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Optimization of Sugarcane Bagasse Conversion Technologies Using Process Network Synthesis Coupled with Machine Learning

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ABSTRACT

Sugarcane bagasse is a commonly generated item from the food industry in the world—the amount of sugarcane bagasse production is increasing yearly. In 2017, the reported sugarcane production in Malaysia was 30,000 kg, which resulted in 9,800 kg of sugarcane bagasse. Sugarcane bagasse produces steam as waste management in Malaysia or simply in landfills. This study aims to optimize sugarcane bagasse conversion technologies using process network synthesis. A superstructure of sugarcane bagasse was created via P-Graph, with multiple pathways or processes being considered. Data needed for the sustainability assessment of each pathway was acquired from various journal sources, including conversion fraction, operating and capital cost, greenhouse gas emission, and the selling price of products were implemented into the superstructure. Then, the data from the feasible structure generated would be analyzed using machine learning via Waikato Environment for Knowledge Analysis software. The data sets were analyzed using this software using the selected algorithm as P-graph developed 17 feasible solution structures. All 17 generated solution structures were analyzed using six different classifier algorithms. The multilayer perceptron algorithm had the best and the least error in classifying the data. Hence, the multilayer perceptron algorithm proved that the correlation between products produced from sugarcane bagasse and the profitability of the process was significant. Therefore, the model can be a basis for determining the best process for sugarcane bagasse conversion technologies.

Keywords: Biomass conversion technologies, machine learning, process network synthesis, sugarcane bagasse

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INTRODUCTION

Saccharum officinarum L., or sugarcane, is a perennial grass that becomes the main source producing sugar for beverages and food. In this industry, the major by-product of sugarcane is bagasse (Sindhu et al., 2016). Bagasse is produced from the extraction or milling process, generating roughly 32 dry weights % from a ton of sugarcane (Ameram et al., 2019). Conversion technologies are the main pillar in accomplishing a zero-waste goal (Lee et al., 2020). Besides reducing greenhouse gas emissions, they also create a beneficial product. Conversion technologies can be categorized into four main conversion types, which will be the focal point here. Firstly, a thermal treatment with air without energy valorization converts waste into gaseous liquid and solid (Puna & Teresa, 2010). The most common thermal conversion technology currently used is burning sugarcane bagasse as fuel for the boiler. Besides, biochemical conversion comprises using yeast and/or specialized bacteria to produce useful energy by converting biomass or waste (Baker, 2018). The conversion of sugarcane bagasse via anaerobic digestion is considered an encouraging plan since the by-product of the process, digestate could be used as fertilizer, and the product from the fermentation, biogas, could be sold as a bio-methane gas by the sugarcane plants (Janke et al., 2015). In this biomass conversion technology, chemicals transform waste into valuable products (Baker, 2018). The process involves but is not limited to pyrolysis, depolymerization, hydrolysis, or gasification. The final type of conversion technology is physical or mechanical conversion. The complex lignocellulosic properties of sugarcane bagasse made them suitable for carbon sources for fungal cultures (Sidana & Farooq, 2014).

Many existing conversion technologies for sugarcane bagasse have advantages and disadvantages. Many research papers on viable sugarcane bagasse conversion technologies have been published. However, at the moment, there is a minimal study on the performance of conversion technologies for sugarcane bagasse to be placed in Malaysia. The sugarcane bagasse conversion technologies are not developing as projected, even though having several critical information regarding the sugarcane bagasse (Monteiro et al., 2016). Besides, the high initial capital investment and long payback period carry a significant financial risk, which caused investors to be skeptical about venturing into sugarcane bagasse management (Bufoni et al., 2016). Thus, optimizing sugarcane bagasse conversion technologies is vital by utilizing process network synthesis to compute the most optimal pathway.

Process network synthesis involves an algorithm to be followed in other problem-solving operations (Friedler et al., 1992). In solving the process network synthesis efficiently and rigorously, the P-graph framework provides a mathematical approach for solving process synthesis problems and analyzing the resultant flowsheets with the aid of the built-in optimizer (Bertok & Heckl, 2016). The P-graph includes selecting and sizing processing chemical plant predefined parameters such as raw material, operating unit, and conversion rate (Cabezas et al., 2015). The P-graph method offers advantages such as adding a graphical interface, efficient algorithms, and optimal results (Varbanov et al., 2017). Machine learning is an application of artificial intelligence that uses intelligent software to enable machines to conduct their employment competently (Witten et al., 2017). Data mining is widely used in machine learning to discover knowledge (Negnevitsky, 2011). Data mining is a computer science subdomain that can execute an implicit extraction from databases. A set of algorithms have been designed to discover a pattern of knowledge (Kulkarni & Kulkarni, 2016). However, the classification process, which includes rules to separate raw data into a predefined class, has become a significant issue (Naik & Samant, 2016).

This study applied the P-graph model to optimize sugarcane bagasse conversion technologies in Malaysia. As a result, the optimal technology to manage sugarcane bagasse was selected. Waikato Environment for Knowledge Analysis (WEKA) offers a platform of an established learning algorithm that can be easily applied to the dataset. P-graph and WEKA applications for sugarcane bagasse conversion technologies are still limited. Most P-graph cases involved crops such as rice husks and palm oil biomass (Sangalang et al., 2021; Tin et al., 2017). The integration of P-graph and WEKA was introduced for the municipal solid waste management case study (Ali et al., 2021). Therefore, this study aimed to provide an integrated framework to increase the decision-making tool's efficiency for sugarcane bagasse conversion technologies. Hence in this paper, the focus was shifted to several of the latest available conversion technologies. These were analyzed using a process network synthesis and machine learning framework in determining the most feasible optimum and systematic pathways.

MATERIALS AND METHODS

General Framework

Figure 1 shows the steps for generating a feasible process flow diagram for sugarcane bagasse conversion technologies. This raw material will be converted into the intermediate and final product via network synthesis through four conversion types: biological, chemical, mechanical, and thermal. These conversion technologies were selected based on technologies commonly found to convert biomass. Working with process network synthesis requires data collection for conversion technologies' efficiency and capital and operating expenditure. Common conversion technologies help to design a complete process flow for the superstructure. The sugarcane bagasse undergoes anaerobic digestion to produce biogas and bioethanol for the biological pathway. Also, the mechanical or physical conversion would grind the raw material into smaller sizes to produce brick supplement, fungal culture, and multi-armor composite.

On the other hand, thermal conversion has an intermediate product, high-pressure steam, for electricity generation and other uses at the plant. The intermediate product of this process is ash from the burned sugarcane bagasse. This intermediate product will be further mechanically processed to produce supplementary cement. This research study uses a P-graph model to analyze sugarcane bagasse conversion technologies' economic performance and environmental impact. It evaluated the selected and optimized pathway of sugarcane bagasse conversion technologies.

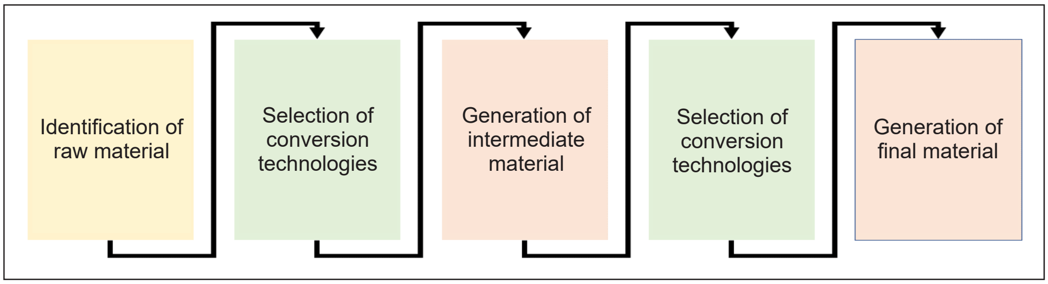

Figure 1. Process flow diagram for generation of sugarcane bagasse conversion technologies

Methodology for Process Network Synthesis

Identification of Materials and Streams. In this study, there is only one process feedstock. There are ten types of output or products along with their intermediate product. Table 1 shows the list of raw materials, intermediate products, and outputs of the process.

Table 1
List of material considered in this study

No	Symbols	P-Graph Classification	Description
1	SCB	Raw Material	Sugarcane Bagasse
2	COM_GAS	Intermediate Product	Combustible gas from the burning of sugarcane bagasse in an incinerator
3	Biochar	Output	Biochar
4	SCBA	Intermediate Product	Sugarcane bagasse ash, a by-product from the incineration of raw material
5	ETOH	Output	Bio-ethanol from fermentation
6	Electricity	Output	Electricity generated
7	Heat	Output	Heat generated
8	Methane	Intermediate product	Methane from an anaerobic digester
9	Digestate	Intermediate product	A by-product from the fermentation process
10	Grinded_SCB	Output	Ground sugarcane bagasse by using a grinder
11	Liquid_Fertilizer	Output	Fertilizer in a liquid state that is produced from digestate after treatment
12	Solid_Fertilizer	Output	Fertilizer in solid-state that is produced from digestate after treatment
13	GHG_Emission	Output	Greenhouse gases emission from conversion technologies

Note. Two inputs need to be inserted into the p-graph model: price and flow rate of the material and product.

Identification of Operating Units. For this case study, 11 operating units are included in the flowsheet-generation problem, as shown in Table 2, to be solved algorithmically with P-graphs.

Table 2
List of operating units considered in this study

No	Symbols	Description
1	COMBUSTION	Incinerator for sugarcane bagasse
2	BOILER	Boiler for the generation of heat and electricity.
3	AD	Anaerobic digester.
4	GAS_TURBINE	Turbine for the generation of heat and electricity.
5	F_D_ACID	Fermentation with dilute acid pre-treatment.
6	F_D_ALKALINE	Fermentation with dilute alkaline pre-treatment.
7	F_HW	Fermentation with hot water pre-treatment.
8	F_SE	Fermentation with steam explosion pre-treatment.
9	AD	Anaerobic digestion.
10	GASIFICATION	The gasifying process generates heat and electricity
11	GRINDER	Grinding machine that makes the sugarcane bagasse into smaller sizes.
12	Pre-treatment	Treatment for digestate to produce fertilizers.
13	Landfilling	Landfilling for waste

Note. Two inputs need to be inserted into the p-graph model: price and conversion to the material's product.

Maximal Superstructure and Solution Structure Generation. The maximal structure generation (MSG) and solution structure (SSG) algorithms execute the P-graph task. As aforementioned, MSG creates a union of all feasible solution structures, whereas SSG identifies the maximum combinatorically feasible solution structures while eliminating the unfeasible solutions from the results. Besides, SSG also allows the determination of an optimal structure for each feasible network. The generation of MSG and SSG ensures the network's consistency. Major processes and operating units are labeled in the superstructure. Overall performance data, such as conversion yield, are incorporated into the process and cluster operations.

Optimization of Superstructure. The SSG algorithm's generated result is selected using an accelerated branch-and-bound (ABB) algorithm to design an optimum process network where information such as flow rates and costs are added. As a result, the optimum feasible solution which provides the best and near-optimum is selected. The feasible solutions are further evaluated based on their environmental impact and economic performance. In this research, 2 cases are being considered: the design for maximum economic performance and minimal environmental impact.

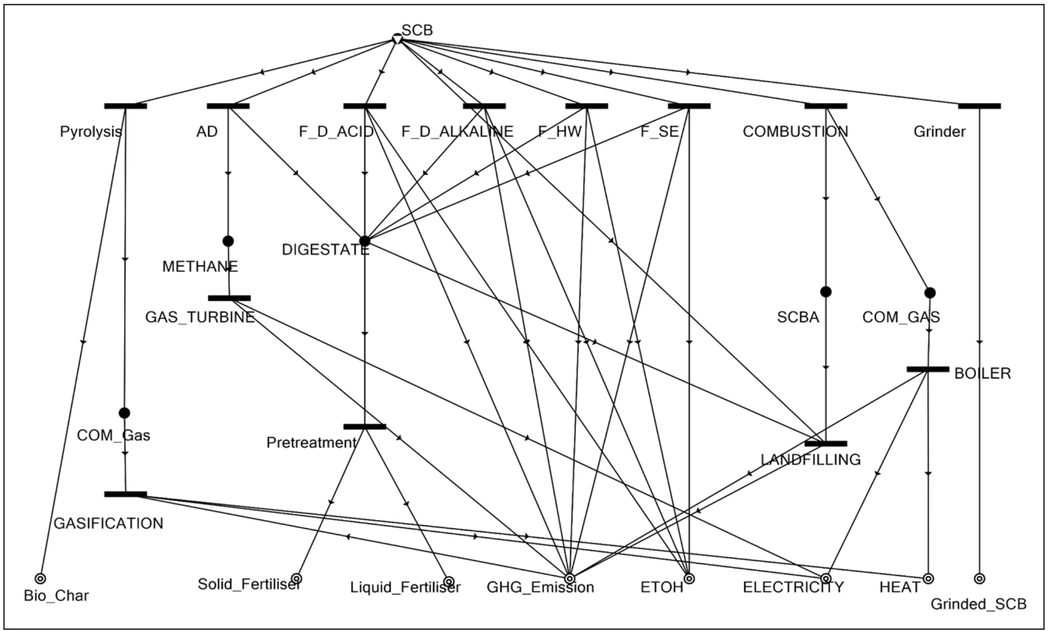

Figure 2. Superstructure for sugarcane bagasse conversion technologies

Integration of Machine Learning

The integration of Machine Learning to process network synthesis was done using WEKA. WEKA is a machine learning software that identifies hidden information from a raw dataset. This research analyzed the raw dataset using a set of algorithms. Six algorithms were selected to conduct the classification process in this research. The algorithms used are Logistics, Simple Logistics, Multilayer Perceptron, Stochastic Gradient Descent, IBk, and Kstar.

Simple Logistics is a simplified algorithm to encapsulate linear logistic regression. In WEKA, the Logistic algorithm was built based on multinomial logistic regression with a ridge estimator to build a class. The model for this algorithm fits the model's simple and stable process, which resulted in a low variance with a potentially high bias (Landwehr et al., 2003).

Implementing Stochastic Gradient Descent in WEKA is used to learn several linear models, such as binary class logistic regression and squared loss. In addition, the Multilayer Perceptron algorithm is assumed as a provider for nonlinear modeling between an input vector and a corresponding output vector. Besides being capable of modeling higher-order statistics, the algorithm can become an efficient prediction filter for nonlinear series because of their nonlinear nature (Gupta & Sinha, 2000).

In WEKA, the nearest neighbor algorithm was implemented in the form IBk algorithm, which selects the appropriate K value based on cross-validation. The next algorithm is an instance-based classifier, a classification of test instances based on the class of the training instances that are similar to it. However, the difference between this algorithm and the other instance-based learner is that it uses an entropy-based distance function (Cleary & Trigg, 1995). The WEKA implementation for this is K* algorithm.

The acquired data from feasible solution structures were assembled in how the data can be mined using a group of algorithms in Explorer WEKA. All these algorithms are available in the WEKA feature, which is Explorer. Thus, the detailed result of the feasible solution structure was analyzed using WEKA. The 2 raw datasets involved in machine learning are product flow rate and its profitability and type of product and its profitability.

Each algorithm trained the dataset by allocating 70% of the data set to be analyzed and subsequently trained. Meanwhile, 30% of the data was used as a validation set. The performance of each algorithm is compared. The performance of each model was observed based on the model kappa statistics value, mean absolute error, root mean squared error, percentage relative absolute error, and percentage root relative squared error.

The algorithm that managed to identify hidden information with a significant performance that resulted in the least error would be chosen to be used as the algorithm the basis for decision tools.

RESULTS AND DISCUSSION

Simulation and Selection of the Best Solution Structures

Seventeen feasible solution structures have been produced by utilizing P-Graph Studio—all 17 feasible structures as attached in the supplementary data section. The structures were computed by Accelerated Branch and Bound (ABB) algorithm. The algorithm produced the most optimized solution structures of a Process Network Synthesis with a high-efficiency determination by reducing solution space. It eradicated any amalgamation of infeasible and superfluous solutions. Every solution structure produced is a subset of the maximal solution structure, signifying a probable network confirmation for the process network synthesis problem. ABB algorithm could also identify the best resolution with a specified set of conditions. All 17 produced feasible solution structures have been chosen to be acknowledged and scrutinized. The best solution structures were chosen from out of 17, which involved some operating units. The best solution structures will be further discussed.

Eight main operating units were included in the process network synthesis as conversion technologies to convert the sugarcane bagasse into products (Figure 2). The eight operating units involved three conversion technologies: biological, thermal, and mechanical. Also, five intermediate operating units converted either the intermediary product into the final product or by-products from the main operating units.

One of the biological conversion technologies was fermentation with four different pre-treatment types: dilute acid pre-treatment, dilute alkaline pre-treatment, hot water pre-treatment, and steam explosion pre-treatment. The main product of these conversion technologies was bio-ethanol. Another biological conversion technology was an anaerobic digester that yielded methane as its main product. Both rendered the same by-product, specifically digestate, produced during the distillation process of ethanol.

Meanwhile, for thermal conversion and mechanical conversion, each had one primary operating and process, which were pyrolysis and incinerator that produced bio-char and combustible gas, respectively as their main products, and grinder, which simply grinds sugarcane bagasse into smaller sizes as a raw material in the manufacturing of fungal substrate, composite of multi-layered armor, and brick production.

As for the intermediate operating units, combustible gas from pyrolysis and incinerator went through the gasification process and boiler to produce heat for steam production, electricity, and greenhouse gases. The combustible gas production by incinerator generated a sugarcane bagasse ash, which can be sold to manufacturers of brick or cement as supplementary material. Methane, the main product of an anaerobic digester, could generate electricity via a gas turbine. The digestate from biological conversion technologies was in a significant amount. Practically, this by-product would undergo treatment to be transformed into fertilizers.

These conversion technologies and their product were compared to the performance of landfilling as the most common method for waste management in Malaysia. Based on the superstructure diagram in Figure 2, P-graph represents the sugarcane bagasse process network. Each conversion structure was specifically designated with its required information, such as the conversion rate of raw material to its respective product, capital, operating cost of conversion technologies, and the selling price of the product.

Only one raw material was analyzed in this research, namely sugarcane bagasse. The amount of raw material used was acquired from Malaysia's maximum value of sugarcane bagasse. All structures involved different conversion technologies and different types of products with varying volumes. Thus, the total net profit and the emission of greenhouse gases differed with various conversion technologies. All generated feasible solution structures did not

Table 3
Summary of greenhouse gases emission and net profit

Solution structures	Net profit/ year (MYR)	Greenhouse gases emission/year (m^3)
Solution 1	8,894.01	2,006.40
Solution 2	8,652.88	3,244.80
Solution 3	7,982.90	1,958.40
Solution 4	6,426.90	-
Solution 5	6,099.25	2,880.00
Solution 6	3,619.00	-
Solution 7	-15,760.10	-
Solution 8	-19,561.98	2,006.40
Solution 9	-20,129.64	1,958.40
Solution 10	-21,282.58	3,244.80
Solution 11	-22,404.30	2,880.00
Solution 12	-30,315.96	-
Solution 13	-31,607.28	2,666.40
Solution 14	-48,295.92	-
Solution 15	-61,014.36	2,666.40
Solution 16	-82,740.48	-
Solution 17	-319,971.55	288.00

include landfilling as part of the solutions. The result from P-Graph was assorted according to the best structures that granted the highest net profit with 8,000 working hours per year for inclusive plant operation in 10 years. Table 3 summarizes greenhouse gas emissions and net profit for each feasible solution structure.

Out of the 17 feasible solution structures, only 6 were profitable, as in Table 3, with the highest profit being 8,894.01 MYR per year. The greenhouse gas emission simulated using the P-Graph Studio for each solution structure was exhibited in Table 4 with the operating unit that influenced the emission rate as in Table 3. The result showed that 6 of 17 feasible solution structures produced no greenhouse gases. The highest generation of the gases involved all fermentation with varying pre-treatment processes. Apart from that, boiler and gas turbines also produce greenhouse gases.

Table 4
Summary of involved operating unit that affected the GHG emission

Types of operating units	Availability in feasible structure
Boiler	Structure 17
Fermentation with dilute acid pre-treatment	Structure 2 Structure 10
Fermentation with dilute alkaline pre-treatment.	Structure 3 Structure 9
Fermentation with hot water pre-treatment	Structure 1 Structure 8
Fermentation with steam explosion pre-treatment.	Structure 5 Structure 11
Gas Turbine	Structure 13 Structure 15

Maximum Economic Performance Model

Six feasible solution structures were profitable out of 17. These 6 solution structures only produced a single final product for each pathway, as in Table 5. From 6, only 4 profitable solution structures produced bioethanol. The 4 profitable solution structures were feasible 1,2,3 and 5. Even though the amount of digestate produced for each fermentation process is significant, the by-product did not undergo further processes to be converted into a value-added product, namely fertilizer. It was because of the high cost of operating units of digestate treatment. The P-Graph Studio did, however, simulate a process pathway that included additional processing of digestate. The generated pathways were represented in the feasible solution structures 9, 10, 11, and 12. All of them had an enormous operating cost which caused the cost of the product to fail to generate any profit. Meanwhile, feasible solution structures 4 and 6 yielded biochar and ground sugarcane bagasse.

A comparison study was conducted for the 6 profitable structures to maximize the use of sugarcane bagasse to generate a significant turnover. The imminent values that were highlighted were net profit margin and payback period. The net profit margin was calculated by dividing net profit by revenue. At the same time, the payback period was vital to know the duration to regain the investment. This information is shown in Table 6.

Based on the tabulated data in Table 6, solution structure 6 is the most attractive economic model. However, since solution structure 6 product was ground sugarcane bagasse, the market for this product is small compared to bioethanol and biochar. Hence, solution structure 1 was chosen as the best model for maximum economic performance, producing bioethanol.

Table 5
Summary of product produced for each solution structure

Types of products	Availability in feasible structure
Biochar	Structure 4 Structure 7 Structure 14 Structure 16
Electricity	Structure 7 Structure 13 Structure 14 Structure 15 Structure 16 Structure 17
Bioethanol	Structure 1 Structure 2 Structure 3 Structure 5 Structure 7 Structure 8 Structure 9 Structure 10 Structure 11
Grinded Sugarcane Bagasse	Structure 6
Heat	Structure 7 Structure 14 Structure 16 Structure 17
Liquid Fertilizer	Structure 8 Structure 9 Structure 10 Structure 11 Structure 12 Structure 15 Structure 16
Solid Fertilizer	Structure 8 Structure 9 Structure 10 Structure 11 Structure 12 Structure 15 Structure 16
Sugarcane Bagasse Ash	Structure 17
Methane	Structure 12

Table 6
Net profit margin and payback period for profitable pathway

Solution Structures	Net Profit Margin	Payback Period (year)
Solution 1	75%	2.49
Solution 2	73%	2.66
Solution 3	73%	2.73
Solution 4	74%	2.56
Solution 5	70%	3.04
Solution 6	75%	2.46

Minimum Environmental Impact Model

As aforementioned, out of 17 feasible solution structures, 6 solution structures produced no greenhouse gases. The greenhouse gas emission rate is summarized in Table 3. Notably, carbon dioxide gas was not considered a greenhouse house gas but a carbon neutral (Kiatkittipong et al., 2009). The emission of greenhouse gases originated from fuel consumption for each conversion technology. Also, in the case of landfilling, the escaped primary anaerobic compounds such as methane and ammonia gas contributed to the increase of greenhouse gases.

Thus, the feasible structure with the minimal environmental impact on the environment was solution structure 4. Besides the fact that this solution structure has zero greenhouse gases, it can also generate maximum economic performance. The operating unit that was involved in this solution structure was pyrolysis. Pyrolysis produced two products, an intermediary product, and a final product. The final product was biochar, whereas the intermediary product was combustible gas. According to solution structure 4, the combustible gas was not being used by the gasification process due to the high investment cost of the gasifier.

On the other hand, solution structure 6 also proposed an acceptable, feasible pathway when considering both economic performance and environmental impact, albeit performing worse in the economy than solution structure 4. In this pathway, the sugarcane bagasse was simply ground into smaller sizes for the use of other manufacturers. The solution structure also only used a single operating unit. The operating unit, an industrial-sized grinder, only uses 13.37 kWh of electricity.

If economic performance were not considered, solution structures 7, 12, 14, and 16 would be viable options.

Integration of Machine Learning Via WEKA

P-Graph Studio generated 17 feasible solution structures on how to manage sugarcane bagasse. This set of data was further analyzed by data mining software called WEKA. The acquired data from feasible solution structures were assembled to determine how the data could be mined using a group of algorithms, as listed in Figure 3.

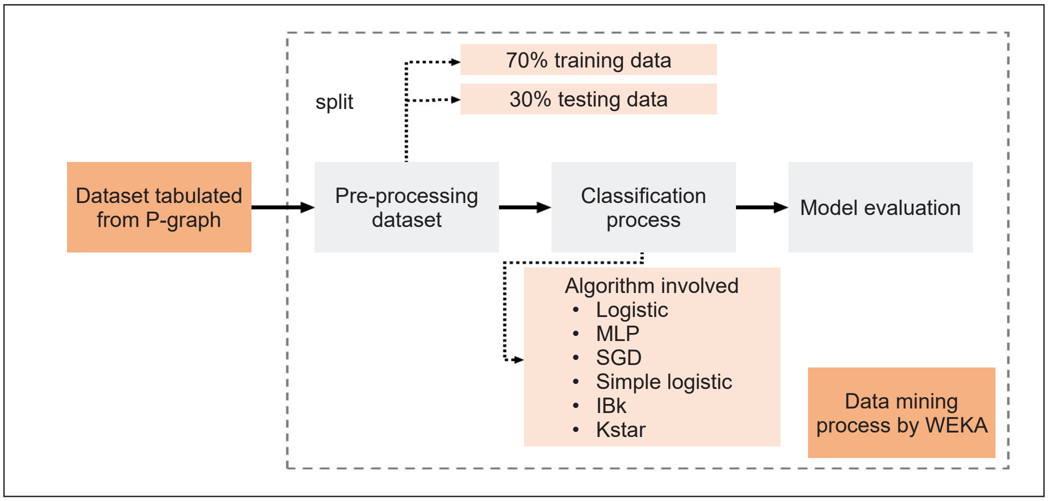

Figure 3. Flow diagram for the data classification process

Each algorithm trained the dataset by allocating 70% of the data set to be analyzed and subsequently trained. Meanwhile, 30% of the data was used as a validation set.

Correlation Between Product Flowrate and Profit

The correlation between product flow rate and profit from the generated data via P-Graph Studio was investigated using a group of algorithms mentioned earlier. In this case, the product flow rate was kept in numerical form, maintaining its original value from the raw data. However, the profit for each solution structure was converted into nominal form, where a profitable solution structure will be classed as “YES,” and an un-profitable solution structure, “NO.” The performance for each algorithm was tabulated in Table 7.

Table 7
Performance for each algorithm for correlation of product flowrate and profit

Algorithm	Correctly Classified, %	Kappa Statistics	Mean absolute error	Root mean squared error	Relative absolute error, %	Root relative squared error, %
Logistic	66.67	0.40	0.33	0.58	55.17	85.89
Multilayer Perceptron	66.67	0.40	0.34	0.56	56.37	82.84
SGD	66.67	0.40	0.33	0.58	55.17	85.89
Simple Logistic	66.67	0.40	0.43	0.57	71.51	84.71
IBk	83.33	0.67	0.21	0.39	34.48	57.57
Kstar	83.33	0.67	0.25	0.46	41.38	67.90

By referring to tabulated results, algorithm IBk and KStar performed better than the others, correctly classifying 83.33% of the data. Whereas the other four algorithms only correctly classified 66.67% of the data. This result was reflected in the Kappa Statistics with 0.67 for IBk and Kstar. This analysis indicated a substantial correlation between product flow rate and profit.

Correlation Between Product and Profit

A similar procedure to the previous analysis, this data mining was performed to investigate the relationship between the final product and net profit generated for each feasible solution structure. Both data sets were input in the form of nominal. The result of each algorithm’s performance was tabulated in Table 8.

Table 8
Performance for each algorithm for correlation of product and profit

Algorithm	Correctly Classified, %	Kappa Statistics	Mean absolute error	Root mean squared error	Relative absolute error, %	Root relative squared error, %
Logistic	66.67	0.40	0.33	0.58	55.17	85.89
Multilayer Perceptron	100.00	1.00	0.07	0.09	11.29	14.12
SGD	83.33	0.67	0.17	0.41	27.59	60.74
Simple Logistic	100.00	1.00	0.21	0.24	34.96	35.87
IBk	100.00	1.00	0.14	0.20	22.85	29.68
Kstar	100.00	1.00	0.14	0.23	23.67	34.70

Based on the result, four algorithms performed efficiently, correctly classifying the data with 100% accuracy. The algorithms were Multilayer Perceptron, Simple Logistic, IBk, and Kstar. The Multilayer Perceptron algorithm performed with the least error of the four algorithms. The result proved a significant relationship between the type of product produced and profitability.

In summary, 17 feasible structures were generated from the superstructure of sugarcane bagasse conversion technologies. Each feasible structure suggests a different pathway for sugarcane bagasse conversion technologies with different net profit and emission generation values. Two models were evaluated from feasible generated structures: maximal economic performance and minimal environmental impact. 6 feasible solution structures were profitable out of 17, while 6 solution structures produced no greenhouse gases. Besides, instead of manually selecting the best model for maximal economic performance and minimal environmental impact, WEKA helps analyze each dataset from the p-graph. For the algorithm model with the correlation between product flow rate and profit, the result was reflected in the Kappa Statistics with 0.67 for IBk and Kstar. At the same time, the Multilayer Perceptron algorithm performed with the 1 value of Kappa Statistic and the least error for the type of product produced and its profitability.

CONCLUSION

This study simulated the feasibility of sugarcane bagasse conversion technologies via process network synthesis. The model can be a basis for determining the best process for sugarcane bagasse conversion technologies. Besides, the relationship between parameters in this case study can be evaluated with machine learning. Machine learning proves that the types of products produced in sugarcane bagasse influenced the profitability of the process flow.

The information to set up the P-Graph was gathered from various resources. Therefore, this study is done with the limitation of information availability. The information needed for the costing aspect and conversion yield varied with different resources. Thus, a real case study in Malaysia should be conducted to acquire a more accurate simulation. Also, integrating Excel into WEKA would be useful and supplementary to an already robust data mining machine. This addition would simplify the analysis of each algorithm used in data mining via WEKA, as Excel is one of the most conventional and user-friendly software.

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