142.85±0.94%, MBAC of 34.73±5.67%, and yield of 95.26±3.23%. The use of RSM for modeling design is an efficient technique to investigate and optimize microwave treatment to improve the absorption capacity and yield of PRS.

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