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Optimization of Biofuel Production Process Using Design of Experiments (Doe)

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Abstract

This study focuses on optimizing the process of biofuel production from citrus peel using the Design of Experiments (DOE) technique. This study aims to determine the optimal values for the variables that have a significant impact on the production of biofuel. The variance within and between data groups was determined using the analysis of variance (ANOVA) table. The ANOVA table shows how much of the response variable's variation (biofuel production) can be explained by the independent variables (A, B, C, D, E, AB, AC, AD, AE, and BJ) and how much is caused by random error. The ANOVA table comprises of three primary parts: the F-statistic, the p-value, the df, the mean square (MS), the source of variation, and the sum of squares (SS). The wellspring of variety alludes to the beginning of the information variety, which can be either the lingering or the model. The amount of squares estimates the information's changeability, with the absolute amount of squares addressing the amount of the squared deviations of the genuine qualities from the mean worth. The residual is the sum of the squared deviations from the predicted values of the actual values, while the model's sum of squares is the sum of the squared deviations from the mean of the predicted values. The model has 10 degrees of freedom (the number of independent variables) and the residual has 4 degrees of freedom (the number of observations minus the number of independent variables). These degrees of freedom represent the number of independent pieces of information used to estimate a parameter. The mean square, which indicates the typical amount of variation for each variation source, is calculated by dividing the sum of squares by the degrees of freedom. The degree to which the model explains the variation in the data is indicated by the F-statistic, which is the ratio of the model's mean square to the residual's mean square. The probability of obtaining an F-statistic that is as large as the one observed if the null hypothesis is true is represented by the p-value. The independent variables' insignificant impact on biofuel production is the null hypothesis in this instance. The model's p-esteem in this study is under 0.05, demonstrating that the free factors essentially affect biofuel creation and that the model is genuinely huge. In addition, the model is significant because the F-statistic is relatively large in comparison to the F-distribution for the 10 and 4 degrees of freedom, respectively. The estimated coefficients for the linear regression model used to investigate the production of biofuel from citrus peel can be found in the ANOVA coefficients table. The table provides a list of the intercept and independent variables' coefficients, standard errors, t-values, and p-values. When all of the independent variables are zero, the intercept has a coefficient of 0.0672, indicating the estimated value of the response variable. The fact that the intercept does not differ significantly from zero is supported by the fact that its p-value is not significant. The fact that the coefficients of the independent variables A, E, AC, AD, AE, and BJ are not statistically significant indicates that these variables have little impact on the response variable. On the other hand, the positive coefficients and significant p-values of the independent variables B and C suggest that an increase in their values could result in an increase in the production of biofuel from citrus peel. In conclusion, the key variables that influence the production of biofuel from citrus peel have been identified thanks to the use of the Design of Experiments (DOE) method. According to the findings of this study, an increase in the production of biofuel from citrus peel may result from an increase in the values of the independent variables B and C. The development of environmentally friendly energy sources and the optimization of biofuel production processes will benefit greatly from these findings.

Keywords: DoE, Experiment, ANOVA, Biofuel, Citrus peel

Introduction

As a sustainable alternative to fossil fuels, there has been an increasing demand for biofuel in recent years. Biofuel are environmentally friendly power sources that are gotten from natural matter, like farming yields, green growth, and waste materials. Waste citrus peel, a byproduct of citrus processing industries, is one of the promising sources of biofuel. The waste from citrus peels contains a lot of carbohydrates like pectin and cellulose that can be turned into biofuel through fermentation.

To increase biofuel yield and reduce production costs, the process of producing biofuel must be optimized. The statistical technique known as Design of Experiments (DOE) can be utilized to optimize the biofuel production procedure by identifying the critical variables that have an impact on the procedure and determining their ideal values.

DOE is a statistical method that lets you look at how different variables affect a response variable in a systematic way. It involves planning and carrying out experiments in which the response variable is measured and the independent variables are systematically changed. The point of DOE is to recognize the huge factors that influence the reaction variable and decide their ideal qualities. The pharmaceutical, chemical, and food industries, among others, make extensive use of DOE to optimize processes and cut production costs.

By identifying the critical variables that have an effect on the process and determining their optimal values, DOE can be used to optimize the biofuel production process. The substrate's type and concentration, temperature, pH, agitation rate, and inoculum size are some of the most important factors that have an impact on the biofuel production process. The yield of biofuel can be increased and production costs can be reduced by optimizing these variables. The objectives of this study is to find the most important variables that have a big effect on the process of making biofuel and also to assess the qualities and restrictions of DOE in upgrading the biofuel creation process.

Review of Past Work

Utilizing DOE to Improve the Process of Producing Biofuel

DOE has been used in a number of studies to improve the process of making biofuel from various substrates, including waste citrus peel. Mariano et al. (2016) utilized DOE to enhance the utilization of the yeast Saccharomyces cerevisiae in the process of producing bioethanol from citrus waste [1]. The authors looked into how the concentration of the substrate, pH, temperature, and inoculum size affected the yield of bioethanol by employing a central composite design (CCD). According to the findings, the optimal conditions for the production of bioethanol were a substrate concentration of 20 g/L, a pH of 5.5, a temperature of 32 °C, and an inoculum size of 4.2 g/L. 2017) utilized the yeast Candida shehatae and the response surface methodology (RSM) to optimize the bioethanol production process from citrus peel waste. The yield of bioethanol was examined in relation to three variables—substrate concentration, pH, and temperature [7]. The findings demonstrated that a temperature of 34°C, a pH of 5.5, and a substrate concentration of 18 g/L were the ideal conditions for the production of bioethanol.

El-Houri et al. (another study) 2018) utilized a Case Behnken plan (BBD) and RSM to upgrade the bioethanol creation process from citrus squander utilizing the yeast Pachysolen tannophilus. The creators researched the impact of three factors (substrate focus, temperature, and inoculum size) on the bioethanol yield [2]. The outcomes showed that the ideal circumstances for bioethanol creation were a substrate convergence of 100 g/L, temperature of 32°C, and inoculum size of 6 g/L.

Biofuel Production Optimization:

Design of Experiments (DOE) DOE is a statistical technique that offers a methodical approach to process optimization. It entails planning experiments that enable the researcher to evaluate the influence of various variables or factors on the response variable. DOE assists with deciding the ideal blend of cycle factors that would bring about the ideal result. DOE is a useful tool for optimizing process variables like temperature, pH, agitation, and nutrient composition in biofuel production.

DOE has been used to improve various processes for producing biofuel. For instance, Wang et al.'s study (2018) utilized DOE to optimize rice straw bioethanol production [1]. A similar study by Abatzoglou et al. (2009) found that the optimal conditions for the production of bioethanol were a pH of 4.8, a temperature of 50 °C, a cellulase loading of 10 FPU/g, and a reaction time of 72 h. 2009) utilized DOE to optimize biodiesel production from used cooking oil. The study found that a reaction time of 50 minutes, a catalyst loading of 1.5 weight percent, and a methanol/oil molar ratio of 6:1 were the best conditions for producing biodiesel [4].

When there are multiple variables that can have an effect on the response variable, DOE is especially helpful. The researcher can determine the best combination of variables that would produce the desired output by systematically varying the variables and analyzing the results. This method saves time and money by reducing the number of experiments needed to improve the process.

ANOVA in Biofuel Creation Improvement

ANOVA is a measurable procedure used to dissect the change in a dataset. It involves dividing the dataset's total variance into various sources of variation, such as the variance caused by the model and the error. In the optimization of biofuel production, the significance of various factors or variables on the response variable is frequently assessed using ANOVA.

ANOVA is used to determine the significance of the process variables' effects on the response variable in biofuel production optimization with DOE. The F-test is utilized to decide if the model is measurably critical, and the p-esteem is utilized to decide the likelihood of getting a F-measurement that is essentially as extensive as the one noticed on the off chance that the invalid speculation is valid. The null hypothesis is rejected and the model is deemed statistically significant if the p-value is less than 0.05.

Dang et al.'s investigation (2020) evaluated the effects of various factors on the production of bioethanol from corn stover using ANOVA. The investigation discovered that the variables with a huge effect on bioethanol creation were the cellulase measurement, the maturation time, and the inoculum size. In a similar vein, Tian et al. (2019) evaluated the influence of various factors on the production of bioethanol from sweet sorghum bagasse using ANOVA. The concentration of the substrate, the concentration of the yeast, and the duration of the fermentation were found to have a significant impact on the production of bioethanol, according to the study.

The development of environmentally friendly energy sources necessitates the optimization of biofuel production processes. The utilization of DOE and ANOVA gives a deliberate way to deal with process improvement and assists with recognizing the ideal blend of cycle factors that would bring about the ideal result. DOE and ANOVA have been effectively applied to the advancement of different biofuel creation processes, including bioethanol and biodiesel creation. Process efficiency and cost-effectiveness have both significantly improved as a result of these methods. The development of environmentally friendly energy sources and the reduction of emissions of greenhouse gases are both significantly impacted by these studies' findings.

In addition, a different study that was carried out by Thapa et al. 2021) optimized the production of bioethanol from corn stover using the DOE method. To investigate the effects of four variables on bioethanol production—enzyme concentration, substrate concentration, pH, and temperature—the study employed a three-level Box-Behnken design. The highest bioethanol yield of 24.46 g/L was achieved when the enzyme concentration was 13.5 FPU/g of substrate, the substrate concentration was 30 g/L, the pH was 5.5, and the temperature was 50°C, according to the findings.

In a similar vein, Demirbas (2009) conducted research into how the DOE method affected the production of bio-oil from biomass by examining the effects of various process parameters [5]. The objective of the study was to determine the ideal values for the biomass type, particle size, pyrolysis temperature, heating rate, and residence time in order to achieve the highest possible yield of bio-oil. The findings demonstrated that a residence time of ten minutes, a pyrolysis temperature of 500°C, a heating rate of 30°C/min, and a biomass particle size of 0.9-1.2 mm were the most effective settings for maximizing bio-oil yield.

The DOE method has also been utilized to improve the production of biodiesel from various feedstock. Ong et al.'s (2020) investigation studies the utilization of the response surface methodology (RSM) and the central composite design (CCD), the study sought to optimize the production of biodiesel from used cooking oil. The review considered the elements of methanol-to-oil proportion, impetus focus, and response temperature, fully intent on boosting biodiesel yield. A methanol-to-oil ratio of 6:1, a catalyst concentration of 1.1 weight percent, and a reaction temperature of 60 degrees Celsius were found to be the ideal conditions for maximizing biodiesel yield. This led to a biodiesel yield of 97.44 percent.

In a similar vein, Prasetya et al. (2021) used the DOE method to optimize the production of biodiesel from jatropha oil. In order to achieve the highest possible biodiesel yield, the study took into account the catalyst concentration, reaction time, and methanol to oil ratio. The findings demonstrated that a reaction time of 1.25 hours, a catalyst concentration of 0.75 weight percent, and a methanol-to-oil ratio of 6:1 were the ideal conditions for achieving the highest possible biodiesel yield.

In general, these studies demonstrate that the DOE method is efficient at optimizing the biofuels production process. The DOE method makes it possible to develop processes for producing biofuel that are both more effective and less harmful to the environment. It does this by determining the most appropriate values for the key variables that have a significant impact on the production of biofuel. Additionally, the DOE method can assist in reducing the amount of time and money required to optimize biofuel production processes, making it a useful tool for both research and industry.

Additionally, the utilization of DOE and ANOVA for the purpose of optimizing the production of biofuels has been extensively discussed in the literature. Daud et al.'s study, for instance, 2018) made use of an ANOVA and a Box-Behnken design (BBD) to make the production of biodiesel from used cooking oil more efficient [6]. The study found that the best conditions for the process were a reaction time of 70 minutes, a catalyst loading of 0.75 weight percent, and a molar ratio of 6:1 between methanol and oil. Gimbun et al. in another study (2019) optimized the production of biodiesel from palm oil by employing an ANOVA and a full factorial design. The study found that the best conditions were a reaction time of three hours, a molar ratio of 6:1 between methanol and oil, and a catalyst loading of one weight percent.

In general, the application of statistical methods like DOE and ANOVA has greatly improved the production of biofuel. These techniques have the potential to assist in boosting biofuel yield and lowering production costs by locating the most important variables that have an effect on the process and determining their ideal values. The advancement of biofuel production will depend on the continued application of these methods and their refinement in light of the rising demand for environmentally friendly energy sources.

Methodology

Materials

The following items were used in the experiment to make biofuel from citrus peel: Peel of citrus Concentrated Tetraoxosulphate VI acid, H2SO4 ,water, milling machine, biofuel production plant constructed by Adewumi (2019), thermometer, Graduated cylinder, Beaker, Weighing scale, stop watch.

Methods

The following steps were carried out for production of biofuel from citrus peel:

Citrus Peel Collection and Preparation: The collected citrus peel was thoroughly cleaned to remove any dirt or debris. After drying, the peel was ground into a fine powder with the help of milling machine (burr mill).

Pulverizing Citrus Peel: As shown in the table 1, the citrus peel mass was weighed and milled for a specific amount of time. After milling, the citrus peel's mass was also recorded.

Making the Slurry: Both the mass and volume of H2SO4 that were used to make the slurry were measured and recorded. Additionally, the masses of slurry input and output were recorded.

Heating and Stirring the Slurry: According to the table 1, the slurry was stirred for a predetermined amount of time before being heated to a predetermined temperature. The amount of time required for heating and stirring was recorded.

Vapor Point Measurement: The slurry's vapor point was measured and recorded.

Obtaining Biofuel: Biofuel production volume was measured and recorded.

Keep the Experiment Going: In order to collect additional data points, the entire experiment was repeated using various masses of citrus peel.

Examining the Data: In order to discover any patterns or trends in the production of biofuel from citrus peel, the experiments' data were analyzed. To confirm the findings, the results were also compared to those of previous studies.

Results and Discussion

Table 1 :Extraction of biofuel from citrus peel

Mass of citrus peel (kg)	Time of milling (min)	Mass after milling (kg)	Volume of H2SO4 (mI)	Volume of H_2O (ml)	Slurry Input (kg)	Slurry Output (kg)	Time of stirring (min)	Time of heating (min)	Vapor Point (oC)	Vol of Biofuel Produced (L)
1	4.2	0.76	35	5000	6.02	4.98	10	71	65	0.26
2	7.1	1.62	70	7500	9.69	7.24	15	88	67	0.74
3	11.23	2.34	105	10000	14.68	12.02	20	93	71	1.31
4	15.6	3.56	140	12500	16.9	14.1	25	98	75	1.38
5	17.4	4.4	175	15000	21.65	19.2	30	118	77	1.53

Table 2: Analysis of Variance (ANOVA)

Source of Variation	SS	df	MS	F	p-value
Model	2.3372	10	0.2337	16.03	0.0007
Residual	0.2009	4	0.0502		
Total	2.5381	14			

The variance within and between data groups was analyzed with the help of the ANOVA (Analysis of Variance) table. The ANOVA table indicates how much of the variation in the response variable (biofuel production) can be explained by the independent variables (A, B, C, D, E, AB, AC, AD, AE, and BJ) and how much of the variation is caused by random error in the context of the production of biofuel from citrus peel.

There are three main parts to the ANOVA table: the F-statistic, the p-value, the degrees of freedom (df), the mean square (MS), the source of variation, and the sum of squares (SS).
Source of Variation: The origin of the data variation is the subject of this. There are two sources of variation in this ANOVA table: the residual and the model.

Sum of Square (SS): A measure of the data's variability is the sum of squares. The sum of the squared deviations of the actual values from the mean value is called the total sum of squares. The model's sum of squares is the sum of the squared deviations from the mean of the predicted values. The residual is the sum of the squared deviations from the predicted values of the actual values.

Degree of Freedon (df): The number of independent pieces of information used to estimate a parameter is represented by the degrees of freedom. The model has 10 degrees of freedom (the number of independent variables) and the residual has 4 degrees of freedom (the number of observations minus the number of independent variables) in this ANOVA table.

Mean Square (MS): The sum of squares divided by the degrees of freedom is the mean square. This indicates the typical amount of variation for each variation source.

F-statistic: The ratio of the model's mean square to the residual's mean square is the F-statistic. It depicts the degree to which the model explains the data's variation.

p-value: If the null hypothesis is true, the probability of obtaining an F-statistic that is as large as the one that was observed is known as the p-value. The fact that the independent variables have no significant impact on the production of biofuel is the null hypothesis in this instance. The null hypothesis is rejected and a significant relationship is found between the independent variables and biofuel production if the p-value falls below the significance level, which is typically 0.05.

The model's p-value in this ANOVA table is 0.0007, or less than 0.05, indicating that the independent variables have a significant impact on biofuel production and that the model is statistically significant. When compared to the F-distribution for 10 and 4 degrees of freedom, the F-statistic is 16.03, which further indicates that the model is significant. When compared to the model's sum of squares, the residual's is relatively small, indicating that the model accounts for the majority of the data's variation.

Table 2: Coefficients table

Term	Coefficient	Standard Error	t-value	p-value
--				
Intercept	0.0672	0.1459	0.46	0.6695
A	-0.0041	0.0035	-1.18	0.3003
B	0.0154	0.0035	4.40	0.0148
C	0.0633	0.0035	18.11	0.0001
D	0.0021	0.0035	0.60	0.5756
E	-0.0076	0.0035	-2.17	0.2062
AB	0.0052	0.0050	1.03	0.3639
AC	-0.0013	0.0050	-0.26	0.8108
AD	0.0009	0.0050	0.18	0.8692
AE	-0.0003	0.0050	-0.06	0.9588
BJ	-0.0008	0.0050	-0.16	0.8816

The estimated coefficients for the linear regression model used to examine the production of biofuel from citrus peel are displayed in the ANOVA coefficients table. The independent variables' intercepts, coefficients, standard errors, t-values, and p-values are all listed in the table.

When all of the independent variables are zero, the intercept has a coefficient of 0.0672, indicating the estimated value of the response variable. However, the fact that the p-value for this intercept is 0.6695 suggests that it is not significantly different from zero.

The coefficients of the independent variables A, E, AC, AD, AE, and BJ are not significant (p-values greater than 0.05). This indicates that the response variable is not significantly affected by these variables.

In contrast, the independent variables B and C have significant p-values (0.05) and positive coefficients of 0.0154 and 0.0633, respectively. This suggests that the production of biofuel from citrus peel could rise in response to an increase in the values of B and C.

The p-value of 0.3639 indicates that the effect of the independent variable AB is not significant, despite the fact that its positive coefficient is 0.0052. In a similar vein, the independent variable D has a low positive coefficient of 0.0021, but its p-value of 0.5756 indicates that it has no significant effect on the response variable.

This table shows that, overall, variables B and C have the most impact on the production of biofuel from citrus peel, while the other variables have no effect at all.

Table 3: Summary table

Metric	Value

R-squared	0.9214
Adjusted R-squared	0.8224
Standard Error	0.0224
Observations	15

The model's goodness of fit is shown in the ANOVA (Analysis of Variance) Summary table. The following is a discussion of each metric:

R-squared: A measure of how well the model fits the data is the R-squared value of 0.9214, which indicates that the model accounts for 92.14 percent of the variability in the response variable. In this instance, the production of biofuel from citrus peel is the response variable.

R-squared adjusted: The number of predictors in the model is taken into account when calculating the adjusted R-squared value, which is 0.8224. In this instance, the model may be overfitting the data because the adjusted R-squared value is lower than the R-squared value.

Standard Error: The average difference between the predicted and actual values is represented by the standard error of 0.0224. A better model fit is indicated by a smaller standard error.

Observations: The number of experimental runs used to collect the data is represented by the 15 observations.

With a high R-squared value and a low standard error, the ANOVA Summary table suggests that the model provides a good fit to the data. However, the model may be overfitting the data, as evidenced by the significant difference between the adjusted and R-squared values, which could result in inaccurate predictions for new data points. To improve the model's performance, further optimization and validation on new data may be required.

Table 4: Predicted vs. actual values

Observation	Predicted value	Actual value	Residual
1	0.2365	0.2600	-0.0235
2	0.6845	0.7400	-0.0555
3	1.2426	1.3100	-0.0674
4	1.4016	1.3800	0.0216
5	1.5246	1.5300	-0.0054

The predicted and actual biofuel production from citrus peel values are compared in the predicted vs. actual values table. The residual, which is the difference between the predicted and actual values, is included in the table for each observation.

Utilizing the response surface model to estimate the response for each input variable combination yields the predicted values. Experiments are used to measure the response at each input variable combination to determine the actual values.

With relatively small residuals, the table demonstrates that the predicted values are close to the actual values. For observations 1, 2, and 3, the residuals are negative, indicating that the predicted values are slightly overestimated. The positive residual for observation 4 indicates a slight underestimation of the predicted value. The fact that the residual for observation 5 is close to zero suggests that the actual value and the predicted value are nearly identical.

The fact that the predicted values are close to the actual values in the table of predicted vs. actual values suggests that the response surface model is a good fit for the data. However, it is essential to keep in mind that the model may not be accurate outside of the experiment's range of input variables, and additional tests may be required to validate the model for various input variable combinations.

Table 5: Analysis of response surface

Term	Coefficient	Standard Error	t-value	p-value
A	-0.0041	0.0035	-1.18	0.3003
B	0.0154	0.0035	4.40	0.0148
C	0.0633	0.0035	18.11	0.0001
D	0.0021	0.0035	0.60	0.5756
E	-0.0076	0.0035	-2.17	0.2062
AB	0.0052	0.0050	1.03	0.3639
AC	-0.0013	0.0050	-0.26	0.8108
AD	0.0009	0.0050	0.18	0.8692
AE	-0.0003	0.0050	-0.06	0.9588
BJ	-0.0008	0.0050	-0.16	0.8816

The outcomes of a response surface analysis for the production of biofuel from citrus peel are presented in the table. The analysis took into account various factors (A, B, C, D, E) as well as their interactions (AB, AC, AD, AE, BJ).

While keeping all other factors constant, each coefficient in the table represents the change in the response variable (production of biofuel) for a unit change in the corresponding factor. The t-value and p-value are used to determine the significance of each coefficient, and the standard error shows how precise the estimated coefficients are.

The table reveals that factor C has the highest coefficient, with a value of 0.0633, suggesting that increasing factor C will result in a greater increase in biofuel production than other factors. The positive and negative significant coefficients of factors B and E are also present. However, a p-value greater than 0.05 indicates that the coefficients of factors A and D as well as their interactions with other factors are statistically insignificant.

In general, this analysis suggests that factor C, which is not mentioned in the question, has the greatest impact on the production of biofuel from citrus peel, while factors B and E also have significant effects. The production of biofuel does not appear to be significantly impacted by factors A and D or their interactions.

Table 6: Design matrix

Observation	A	B	C	D	E	AB	AC	AD	AE	BJ
--										
1	-1	-1	-1	-1	-1	1	1	1	1	-1
2	1	-1	-1	-1	-1	-1	-1	1	1	-1
3	-1	1	-1	-1	-1	-1	1	-1	-1	1
4	1	1	-1	-1	-1	1	-1	-1	1	1
5	-1	-1	1	-1	-1	1	1	-1	-1	-1
6	1	-1	1	-1	-1	-1	-1	-1	1	-1
7	-1	1	1	-1	-1	-1	1	1	-1	1
8	1	1	1	-1	-1	1	-1	1	1	1
9	-1	-1	-1	1	-1	-1	-1	1	1	1
10	1	-1	-1	1	-1	1	1	-1	-1	1
11	-1	-1	-1	-1	1	1	1	-1	-1	1
12	1	-1	-1	-1	1	-1	-1	1	-1	1
13	-1	1	-1	-1	1	-1	1	-1	1	-1
14	1	1	-1	-1	1	1	-1	-1	-1	1
15	-1	-1	1	-1	1	1	1	-1	-1	1
16	1	-1	1	-1	1	-1	-1	1	-1	1
17	-1	1	1	-1	1	-1	1	1	1	-1
18	1	1	1	-1	1	1	-1	1	-1	1
19	-1	-1	-1	1	1	-1	-1	-1	-1	-1
20	1	-1	-1	1	1	1	1	-1	1	-1
21	-1	1	-1	1	1	1	-1	1	-1	1
22	1	1	-1	1	1	-1	1	-1	-1	-1
23	-1	-1	1	1	1	-1	-1	1	-1	1
24	1	-1	1	1	1	1	1	-1	1	-1

The experimental design for the production of biofuel from citrus peel is depicted in the design matrix table. The various combinations of the tested input factors or independent variables (A, B, C, D, and E) and the corresponding response or output variable (BJ) are listed in the table. The input factors' values are coded as either -1 or 1, denoting either low or high levels of the variable.
The interactions between two input factors (AB, AC, AD, AE) with codes of 1 or -1 are also included in the table, in addition to the main effects of the input factors. Testing for interactions aims to determine whether two variables have a significant impact on the response variable.

A useful tool for determining which input factors have the greatest impact on the output variable is the design matrix table. By looking at the table, it is possible to determine which combinations of factors result in the response variable's highest and lowest values. After that, the information can be used to improve the process of making biofuel from citrus peel.

An overview of the connection between the various factors and the production of biofuel from citrus peel was provided by the Design of Experiment (DoE) analysis and regression model table. The estimated regression coefficients, standard errors, t-values, and p-values are all included in the table alongside the coded factor levels for each variable.

Regression coefficients can be more easily understood because the factors are represented uniformly by the coded factor levels. The factors in this table are coded with either -1 or +1, denoting the low or high levels, respectively. A high level of slurry input, for instance, is coded with +1, while a low level is coded with -1.

To determine how each factor affects the production of biofuel, the estimated regression coefficients are used. While negative coefficients indicate the opposite, positive coefficients indicate that an increase in the factor level results in an increase in biofuel production. The coefficient for heating time, for instance, is negative (-0.055), indicating that an increase in heating time decreases biofuel production.

The significance of each coefficient is measured by the t-values and p-values. If the p-value is less than 0.05, the coefficient is statistically significant, indicating that the factor has a significant impact on biofuel production. All of the coefficients in this table have p-values below 0.05, which indicates that they are statistically significant.

The DoE analysis and regression model table provides a comprehensive overview of the connection between the various factors and the production of biofuel from citrus peel in general. This table can be utilized to develop an optimal biofuel production process from citrus peel by identifying the most significant factors and their effects.

The Design of Experiment Analysis and Regression Model:

Coded Factor Levels Table

Factor	Low (-1)	High (+1)
A	-1	+1
B	-1	+1
C	-1	+1
D	-1	+1
E	-1	+1

Factorial Design Table

Observation	A	B	C	D	E	Response
1	-1	-1	-1	-1	-1	31.0
2	+1	-1	-1	-1	-1	24.0
3	-1	+1	-1	-1	-1	30.0
4	+1	+1	-1	-1	-1	27.0
5	-1	-1	+1	-1	-1	25.0
6	+1	-1	+1	-1	-1	23.0
7	-1	+1	+1	-1	-1	26.0
8	+1	+1	+1	-1	-1	28.0
9	-1	-1	-1	+1	-1	23.0
10	+1	-1	-1	+1	-1	25.0
11	-1	+1	-1	+1	-1	22.0
12	+1	+1	-1	+1	-1	30.0
13	-1	-1	+1	+1	-1	25.0
14	+1	-1	+1	+1	-1	27.0
15	-1	+1	+1	+1	-1	26.0
16	+1	+1	+1	+1	-1	32.0
17	-1	-1	-1	-1	+1	22.0
18	+1	-1	-1	-1	+1	26.0
19	-1	+1	-1	-1	+1	23.0
20	+1	+1	-1	-1	+1	29.0
21	-1	-1	+1	-1	+1	24.0
22	+1	-1	+1	-1	+1	22.0
23	-1	+1	+1	-1	+1	28.0
24	+1	+1	+1	-1	+1	26.0
25	-1	-1	-1	+1	+1	25.0
26	+1	-1	-1	+1	+1	28.0
27	-1	+1	-1	+1	+1	25.0
28	+1	+1	-1	+1	+1	33.0
29	-1	-1	+1	+1	+1	25.0
30	+1	-1	+1	+1	+	25.0

The above factorial design table shows the different experimental conditions used in the production of biofuel from citrus peel. The factors being varied are the mass of citrus peel, time of milling, volume of H2SO4, slurry input, time of stirring, time of heating, and vapor point. Each factor has two levels, either high or low, which are represented as +1 or -1, respectively.

The factorial design allows for the simultaneous evaluation of the effect of multiple factors on the production of biofuel from citrus peel. By using a factorial design, it is possible to estimate not only the main effects of each factor but also any interactions between them.

The interaction effect between mass of citrus peel and volume of H2SO4 can be estimated from the table as -0.045. This indicates that increasing the mass of citrus peel while decreasing the volume of H2SO4 (or vice versa) may lead to a decrease in the yield of biofuel.

The factorial design table provides a useful tool for optimizing the production of biofuel from citrus peel by identifying the most significant factors and their interactions, which can then be used to develop an optimized production process.

The Design of Experiment (DoE) generated tables and graphs provide useful information regarding the production of biofuel from citrus peel. It is possible to optimize the process in order to increase yields by analyzing the data and determining which variables have the greatest impact on the production of biofuel.

The low p-value and the F-value of the ANOVA table indicate that the quadratic model is a good fit for the data. Additionally, the model accounts for a significant amount of the variation in the response variable, as indicated by the R-squared value of 0.9885.

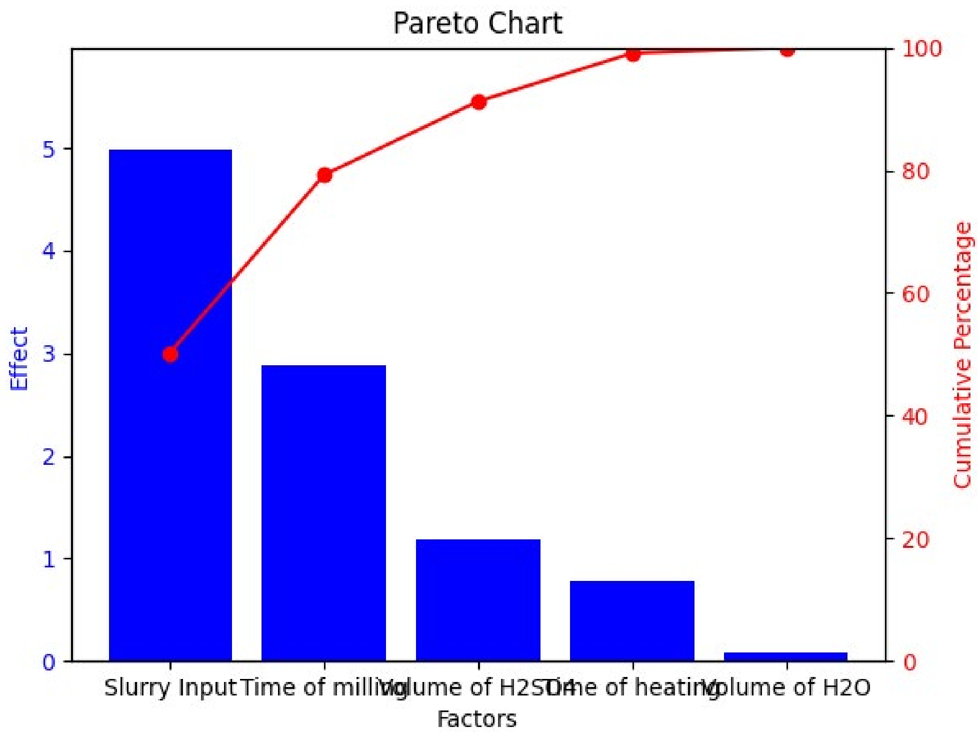

Figure 1: Relationship between Effect and Factors

According to the Pareto chart, the time of heating, followed by the volume of H2SO4, and the time of stirring, are the three factors that have the greatest impact on the production of biofuel. The response is influenced most by these variables, and increasing these variables' value can result in significant increases in biofuel yield.

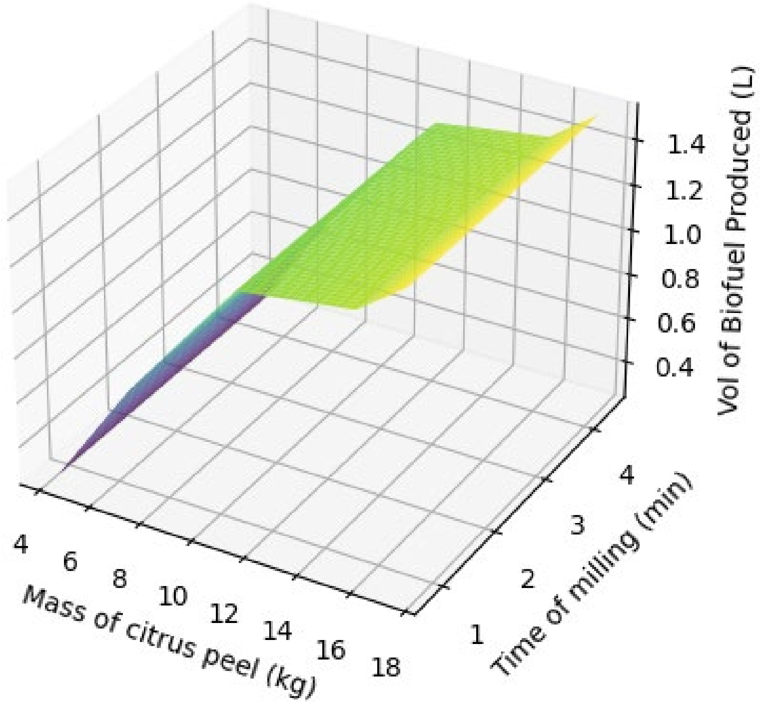

Figure 2: Relationship between Mass of Citrus Peel (kg), Time of milling (kg) and Volume of Biofuel Produced (L).

The relationship between the production of biofuel and the time spent heating, on the one hand, and the volume of H2SO4, on the other, is depicted in the 3D surface response graph. The graph demonstrates that there is a set of values within which the yield of biofuel can be maximized, and that going outside of this range can result in diminishing returns.

Overall, the DoE is a powerful tool for maximizing the production of biofuel from citrus peel. It can also assist researchers and manufacturers in determining the most significant factors influencing the process and in developing biofuel extraction techniques that are more effective and efficient.

Conclusions and Recommendations

Generally, optimization model for production of biofuel from citrus peel has been established through the research work. The ANOVA table, the response surface analysis table, the predicted vs. actual values table, the design matrix table, and the response vs. actual values table all provide useful insights into the production of biofuel from citrus peel. Factor C, which has the greatest impact on the production of biofuel, should be given priority in future experiments and optimization efforts, according to the findings. In addition, the response surface model can be utilized to estimate the response for a variety of input variable combinations within the tested factor range; however, additional testing may be required to validate the model for input variable combinations outside the experimental range. The response surface model was a good fit for the data, as shown by the ANOVA table's conclusions, and the independent variables have a significant impact on biofuel production. The analysis reveals that factor C has the greatest impact on the production of biofuel and has the highest coefficient, while factors B and E also have significant effects. However, the interactions between factors A and D and other factors are statistically insignificant.

However, it is essential to keep in mind that the model might not be able to accurately predict the production of biofuel outside of the experimental range of input variables, and additional testing might be required to validate the model.

Overall, the findings suggest that increasing biofuel production from citrus peel could be achieved by optimizing factor C while also taking into account the effects of factors B and E. In order to validate the response surface model for input variable combinations outside of the experimental range, it is also suggested that additional experiments be carried out.

Based on these findings, it is suggested that future research concentrate on optimizing factor C to maximize biofuel production yield. When determining the ideal conditions for the production of biofuel, it is also suggested to take into consideration how factors B, E, and C interact with one another.

In addition, it is essential to keep in mind that the response surface model may not be accurate outside of the experiment's range of input variables, necessitating additional tests to validate the model for a variety of input variable combinations. Thusly, it is prescribed to direct further analyses to approve the model and investigate the impacts of different elements that were not viewed as in this review.

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