



Research Article

Integrating Statistical Modelling and Financial Analysis to Optimize Bioethanol Production

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ABSTRACT

The growing demand for sustainable alternatives to fossil fuels has positioned bioethanol as a promising renewable energy source. However, few studies integrate factorial and regression-based process optimization with scalable financial analysis to valorize underutilized *Chrysophyllum albidum* (African star apple) for bioethanol production, limiting comprehensive frameworks that link process efficiency to economic feasibility. This study re-analysed an existing experimental dataset on bioethanol production from *C. albidum* to evaluate strategies for improving decision-making through integrated statistical modelling and scalable financial analysis. Four key process factors quantified for their effects on the ethanol yield were pH, yeast dosage (YD), fermentation time (FT), and incubation temperature (IT). A full factorial design coupled with regression modelling revealed that pH was the dominant factor, followed by YD and FT, while IT had a minimal effect. IT was excluded to refine the model, which subsequently demonstrated high predictive power within the specified design space ($R^2 = 0.972$, Adj. $R^2 = 0.948$). Informed by the statistical trade-off between FT and yield, a financial impact assessment compared two runs of optimized condition (pH 5.0, YD 4.5% wt/v, IT 35°C, FT 72 h) with three runs of an alternative scenario (pH 5.0, YD 4.5% wt/v, IT 35°C, FT 24 h) revealed by the statistical analysis. Crucially, the financial analysis demonstrated that the technically optimized condition was not the most economical; the alternative scenario delivered a lower unit cost. The findings underscore the importance of integrating process optimization with cost analysis to identify conditions that balance technical yield with financial sustainability for scalable bioethanol production, demonstrated here through a scenario-based financial comparison framework applied to underutilized African star apple.

Keywords: Bioethanol production, *chrysophyllum albidum*, process optimization, financial analysis, full factorial design.

INTRODUCTION

Despite growing interest in renewable alternatives, the global economy remains heavily reliant on fossil fuels for electricity generation, transportation, and industrial activities, underscoring the urgent need for optimized and economically viable bioethanol production pathways. Their combustion releases greenhouse gases, which have intensified environmental pollution and driven climate change in recent decades [1]. Rapid population growth and industrial expansion have further accelerated energy demand, worsening the environmental burden. Moreover, fossil fuels are non-renewable, and the decline in global reserves continues to impact fuel imports and oil production capacity [1], [2], [3]. This diminishing supply, coupled with their negative environmental footprint, has spurred global research interest in sustainable and eco-friendly alternatives [4].

Among renewable options, bioethanol ($\text{CH}_3\text{CH}_2\text{OH}$) has emerged as the most widely adopted alcoholic biofuel [4], [5], [6]. Henry Ford once referred to ethanol as the “fuel of the future,” a statement that continues to resonate today [4], [7]. Derived from renewable agricultural resources, ethanol is less toxic than other alcohol fuels and produces relatively benign by-products when incompletely oxidized [7]. Its growing role in the transport sector stems from cleaner combustion, reduced reliance on oil imports, and local economic benefits, all of which depend on optimized production processes and robust cost analysis for practical implementation [8].

Beyond its use as a transport biofuel, ethanol has gained prominence in the food, beverage, pharmaceutical, and chemical industries [4], [5], [7]. In food processing, ethanol serves as a preservative, solvent, and flavor enhancer, while in pharmaceuticals, it functions as a disinfectant, antiseptic, and extraction medium for active compounds [4], [9], [10]. Industrial applications extend to bio-based plastics, cosmetics, and personal care products, as well as blending in household cleaning agents [5], [6], [8]. These multiple applications underscore the versatility of ethanol as both a clean energy carrier and an industrial raw material.

Bioethanol production relies primarily on sugars, starches, and lignocellulosic biomass, with the yield strongly influenced by the biochemical composition of the chosen feedstock. The process typically involves microbial fermentation, where microorganisms such as *Saccharomyces cerevisiae* and *Zymomonas mobilis* efficiently convert fermentable sugars into ethanol [5]. Recent advances in second-generation bioethanol have also opened up opportunities to valorize agricultural residues and food-processing waste, thus reducing competition with food crops and enhancing the sustainability profile of bioethanol [11]. Despite advances in biomass-to-ethanol conversion technologies, full-scale commercial adoption remains limited by feedstock variability and production efficiency [5], [6], [12]. Factors such as temperature, pH, substrate concentration, and yeast dosage determine ethanol yield, making optimization of these process conditions essential [13]. Because these variables interact in complex and often non-linear ways, particularly during scale-up from laboratory to commercial systems, statistical modelling is critical for systematically evaluating their combined effects and minimizing uncertainty in process performance [14], [15], [16]. These approaches not only highlight the most influential variables but also guide resource allocation, ensuring a greener and cost-effective production system aligned with low-carbon objectives [5], [6], [17].

In this context, underutilized biomass resources such as the African star apple (*Chrysophyllum albidum*) present an untapped opportunity. Its seasonal availability and reported variability in physicochemical composition make it a suitable case for applying integrated statistical modelling and financial analysis to optimize process performance and assess economic viability under realistic production conditions. Indigenous to Nigeria and known locally as agbalumo, udara, or ehya, the fruit pulp is rich in sugars, carbohydrates, and proteins, making it suitable for bioethanol production [10], [18]. However, its rapid deterioration within five days under ambient conditions [19] results in significant post-harvest losses, with large quantities wasted annually. Valorizing these losses through bioethanol conversion not only mitigates environmental concerns from discarded fruit skins and seeds but also creates added economic value for farmers [20], [21], [22]. Earlier studies have shown that fruit wastes such as orange peels, banana peels, pineapple juice, persimmon peels, and other fruit residues can be successfully transformed into bioethanol [23], [24], [25], [26], [27], [28]. The cheap and readily available *Saccharomyces cerevisiae* (baker's yeast) have also remained the microorganism of choice for fermentation due to its ethanol tolerance and rapid conversion rates [29], [30]. This reinforces the potential of African star apple as a competitive feedstock for sustainable bioethanol production.

Building on the work of Ogbodo et al. [31], who optimized African star apple bioethanol production using response surface methodology (RSM), this study advances the analysis by quantifying the relative contribution of key production variables—pH, yeast dosage (YD), incubation temperature (IT), and fermentation time (FT)—and linking their statistical significance to economic performance indicators. Understanding the statistical weight of each

variable is essential for guiding production decisions, particularly under limited-resource scenarios [12], [14], [17]. By integrating statistical process modelling with a techno-economic analysis framework, this study seeks to improve process efficiency and reduce production costs by translating statistically optimized operating conditions into capital and operating cost estimates, profitability indicators, and minimum ethanol selling price, thereby positioning African star apple as a technically and economically viable bioethanol feedstock for green and sustainable bioethanol production [16], [31], [32].

Earlier studies on bioethanol production from biomass have primarily emphasized process optimization [16], [24], [27], with comparatively limited attention to linking these outcomes to structured economic evaluation. Accordingly, the study adopts a unified methodological framework in which statistically derived process–response models are directly coupled with economic performance metrics, enabling optimized technical outcomes to be evaluated concurrently against cost, profitability, and feasibility criteria. This integration enables statistical optimization outputs to be evaluated alongside economic indicators, supporting alignment between process performance and cost considerations within the study design. This approach provides a structured basis for production planning by evaluating process performance alongside cost implications within a consistent analytical workflow.

While many studies examine bioethanol production through experimental, optimization, or economic analyses, fewer explicitly link statistically derived process conditions to quantified financial outcomes within a unified analytical framework, as carried out in the present work. This integrated strategy enables a direct translation of optimized process parameters into economic performance indicators, allowing decision-making to be guided simultaneously by process efficiency and economic viability. As a result, the study advances beyond prior integrated approaches by identifying operating conditions that are not only technically optimal but also financially sustainable, thereby offering a more realistic and implementable pathway for sustainable bioethanol production from *C. albidum* and within the defined analytical framework.

METHODS

A This study re-analysed the experimental dataset reported by Ogbodo et al. [31] with the objective of extending process optimization through integrated statistical modelling, advanced data visualization, and financial impact assessment to support cost-informed production decisions. Although Ogbodo et al. [31] effectively optimized bioethanol production from African star apple using response surface methodology, the study did not quantify the relative contribution of individual process factors nor link the optimized conditions to economic performance, thereby limiting its applicability for production planning. The factors and their respective levels (various conditions of fermentation) for design of experiments (DOE) and optimization are given in Table 1.

The data was re-evaluated using statistical tools such as IBM Statistical Package for the Social Sciences (SPSS) software, Python, and online DATAtab [33]. Statistical analyses were conducted using IBM SPSS Statistics (version 27.0.1) for factorial design evaluation and ANOVA. Python (version 3.12.7; libraries including SKlearn, pandas, matplotlib, seaborn, and statsmodels) was used for regression modelling, data processing, and visualization.

Table 1. Input factors for producing bioethanol

Process input parameters	Unit	Low	Moderate	High
pH	na	4.00	5.00	6.00
Incubation temperature	°C	25	35	45
Fermentation time	hours	24	72	120
Yeast dosage	% w/v	3.5	4.5	5.5

Table 2. Ethanol yield from combination of the production factors [31]

Runs	Factors				Response
	A: pH	B: YD	C: IT	D: FT	Ethanol Yield
1	4	3.5	25	24	1.75
2	6	3.5	25	24	3.32
3	4	5.5	25	24	2.34
4	6	5.5	25	24	5.86
5	4	3.5	45	24	1.78
6	6	3.5	45	24	4.21
7	4	5.5	45	24	2.64
8	6	5.5	45	24	6.63
9	4	3.5	25	120	2.55
10	6	3.5	25	120	4.61
11	4	5.5	25	120	3.09
12	6	5.5	25	120	8.95
13	4	3.5	45	120	2.19
14	6	3.5	45	120	5.71
15	4	5.5	45	120	4.25
16	6	5.5	45	120	9.93

DATAtab was applied for supplementary Pareto chart generation. Where overlapping analyses were performed, SPSS outputs were used as the primary statistical reference, while Python results were used for validation and extended visualization. The optimization analysis integrated factorial and regression outputs by selecting factor combinations that satisfied statistical significance ($p < 0.05$), high model fit, and practical feasibility within the experimental design space.

Factorial analysis with design of experiment (DOE) is a well-established statistical method for empirical modeling of variable factors and studying the main effects or interaction effects of the factors on the dependent variable [14], [15]. The linear regression models simplify and enhance the factor analysis. The DOE was implemented using SPSS and with the aid of python-written programming code. The Python-based scripts were employed to perform additional data processing, regression analysis, and advanced visualization, enabling extended interrogation of factor behaviour.

The factor variables (also known as the control independent variables) set in this bioethanol yield study are the pH, YD, IT, and FT. The response variable (also known as the dependent variable) is the ethanol yield. Table 2 shows the ethanol yield from different combination of the production factors (process parameters). Three levels were originally intended for the design. However, due to the limited experimental runs at the moderate level (5.0, 35, 72, and 4.5 for pH, YD, IT, FT, respectively), a two-level design at the low and high levels were later considered for analysis. Although restricting the analysis to a two-level design may limit the model's ability to represent non-linear behaviour at intermediate factor values, it remains sufficient for the objectives of this study, which focus on identifying dominant main effects, interaction patterns, and relative factor contributions for comparative and decision-oriented analysis. A full factorial design of 2^4 (four factors at two levels) was analysed. As the design was unreplicated, factor significance was evaluated using effect screening and ANOVA under an assumed negligible higher-order interaction framework.

Equation 1 was used to estimate the total number of runs required and a total of 16 runs was obtained. Equation 2 was used to transform the variables from their original value to coded forms for easy analysis.

$$N = L^K \quad (1)$$

where N represents the number of experimental runs, L denotes the number of factor levels, and K is the number of factors.

$$x_i = \frac{v_i - v_m}{(v_h - v_l)/2} \quad (2)$$

where x_i is the coded value of the i th factor, v_i is the corresponding actual value, v_m is the midpoint (mean) of the actual values, v_h is the high actual value, and v_l is the low actual value.

The experimental factors were coded x_1 for pH, x_2 for yeast dosage, x_3 for incubation temperature, and x_4 for fermentation time, with corresponding uncoded variables denoted as pH, YD, IT, and FT, respectively. The general form of the full factorial model fitted included terms for all main effects and interaction effects up to the fourth order. The analysis matrix is presented in Table 3. For a 2^4 full factorial design, “-1” and “+1” are set to represent the low and high setting of a factor, respectively. The results of the bioethanol yield experiment are fitted into the analysis matrix as shown in Table 3. Building on the insights gained from data visualization and statistical modelling, the next phase of the methodology focused on evaluation of the economic viability of the identified factor combinations.

Financial analysis was conducted using cost-based modelling to compare process scenarios normalized to equivalent total ethanol output (~20 g). Cost comparisons were based on aggregated batch requirements needed to achieve comparable output levels, enabling consistent evaluation across differing yields and fermentation durations. Two batches based on the optimized factors reported by Ogbodo et al. [31] were evaluated against three batches from an alternative scenario. Bioethanol yield data were obtained from laboratory experiments using 15 g of *C. albidum*

Table 3. Analysis matrix representing model pattern of the bioethanol yield

Runs	Factors				Response
	A: pH	B: YD	C: IT	D: FT	Ethanol Yield
1	-1	-1	-1	-1	1.75
2	1	-1	-1	-1	3.32
3	-1	1	-1	-1	2.34
4	1	1	-1	-1	5.86
5	-1	-1	1	-1	1.78
6	1	-1	1	-1	4.21
7	-1	1	1	-1	2.64
8	1	1	1	-1	6.63
9	-1	-1	-1	1	2.55
10	1	-1	-1	1	4.61
11	-1	1	-1	1	3.09
12	1	1	-1	1	8.95
13	-1	-1	1	1	2.19
14	1	-1	1	1	5.71
15	-1	1	1	1	4.25
16	1	1	1	1	9.93

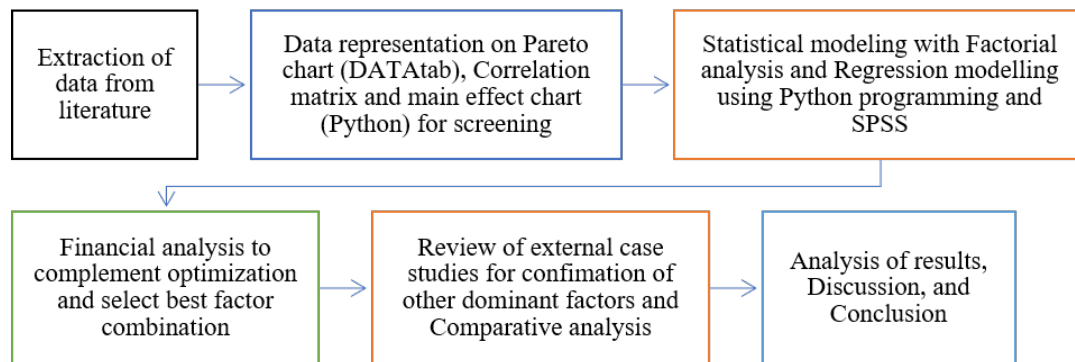


Figure 1. Simplified flow chart of research study

hydrolysed with 200 mL of 5 % dilute sulphuric acid at 50 °C for 30 minutes. Cost estimates included biomass, yeast, acid, and electricity inputs, while pH adjustment costs were excluded due to their relatively minor contribution; this assumption constrains the analysis to major cost drivers and may understate cost differences attributable to pH variation. Notwithstanding, both scenarios commenced at the same initial pH, and the two batches under the optimized condition are, to an extent, offset by the reduced fermentation time observed in the alternative scenario, which supports the internal consistency of the comparison within the defined system boundary. Economic performance was assessed using production cost per batch and cumulative cost to reach the target output.

To benchmark the behaviour of process factors influencing bioethanol yield from *C. albidum*, a comparative analysis was performed using laboratory-scale datasets reported for sugar beet, sugarcane molasses, and sugarcane juice. These feedstocks were selected based on their high bioethanol potential and the availability of detailed experimental design (DOE) data. Model simplification was applied when degrees of freedom were insufficient to estimate higher-order interactions reliably; in such cases, non-significant highest-order terms ($p > 0.05$) were removed consistently across all datasets. The resulting factor-influence patterns were compared with those of *C. albidum* to assess differences in process sensitivity and control requirements across feedstocks.

Finally, the collated data from the re-evaluation were subjected to statistical analysis using a significance threshold of $p < 0.05$, with model adequacy assessed through R^2 , and interaction effects evaluated within the limits of the factorial design to support interpretation of the results. Figure 1 is a simplified flow chart describing the study.

RESULTS AND DISCUSSION

The Pareto plot and the correlation matrix

The initial results demonstrate that ethanol yield increased with higher levels of process factors, with pH exerting the strongest effect followed by yeast dosage, and these interrelationships are further clarified through graphical visualization. The Pareto plot and the correlation matrix collectively highlight the roles of various process parameters in determining the outcome.

Pareto Plot Analysis

Figure 2 is the Pareto chart showing the absolute values of the standardized effects from the largest to the smallest. The reference line on the chart is at 12.71 showing that any effect that crosses the line are statistically significant. The largest effect that is the pH main effect while the smallest effect is the interaction effect between YD, IT, and FT. As shown in Figure 2, the Pareto plot demonstrates that pH has the most significant influence on ethanol yield. This

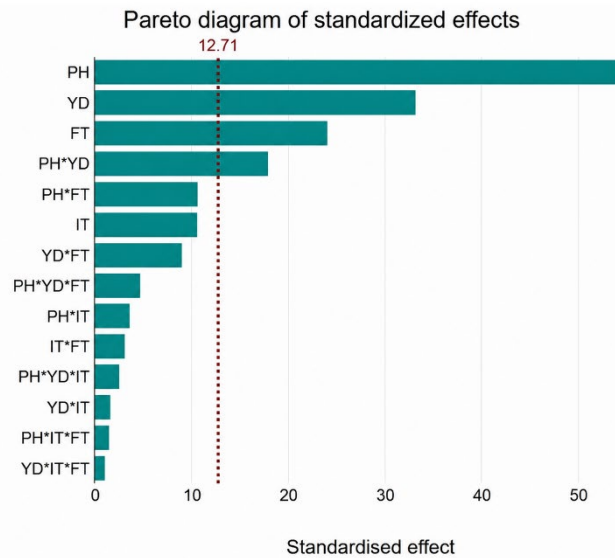


Figure 2. Pareto Diagram of the standardized effects

indicates that maintaining the optimal pH is critical for maximizing ethanol production, likely because pH affects the activity of yeast and enzymatic reactions during fermentation. Yeast dosage has the second highest importance, showing that the amount of yeast introduced directly impacts the fermentation efficiency and ethanol yield. Fermentation time is the third most important factor, indicating that longer fermentation times allow for more substrate conversion, albeit with diminishing returns. Finally, incubation temperature has a minimal importance of the four factors (main effects), suggesting that within the studied range, it has a relatively small effect on ethanol production. The chart (Figure 2) also shows that only the PH-YD is the interaction effect that are statistically significant and can therefore strongly influence ethanol yield.

Correlation Analysis

The correlation matrix as shown in Figure 3 further supports these findings. The correlation matrix revealed near-zero associations among the predictor variables, indicating an absence of multicollinearity concerns in the model. A strong positive correlation (0.74) exists between pH and ethanol yield. This aligns with the feature importance analysis and underscores the need to optimize pH for improved outcomes. A moderate positive correlation (0.46) is observed at yeast dosage and ethanol yield which suggests that increasing yeast dosage can enhance ethanol production. However, the relationship is less pronounced than that of pH. Fermentation time showed a weak positive correlation (0.33) with ethanol yield, which indicates that while fermentation time contributes to ethanol yield, its impact is less significant compared to pH and yeast dosage. Lastly, at incubation temperature and ethanol yield a negligible correlation (0.13) is observed and confirms that within the tested temperature range, this parameter has minimal influence on the ethanol yield. The weak correlation and negligible contribution of incubation temperature (IT) to ethanol yield provided the rationale for omitting IT from subsequent statistical modelling.

Relationship between Factors and Ethanol yield

The presented Figure 4 depicts the relationships between ethanol yield and the four independent variables: pH, YD, IT, and FT. A positive linear trend and a rapid increase in ethanol yield is observed as pH, YD, IT, and FT increases.

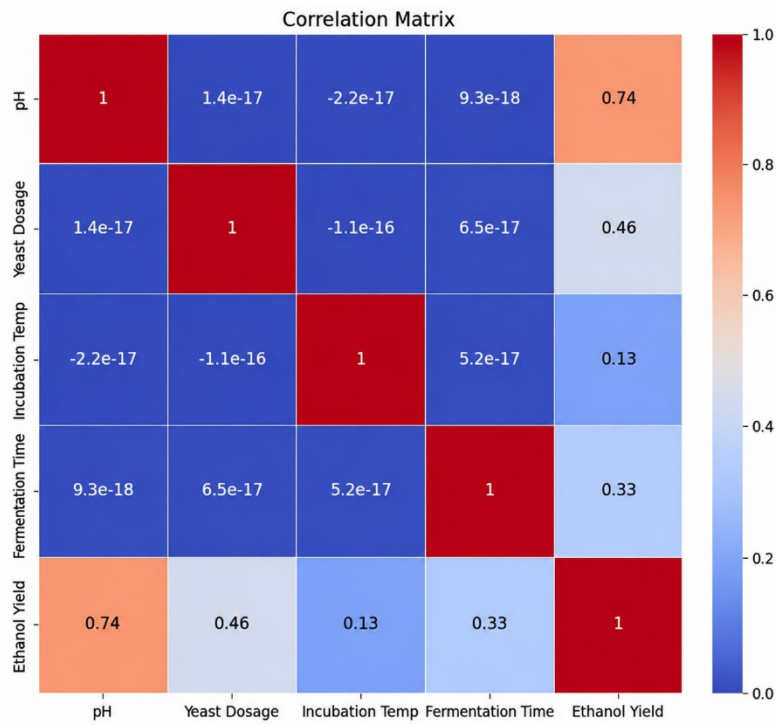


Figure 3. Correlation Matrix

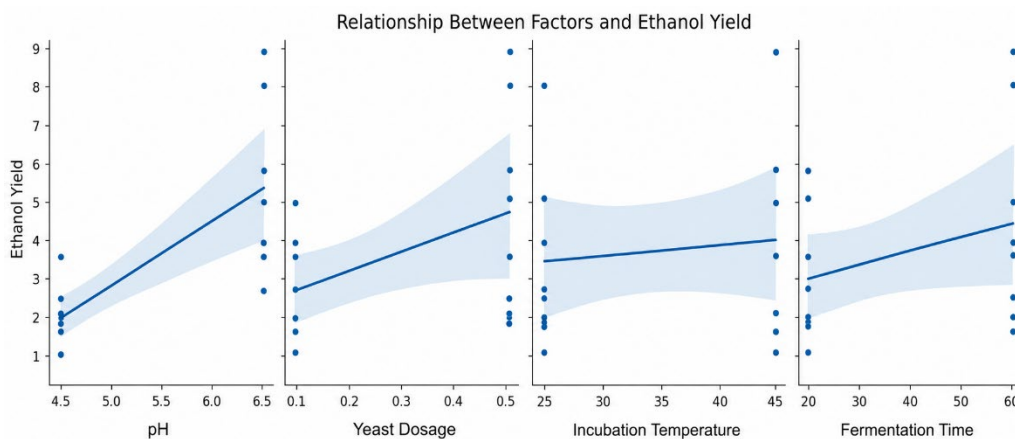


Figure 4. Chart of Main effects

The regression line is almost flat and a slight increase in ethanol yield is observed as Incubation temperature increases. The trends confirm and correspond with the feature importance analysis and correlation matrix analysis. Other factors that have been reported to boost ethanol yield are better yeast strain use and biomass particle size reduction [17]. Since these factors were not varied in the source data, they represent a limitation or an area for future research.

3D Visualization Analysis

The 3D scatter plot (Figure 5) highlights the relationship between pH, yeast dosage, fermentation time and ethanol yield. From the Figure 5, it can be observed clearly that ethanol yields are associated with moderate to high pH, moderate yeast dosage and long fermentation time. This plot also confirms potential interaction effects.

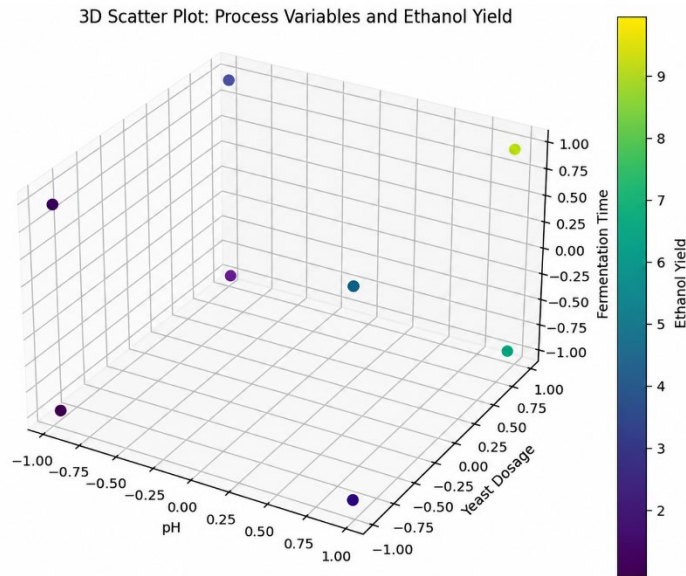


Figure 5. 3D Scatter Plot of Process Variables and Ethanol Yield

Statistical Analysis of Key Factors influencing Ethanol Yield

Incubation temperature (IT) was excluded from the statistical analysis due to statistical insignificance and a negligible correlation to simplify the model. The exclusion of IT aligns with both statistical (overfitting) and biological rationale, as its weak correlation (0.13) and lack of interaction effects suggest minimal impact on ethanol yield. The feature importance score and correlation matrix are evident to the exclusion of IT. The interaction model now provides a comprehensive understanding of ethanol yield by capturing the synergistic effects of pH, YD, and FT using a robust OLS regression model as shown in Table 4. The findings highlight the necessity of including interaction terms in predictive models for fermentation processes.

The model demonstrated high explanatory power (R-squared: 0.972, Adj. R-squared: 0.948) and fit, within the analysed range. Among the main effects, pH had the most significant impact on ethanol yield, followed by yeast dosage and fermentation time, with all three variables demonstrating statistical significance ($p < 0.01$) as shown in table 4. Interaction analysis highlighted a meaningful synergy between pH and yeast dosage, while other higher-order interactions were less impactful, suggesting the dominance of main effects over complex interdependencies.

Table 4. OLS Regression Result

	coef	std err	T	P> t	[0.025	0.975]
Intercept	4.3631	0.141	30.847	0.000	4.037	4.689
pH	1.7894	0.141	12.651	0.000	1.463	2.116
YD	1.0981	0.141	7.764	0.000	0.772	1.424
pH:YD	0.5919	0.141	4.185	0.003	0.266	0.918
FT	0.7969	0.141	5.634	0.000	0.471	1.123
pH:FT	0.3506	0.141	2.479	0.038	0.024	0.677
YD:FT	0.2969	0.141	2.099	0.069	-0.029	0.623
pH:YD:FT	0.1531	0.141	1.083	0.311	-0.173	0.479

Table 5. ANOVA

	sum_sq	Percentage Contribution	Df	F	PR (>F)
pH	51.229806	55.32	1.00	160.046256	0.000001
YD	19.294056	20.84	1.00	60.276267	0.000054
pH:YD	5.605056	6.05	1.00	17.510671	0.00306
FT	10.160156	10.97	1.00	31.741189	0.00049
pH:FT	1.967006	2.12	1.00	6.145094	0.038175
YD:FT	1.410156	1.52	1.00	4.405448	0.069054
pH:YD:FT	0.375156	0.41	1.00	1.17202	0.310535
Residual	2.56075	2.77	8.00	NaN	NaN

The ANOVA table (Table 5) highlights the individual contributions of the factors to ethanol yield. Among the variables, pH accounted for the largest sum of squares (51.229), reinforcing its dominant role in influencing ethanol yield. This is equivalent to 55% of the total contribution. Yeast dosage and fermentation time also showed significant effects, with their respective F-statistics (60.276 and 31.741) confirming their contributions. These main effects correspond to 21% and 11% of the total, respectively. This shows that the three main effects of pH, YD, and FT account for 87% of the total contribution to ethanol yield. Interaction terms, while generally weaker, were still relevant in understanding the combined effects of variables. All the interaction terms between the three main effects accounted for 10% of the total contribution.

The ANOVA results further validated the importance of the selected variables, with pH accounting for the largest variation. These findings align with existing literature and highlight the importance of optimizing pH, YD, and FT for maximizing ethanol production efficiency. The percentage contribution analysis clearly shows that, in all, the main effects of pH, YD, and FT and their interaction effects contribute about 97.23% to the ethanol yield. The remaining 2.77% is contributed by the main effect of incubation time (2.11%) and the two-way, three-way, and four-way effects of its interaction with other factors (0.66%). This further justify the exclusion of the IT from the effects.

To maximize ethanol yield in fermentation processes of African star apple, emphasis should be placed on optimizing the three primary factors identified in this study: pH, YD, and FT [16], [17], [32]. Maintaining an optimal pH range is essential, as it has the most significant and direct effect on ethanol yield. Adjusting YD alongside pH can enhance fermentation efficiency, ensuring effective microbial activity without resource wastage. Fermentation time must also be optimized to balance substrate conversion and operational efficiency, avoiding excessive durations that may lead to diminishing returns.

Increase or reduction in time can affect yeast growth and ethanol production as well as increased sugar concentration and low water activity can affect cell growth and viability, which can reduce ethanol fermentation rate [34]. The study carried out by Adangati et al. [12] shows that the optimal pH range for yeast fermentation is between 4.5 and 5.5. Yeast cells are sensitive to pH changes, and high pH values can disrupt cellular functions, leading to reduced ethanol production and increased contamination risk. Each microorganism has its specific pH when they best enhance certain required reaction. Therefore, pH adjustment will be needed to ensure optimal fermentation conditions, which can be achieved through the addition of acidic or basic substances such as Hydrochloric acid (HCL), Citric acid, Phosphoric acid, Sodium hydroxide (NaOH), Potassium hydroxide (KOH) etc. Maintaining optimal pH levels is crucial to support healthy yeast growth, efficient fermentation, and maximal bioethanol production.

Yeast dosage is another vital parameter that influences bioethanol yield. The optimal YD varies depending on the specific yeast strain and fermentation conditions [35]. A general range is between 106 and 108 cells/mL, and using the optimal yeast dosage is essential to achieve efficient fermentation [36], [37], [38]. Insufficient yeast can lead to incomplete fermentation, resulting in reduced ethanol yields and increased residual sugars. On the other hand, excessive yeast can result in unnecessary costs and potential contamination. Therefore, YD optimization is crucial to achieve optimal fermentation conditions. By optimizing YD, bioethanol producers can improve fermentation efficiency, reduce costs, and increase ethanol yields.

The optimal fermentation time varies depending on the specific yeast strain, substrate, and fermentation conditions. The most commonly used FT is 72 hours [37], and using this optimal FT is essential to achieve efficient fermentation. When the fermentation time is too short, the micro-organisms will have limited growth, leading to inefficient fermentation, reduced ethanol yield and increased residual sugar. When FT is too long, it has toxic effect on microbial growth due to high concentration of ethanol in the broth, increased contamination risk and energy cost. Therefore, FT optimization is crucial to achieve optimal fermentation conditions, which can be achieved through experimental design and response surface methodology (RSM). By optimizing FT, bioethanol producers can improve fermentation efficiency, reduce costs, and increase ethanol yields.

The exclusion of the incubation temperature does not negate the possibility that IT could play a role under different experimental conditions. Temperature affects yeast metabolism and ethanol formation [24], [30], [34]. The optimal temperature range for yeast fermentation is between 25°C and 35°C, and temperatures outside this range can have detrimental effects on yeast growth and fermentation [9]. Very high temperatures can inhibit cellular functions, leading to reduced ethanol production, increased contamination risk, and death of yeast [9]. Temperature has extreme effect on the activity of enzymes involved in fermentation. Hence, temperature control is crucial to maintain optimal fermentation conditions. By maintaining optimal temperatures, bioethanol producers can support healthy yeast growth, efficient fermentation, and maximal bioethanol production. The effect of IT can however be low when other factors are put into consideration, like in this case.

To ensure its real importance is accurately assessed, further research should focus on expanding the dataset to include a wider range of ITs. By incorporating more diverse data, the potential effects of IT can be better isolated and evaluated without compromising the integrity of the model. One approach to achieve this is by conducting controlled experiments where pH, YD, and FT are held constant while varying IT systematically. This would allow researchers to assess its independent effect on ethanol yield as reported in some previous work. Adaganti et al. [12] compared three IT in their work and got a better ethanol yield at 72 hrs. Similarly, Mohammed et al. [38] took samples after incubation at 20°C, 25°C, 30°C, 35°C and 40°C, result shows that the optimum FT for yeast isolate MHYI is 30 °C. Below 30 °C or above it, the production of ethanol is reduced. When the effect of IT on ethanol yield is independently considered, there has to be an optimal level that strongly favours the yield.

Another approach is to explore interaction effects between IT and other variables (e.g., pH or YD) to determine whether IT influences ethanol yield in combination with these factors. To prevent modeling issues, it is recommended to apply techniques such as regularization (e.g., Ridge or Lasso regression) or Principal Component Analysis (PCA) to address multicollinearity, should it arise when including incubation temperature in future models [14], [17]. These methods will ensure that the model remains stable and interpretable. Furthermore, advanced machine learning algorithms, such as Random Forest or Gradient Boosting Machines, could be employed to evaluate the relative importance of incubation temperature alongside other variables. These methods are less sensitive to multicollinearity and can provide deeper insights into nonlinear relationships. By adopting these measures, future research can robustly determine whether incubation temperature has a meaningful impact on ethanol yield and, if so, how it interacts with other critical factors to influence fermentation outcomes. These steps will ensure a

comprehensive understanding of all process parameters while maintaining the robustness and accuracy of data modeling.

The hydrolysis efficiency of starch therefore determines the overall efficiency of bioethanol production from starch [6]. In this context, the influence of pH, temperature, fermentation time, and yeast dosage on ethanol yield can be attributed in part to their effects on the efficiency of starch breakdown; without effective hydrolysis to release sugars, yeast fermentation is inherently constrained. Other factors that have been confirmed as contributory factors to starch-ethanol conversion are carbon source concentration [38], better yeast strain use and biomass particle size [17].

Combining Factorial and Regression Analysis with Optimization study

Ogbodo et al. [31] applied a standard response surface methodology (RSM) design using the central composite design (CCD) to conduct an optimization study and arrived at the optimal conditions of 5.0, 4.5% wt/v, 35°C, and 72 hours for pH, YD, IT, and FT, respectively. This combination resulted in an ethanol yield of 9.89–10.14 g/cm³. However, the factorial analysis with linear regression modelling carried out here shows that incubation temperature contributes less than 3% while fermentation time contributes less than 15%. The relatively low temperature sensitivity observed within the analysed design space suggests reduced dependence on thermal control under the studied conditions. This could further necessitate the consideration of lower temperature ranges like 25°C – 35°C as opined by Featherstone [9] and Mohammed et al. [38].

The contribution of FT also accounts for why it takes the recommended 72 hours [12], [37] to achieve an optimal yield. Maintaining the fermentation time at 72 hours will amount to consuming more energy in the process just to contribute an additional 15% to the yield. A better initiative may be to sacrifice some quantity of yield by keeping the time at just 24 hours and saving energy. This is a more green and low-energy (low-carbon) approach to achieving a green product, bioethanol. As a confirmation, an ethanol yield of 7.41 g/cm³ was recorded at an experimental run combining pH, YD, IT, and FT of 5.0, 4.5 % wt/v, 35 °C, and 24 hours, respectively. This result is about 27% less than the former ethanol yield obtained under the same condition but, at an FT of 72 hours. This trade-off between yield and processing time directly motivates the integrated financial analysis presented in the following section to determine the most sustainable operating point. The factorial and regression analyses therefore show the trend of the contribution of the factors and their effect on the production. Additional experimental runs with new combinations may suggest better optimization conditions.

Financial Impact Assessment

A financial impact assessment to produce about 20g of bioethanol was conducted using two batches of Ogbodo et al. [31]’s optimization factors and three batches of an alternative scenario. Table 6 shows the bioethanol yield reported by [31] from 15 g of African Star Apple (*C. albidum*) hydrolysed with 200 ml of 5% dilute sulphuric acid (H₂SO₄) heated at 50°C for 30 minutes. The study assume the cost of African star apple, yeast, the 5% dilute sulphuric acid, and electricity or power to be i.e \$0.067/g, \$0.25/L, \$15.32/L, and \$0.25/kWh, respectively. The cost data were obtained as follows: the price of African star apple from Bodija Market in Ibadan, Nigeria; the prices of yeast and 5% dilute sulphuric acid from Sigma-Aldrich; and electricity tariffs from local power charges in Nigeria. The cost of adjusting the pH value of the sample with sodium hydroxide before addition of yeast to the hydrolysed sample is negligible and was not accounted for. The rationale for scaling the batches was to enable comparison of scenarios that produce approximately the same total of ~20 g of bioethanol. The financial impact assessment compared three batches of the alternative scenario with two batches of Ogbodo et al.’s [31] optimization factors, revealing that although Ogbodo’s combination produced higher ethanol per batch (10.14 g vs 7.41 g), the alternative scenario

Table 6. Bioethanol yield from two experimental runs [31]

Factors	Unit	Alternative Scenario	Optimized factors [31]
pH	Na	5	5
Yeast dosage (YD)	wt/v	4.5	4.5
Incubation temperature (IT)	°C	35	35
Fermentation time (FT)	Hours	24	72
Ethanol Yield (Output)	G	7.41	10.14

Table 7. Per-batch cost breakdown

Cost item	Calculation (per batch)	Alternative scenario (\$)	Ogbodo et al. [31] (\$)
Raw apple (15 g)	$15 \times \$0.067$	1.005	1.005
5% H ₂ SO ₄ (200 mL)	$0.200 \text{ L} \times \$15.32$	3.064	3.064
Yeast (≈ 9 mL)	$9 \text{ mL} \times (\$0.25 / 1000 \text{ mL})$	0.00225	0.00225
Hydrolysis heating (30 min @ 1.0 kW)	$1.0 \text{ kW} \times 0.5 \text{ h} \times \$0.25/\text{kWh}$	0.125	0.125
Incubator (0.2 kW \times FT)	$0.2 \text{ kW} \times \text{FT (h)} \times \$0.25/\text{kWh}$	1.200000 (FT=24 h)	3.600000 (FT=72 h)
Total cost per batch		5.39625	7.79625

Table 8. Aggregated comparison — requested batch counts

Metric	Alternative Scenario (3 batches)	Ogbodo et al. [31] (2 batches)
Ethanol yield per batch (g)	7.41 g	10.14 g
Total ethanol produced	$7.41 \times 3 = 22.23 \text{ g}$	$10.14 \times 2 = 20.28 \text{ g}$
Total cost (sum of batches)	$3 \times \$5.39625 = \16.18875	$2 \times \$7.79625 = \15.59250
Total cost of 20g of ethanol (normalized)	\$14.56478	\$15.37722
Cost per gram ethanol (total cost \div total g)	$\$16.18875 \div 22.23 = \$0.728239 / \text{g}$	$\$15.59250 \div 20.28 = \$0.768861 / \text{g}$

achieved superior performance when scaled to three runs, yielding 22.23 g of ethanol against 20.28 g for [31], and at a lower unit cost (\$0.728/g vs \$0.769/g). Therefore, the cost of producing 20 g of ethanol by the alternative scenario is \$14.56478, 5.6% lower than by the optimized combination, which costs \$15.37722. Tables 7 and Table 8 details the breakdown of per-batch cost breakdown and aggregate comparison between the two, respectively.

The analysis highlighted that raw apple and dilute sulphuric acid dominate overall costs, contributing about 52%–75% of total expenses, while fermentation time (22%–46%) significantly influences energy consumption, with the alternative scenario's shorter 24-hour fermentation reducing incubator energy costs relative to Ogbodo's 72-hour fermentation. A rise in the price of African star apple would increase total costs proportionally across all scenarios, while an increase in acid cost would exert the greatest pressure on the economics given its high share of batch cost, and higher electricity tariffs would particularly penalize long-fermentation processes such as Ogbodo's. The implication of integrating financial analysis with optimization results is that the most chemically or biologically optimized condition may not always be the most economically viable. The alternative scenario demonstrates that lower yield per batch can be offset by shorter cycle times and lower energy use within the defined cost structure, making financial analysis an essential complement to optimization studies for guiding practical and scalable bioethanol production decisions within the analysed scenarios.

A key factor also contributing to the cost advantage of the alternative scenario is the relatively low temperature sensitivity of *C. albidum* fermentation, which reduces the need for prolonged heating and thermal regulation compared with Ogbodo et al.'s optimized process, thereby lowering energy demand and associated heating costs while maintaining competitive ethanol yields.

Effect of Production Factors on Bioethanol Yield from Other Sources

This subsection examines the effects of production factors on bioethanol yield from established feedstocks such as sugar beet, sugar cane molasses, and sugar cane juice, thereby providing a comparative framework that highlights similarities and differences in process performance and yields across diverse biomass sources. This analysis contextualizes the uniqueness of *C. albidum*'s factor sensitivity and reinforces the need for feedstock-specific integrated analysis. Three case studies involving sugar beet, sugar cane molasses, and sugar cane juice were considered. The plants considered were carefully selected due to their high potential for bioethanol. Laboratory production data for the plants were reported by [16], [32], [39], respectively.

Case 1: Production of bioethanol from sugar beet

Altınışık et al. [16] investigated the yield of bioethanol from sugar beet molasses. Table 9 represents the result (ethanol yield) from the experimental runs involving various combinations of the process factors. The process factors (independent) investigated are fermentation time (F_Time), temperature (Temp), pH, and molasses concentration (MC), while the dependent variable is ethanol efficiency (EE).

Table 10 (ANOVA Table) represents the Tests of Between-Subjects Effects considering the four factors. This table shows that the main effect of MC (39.20%) is the most dominant factor influencing EE, followed by Temp (34.15%) and pH (1.09%). F_Time had the least effect by contributing only 0.53% to the EE. Analysis of the overall effects

Table 9. Analysis matrix representing model pattern of the bioethanol yield [16]

Run	A: Fermentation Time (h)	B: Temperature (°C)	C: pH	D: Molasses Concentration (gL ⁻¹)	E: Ethanol efficiency (%)
1	48	30	4.5	150	72
2	96	30	4.5	150	73
3	48	38	4.5	150	45
4	96	38	4.5	150	46
5	48	30	5.5	150	69
6	96	30	5.5	150	72
7	48	38	5.5	150	67
8	96	38	5.5	150	64
9	48	30	4.5	250	59
10	96	30	4.5	250	62
11	48	38	4.5	250	40
12	96	38	4.5	250	41
13	48	30	5.5	250	46
14	96	30	5.5	250	51
15	48	38	5.5	250	43
16	96	38	5.5	250	46

Table 10. ANOVA Table (four factors)

Tests of Between-Subjects Effects						
Source	Type III Sum of Squares	Percentage Contribution	Df	Mean Square	F	Sig.
Corrected Model	2293.750 ^a		14	163.839	72.817	.092
Intercept	50176.000		1	50176.000	22300.444	.004
F_Time	12.250	0.53	1	12.250	5.444	.258
Temp	784.000	34.15	1	784.000	348.444	.034
pH	25.000	1.09	1	25.000	11.111	.186
MC	900.000	39.20	1	900.000	400.000	.032
F_Time * Temp	6.250	0.27	1	6.250	2.778	.344
F_Time * pH	.250	0.01	1	.250	.111	.795
F_Time * MC	6.250	0.27	1	6.250	2.778	.344
Temp * pH	361.000	15.72	1	361.000	160.444	.050
Temp * MC	16.000	0.70	1	16.000	7.111	.228
pH * MC	169.000	7.36	1	169.000	75.111	.073
F_Time * Temp * pH	2.250	0.10	1	2.250	1.000	.500
F_Time * Temp * MC	.250	0.01	1	.250	.111	.795
F_Time * pH * MC	2.250	0.10	1	2.250	1.000	.500
Temp * pH * MC	9.000	0.39	1	9.000	4.000	.295
Error	2.250	0.10	1	2.250		
Total	52472.000		16			
Corrected Total	2296.000		15			

^a. R Squared = 0.999 (Adjusted R Squared = .985)

Table 11. ANOVA Table excluding Fermentation Time (F_Time)

	sum_sq	Df	F	PR (>F)
Temp	784	1	196	6.57E-07
pH	25	1	6.25	3.69E-02
Temp:pH	361	1	90.25	1.24E-05
MC	900	1	225	3.85E-07
Temp:MC	16	1	4	8.05E-02
pH:MC	169	1	42.25	1.88E-04
Temp:pH:Conc	9	1	2.25	1.72E-01
Residual	32	8	NaN	NaN

contributed by each factor (main and interaction effects) reveals that Temp. takes the lead with 51.44%, followed by MC (48.13%), pH (24.87%), and then F_Time. The main and interaction effects of F_Time combined contributed only 1.39% to the entire EE.

To further verify the effect of F_Time, the ANOVA table was constructed excluding it as shown in Table 11. This resulted in the development of a model with an R-squared value of 0.986, indicating that it can comfortably predict the output (EE) with 98.6% accuracy. This shows that the first three factors (Temp, MC, and pH) contributing the most to the ethanol efficiency should be focused on while less attention can be paid to the F_Time. The reduced

model suggests that fermentation time contributes minimally within the analysed range, with high model fit indicating strong explanatory capacity under the specified conditions. The optimized conditions of 200 gL⁻¹, 5.0, 30 °C, and 72 h were reported for MC, pH, Temp and F_time, respectively, by the authors.

Case 2: Bioethanol yield from sugarcane molasses

El-Gendy et al. [32] investigated the yield of bioethanol from sugar cane molasses. Table 12 represents the bioethanol yield from the experimental runs involving various combinations of the process factors. The independent process factors investigated are incubation period (IT), incubation temperature (I_Temp), pH, and molasses concentration (MC), while the dependent variable is bioethanol yield (BY).

Table 13 (ANOVA Table) represents the Tests of Between-Subjects Effects considering the four factors. This table shows that the main effects of the four factors have a very insignificant contribution (0.80%) to the bioethanol yield, while the interaction effects contributed the remaining 98.20%. Analysis of the overall effects contributed by each factor (main and interaction effects combined) reveals that pH contributed the most with 64.00%. This is followed by IT (55.61%), I_Temp (42.67%), and MC (39.35%). The main and interaction effects of MC contributed 39.35% to the entire BY. This shows that all four factors including incubation period contributed to the bioethanol yield and should be given adequate attention. The conditions of the four factors that produced the maximum bioethanol production should therefore be maintained. According to the authors, the optimized conditions of 18%, 5.6, 38°C, and 71 h for MC, pH, Temp, and F_time, respectively, produced the maximum bioethanol.

Case 3: Bioethanol production from Sugar cane juice

Suleiman et al. [39] carried out an optimization study on the production of bioethanol from sugar cane juice by varying four factors at two levels: Temperature (°C) – 30, 40; Time (Hrs) – 72, 96; Conc. of Fungi (g) – 1, 2; and Feedstock (g) – 200, 300; and recorded the Bioethanol yield (%). The findings of the study showed that the main

Table 12. Analysis matrix representing model pattern of the bioethanol yield [32]

Runs	X1: Incubation Period (h)	X2: Initial pH	X3: Incubation temperature (°C)	X4: Molasses concentration (wt.%)	Bioethanol yield (g/L)
1	24	5	20	15	36.73
2	72	5	20	15	74.39
3	24	7	20	15	65.00
4	72	7	20	15	12.00
5	24	5	40	15	39.66
6	72	5	40	15	230.93
7	24	7	40	15	7.00
8	72	7	40	15	50.00
9	24	5	20	25	14.18
10	72	5	20	25	10.00
11	24	7	20	25	220.45
12	72	7	20	25	54.00
13	24	5	40	25	5.00
14	72	5	40	25	88.86
15	24	7	40	25	65.00
16	72	7	40	25	17.00

Table 13. ANOVA Table (four factors)

Tests of Between-Subjects Effects						
Dependent Variable: Bioethanol Yield						
Source	Type III Sum of Squares	Percentage Contribution	df	Mean Square	F	Sig.
Corrected Model	71187.697 ^a		14	5084.836	10.501	.238
Intercept	61281.003		1	61281.003	126.556	.056
IT	442.682	0.62	1	442.682	.914	.514
pH	5.406	0.01	1	5.406	.011	.993
I_Temp	17.431	0.02	1	17.431	.036	.881
MC	106.193	0.15	1	106.193	.219	.721
IT * pH	17759.560	24.78	1	17759.560	36.677	.104
IT * I_Temp	13001.701	18.14	1	13001.701	26.851	.121
IT * MC	7818.981	10.91	1	7818.981	16.148	.155
pH * I_Temp	12188.160	17.01	1	12188.160	25.171	.125
pH * MC	14769.541	20.61	1	14769.541	30.502	.114
I_Temp * MC	4298.114	6.00	1	4298.114	8.876	.206
IT * pH * I_Temp	46.240	0.06	1	46.240	.095	.809
IT * pH * MC	190.440	0.27	1	190.440	.393	.643
IT * I_Temp * MC	116.208	0.16	1	116.208	.240	.710
pH * I_Temp * MC	427.042	0.60	1	427.042	.882	.520
Error	484.220	0.68	1	484.220		
Total	132952.920		16			
Corrected Total	71671.918		15			

^a R Squared = 0.993 (Adjusted R Squared = .899)

effects of Temperature, Time, Fungi Concentration, and Feedstock contributed 1.87%, 0.42%, 82.72%, and 0.10%, respectively. The overall contributions (main and interaction effects) of each factor to the bioethanol yield was Temperature (6.96%), Time (6.39%), Fungi Concentration (94.35%), and Feedstock (13.62%). This shows that Incubation temperature and fermentation time have the least effect on the sugar cane ethanol yield.

Compared across the three external cases, the pattern of factor influence on bioethanol yield differs markedly from that of *C. albidum*. For African star apple, pH, yeast dosage, and fermentation time collectively accounted for about 87 % of the total variation in yield, with incubation temperature contributing minimally. In contrast, temperature and substrate concentration dominated in the sugar beet and sugarcane cases, while fermentation time exerted the weakest effect. The sugarcane molasses system showed strong interaction effects among temperature, pH, and incubation period, indicating a more temperature-sensitive fermentation process than that of African star apple, where pH alone was decisive. Similarly, the sugarcane-juice process was governed largely by microbial concentration rather than time or temperature. While these comparisons provide useful insight, differences in experimental design, factor definitions, and modelling approaches across the external cases limit direct equivalence. Against this backdrop, the pattern of factor influence differs from that observed for *C. albidum*. Overall, bioethanol production from *C. albidum* is more pH-dependent and less temperature-sensitive within the analysed conditions. This may reflect a fermentation system governed more by biochemical conditions than thermal control [40]. Under the evaluated cost scenarios, this behaviour is associated with reduced energy demand.

CONCLUSION

This study integrated statistical modelling with financial analysis to support cost-informed optimization of bioethanol production from *Chrysophyllum albidum*. To achieve this, feature importance analysis, correlation matrix analysis, ordinary least squares (OLS) regression, and analysis of variance (ANOVA) were jointly applied to quantify factor effects, interactions, and predictive relationships. The results demonstrate, through a unified statistical–financial framework applied specifically to *C. albidum* and within this study context, that identifying technically optimal conditions alone is insufficient without parallel assessment of their economic consequences. Statistically, pH, yeast dosage, and fermentation time were the dominant contributors to ethanol yield, while incubation temperature showed minimal influence; this reduced temperature sensitivity creates an opportunity for energy-saving trade-offs, particularly through adjustment of fermentation duration. When production scenarios were scaled to comparable ethanol output targets, shorter fermentation cycles were found to improve economic efficiency and throughput despite slightly lower per-batch yields, highlighting the influence of energy consumption within the specified costing assumptions.

Beyond the single-feedstock analysis, comparative evaluation with sugar beet, sugarcane molasses, and sugarcane juice systems revealed that *C. albidum* exhibits a distinct, pH-driven fermentation behaviour with lower thermal dependence, although these contrasts should be interpreted within the differing analytical structures of the benchmark cases. Within the scope of this study, these findings support the consideration of African star apple as a potentially favourable feedstock under conditions where reduced thermal demand contributes to cost efficiency. Overall, the study shows that the most technically optimized conditions are not necessarily the most economical, and that integrating factorial screening, trade-off analysis, and scalable financial modelling provides a more comprehensive pathway toward sustainable bioethanol production. The proposed framework, comprising statistical screening of dominant factors, evaluation of yield–cost trade-offs, and batch-scaled financial assessment, provides a structured approach for linking process performance with economic outcomes, with potential applicability to similar biomass systems under comparable analytical conditions.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest regarding this manuscript.

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DATA AVAILABILITY STATEMENT

The data analyzed in this study are presented in (Ogbodo et al., 2023). Readers are directed to that publication for full access to the data.

DECLARATION OF AI TOOLS USAGE

During the preparation of this manuscript, Quilbot and ChatGPT were used to support basic grammatical polishing, language refinement, and enhance sentence flow. All AI-generated outputs were critically reviewed, verified, and thoroughly edited by the authors to ensure accuracy, clarity of expression, and adherence to academic standards. The authors take full responsibility for the integrity, originality, and content of this manuscript.

References

- [1] M. Manfroni, S. G. F. Bukkens, and M. Giampietro, "The declining performance of the oil sector: Implications for global climate change mitigation," *Appl. Energy*, vol. 298, p. 117210, Sept. 2021, doi: 10.1016/j.apenergy.2021.117210.
- [2] X. Pang et al., "The dead line for oil and gas and implication for fossil resource prediction," *Earth Syst. Sci. Data*, vol. 12, no. 1, pp. 577–590, Mar. 2020, doi: 10.5194/essd-12-577-2020.
- [3] M. A. Yaverino-Gutiérrez et al., "Perspectives and Progress in Bioethanol Processing and Social Economic Impacts," *Sustainability*, vol. 16, no. 2, p. 608, Jan. 2024, doi: 10.3390/su16020608.
- [4] I. Edeh, "Bioethanol Production: An Overview," in *Bioethanol Technologies*, F. Inambao, Ed., IntechOpen, 2021. doi: 10.5772/intechopen.94895.
- [5] H. Zabed, J. N. Sahu, A. Suely, A. N. Boyce, and G. Faruq, "Bioethanol production from renewable sources: Current perspectives and technological progress," *Renew. Sustain. Energy Rev.*, vol. 71, pp. 475–501, May 2017, doi: 10.1016/j.rser.2016.12.076.
- [6] J. Li, R. Zhao, Y. Xu, X. Wu, S. R. Bean, and D. Wang, "Fuel ethanol production from starchy grain and other crops: An overview on feedstocks, affecting factors, and technical advances," *Renew. Energy*, vol. 188, pp. 223–239, Apr. 2022, doi: 10.1016/j.renene.2022.02.038.
- [7] S. Minter, *Alcoholic Fuels*, 1st ed. CRC Press, 2016. doi: 10.1201/9781420020700.
- [8] T. Mizik, "Economic Aspects and Sustainability of Ethanol Production—A Systematic Literature Review," *Energies*, vol. 14, no. 19, p. 6137, Sept. 2021, doi: 10.3390/en14196137.
- [9] S. Featherstone, *A Complete Course in Canning and Related Processes*. Elsevier, 2016. doi: 10.1016/C2013-0-16340-4.
- [10] P. Adadi, E. O. Mensah, R. V., Asase, and J. A. Essiedu, "Exploring the nutritional, phytochemical, and functional potential of African star apple (*Chrysophyllum albidum*) and its byproducts: A review of bioactivities and food applications," *Food Res. Int.*, 118804, https://doi.org/10.1016/j.foodres.2026.118804.
- [11] C. M. Igwebuike, S. Awad, and Y. Andrés, "Renewable Energy Potential: Second-Generation Biomass as Feedstock for Bioethanol Production," *Molecules*, vol. 29, no. 7, p. 1619, Apr. 2024, doi: 10.3390/molecules29071619.
- [12] S. Y. Adaganti, V. S. Yaliwal, B. M. Kulkarni, G. P. Desai, and N. R. Banapurmath, "Factors Affecting Bioethanol Production from Lignocellulosic Biomass (*Calliandra calothyrsus*)," *Waste Biomass Valorization*, vol. 5, no. 6, pp. 963–971, Dec. 2014, doi: 10.1007/s12649-014-9305-8.
- [13] A. Tesfaw, E. T. Oner, and F. Assefa, "Optimization of ethanol production using newly isolated ethanologenic yeasts," *Biochem. Biophys. Rep.*, vol. 25, p. 100886, Mar. 2021, doi: 10.1016/j.bbrep.2020.100886.
- [14] D. C. Montgomery, *Design and analysis of experiments*, Ninth edition. Hoboken, NJ: John Wiley & Sons, Inc, 2017.
- [15] O. O. Akinsete and H. O. Aliu, "Experimental and factorial design analysis of viscosity and fluid loss control of water-based mud treated with pineapple leaves," *Egypt. J. Pet.*, vol. 32, no. 1, pp. 57–64, Mar. 2023, doi: 10.1016/j.ejpe.2023.02.003.

- [16] S. Altınışik, F. U. Nigiz, S. Gürdal, K. Yılmaz, N. B. Tuncel, and S. Koyuncu, "Optimization of bioethanol production from sugar beet processing by-product molasses using response surface methodology," *Biomass Convers. Biorefinery*, vol. 15, no. 7, pp. 9875–9888, Apr. 2025, doi: 10.1007/s13399-024-05786-w.
- [17] D. Amaefule et al., "Effect of Production Factors on the Bioethanol Yield of Tropical Sawdust," *Int. J. Energy Res.*, vol. 2023, pp. 1–10, Apr. 2023, doi: 10.1155/2023/9983840.
- [18] H. O. Ibrahim, O. Osilesi, O. O. Adebawo, F. D. Onajobi, K. O. Karigidi, and L. B. Muhammad, "Nutrients Compositions and Phytochemical Contents of Edible Parts of *Chrysophyllum albidum* Fruit," *J. Nutr. Food Sci.*, vol. 07, no. 02, 2017, doi: 10.4172/2155-9600.1000579.
- [19] F. A. Bello and A. A. Henry, "Storage effects and the postharvest quality of African star apple fruits (*Chrysophyllum africanum*) under ambient conditions," *Afr. J. Food Sci. Technol.*, vol. 06, no. 01, 2015, doi: 10.14303/ajfst.2015.011.
- [20] O. M. Odeyemi and O. A. Fawole, "African Star Apple (*Chrysophyllum albidum*)," in *Handbook of Phytonutrients in Indigenous Fruits and Vegetables*, D. Sivakumar, M. Netzel, and Y. Sultanbawa, Eds., GB: CABI, 2022, pp. 376–389. doi: 10.1079/9781789248067.0026.
- [21] O. M. Abel, A. S. Chinelo, I. Cynthia, and G. K. Agbajor, "Evaluation of African Star Apple (*Chrysophyllum albidum*) Seed Oil as a Potential Feedstock for Industrial Application," *Asian J. Appl. Chem. Res.*, pp. 31–42, Dec. 2020, doi: 10.9734/ajacr/2020/v7i130174.
- [22] D. V. Adegunloye, T. M. Olotu, I. A. Sanusi, and E. M. Sanni, "Preliminary Assessment of African Star Apple Seeds (*Chrysophyllum Albidum*) as Potential Feedstock for Production of Bioethanol," *Daffodil Int. Univ. J. Sci. Technol.*, vol. 17, no. 1, pp. 1–5, 2022.
- [23] G. D. A. Minussi et al., "Transforming orange waste with yeasts: bioprocess prospects," *Rev. Bras. Ciênc. Ambient.*, vol. 59, p. e1859, Apr. 2024, doi: 10.5327/Z2176-94781859.
- [24] S. T. Mgeni, L. A. Mtashobya, and J. K. Emmanuel, "Bioethanol production from pineapple fruit waste juice using bakery yeast," *Heliyon*, vol. 10, no. 19, p. e38172, Oct. 2024, doi: 10.1016/j.heliyon.2024.e38172.
- [25] G. H. Klein et al., "Utilization of banana peel waste for the production of bioethanol and other high-value-added compounds," *Food Humanity*, vol. 3, p. 100376, Dec. 2024, doi: 10.1016/j.foohum.2024.100376.
- [26] J. B. Omoolorun, F. T. Afolabi, S. E. Olufemi, and S. M. Adeyemo, "Bioethanol Production from Decaying Oranges and Pineapple Juice Using Ethanol Tolerant-Yeast," *J. Adv. Biol. Biotechnol.*, vol. 26, no. 11, pp. 33–49, Dec. 2023, doi: 10.9734/jabb/2023/v26i11665.
- [27] N. Sorour et al., "Biofuel production by *Candida tropicalis* from orange peels waste using response surface methodology," *Potravinarstvo Slovak J. Food Sci.*, vol. 17, pp. 862–885, Nov. 2023, doi: 10.5219/1913.
- [28] I. Zah, Y. Tsukuda, Y. Yamaguchi, A. Ogita, and K. Fujita, "Persimmon tannin promotes the growth of *Saccharomyces cerevisiae* under ethanol stress," *J. Sci. Food Agric.*, vol. 104, no. 10, pp. 6118–6126, Aug. 2024, doi: 10.1002/jsfa.13439.
- [29] S. H. Mohd Azhar et al., "Yeasts in sustainable bioethanol production: A review," *Biochem. Biophys. Rep.*, vol. 10, pp. 52–61, July 2017, doi: 10.1016/j.bbrep.2017.03.003.
- [30] F. Da Silva Fernandes, É. S. De Souza, L. M. Carneiro, J. P. Alves Silva, J. V. B. De Souza, and J. Da Silva Batista, "Current Ethanol Production Requirements for the Yeast *Saccharomyces cerevisiae*," *Int. J. Microbiol.*, vol. 2022, pp. 1–14, Aug. 2022, doi: 10.1155/2022/7878830.
- [31] N. J. Ogbodo, C. Esonye, and M. Omotioma, "Assessment of African star apple (*chrysophyllum albidum*) fruit pulp as a potential feedstock for bioethanol production," *J. Niger. Soc. Chem. Eng.*, vol. 38, no. 1, 2023, [Online]. Available: https://www.nsche.org/Journal/assets/JNSChE/2023%20Edition/Articles/ASSESSMENT_OF_AFRICAN_STAR_APPLE_%28CHRYSOPHYLL_6870.pdf

- [32] N. Sh. El-Gendy, H. R. Madian, and S. S. A. Amr, "Design and Optimization of a Process for Sugarcane Molasses Fermentation by *Saccharomyces cerevisiae* Using Response Surface Methodology," *Int. J. Microbiol.*, vol. 2013, pp. 1–9, 2013, doi: 10.1155/2013/815631.
- [33] T. DATAtab, Online Statistics Calculator. (2025). DATAtab e.U., Graz, Austria. [Online]. Available: (<https://datatab.net>)
- [34] E. Timmermans, A. Bautil, K. Brijs, I. Scheirlinck, R. Van Der Meulen, and C. M. Courtin, "Sugar Levels Determine Fermentation Dynamics during Yeast Pastry Making and Its Impact on Dough and Product Characteristics," *Foods*, vol. 11, no. 10, p. 1388, May 2022, doi: 10.3390/foods11101388.
- [35] T. Tadesse, D. Dase, A. D. Koricha, and K. Bacha, "Optimization of Bioethanol Production Using Response Surface Methodology for Stress-Tolerant Wild Yeasts Isolated from Natural Forests," *Int. J. Energy Res.*, vol. 2024, no. 1, p. 7086047, Jan. 2024, doi: 10.1155/2024/7086047.
- [36] V. L. Belini, G. A. P. Caurin, P. Wiedemann, and H. Suhr, "Yeast fermentation of sugarcane for ethanol production: Can it be monitored by using in situ microscopy?," *Braz. J. Chem. Eng.*, vol. 34, no. 4, pp. 949–959, Oct. 2017, doi: 10.1590/0104-6632.2017034420160162.
- [37] E. Hawaz et al., "Optimization of bioethanol production from sugarcane molasses by the response surface methodology using *Meyerozyma caribbica* isolate MJTm3," *Ann. Microbiol.*, vol. 73, no. 1, p. 2, Jan. 2023, doi: 10.1186/s13213-022-01706-3.
- [38] H. Mohamed, A. A. Mervat, A. E. Seham, and H. E. Hussein, "Factors Affecting Bioethanol Production from Hydrolyzed Bagasse," *Int. J. Adv. Res. Biol. Sci. IJARBS*, vol. 3, no. 9, pp. 130–138, Sept. 2016, doi: 10.22192/ijarbs.2016.03.09.019.
- [39] B. Suleiman, S. A. Abdulkareem, E. A. Afolabi, U. Musa, I. A. Mohammed, and T. A. Eyikanmi, "Optimization of bioethanol production from nigerian sugarcane juice using factorial design," *Adv. Energy Res.*, vol. 4, no. 1, pp. 69–86, Mar. 2016, doi: 10.12989/ERI.2016.4.1.069.
- [40] D. G. Adekanmi and A. E. Olowofoyeku, "African Star Apple: Potentials and Application of Some Indigenous Species in Nigeria," *J. Appl. Sci. Environ. Manag.*, vol. 24, no. 8, pp. 1307–1314, Sept. 2020, doi: 10.4314/jasem.v24i8.1

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