RESEARCH ARTICLE

Optimization of sugar production from Durian seeds via alkaline hydrolysis for second-generation bioethanol production

Theofany Harley Chriswardana1,*, Yheni Mulyaningsih1, Yhana Mulyaningsih1, Aditiya Harjon Bahar1 and Teuku Meurah Indra Riayatsyah2,*

1Mechanical Engineering Department, Faculty of Engineering and Technology, Sampoerna University, Jl. Raya Pasar Minggu, Kav. 16, Jakarta, 12780, Indonesia
2Mechanical Engineering Department, Institut Teknologi Sumatera, Lampung, 35365, Indonesia

*Corresponding author. E-mail: theofany.harley@gmail.com

Abstract

As one way to eliminate the issues found in the preceding generation, feedstock exploration in second-generation bioethanol production remains an issue, especially for a tropical country such as Indonesia. From exotic fruit by-products, durian holds a promising perspective that rests on its abundance, superb carbohydrate content and limited usage until now. This work presents the first-ever utilization of durian seeds for sugar production under optimized conditions through alkaline hydrolysis. A simple form of sugar was extracted by varying four parameters, namely substrate loading, NaOH concentration, hydrolysis time and hydrolysis temperature. Response surface methodology based on the Box-Behnken design was employed to outline the most optimum parameter values. Analysis of variance revealed that the quadratic model fit the data appropriately with the order of significance as substrate loading > hydrolysis time > NaOH concentration > hydrolysis temperature. The optimized conditions for reducing sugar yield, as high as 2.140 g/L, corresponded to <50 g/L substrate loading, 0.522 M NaOH, 60 minutes of hydrolysis time and 80°C hydrolysis temperature. The possible ethanol content of 1.094 g/L was also expected under optimized conditions, demonstrating great potential in second-generation bioethanol production.
Graphical Abstract

Keywords: second-generation bioethanol; durian seeds; alkaline hydrolysis; optimization; response surface methodology (RSM); Box-Behnken design (BBD); reducing sugar; ethanol content

Introduction
To date, central sectors, such as industrial plants and transportation, continue to be at the forefront of energy consumption, as they have been for decades. That fact unfortunately supports the worrying contexts that propel the energy crisis to the next level. At the same time, discharged emission (e.g. CO₂) is inevitable; therefore, more trapped gas in the atmosphere is ensured in accelerating global warming [1, 2]. It is then clear that alternative energy that promotes the ‘renewability and clean’ concept is at the urgent phase. In the search for renewable and clean energy, bioethanol, the most-produced biofuel, has been at the top of the list. Aside from its shorter carbon chain that promotes lower emission, its use is also supported by more favourable combustion characteristics including a high octane number, short ignition timing, enhanced flame speed, etc. compared with its counterparts [3, 4].

The first generation of bioethanol mostly uses edible crops (e.g. corn, cassava, potato) [5, 6]. However, a major issue regarding the world’s food security has been raised, since land areas are expected to be used for bioethanol production rather than for meeting the global primary need for food, especially for low- and middle-income countries. Massive fertilizer and pesticide pollution was also concerning [7, 8]. Crossing out those listed issues, second-generation bioethanol rests on lignocellulosic, non-edible feedstocks. Moreover, second-generation feedstock is composed of carbohydrate that is convertible into fermentable sugar—basically the bioethanol precursor [9–11].

Located in the tropical region, Indonesia has countless possible options for feedstock that especially derive from exotic fruits. Durian has been favoured by many throughout the years, increasing in annual production. In 2017 alone, durian production was 795,211 tons with an 8.13% growth rate from the preceding year [9]. Previous study has reported that only 30% of the whole fruit is consumable, leaving 70% of it as waste (20–25% is in the form of seed and another 75% is in the form of the shell). In durian seeds, at least 95% of the kernel (peeled, inner part of the seed) is present [9, 12]. That being said, ~132,203 tons of kernel seed are discharged.

The chemical components of durian seeds are summarized in Table 1. It is interesting to highlight that carbohydrate is the major component of durian seeds, ranging from 43.6% to 76.80%, depending on the treatment (e.g. peeled and unpeeled form of seed) and method. Until now, innovations involving kernel powder, especially in food production, have been rather limited. Therefore, utilizing it as feedstock in second-generation bioethanol is a
tempting concept. Moreover, the carbohydrate content of durian seeds is higher than that of other Indonesian exotic fruits (i.e. sweet orange, snake fruit, papaya, jackfruit, rambutan and avocado) [13–18].

Based on the study reported by Amin and Arshad [12], peeled and unpeeled powdered durian seed affects the production of the carbohydrate content. The proximation of durian-seed content by Amin and Arshad was carried out according to the Association of Official Agricultural Chemists method and viscosity analysis [21]. Meanwhile, Mulyati et al. [20] used the physical and chemical methods of characterization, including colour, taste, and ash content; protein content; water content; fat content; and carbohydrate content [21].

The conversion of the complicated carbohydrate content in biomass into a simple sugar form (i.e. a reducing sugar) is achievable through hydrolysis. The process works by adding water molecules to separate the chain. In a series of bioethanol-production steps, the simpler sugar form is highly notable because the digestions performed by organisms in the fermentation stage cannot be used for complex sugars. The quality of the hydrolysed biomass, known as the hydrolysate, therefore is important in realizing ethanol content. Previous studies have used durian seeds with different hydrolysis approaches [22]. Purnomo et al. [23] proposed catalyst-free subcritical water hydrolysis under various temperatures, times, pressures and solid-to-water ratios. The method requires a very high temperature and sealed reactor with a continuous nitrogen supply. Meanwhile, Sebayang et al. [24] used enzymatic hydrolysis. Those two methods need particular equipment and, with enzymes, higher costs are estimated in the production process. Alkaline hydrolysis removes the aforementioned limitations and has been widely used in bioethanol production. Moreover, the use of alkaline hydrolysis disintegrates lignocellulosic matrix that would eventually improve the quality of the hydrolysate through the release of sugar [25].

The strategy of using alkaline hydrolysis would be made more efficient and effective by understanding the parameters influencing the reducing-sugar yield for bioethanol production. With that in mind, optimization is very essential. Through optimization study, the production efficiency can be improved significantly, which can be further utilized in determining the feasibility of the end product in the commercial market [26, 27]. Response surface methodology (RSM) is one commonly used method owing to its capability of identifying the response of the desired output by generating restricted experimental numbers. RSM has been employed in the optimization studies of various biofuels [28–32]. Moreover, this method aids in improving the efficiency of thorough biofuel production in terms of the workload, operation time and operating cost [33, 34]. Among RSM types, the Box-Behnken design (BBD) has been deemed as efficient in avoiding redundant combinations [35, 36]. Fig. 1 illustrates the BBD method and shows distributed dots representing the number of experimental runs. The design presents the middle points of every edge and the central point, excluding the extremes, and points at each corner of the box, which hence allows
the generation of an experimental design that enables the user to self-formulate a lower number of experiments \((N)\), as governed by Equation 1:

\[
N = 2k (k - 1) + C_0
\]

where \(k\) is the number of set variables of factors and \(C_0\) is the central-point total. The efficiency improvement by BBD is also due to its principle of not including the data points at the limits of the ranges, and this suggests the mitigation of experiments under such extreme practical conditions [37].

Bioethanol production as an alternative fuel in Indonesia has been initiated by several companies in order to reduce gas emissions to protect against environmental impacts, such as polar melting and UV radiation. The production process uses a variety of feedstocks starting from the first to third generations (e.g. corn, sugarcane, algae, etc.) with a different method of treatment (e.g. alkaline hydrolysis, high pressurizing, microwave irradiation and acidic hydrolysis, etc.) [39–41]. However, the use of durian-seed starch with alkaline hydrolysis seems still sparse.

The objective of this study was to optimize the important parameters in alkaline hydrolysis (substrate loading, alkaline concentration, hydrolysis time and hydrolysis temperature) for durian seeds in second-generation bioethanol production. As the combination of used feedstock and method has not been settled yet, this study serves as the first-ever report. This provides a notion and offers critical baseline information for further research, development and implementation in the industry.

1 Materials and method

In this study, RSM based on the BBD method was employed to formulate the design of the experiment (DoE). All the generated numbers of runs from the DoE were then brought into the hydrolysis stage. The reducing-sugar values from the hydrolysis stage were then fitted using analysis of variance (ANOVA) followed by optimization and calculation of the ethanol content. The schematic of the whole process is summarized in Fig. 2 and each detail is presented as follows.

1.1 Durian-seed pretreatment preparation for alkali hydrolysis

Durian seeds were gathered from the local durian stalls in Lumajang, East Java, Indonesia. The durian seeds were cleaned and peeled in order to remove any dirt on the skin, leaving the inner part only. Next, using an oven, the seeds were dried at 120°C for 8 hours to eliminate the moisture content. As for the mechanical pretreatment, the dried seeds were crushed and ground into powder using a pestle and mortar. To maintain the consistency of the particle sizes, the powder was sieved using a filter size of 850 \(\mu\)m.

1.2 Alkaline hydrolysis

The alkaline reagent in this study was sodium hydroxide (NaOH) of analytical grade from Merck, which was directly used without further process and purification. The parameters of the hydrolysis followed the generated...
The experimental runs obtained from the DoE, as specified in the next section. The alkaline hydrolysis process of the durian seeds was started by dissolving different feedstocks (1–5 g) into a 100-mL flask of distilled water that later in this study is referred to as 10–50 g/L substrate loading. Next, NaOH pellets were added into the solution at a concentration of 0.5–1.5 M. Then, the solutions containing feedstock and NaOH were treated in a 40-kHz frequency ultrasonic instrument for 5 minutes. After the sonication process, the mixture was put into a water bath for the heating process and treated at temperatures of 30°C, 60°C and 90°C for respective durations of 30, 60 and 90 minutes. The mixture product of the hydrolysis process or so-called hydrolysate was next centrifuged at 4000 r.p.m. for 15 minutes to separate the solid residue. To obtain accurate and precise results in the sugar assay, the triplicate experiment method was applied. This is essential to validate the empirical data of the observed value and identify any measurement that falls outside the expected data range.

1.3 RSM based on the BBD of hydrolysis parameters

The experiment was started with the formulation of the DoE using Stat-Ease Design Expert 10 software. The range for each operating parameter that defines the hydrolysis (i.e. substrate loading, NaOH concentration, hydrolysis time, hydrolysis temperature) was set according to Table 2. There were four experimental parameters in this study. Due to the abundance of tropical waste in Indonesia, powdered durian seeds were chosen as the feedstock at an amount of 10–50 g/L. Alkaline hydrolysis using NaOH was selected as the chemical pretreatment method due to its advantage of high digestibility and high fermentation efficiency of 0.5–1.5 M [42]. In order to accelerate the hydrolysis process, the respective time and temperature shown in Table 2 were applied using a water-bath instrument. The selected range of hydrolysis parameters was used to find the correlation with the BBD experiment. This correlation then was observed using statistical method software called Stat-Ease Design Expert.

After setting up the range and level for the hydrolysis parameters, there were 29 runs that were brought to the hydrolysis stage to yield reducing sugar. The reducing-sugar analysis in this study is explained further in Section 1.5. Then, the reducing-sugar data from the experiment were examined using regression analysis directly by ANOVA using Stat-Ease Design Expert 10 software to define the characteristics of the model. The response model of the reducing-sugar concentration was fitted according to Equation 2:

$$\gamma_{RS} = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \beta_{ii} x_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \beta_{ij} x_i x_j$$

(2)

where $\gamma_{RS}$ is the reducing-sugar concentration (g/L) as its response, $\beta_0$ is the coefficient of interception, $\beta_i$ is the linear coefficient, $\beta_{ii}$ is the quadratic coefficient, $\beta_{ij}$ is the coefficient of interaction, $x_i$ is the first parameter and $x_j$ is the second parameter.

1.4 Optimization method

After the reducing-sugar concentration for all samples was obtained, an optimization scheme was applied to achieve the optimum condition that would give benefit in terms of time and cost, and it was carried out using Stat-Ease Design Expert 10 software. With the four parameters that were applied in this experiment, the optimization method was aimed at finding the optimum conditions and the method was chosen owing to its low time-consuming advantage [34]. The adjustment of each parameter in the optimization process of this study is presented in Table 3. Both the substrate-loading and reducing-sugar-concentration parameters were set to be maximized. Maximizing the substrate loading was mainly reasoned due to the abundance of tropical waste sources in Indonesia while optimizing the reducing-sugar concentration was the interest of this study. To lower the cost of production, the NaOH concentration was set to be minimized. Meanwhile, the hydrolysis time and temperature were selected based on the instrument limitations. Faithful Thermostatic Water Bath apparatus was used to perform the hydrolysis process. The temperature range was between 5°C and 100°C, where 80°C was selected as the optimized temperature for durian-seed hydrolysate. The value was chosen to avoid boiling, since the highest range in this study was 90°C. Tolerance of the instrument value should be included to obtain results.

1.5 Reducing-sugar and ethanol analysis

The dinitrosalicylic acid (DNS) method was employed in this experiment to measure the reducing-sugar concentration of the hydrolysate [30]. A suitable wavelength of 540 nm was selected to analyse the reducing-sugar concentration using a UV–Vis spectrophotometer (OPTIMA SP-3000 Nano) with a tolerance of ±0.005 Abs.

In this study, the ethanol content of the feedstock was measured theoretically by multiplying the obtained optimized reducing-sugar concentration by 0.511. The value represents the maximum ethanol yield per unit of glucose,
Table 3: Hydrolysis numerical optimization set-up

| Parameters            | Goal       | Importance | Range | Range |
|-----------------------|------------|------------|-------|-------|
| Substrate loading     | Maximize   | *****      | 10    | 50    |
| NaOH concentration    | Minimize   | *****      | 0.5   | 1.5   |
| Hydrolysis time       | In range   | ***        | 30    | 60    |
| Hydrolysis temperature| Equal to   | ***        | 80    |       |
| Reducing-sugar concen. | Maximize   | *****      | 0.347 | 2.943 |

**** = most important to * = least important.

also known as the ethanol conversion factor [31–33]. The value was obtained by following the method of Galuti et al. [43] with several adjustments and assumptions, which included the carbohydrate content of the durian seed being assumed to be equal to that of the corn starch used as the original feedstock in the reference. The authors considered the moisture content, starch fraction, conversion glucose from starch theoretically (1.111 kg glucose/kg starch), conversion ethanol from glucose in fermentation theoretically (0.511 kg ethanol/kg glucose) and average ethanol density (0.789 kg/L).

2 Results and discussions

2.1 Box-Behnken optimization of the hydrolysis parameter

The BBD results from both experiments and predictions are summarized in Supplementary Data Table S1 (in the online Supplementary Data). Meanwhile, the ANOVA results are presented in Supplementary Table S2 (in the online Supplementary Data). It is revealed that a model significance, which, according to Das et al. [45] and Ruangmee and Sangwichien [46], presents validity of the quadratic model in fitting the data. The second-order equation for the reducing sugar derived on the basis of Equation 3 is written as follows:

\[
\gamma_{RS} = 1.73 + 1.02X_1 + 0.23X_2 + 0.30X_3 + 0.20X_4 + 0.21X_1X_2 + 0.20X_1X_3 + 0.24X_1X_4 - 0.11X_2X_3 + 0.23X_2X_4 + 0.01X_3X_4 - 0.11X_1^2 - 0.15X_2^2 - 0.27X_3^2 - 0.19X_4^2
\]  

(3)

where \( \gamma_{RS} \) is the reducing-sugar concentration (g/L), \( X_1 \) is the substrate loading (g/L), \( X_2 \) is the NaOH concentration (M), \( X_3 \) is the hydrolysis time (minutes) and \( X_4 \) is the hydrolysis temperature (°C). The relative interaction between the parameters can be determined by its coefficient in Equation 3, in which substrate loading is shown to be the most significant influence parameter. Both positive and negative values of the regression coefficient were obtained, as seen from the equation. This denotes both synergetic and antagonistic effects towards the response (i.e. reducing sugar) [47]. Moreover, in order to check the significance of the variable, the P-value was evaluated. On the P-value, all the variables \( X_1, X_2, X_3, \) and \( X_4 \) at both the linear and quadratic levels were found to be significant, since \( P < 0.01 \), whereas, at the interactive level, \( X_1X_3 \) and \( X_2X_4 \) were insignificant, with \( P > 0.01 \).

An experimental uncertainty study is essential to evaluate the error from the obtained results of the experiment. Errors and uncertainties are naturally occurring due to the laboratory environment, measurement readings, instrument calibration and the selection of instruments, which cause certain risks and errors [48]. The uncertainty formula is shown in Equation 4 as follows:

\[
(u) = \sqrt{\frac{\sum (x_i - \mu)^2}{n^2 - n}}
\]

(4)

where \( u \) is uncertainty value, \( x_i \) is \( i \)th reading value, \( \mu \) is the mean of the data set and \( n \) is the number of readings in the data set. In this study, the triplicate method of data experimentation is used in order to produce an accurate and precise result. By following Equation 4, the results of the reducing-sugar experiment has an uncertainty value of <0.057 g/L, or <2% of all of the experimental data set. This value shows good agreement while the experiment occurs.

According to Guan and Yao [49], for the model to realize a good fit, a coefficient of determination or \( R^2 \) of ≥0.80 must be achieved. The \( R^2 \) in this case was found to be 0.9916, which essentially fulfils this condition. Moreover, the relevance of the model and the experiment is 99.16% with 0.84% of total variance, which is not described by the model. So, the relative error of regression analysis shown in the graph is only 0.84%, which indicates the good fit between predicted and experimental. This was further confirmed by the adjusted \( R^2 \) with a value of 0.9832, which also implies model significance (as illustrated in Fig. 3, where data points lie on the regression line), and thus the model is suitable for predicting the optimization. For the coefficient of variation or C.V., Sen et al. [50] explain that a small value justifies the degree of precision and reliability where, in this study, a low value of 6.94% was obtained from the model, thus showing good precision and reliability.
2.2 Relationship between independent parameters

Substrate loading, NaOH molarity, hydrolysis time and hydrolysis temperature are known as the operating parameters in this study. During the hydrolysis process, the four operating parameters were set into variations to determine the relationship among the parameters towards the reducing-sugar concentration. The result of the hydrolysis process was then processed using the Stat-Ease Design Expert Software to generate a 3D response surface, as shown in Fig. 4.

2.2.1 Effect of substrate loading

Fig. 4a, depicting the reducing sugar that resulted from the interaction of the substrate loading and the NaOH concentration, shows that a dramatic increase in the reducing sugar accompanies an increase in both individual parameters. Likewise, Fig. 4c and d represent the substrate loading–hydrolysis time and substrate loading–hydrolysis temperature towards the reducing sugar and show synergetic behaviour between the employed parameters, proven by the in-line increment. As for the individual terms, substrate loading has the most superior effect, excelling over the other hydrolysis parameters (i.e. NaOH concentration, hydrolysis time and hydrolysis temperature).

The effect of the addition of substrate loading on the reducing-sugar concentration is also confirmed by typical studies [39, 51, 52]. The result of the studies asserts that glucose concentration increases proportionally with an increase in substrate loading. However, a contrary result has also been revealed by previous studies, where the efficiency of the substrate loading added was found to give an adverse trend. From the studies about bioethanol production using corn and potato-peel waste with a substrate loading of 5%, 10% and 15%, a loading of ≤10% was noted to give the highest increase in sugar-yield production [51–54]. This gives an indication that different feedstocks have a possibility to end up with different trends, and this can depend on the substrate loading.

2.2.2 Effect of NaOH concentration

Fig. 4d and e, unlike Fig. 4a, appear to show insignificant reducing-sugar concentrations. In comparison to when the NaOH concentration and substrate loading interact (Fig. 4A), the NaOH concentration and hydrolysis time produce a smaller amount of reducing sugar (Fig. 4d). Typical results also exist with the hydrolysis temperature (Fig. 4e). NaOH concentration as a single parameter also benchmarks insignificant reducing-sugar yield. The behaviour in this study is known to be relatively different from that in the study conducted by Trevorah and Othman [25], which shows that NaOH concentration added during the hydrolysis and pretreatment process was proven to enhance the reducing-sugar and ethanol yield [55]. However, it should be taken into consideration that it is possible that such an occurrence only happened in this study, considering the small concentration and relatively moderate increment used during the experiments.

2.2.3 Effect of hydrolysis time

Fig. 4b, d and f present the effect of the hydrolysis time on the reducing-sugar concentration. All in all, an increase in hydrolysis time is found to not contribute to a valuable increase in the reducing-sugar yield. This condition is in contrast with the result acknowledged from previous studies in which a longer time allocated for hydrolysis is in correlation with noticeably higher reducing-sugar harvest [56, 57]. However, under certain conditions, it has been found that an increase in the hydrolysis time does not necessarily enhance the amount of sugar produced anymore. Apriani et al. [58] observed that, from a hydrolysis variation of 30, 60, 90 and 120 minutes, the highest sugar was yielded with 90 minutes of hydrolysis time. This behaviour is also supported by a comparative study [59] of wheat straw that had been pretreated with alkali for 0.5–2.5 hours, where a time of 1.5 hours was noted to provide the highest sugar production and the efficiency started to decrease afterwards. Also, the study performed by Agustini et al. [60] revealed that the highest sugar yield was obtained by a sample with 75 minutes of hydrolysis time then followed by a sample with 105 minutes of hydrolysis time. This behaviour is also supported by a comparative study [59] of wheat straw that had been pretreated with alkali for 0.5–2.5 hours, where a time of 1.5 hours was noted to provide the highest sugar production and the efficiency started to decrease afterwards. Also, the study performed by Agustini et al. [60] revealed that the highest sugar yield was obtained by a sample with 75 minutes of hydrolysis time then followed by a sample with 105 minutes of hydrolysis time. The decrease in the hydrolysis trend might depend on a certain threshold that most likely is the limit and the reason why the result goes adversely. Moreover, under a particular condition, it is expected that longer treatment involving NaOH could possibly disrupt some portions of cellulose and hemicellulose, which leads to a lower concentration of reducing sugar being produced [59].
2.2.4 Effect of the hydrolysis temperature

The effect of the hydrolysis temperature towards reducing-sugar production is illustrated in Fig. 4c, e and f. With a temperature range of 30–90°C, the effect of the increase in hydrolysis temperature on the reducing sugar as the hydrolysis output is not significant. This behaviour is contrary to the reported study in which a prominent sugar yield was observable with an increase in the hydrolysis temperature [41]. Nonetheless, as it is further observed, the reducing-sugar content starts to increase up to a hydrolysis temperature of
60°C, then starts to decrease. This finding is similar to those of previous studies in which an increase in the hydrolysis time no longer contributes to a prominent increase in the sugar produced at some points [60–62]. The efficiency decreases instead because the structure of the reducing-sugar component might be damaged at one point [63, 64].

2.3 Optimization of the reducing-sugar concentration

The next stage after the hydrolysis process was optimization. With the optimization scenario listed in Table 3 (Section 1.4), 13 solutions were generated by the software. The solutions are listed in Table 4 along with the reducing-sugar values from the hydrolysis and the theoretical ethanol from the fermentation process.

Table 4: Reducing-sugar and theoretical ethanol concentration optimization

| No. | Substrate (g/L) | NaOH (M) | Time (minutes) | Temperature (°C) | Reducing sugar (g/L) | Theoretical ethanol (g/L) | Desirability |
|-----|----------------|----------|----------------|------------------|----------------------|--------------------------|--------------|
| 1   | 50.00          | 0.506    | 60.00          | 80.00            | 2.113                | 1.080                    | 0.878        |
| 2   | 50.00          | 0.506    | 60.00          | 80.00            | 2.112                | 1.079                    | 0.878        |
| 3   | 50.00          | 0.510    | 60.00          | 80.00            | 2.119                | 1.083                    | 0.878        |
| 4   | 50.00          | 0.500    | 60.00          | 80.00            | 2.103                | 1.075                    | 0.878        |
| 5   | 50.00          | 0.515    | 60.00          | 80.00            | 2.129                | 1.088                    | 0.878        |
| 6   | 50.00          | 0.522    | 60.00          | 80.00            | 2.140                | 1.094                    | 0.878        |
| 7   | 50.00          | 0.500    | 59.96          | 80.00            | 2.101                | 1.074                    | 0.878        |
| 8   | 50.00          | 0.551    | 60.00          | 80.00            | 2.192                | 1.120                    | 0.877        |
| 9   | 50.00          | 0.508    | 59.51          | 80.00            | 2.106                | 1.076                    | 0.876        |
| 10  | 49.87          | 0.529    | 60.00          | 80.00            | 2.148                | 1.098                    | 0.876        |
| 11  | 50.00          | 0.579    | 60.00          | 80.00            | 2.238                | 1.144                    | 0.876        |
| 12  | 49.97          | 0.529    | 59.34          | 80.00            | 2.139                | 1.093                    | 0.875        |
| 13  | 49.78          | 0.517    | 60.00          | 80.00            | 2.125                | 1.089                    | 0.875        |

High desirability values were acquired for all the solutions, where the first seven were found to be 87.8%. Among them, solution 6 is noted to be the optimum condition with the highest possible reducing-sugar and ethanol concentration produced. From the solution, reducing sugar of 2.140 g/L was expected to be yielded under 50 g/L of substrate loading, 0.522 M NaOH concentration, 60 minutes of hydrolysis time and 80°C hydrolysis temperature.

The basic idea of desirability is the mathematical transformation to create a single response to the problem after creating the regression model to optimize the hydrolysis process [65]. The desirability function approach (DFA) is used to solve the statistical multi-parameter problems and optimize the result in terms of the range from 0 to 1 (0–100%), in which value 0 indicates that the response lies outside the desirability confines whereas 1 shows the ideal...
case [65–67]. Thus, in this study, the highest desirability and the highest reducing-sugar production are favourable to be the objectives, located at solution number 6. The DFA of the hydrolysis parameter is shown in Fig. 5 with its corresponding reducing-sugar production.

As shown in Fig. 5, the significant effect on producing the reducing sugar is validated by the substrate-loading parameter, while the insignificant effect occurs for the hydrolysis temperature parameter. The NaOH molarity parameter has higher reducing-sugar production at the higher concentration but, in order to minimize the bioethanol production cost, the goal of this parameter is set to be minimized, as explained in Table 3. The hydrolysis time has a range between 30 and 60 minutes, where the highest desirability is at 60 minutes. The selected time range is aimed to achieve the time-efficiency of the bioethanol production.

2.4 Theoretical ethanol concentration

In this study, the ethanol content was calculated theoretically, as detailed previously in Section 1.5. As a result, from Table 4, a theoretical ethanol concentration of 1.094 g/L was found to be the highest value when the numerical optimization was applied. In practice, the theoretical ethanol value obtained in this study can be used as a benchmark when the fermentation stage is carried out. Compared with the study of Mofijur et al. [68] using the feedstock of empty fruit bunches of palm oil, this study resulted in a 13-times higher production of reducing sugar. Although the previous research found that, at the experimental level, only 87–95% of the theoretical ethanol yield is harvested [69], the estimated ethanol production in this study indicates that the durian seeds as the second-generation feedstock have great potential in bioethanol production among other second-generation feedstocks.

3 Conclusion

The hydrolysis process of durian seeds using an alkaline reagent has been optimized by using the RSM with a BBD chosen as the experimental design. With the working parameter of the hydrolysis process applied (10–50 g/L of substrate loading, 0.5–1.5 NaOH concentration, 30–90 minutes of hydrolysis time and 30–90°C hydrolysis temperature), the 29 experimental data points were generated and the experiment was conducted to achieve the reducing-sugar content of the selected feedstock. The quadratic model from the ANOVA was found to be well fitted and adequate to determine the relationship of each parameter to the reducing-sugar production with the sequence of the most affecting variable as substrate loading > hydrolysis time > NaOH concentration > hydrolysis temperature. The model was thus used for the optimization process. From the numerical optimization, the optimum condition is: 50 g/L substrate loading, 0.522 M NaOH concentration, 60 minutes of hydrolysis and 80°C hydrolysis temperature, resulting in a respective reducing-sugar concentration and theoretical ethanol content of 2.140 and 1.094 g/L.

In this present study, the next steps such as batch fermentation and ethanol assay should be performed to confirm the ethanol content of the feedstock that was computed theoretically. Other than that, knowing the potential of durian seeds as suitable feedstock, it is believed that there are many procedural possibilities throughout the experiment and a different experimental set-up and method may result in different possible outputs. Moreover, extensive work is required to further investigate the economic feasibility of durian seeds as feedstock in the biofuel sector. Future improvement will focus on the study of energy-efficient and cost-effective methods for production, study on the high-yield extraction method and study on the existing technologies to increase productivity. The improvement in studies will provide a more comprehensive discussion as a guideline to address the technical challenge. Regardless of all the challenges in bioethanol production, the results show convincingly that bioethanol has a promising position in the sustainable energy resources market, considering the declining supplies of fossil fuels and the demand for clean energy sources.

Supplementary data

Supplementary data is available at Clean Energy online.

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Conflict of Interest

None declared.

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