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Optimization of Maltodextrin Production from Pineapple Stem Waste Using Response Surface Methodology

Optimasi Produksi Maltodextrin dari Pati Bonggol Nanas Menggunakan Metodologi Permukaan Respon (RSM)

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ABSTRACT

The enzymatic hydrolysis of starch from pineapple stem waste for maltodextrin production was successfully optimized using Response Surface Methodology (RSM). The study identified enzyme concentration and hydrolysis time as critical factors significantly influencing reducing sugar concentration and DE values. Under the optimal conditions (16 µL enzyme/30 gram of dry starch and 30 minutes hydrolysis time), the model predicted a reducing sugar concentration of 13.9%. However, the experimental validation produced an actual yield of 13.21%. The model RSM demonstrated a reliability level of 95.05% (moderately accurate), with deviations primarily due to experimental variability and model limitations. ANOVA analysis confirmed the model's validity with an R^2 value of 0.9873, while residual analyses supported its adequacy and predictive accuracy. The 3D surface response analysis highlighted the critical thresholds for optimizing reducing sugar production. This study provides a sustainable solution for valorizing pineapple stem waste into industrially valuable maltodextrin, supporting environmental conservation and the circular economy. Further studies are recommended to investigate the impact of enzyme characteristics, substrate pretreatment methods, and large-scale process validation to enhance the efficiency and commercial viability of maltodextrin production from pineapple stem waste.

Keywords: Dextrose equivalent (DE); maltodextrin; pineapple stem waste; response surface methodology (rsm); starch hydrolysis

ABSTRAK

Hidrolisis enzimatis pati dari limbah bonggol nanas untuk produksi maltodekstrin telah berhasil dioptimasi menggunakan Metodologi Permukaan Respon (RSM). Penelitian ini mengidentifikasi bahwa konsentrasi enzim dan waktu hidrolisis merupakan faktor-faktor kritis yang berpengaruh signifikan terhadap konsentrasi gula pereduksi dan nilai Dextrose Equivalent (DE). Kondisi optimum diperoleh pada konsentrasi enzim sebesar 16 µL/30-gram pati kering dan waktu hidrolisis selama 30 menit, dengan prediksi model menghasilkan kadar gula pereduksi sebesar 13.9%, sementara hasil aktual percobaan menunjukkan sebesar 13,21%. Model menunjukkan tingkat keandalan sebesar 95.04%, dengan deviasi yang terutama disebabkan oleh variabilitas eksperimen dan keterbatasan model. Analisis ANOVA mengonfirmasi validitas model dengan nilai R^2 sebesar 0.9873, dan analisis residual mendukung kecukupan serta akurasi prediktif model. Analisis respons permukaan 3D menunjukkan ambang kritis dalam optimasi produksi gula pereduksi. Secara keseluruhan, model RSM yang telah divalidasi ini memberikan pendekatan yang efektif untuk optimasi proses produksi maltodekstrin secara industri. Namun demikian, validasi eksperimen secara berkelanjutan tetap disarankan guna memastikan konsistensi dan meningkatkan reliabilitas prediktif model.
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Kata kunci: *Dextrose equivalent (DE); hidrolisis pati; limbah bonggol nanas; maltodekstrin; metodologi permukaan respon (RSM)*

INTRODUCTION

Maltodextrin, a hydrolysis product of starch, is extensively utilized in the food, pharmaceutical, and chemical industries due to its desirable functional properties, including high solubility, mild sweetness, and efficacy as a filler in diverse applications (Cabeza et al., 2025). The production of maltodextrin necessitates meticulous control over starch hydrolysis to achieve a targeted Dextrose Equivalent (DE), which significantly influences its physicochemical properties and suitability for various industrial applications (Rosida et al., 2020). Currently, the most common starch sources for maltodextrin production include cassava, corn, potato, and rice starches, owing to their favorable hydrolysis properties (Vilpoux & Santos Silveira Junior, 2023). Given the increasing emphasis on sustainability and resource optimization, the valorization of agricultural waste has emerged as a promising strategy. Pineapple stem waste (PSW), an abundant agro-industrial by-product, offers significant potential as an alternative starch source. Its utilization not only addresses environmental concerns by reducing biomass waste but also creates economic opportunities through the generation of value-added products like maltodextrin (Paz-Arteaga et al., 2024). Despite the global focus on starch hydrolysis technologies, studies specifically targeting the conversion of PSW into maltodextrin remain scarce (Oonsivilai et al., 2017). Most existing research emphasizes starch sources like cassava, corn, and sago, leaving a substantial knowledge gap regarding the optimization of maltodextrin production from PSW. Addressing this gap is crucial for enhancing the resource efficiency and sustainability of agro-industrial systems.

Previous studies have highlighted the influence of enzyme concentration and hydrolysis time on DE values. Ahmad et al., (2018) demonstrated that hydrolyzing sago starch with 0.09% α-amylase at pH 5.0 and 100°C for 60–240 minutes resulted in DE values ranging from 6.0 to 18.0, emphasizing the critical role of hydrolysis duration. Similarly, Nguyen et al., (2018) found that using an enzyme concentration of 0.15% at 95℃ for 120 minutes produced a DE value of 15.8, confirming the significant impact of enzyme dosage. However, the majority of previous optimization efforts have targeted broader hydrolysis efficiency rather than systematically achieving the precise DE range (18-20) required for maltodextrin production (Yolmeh & Jafari, 2017).

In this study, Response Surface Methodology (RSM) was employed as an optimization tool to systematically determine the optimal enzyme concentration and hydrolysis duration to achieve maltodextrin within the DE range of 18–20. Unlike previous work that broadly optimized hydrolysis, this study focuses specifically on achieving targeted DE levels for industrial application (Joyjamras et al., 2022). pH and temperature were kept constant based on previous findings that optimal α-amylase activity occurs around pH 5.0–6.5 and 95℃ (Veza et al., 2023). Accordingly, this research aims to develop a predictive mathematical model for the enzymatic hydrolysis of PSW starch, contributing to sustainable waste valorization, economic enhancement, and environmental conservation.

METHODOLOGY

Materials

The primary raw materials used in this study were starch extracted from pineapple steam waste (PSW). Analytical-grade chemicals included distilled water (aquades), 1 N sulfuric acid (H_2SO_4), acetyltrimethyl ammonium bromide (ADF), neutral detergent fiber (NDF) solutions comprising EDTA-2Na, $Na_2B_4H_2O_7.10H_2O$, sodium lauryl sulfate, and 3,5-dinitrosalicylic acid (DNS) solution, which were prepared according to standard laboratory procedures (Wang et al., 2019).

Sample Preparation

Starch was extracted from PSW. The extracted starch was dried using a blower oven at 60℃ for 12 h to ensure uniform moisture content, then ground to a 60-mesh of size. The prepared starch was subsequently stored at ± 5℃ until analysis.

Rapid Visco Analyzer (RVA)

The amylographic properties of the starch were determined using an RVA-TecMaster (Perten Instruments, Australia) following standard procedure. Approximately 3.0 grams of starch were suspended in 25 mL of distilled water to create a 10.32% (w/w, dry basis) suspension. The sample was initially mixed at 960 rpm for 10 seconds to ensure uniform dispersion, followed by mixing at 480 rpm during the subsequent heating and cooling cycle. This procedure aligns with the viscosity profile evaluation standards (Xu et al., 2021).

Starch Hydrolysis into Maltodextrin

A starch slurry was prepared by dissolving 30 grams of dried pineapple stem starch in 100 mL of distilled water, followed by heating at 70℃ under constant stirring (30 rpm) using a magnetic stirrer to induce gelatinization. Subsequently, 0.5555 grams of calcium chloride dihydrate ($CaCl_2.2H_2O$) were added to the gelatinized starch solution. The pH of the mixture was then adjusted once to 6.5 using 5N sodium hydroxide (NaOH), without further pH monitoring during hydrolysis. following pH adjustment, α-amylase TERMAMYL 120L was added at varying concentrations (Table 1), expressed in microliters per 30 grams of dry starch. TERMAMYL 120L has an enzymatic activity of 120 KNU per gram of product, where one KNU is defined as the amount of enzyme required to hydrolyze approximately 5.26 grams of starch per hour under standard conditions. Enzymatic hydrolysis was subsequently conducted at 100℃ for specific durations, with the final reaction volume consistently maintained at 100 mL across all treatments.

Enzymatic activity was terminated by adding 8N hydrochloric acid until the pH reached 4.3. The final volume was adjusted to 100 mL with distilled water, homogenized, and centrifuged at 25℃, 4000 rpm for 20 minutes. The supernatant containing maltodextrin was dried using a Buchi Mini Spray Dryer B-290 (Buchi, Switzerland) with parameters set at an $T_{inlet} = 180$℃, $T_{outlet} = 75$℃, and an aspirator setting of 90% (Do et al., 2024). The resulting maltodextrin was frozen at -30℃ and stored until analysis. The Dextrose Equivalent (DE) was determined by quantifying reducing sugars using the 3,5-DNS method (Nurhadi et al., 2025). The DE value was calculated using the equation 1:

$$DE = \frac{\text{reducting sugar (g)}}{\text{total dry samples (g)}} \times 100\% \quad (1)$$

Optimization using Response Surface Methodology (RSM)

The Response Surface Methodology (RSM) with a Central Composite Design (CCD) was applied to evaluate the effects of these independent variables on reducing sugar (y_1). The CCD applied an alpha (α) value of 1.414, appropriate for rotatable designs with two independent variables. The design comprised 10 experimental points, including two replicates for the center point to ensure reproducibility. Data analysis was conducted using Analysis of Variance (ANOVA) to determine the significance of each factor and their interaction. The model's adequacy was evaluated through R^2 values and lack-of-fit tests. Optimization results were visualized using response surface plots, and final model validation was conducted through experimental trials to confirm the model's predictive accuracy (Sitio et al., 2024).

Table 1. Experimental conditions for starch hydrolysis treatments

Run	Enzyme concentration (µL/30 g of dry starch) (X_1)	Hydrolysis time in minutes (X_2)
1	8.0	30±3
2	10.0	30±3
3	4.8	60±3
4	24.0	30±3
5	27.0	60±3
6	16.0	60±3
7	16.0	60±3
8	8.0	98±3
9	16.0	105±3
10	24.0	92±3

Statistical analysis

All experiments were performed in triplicate and reported as the mean ± SD and the p-value at < 0.05 level of significance. The experimental data were analyzed using Design Expert® Software (Version 13.0.5.0, (Stat-Ease Inc., Minneapolis, MN, USA) and an analysis of variance (ANOVA).

RESULTS AND DISCUSSION

Characteristics of sample

This study aimed to analyze the chemical characteristics of PSW as a raw material for maltodextrin production through enzymatic hydrolysis. The analysis results revealed a diverse chemical composition of PSW, consisting of moisture content, ash, starch, amylose, amylopectin, hemicellulose, cellulose, and lignin. These components significantly influence the efficiency of the conversion process into maltodextrin.

The starch content obtained from the PSW was 68.77%±0.226%. This percentage indicates that PSW holds promising potential as a starch source for maltodextrin production. However, this value is slightly lower than the findings of Chu et al. (2021), who reported a starch content of 77.78% ± 0.02%. This variation may be influenced by several factors, including pineapple variety, environmental conditions during plant growth, and processing methods. For instance, suboptimal drying or storage processes could degrade starch and reduce its final yield. Additionally, differences in grinding methods and separation techniques could also affect the starch content. Therefore, optimizing the raw material processing methods is crucial to ensuring the yield of starch (Collares et al., 2012). The measured moisture content was 3.85 ± 0.16%. This low moisture level has positive implications for the stability of the raw material, particularly in terms of storage and handling. Moisture levels below 10% are effective in preventing microbial growth that can spoil the material and extend its shelf life (Van der Veen et al., 2006). Furthermore, low moisture content facilitates the enzymatic hydrolysis process, as excessive moisture can reduce enzymatic efficiency. Thus, maintaining low moisture levels is essential to support the smooth production of maltodextrin.

The ash content of the PSW was 0.42 ± 0.002% (db). This result aligns with (Nath et al., 2023), who reported an ash content of 0.40%, indicating consistency in raw material purity. Low ash content signifies minimal inorganic mineral presence, which is crucial for avoiding disruptions during enzymatic hydrolysis. High ash content can inhibit enzyme activity due to the presence of inorganic inhibitors (Zhao et al., 2023). Therefore, the low ash level in the pineapple core waste is a positive indicator for ensuring the smoothness and effectiveness of the starch-to-maltodextrin conversion process. In terms of starch composition, the amylose and amylopectin contents were 27.45% and 41.34%, respectively. This composition indicates that the starch is dominated by amylopectin, which has a branched and complex structure. Amylopectin requires a longer hydrolysis time compared to amylose due to its complex molecular arrangement (Novia et al., 2025). However, the substantial amylose content provides an advantage, as amylose is more easily hydrolyzed by α-amylase enzymes. Therefore, optimizing the hydrolysis time and enzyme concentration is necessary to maximize maltodextrin yield. Inefficient hydrolysis could result in a final product with a low degree of polymerization, deviating from the desired maltodextrin characteristics.

Table 2. Characteristics of PSW as raw material

No	Analysis Criteria	Percentage (dry basis)	Reference
1	Moisture content	3.85 ± 0.16%	10,64% (Ospankulova et al., 2020)
2	Ash content	0.42 ± 0.002%	0,40 ± 0.00 (Chu et al., 2021)
3	Starch content	68.77 ± 0.226%	77.78 ± 0,02% (Chu et al., 2021)
4	Amylose	27.45%	34,37% (Chu et al. 2021)
5	Amylopectin	41.34%	63,40% (Chu et al. 2021)
6	Hemicellulose	10.23%	*Crude component*
7	Cellulose	11.27%	
8	Lignin	2.56	21.6% (Chu et al. 2021)

Table 3. Amylographic properties of PSW strach

No	Amylographic Property	Temperature (℃)	Viscosity (cP)
1	Pasting point	90.22	2
2	Peak viscosity	95.03	945
3	Hold viscosity	82.64	539
4	Breakdown	-	406
5	Setback	-	413

Additionally, the lignocellulose components-comprising hemicellulose, cellulose, and lignin—were measured at 10.23%, 11.27%, and 2.56%, respectively. The relatively low lignin content is beneficial, as lignin is known to inhibit enzymatic activity during hydrolysis (Cai et al., 2023). Lignin is resistant to enzymatic degradation and can shield cellulose and hemicellulose, thereby reducing hydrolysis efficiency. Therefore, low lignin levels in PSW accelerate hydrolysis and enhance maltodextrin yield. Meanwhile, moderate levels of hemicellulose and cellulose can be processed using pre-treatment methods, such as heating or enzymatic treatment, to break down their complex structures. These processes aim to increase starch availability and expedite enzymatic hydrolysis rates.

Amylographic properties of PSW Starch

The amylographic characteristics of PSW starch, as summarized in Table 3, provide critical insights into its suitability for enzymatic hydrolysis and maltodextrin production. As shown in Table 3, the elevated pasting point (90.22℃) suggests a compact granule architecture necessitating higher thermal input to achieve complete gelatinization, thereby modulating enzymatic accessibility and initial reaction kinetics (Campelo et al., 2020). This relatively high gelatinization temperature may imply increased energy consumption during industrial processing, which could impact production costs; however, it also confers enhanced thermal stability, potentially beneficial for processes requiring extended thermal treatment. The substantial peak viscosity (945 cP) reflects a pronounced water-binding capability, which facilitates efficient starch swelling and subsequent enzymatic degradation (Salimi et al., 2023).

Table 4. Effect of enzyme concentration and hydrolysis time

Run	(X_1)	(X_2)	Reducing Sugar (%)	(DE)	(%) RMS = $100x\sqrt{\frac{\sum_{i-1}^{n}\left\{\frac{y_i-y_i^*}{y_i}\right\}^2}{n}}$
1	8.0	30±3	4,7±0.03	11,42±0.06	
2	10.0	30±3	5,5±0.02	8,41±0.03	
3	4,8	60±3	6,2±0.03	15,02±0.07	
4	24.0	30±3	8,03±0.03	19,26±0.06	
5	27.0	60±3	11,2±0.00	26,03±0.37	
6	16.0	60±3	12,2±0.08	29,19±0.08	0,1964
7	16.0	60±3	12,3±0.08	29,53±0.08	
8	8.0	98±3	17,8±0.09	42,96±0.02	
9	16.0	105±3	19,8±0.03	47,73±0.06	
10	24.0	92±3	22,4±0.06	44,49±0.06	

*X_1 = Enzyme concentration (µL/30 g of dry starch); X_2 =Hydrolysis time in minutes

Table 5. The ANOVA analysis of the model prediction

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	299.83	3	99.94	234.92	< 0.0001	significant
A-konsentrasi enzim	85.91	1	85.91	201.95	< 0.0001	
B-waktu	193.92	1	193.92	455.81	< 0.0001	
AB	8.13	1	8.13	19.10	0.0047	
Residual	2.55	6	0.4254			
Lack of Fit	2.55	5	0.5095	101.90	0.0751	not significant
Pure Error	0.0050	1	0.0050			
Cor Total	302.38	9				
R-squared	89,86					

In amylographic analysis, breakdown viscosity refers to the reduction in viscosity during high-temperature holding, reflecting the stability of starch granules under thermal and mechanical stresses (Dereje, 2021). The moderate breakdown viscosity (406 cP), also presented in Table 3, indicates partial granule disintegration under thermal and mechanical stresses, promoting enzymatic penetration and accelerating hydrolytic conversion (L. Zhang et al., 2024). Such fragmentation behavior may enhance the efficiency of spray-drying operations by facilitating the formation of fine and uniform droplets, thereby improving drying rates and powder quality. The setback viscosity of 413 cP (Table 3) reflects a significant retrogradation propensity in PSW starch (Vamadevan & Bertoft, 2018). Setback viscosity, defined as the increase in viscosity during cooling due to starch molecular reassociation (Dereje, 2021), indicates the tendency of amylose and amylopectin chains to realign and recrystallize. High setback values may adversely affect the solubility and smoothness of the final maltodextrin product. Therefore, controlling the extent of retrogradation through optimized hydrolysis conditions is crucial to producing maltodextrin with desirable physicochemical and functional attributes.

Effect of Enzyme Concentration and Hydrolysis Time

The physicochemical properties of PSW starch significantly influence enzymatic accessibility and hydrolysis kinetics (Lv et al., 2011). High starch content ensures a plentiful substrate supply for enzymatic attack. The amylose-to-amylopectin ratio plays a crucial role: higher amylose levels retard hydrolysis due to their dense, crystalline structure, while elevated amylopectin promotes rapid enzymatic degradation through its amorphous and highly branched configuration (Shen et al., 2021). Moreover, non-starch polysaccharides such as hemicellulose, cellulose, and lignin form physical barriers around starch granules, reducing enzymatic access and hydrolysis rates (H. Zhang et al., 2022). Understanding these physicochemical characteristics provides a critical foundation for interpreting how enzyme concentration and hydrolysis time influence the efficiency of starch breakdown and the production of maltodextrin.

The data presented in Table 4 clearly demonstrate the significant influence of enzyme concentration and hydrolysis time on the percentage of reducing sugars and Dextrose Equivalent (DE) during the enzymatic hydrolysis of PSW starch. This analysis underscores the interplay between these two critical variables and their combined impact on the efficiency of starch conversion into maltodextrin.

Increasing both enzyme concentration and hydrolysis duration generally resulted in higher yields of reducing sugars and elevated DE values. At lower enzyme concentrations and shorter hydrolysis durations, the yields were markedly lower. At a hydrolysis time of 30 minutes, increasing the enzyme concentration from 8.0 µL to 24 µL led to a notable improvement in hydrolysis efficiency, as evidenced by an increase in reducing sugar yield from 4.7% to 8.03% and a rise in DE value from 11.42 to 19.26 respectively. These findings support the general principle that elevating enzyme concentration enhances starch breakdown under fixed reaction durations. Similar observations were reported Serrano-Febles et al. (2025), who demonstrated that higher enzyme dosages significantly improve reducing sugar production and DE levels during enzymatic starch hydrolysis.

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Optimization continued with extended hydrolysis times. The highest yield was recorded in Run 9, utilizing an enzyme concentration of 16 µL and a prolonged hydrolysis time of 105 minutes, resulting in a reducing sugar percentage of 19.8 ± 0.026% and a DE value of 47.73 ± 0.06. These findings align with Sigüenza-Andrés et al. (2022), who emphasized that prolonging hydrolysis duration significantly promotes enzymatic breakdown of starch molecules, thereby increasing reducing sugar production and DE values. However, it is important to note that by definition, maltodextrins possess a DE value of less than 20, while products with DE values exceeding 20 are classified as syrup solids (Chavan et al., 2016). Therefore, in this study, a maximum DE threshold of 20 was established to align with industrial maltodextrin specifications. The response surface modeling was accordingly constrained to target conditions that maximize reducing sugar yield without surpassing a DE value of 20. This constraint ensures that the produced material retains the functional and regulatory characteristics of maltodextrin, rather than transitioning into syrup products. Furthermore, model adequacy was statistically confirmed by the Root Mean Square (%RMS) value of 0.1964, which is well below the acceptable threshold of 10%. A %RMS lower than 10% indicates high predictive accuracy and model validity in response surface methodology applications (Olabinjo, 2024).

It is also important to note that excessively high enzyme concentrations may lead to potential substrate inhibition or aggregation effects, which could paradoxically reduce the hydrolysis efficiency (Gao et al., 2023). Enzyme crowding at high concentrations can hinder effective substrate binding and catalysis, emphasizing the need to optimize enzyme levels rather than indiscriminately increasing them.

Analysis of the accuracy of the model using RSM

Based on the results of the Analysis of Variance (ANOVA) presented in Table 5, the regression model demonstrated high significance, with an F-value of 234.92 and a p-value of 0.0001. This indicates that the model is valid and effectively explains the relationship between the independent variables and the response variable. The enzyme concentration (X_1) had a significant effect on the outcome, with an F-value of 201.95 and a p-value of < 0.0001. Meanwhile, hydrolysis time (X_2) exhibited a more dominant influence, with an F-value of 455.81and a p-value of less than 0.0001. These findings confirm that both factors play crucial roles in influencing the starch hydrolysis process, aligning with previous studies that emphasized the importance of controlling enzyme concentration and reaction time to enhance hydrolysis efficiency (Aderibigbe et al., 2013).

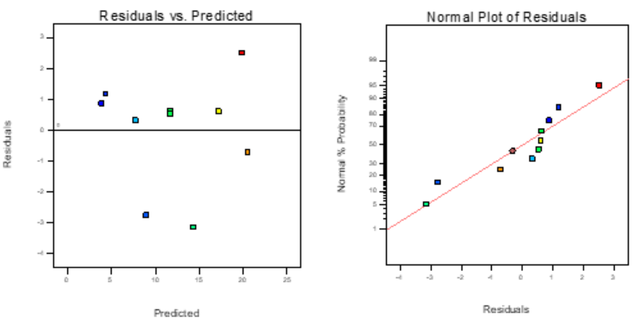

Figure 1. (a) Residual plot graph of reducing sugar concentration against predicted reducing sugar concentration, and (b) normal probability curve for the response of reducing sugar concentration.

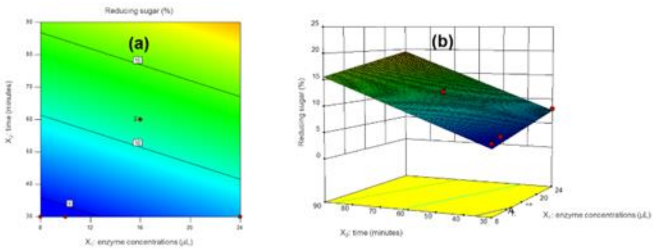

Figure 2. Surface graph of the reducing sugar concentration response (a) and 3D surface response curve of reducing sugar concentration.

Additionally, the lack of fit analysis yielded a p-value of 0.0751, which is not statistically significant at the 95% confidence level. This indicates that the model fits the experimental data adequately, with no meaningful deviation between the predicted and actual values. Moreover, the extremely low pure error (0.0050) reinforces the consistency and reliability of the experimental procedure. The coefficient of determination (R^2) was 0.9873, suggesting that the model explains approximately 98.73% of the variability in reducing sugar concentration. This high R^2 value, combined with a non-significant lack of fit, confirms that the model is both robust and predictive, effectively representing the relationship between enzyme concentration, hydrolysis time, and reducing sugar yield (Mardawati et al., 2018).

The residual analysis in Figure 1 confirms the adequacy of the regression model. The Residuals vs. Predicted plot shows a random distribution around zero, indicating homoscedasticity and the absence of bias. The Normal Probability Plot demonstrates that residuals follow an approximately normal distribution, supporting the model's validity. These results confirm that the model is reliable for predicting reducing sugar concentration (Sasaki & Kohyama, 2012).

The surface graph (Figure 2a) and the 3D curve (Figure 2b) illustrate the relationship between enzyme concentration, hydrolysis time, and the resulting concentration of reducing sugar. The analysis based on the provided images and explanation can be understood through the examination of surface and 3D response graphs, along with the derived mathematical model. The surface and 3D response graphs illustrate that increasing enzyme concentration and hydrolysis time generally results in a significant increase in reducing sugar concentration. This pattern is consistent with findings by (Vasić et al., 2021), observed that enzymatic activity typically accelerates the breakdown of complex sugars into reducing sugars, especially in the initial phases of hydrolysis. However, the trend plateaus after a certain threshold, indicating a saturation point where additional enzyme or prolonged time does not contribute to significant gains in sugar concentration. This plateau is commonly attributed to the substrate's limited availability or enzyme inhibition phenomena. The mathematical model derived from the analysis is expressed as:

$$y = 0.1959 + 0.0856X_1 + 0{,}084X_2 + 0{,}0053X_1X_2 \quad (2)$$

This equation indicates that both enzyme concentration and hydrolysis time have a positive linear influence on the reducing sugar concentration. The coefficients suggest that enzyme concentration (X_1) has a slightly greater impact on the response compared to hydrolysis time (X_2).

Table 6. Validation of the RSM equation model

Optimization Factor	Value	Reducing Sugar Concentration Predicted Response	Actual response	Rehabilitee
Enzyme Concentration (µL)	60	13.9%	13,21%	95.05 %
Time (minutes)	30			

Accuracy Validation of the RSM Equation Model

The validation of RSM model for optimizing reducing sugar production through enzymatic hydrolysis was conducted by analyzing the influence of enzyme concentration and hydrolysis time. The optimization factors were set at an enzyme concentration of 16 µL/30 dry starch and a hydrolysis duration of 30 minutes. Under these conditions, the RSM model predicted a reducing sugar concentration of 13.9%. However, the actual experimental result showed a slightly lower reducing sugar concentration of 13.21%. To assess the model's reliability, a calculation was performed by comparing the actual result to the predicted value, resulting in a reliability percentage of 95.05%. This indicates that the RSM model has a fairly good reliability level, although a deviation of approximately 4.95% from the predicted value was observed. Such deviations may arise due to experimental variability or limitations of the model in capturing all influencing factors in the hydrolysis process. Demonstrated the effectiveness of RSM in optimizing the enzymatic hydrolysis process, highlighting the necessity of experimental validation to confirm model predictions (Chen et al., 2013).

CONCLUSION

The enzymatic hydrolysis of pineapple stem waste (PSW) starch for maltodextrin production was successfully optimized using Response Surface Methodology (RSM). Optimal conditions were determined at an enzyme concentration of 16 µL (0.012% w/w dry starch), and a hydrolysis time of 30 minutes, yielding 13.21% reducing sugars and a DE value of 19.8. The model exhibited good predictive accuracy ($R^2 = 0.9873$) and low error (%RMS = 0.1964%). Despite the good performance, the study was limited to two variables under laboratory conditions. Future work should explore additional factors such as pH, substrate concentration, enzyme type, and process scale-up to enhance industrial applicability.

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