Addressing supply uncertainties using multi-period stochastic economic evaluation

Citation for published version:

Digital Object Identifier (DOI):
10.1016/j.clet.2022.100554

Link:
Link to publication record in Heriot-Watt Research Portal

Document Version:
Publisher's PDF, also known as Version of record

Published In:
Cleaner Engineering and Technology

Publisher Rights Statement:
© 2022 The Authors.

General rights
Copyright for the publications made accessible via Heriot-Watt Research Portal is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy
Heriot-Watt University has made every reasonable effort to ensure that the content in Heriot-Watt Research Portal complies with UK legislation. If you believe that the public display of this file breaches copyright please contact open.access@hw.ac.uk providing details, and we will remove access to the work immediately and investigate your claim.
Addressing supply uncertainties using multi-period stochastic economic evaluation: A graph-theoretic aided element targeting approach

Shirleen Lee Yuen Lo¹, Chun Hsion Lim², Michael Francis D. Benjamin³, Hon Loong Lam⁴, Jaka Sunarso⁵, Bing Shen How⁶,⁷

¹ Biomass Waste-to-Wealth Special Interest Group, Research Centre for Sustainable Technologies, Faculty of Engineering, Computing and Science, Swinburne University of Technology, Jalan Simpang Tiga, 93350, Kuching, Sarawak, Malaysia
² School of Engineering and Physical Sciences, Heriot-Watt University Malaysia, Jalan Venua P5/2, Precinct 5, 62200 Putrajaya, Malaysia
³ Research Center for the Natural and Applied Sciences / Chemical Engineering Department, University of Santo Tomas, España Blvd., 1015, Manila, Philippines
⁴ Department of Chemical and Environmental Engineering, The University of Nottingham, Malaysia Campus, Jalan Broga, 43500 Semenyih, Selangor, Malaysia

ARTICLE INFO
Keywords:
Biomass element life cycle analysis
Monte Carlo
Uncertainties
Multi-period operation
P-graph

ABSTRACT
The challenges to commercialize biomass industry includes biomass supply shortage which is dependent on geographical location and seasonality. Most of the present biomass supply chain studies had not considered incorporation of supply chain uncertainties that may lead to overestimation of financial performance. Therefore, a hybrid framework was proposed via integration of stochastic Monte Carlo Simulation model with element targeting approach (Biomass Element Life Cycle Analysis, BELCA-P-graph model) to perform scheduling and economic analysis for the biomass supply chain. The BELCA-P-graph model aimed to generate a baseline for the feedstock ratio of each input biomass. This was then input into the stochastic model, capable of estimating the financial probability of the supply chain while incorporating supply chain uncertainties (i.e., biomass element characteristics, transportation-related parameters, raw material pricing, biomass availability, market demand, and selling price of final product). Results showed that biomass shortage had decreased the mean Net Present Value (NPV) of the base case scenario (without consideration biomass supply shortage) by 1.39%–12.21%. Storage capacity consideration had decreased the mean NPV by 11.59%–12.21%. The sensitivity analysis found that syngas demand and syngas selling price uncertainty offered significant impact on the mean NPV outcome.

1. Introduction

Biomass-derived industry had caught the attention globally due to the preliminary findings, which showed that the use of fossil fuels as energy source had resulted in an estimated increase in emissions of 10%, 3.6%, 3.6%, and 1.9% in the transportation, industry, power, and buildings sectors, respectively (from 2020 to 2021) (Rivera et al., 2022). The undesirable environmental impacts and the potential depletion of fossil fuels had necessitated the quest for alternative energy sources. The past few decades have seen a growing interest in utilizing biomass, a form of natural waste, as one of the possible alternative feedstocks due to the favourability of the characteristics of biomass feedstocks such as the carbon-neutral attribute of the biomass-derived biofuels combustions (Vassilev et al., 2015). Although biomass is widely available, biomass as feedstock utilization is still limited. This is due to several reasons such as biomass seasonality, and geographical conditions, which could lead to process disruptions. Such disruptions and the corresponding risks in integrated bioenergy systems should be considered to achieve robust and reliable networks (Benjamin et al., 2021a). According to Andiappan et al. (2021), most biomass generated in developing countries (i.e., Malaysia, India, and Thailand) are often trapped in low-value utilization activities such as open field burning (How and Lam, 2017). This serves as a bottleneck that constrains the real availability of biomass for higher-value utilization activities (e.g., fuel production).

Various published articles had investigated the suitability of a specific biomass for a given conversion process. For instance, Lo et al. (2021b) compared the economic feasibility of using three different types of palm-based biomass (i.e., palm kernel shell (PKS), palm mesocarp fibre (PMF), and empty fruit bunches (EFB)) as gasification feedstocks

¹ Corresponding author.
E-mail addresses: slo@swinburne.edu.my (S.L.Y. Lo), l.chun.hsion@hw.ac.uk (C.H. Lim), mdbenjamin@ust.edu.ph (M.F.D. Benjamin), honloong.lam@nottingham.edu.my (H.L. Lam), jsunarso@swinburne.edu.my (J. Sunarso), bshow@swinburne.edu.my (B.S. How).

https://doi.org/10.1016/j.clet.2022.100554
Received 16 February 2022; Received in revised form 27 August 2022; Accepted 28 August 2022
Available online 3 September 2022
2666-7908/© 2022 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).
One of the approaches used in the proposed methodology is stochastic modelling that has the capability to incorporate risks or uncertainties into its model. According to Ngan et al. (2020), risk is defined as the possible scenario that may lead to an unfavorable outcome. Supply chain risks are also one of the key factors that impede the commercialization of the biomass supply chain. Thus, there is a necessity to model the biomass supply chain uncertainties or risks via stochastic modeling. Lo et al. (2021b) performed stochastic techno-economic analysis via development of the Monte Carlo Simulation model for a given palm-based biomass supply chain incorporating several uncertainties (i.e., the supply of biomass, element characteristics of biomass, acquisition cost of biomass, transportation fuel cost, and selling price of syngas). However, the potential issue of biomass shortage was not covered in their developed case study. This motivated the purpose of this research paper to close the gap by considering multiple raw material acquisition sites into the developed multi-period stochastic economic evaluation model.

As highlighted above, the limitation of the previous work on BELCA-P-graph model was that it did not consider the impact of supply chain uncertainties on the performance of the biomass supply chain. Therefore, in this work, a BELCA-P-graph model that subsequently optimized the given biomass supply chain using Monte Carlo Simulation model with scheduling essence in the case of biomass supply shortage was developed. This was achieved firstly via utilization of BELCA-P-graph model to determine the biomass feedstock ratio (ratio for the amount in weight required for each type of biomass) required to be input into the process in order to meet the element acceptance range of the process. This was to obtain the input ratio of each biomass into the process, thus, considering other alternative options of biomass available and not fixated solely on the biomass that are pre-selected by the decision-makers. The result extracted was then used as input for Monte Carlo Simulation model, a stochastic economic evaluation model, which incorporated several supply chain-related uncertainties (i.e., element characteristics of the biomass, transportation-related parameters, raw material acquisition price, biomass availability, market demand, and selling price of value-added product). The biomass supply chain network scheduling and optimization were performed through Monte Carlo Simulation model. Two financial performance indicators were used, i.e., Net Present Value (NPV) and Payback Period (PP). Finally, sensitivity analysis was performed to identify the uncertainty that posed a greater impact on the overall NPV of the biomass supply chain network.

This research paper was structured in the following outline: the problem in this paper was addressed in Section 2. The methodology to solve the problem described was outlined in Section 3. Section 4 then provided a comprehensive description of the case study used to demonstrate the utilization of the developed model. The results obtained for the case study were discussed in detail in Section 5. The concluding remarks and recommendations were presented in Section 6 of this paper.

2. Problem statement

The proposed problem was described as follows: given a set of biomass type $n$ sourced from a set of supply sites $j$ was converted into syngas via gasification in a given processing hub, $k$. To overcome and mitigate the impact of biomass shortage issue, one can consider (i) storing the excessive biomass collected from the successive periods, and (ii) sourcing substituent, where a set of alternative biomass type $n'$ obtained from a set of acquisition sites $j$ can be used as the substituent provided that the corresponding set of biomass element characteristics $q$ falls between the determined element acceptance range of gasification process. Fig. 1 showed the superstructure of the model, where the model aimed to determine the optimal biomass allocation network with the greatest economic performance across time period $t$. 

Fig. 1. Superstructure of proposed model.
3. Methodology

The research methodology proposed in this study was a four-step methodology:

Step 1 (see Section 3.1): This section detailed the data to be collected throughout this study.

Step 2 (see Section 3.2): The development of BELCA-P-graph model was shown in this sub-section.

Step 3 (see Section 3.3): The development procedure of the stochastic economic evaluation model (Monte Carlo Simulation model) was presented in this sub-section where two financial performance indicators (NPV and PP) were evaluated in this study.

Step 4 (see Section 3.4): The last sub-section covered the research methodology used for sensitivity analysis.

3.1. Collection and processing of data

The data required to be collected for this paper included fixed data (the geographical locations of the involved entities (supplies, demands, and processing plant), the corresponding transportation distances between these entities, and the transportation vehicles’ capacity and uncertainties (all attainable historical statistical data of raw material acquisition price (i.e., EFB, PMF, PKS, rice husk (RH), and coal), transportation-related parameters (i.e., transportation fuel price and fuel consumption rate of truck), monthly biomass availability, market demand of syngas, and the selling price of syngas). Subsequently, data pre-processing of the uncertainty variables’ historical statistical data via Equation (1) and Equation (2) was required to convert the pool of data into the mean, μ, and standard deviation, SD where they served as input into the Monte Carlo Simulation model.

\[ \mu = \frac{\sum X}{n} \]  
\[ SD = \sqrt{\frac{\sum (X - \mu)^2}{n - 1}} \]

where X denoted the data for the uncertainty variable, while n referred to the total number of data sets obtained.

3.2. BELCA-P-graph model development

When situation of insufficient supply of the main biomass arise, alternative biomass that were locally available for syngas production have to be sourced so that the demand will not be compromised. However, as mentioned, the elemental acceptance range for a specific process has to be met in order to have non-significant impact on the resulting product’s quality. The application of mass balance concept (i.e., total mass of carbon element entering must be within the range of total mass of carbon element required) in this situation allowed users to determine the feedstock ratio of each input biomass. Note that, in addition to the locally attainable biomass, the option of importation of main biomass was considered as well. This increased the options of biomass possible for input. The BELCA-P-graph model was developed using P-graph Studio version 5.2.4.2 to determine the feedstock ratio of each input biomass (i.e., main biomass supply or alternative biomass supply under biomass shortage circumstances) to meet the elemental acceptance range of the biomass conversion process. As a note, the elemental acceptance range of the biomass conversion process has to be met in order to have non-significant impact on the process. In the case when it is not capable, the main biomass was imported from foreign regions (higher cost in return). Hence, the general equation is demonstrated by Equation (3) and Equation (4).

\[ F_{B,IMPORT}^{n,k,m,y} = F_{B,IMPORT}^{n,k,m,y} - \sum_{j \in k} E_{B,j}^{n,k,m,y} - \sum_{j \not\in k} F_{B,j}^{n,k,m,y} \]  
\[ F_{B,IMPORT}^{n,k,m,y} = S_{B,m}^{Y} \times X^{i} \]  

where \( F_{B,IMPORT}^{n,k,m,y} \) denoted the amount of main biomass required to be imported (tonnes), \( F_{n,j,k,m,y}^{B} \) signified the total weight of biomass, \( n \), from source, \( j \), to be transported to processing hub, \( k \) in the month, \( m \) and year, \( y \), and \( F_{n,k,m,y}^{B} \) denoted other locally attainable biomass, \( n \), to be included as one of the input biomass for the conversion process in the case of biomass shortage (tonnes). \( F_{n,k,m,y}^{B} \) denotes the total amount of biomass required in order to meet the market demand of product (in this case syngas) at the processing hub, \( k \) and \( S_{B,m}^{Y} \) represents the notation for the syngas demand in month, \( m \) and year, \( y \) (tonne syngas). Subsequently, \( X^{i} \) denotes the ratio of the amount of biomass required per amount of syngas (kg biomass/kg syngas).

The element constraint for the BELCA-P-graph model was provided by Equation (5). The constraint described that the sum of element weightage for biomass, \( n \) including the alternative biomass (when required) must be in between the lower boundary, \( E_{q}^{Lower} \), and upper boundary, \( E_{q}^{Upper} \), of the element acceptance range of a specific conversion process. The lower boundary of the total weight required of a specific element was obtained from the multiplication of the lower boundary of the process acceptance range, \( E_{q}^{Lower} \) (wt%) with the total biomass feedstock demand required to meet the syngas demand, \( F_{B,IMPORT}^{n,k,m,y} \).

\[ E_{q}^{Lower} \times F_{B,m,y}^{Lower} \leq \sum_{j} \left( \sum_{x} E_{B,x}^{n,k,m,y} \times F_{B,j}^{n,k,m,y} + \sum_{y} E_{B,y}^{n,k,m,y} \times F_{B,j}^{n,k,m,y} \right) \leq E_{q}^{Upper} \times F_{B,m,y}^{ Lower} \]

The above formulation was translated into the P-graph model (see Fig. 2). Block A of the P-graph model illustrated the element targeting section. The numbers of orange circular nodes and yellow horizontal bars were added accordingly depending on the number of element characteristics considered in the study. Each orange circular node represented one specific biomass element characteristic (i.e., carbon content, moisture content, and etc.). Subsequently, Block B is comprised of the locally attainable biomass (i.e., EFB, PKS, RH, and PMF). The green circular nodes represented the main biomass (EFB, and PMF) and the grey circular nodes represent other locally attainable alternative biomass (PKS, and RH). The weightage of each element for a specific biomass was input in the line as shown in Block C. For instance, the first circular node in Block D represented moisture content, thus, the weight percent of moisture content for EFB (15.77 wt%) was input in the line connecting the horizontal bar for EFB in Block B to the circular node for moisture content in Block D. The circular nodes in Block D combined the weight of each specific biomass element from the input raw materials (i.e., main biomass and alternative biomass sources in Block B and importation of main biomass source in Block F). The total load of each biomass element was evaluated in the brown total element checkers horizontal bar in Block E. Note that the maximum and minimum element acceptance range for the biomass conversion process can be input as the upper and lower limits of the capacity constraints of the brown horizontal bar. Block G depicted the biomass conversion process whereby the red horizontal bar represents biomass conversion process. Information regarding the conversion process such as the capital cost and operating cost are input in the aforementioned red horizontal bar. The black double circular nodes after block G represents the product of the process. The product demand or the required production demand can be in the double circular node.
3.3. Stochastic economic evaluation model development

The overview of steps for the Stochastic Economic Evaluation model development were presented in Fig. 3. The first step involved defining and determining the uncertainties to be considered in the stochastic economic evaluation model. The current study had defined six uncertainties for the developed stochastic economic evaluation model (Monte Carlo Simulation model), i.e., biomass element characteristics, transportation fuel selling price, transportation-related parameters (i.e., fuel consumption rate of vehicles and transportation fuel price), raw material acquisition price, biomass seasonal availability, market demand, and selling price of value-added product. The values of the aforementioned uncertainties were presented in Table S1 of the Supplementary Materials. After input of all required variables, Microsoft Excel software was utilized to perform the Monte Carlo Simulation model. The Monte Carlo Simulation model was run for 10,000 iterations, and the probability density curve for the economic performance indicators was generated. The graphical probability density curve (in terms of NPV and PP) can then be analyzed where the overall μ and SD of the economic performance outcome can be extracted.

The Monte Carlo Simulation model is formulated as follow:

The main function of the developed model was to conduct stochastic evaluation of two economic performance evaluation indicators, i.e., NPV, and PP. Firstly, Equation (6) represented the calculation of NPV on a monthly basis. The PP was achieved at month, m and year, y, when the NPV turns positive.

\[ \text{NPV} = \sum_{m,y} \left( \frac{\text{Balance}_{m,y}}{(1+i)} \right) - C_{\text{CAPITAL}}^{y=1} \]

whereby the symbols of equations were described as follows: Balance\(_{m,y}\) depicts the cash flow balance in each of the plant operating year (shown in Equation (7)), interest rate for the calculation is represented by the notations, i, while m signifies the operating month of an operating year, and y denotes the operational year.

The detailed calculations for Balance\(_{m,y}\) were obtained via Equation (7) whereby it is composed of two significant components that are \(R_{m,y}\), which denotes the revenue obtained from the sales of syngas (USD), and \(C_{\text{OPEX}}\) which indicates the total plant operating cost (OPEX) (USD). Note that the \(R_{m,y}\) can be determined via Equation (8).

\[ \text{Balance}_{m,y} = R_{m,y} - C_{\text{OPEX}} \]

\[ R_{m,y} = S_{m,y}^F \times S_{m,y}^X \]

where \(S_{m,y}^F\) denotes the syngas demand for a specific month and year (tonne), and \(S_{m,y}^X\) represents the syngas selling price (USD/tonne).

Generally, \(C_{\text{OPEX}}\) is composed of three significant components, i.e., the acquisition cost of biomass (\(C_{\text{RM}}\)), total transportation cost of the supply chain (\(C_{\text{TC}}\)), and total drying cost for the biomass (\(C_{\text{D}}\)). Each of them was computed through Equations 10–13.

\[ C_{\text{OPEX}} = C_{\text{RM}} + C_{\text{TC}} + C_{\text{D}}^{m,y} \]

\[ C_{\text{RM}} = \sum_{n,k,m,y} W_{n,k,m,y} \times C_{\text{RM}}^{n,k} \]

\[ C_{\text{TC}} = \sum_{n,k} \left( D_{n,k,m,y} \times N_{\text{Trips}}^{n,k,m,y} \right) + \left( D_{n,k,m,y} \times N_{\text{Trips}}^{n,k,m,y} \right) \times F^P \]

\[ N_{\text{Trips}}^{n,k,m,y} = \frac{V_{n,k,m,y}}{C_{\text{Cap}}^{n,k,m,y}} \]

\[ N_{\text{Trips}}^{n,k,m,y} = \frac{V_{n,k,m,y}}{C_{\text{Cap}}^{n,k,m,y}} \]
where $F_{\text{B}, n_{j,k,m}, y}$ represents the amount of biomass, $n$, required from the acquisition hub, $j$ (tonne), and $C_{\text{BASE},y}$ denotes the acquisition cost of biomass, $n$ (USD/tonne). $D_{\text{T}, y}$ indicates the total distance travelled (round trip) to transport the required biomass, $n$, from the biomass acquisition site, $j$, to the processing hub, $k$ (km). $N_{\text{T}, y}$ indicates the number of trips taken to transport the required biomass, $n$, $D_{\text{Trips}, y}$ signifies the distance travelled to transport syngas from processing hub, $k$ to demand point, $l$ (km). $N_{\text{Trips}, y}$ describes the number of trips taken to transport the required demand of syngas, $S_{\text{Trips}, y}$ denotes the unit price of transportation fuel (USD/L), and $F_{\text{T}, y}$ represents the fuel consumption rate of vehicle (L/km). $N_{\text{Trips}, y}$ can be calculated from the division of the total weight of biomass, $n$, with the capacity of truck, $\text{Cap}_{\text{Truck}}$. The $N_{\text{Trips}, y}$ can be obtained via the division of the total volume of syngas with the capacity of tube trailers, $\text{Cap}_{\text{Trailer}}$ (see Equations (12) and (13) (How et al., 2016)).

The capital investment cost of the biomass gasification plant was estimated based on sixth-tenth rule (see Equation (14)). The equation for Chemical Engineering Plant Cost Index (CEPCI) was utilized to adjust the cost of the plant from the base year to the present year (see Equation (15)).

$$C_{\text{CAPITAL}, y=0} = C_{\text{BASE,CAPITAL}, y=0} \times \left(\frac{\text{CEPCI}_{y=1}}{\text{CEPCI}_{y=0}}\right)^{0.64}$$

(14)

$$C_{\text{CAPITAL}, y=1} = C_{\text{CAPITAL}, y=0} \times \left(\frac{\text{CEPCI}_{y=1}}{\text{CEPCI}_{y=0}}\right)$$

(15)

whereby, $C_{\text{CAPITAL}, y=0}$ described the costing of the desired equipment sizing in year, $y = 0$, $C_{\text{BASE,CAPITAL}, y=0}$ described the baseline cost for different equipment sizing in year, $y = 0$, $\text{CEPCI}$ indicated the desired equipment sizing of study and $\text{CEPCI}$ denoted the equipment sizing for the baseline cost used, where $C_{\text{CAPITAL}, y=1}$ represents the total capital investment cost (CAPEX) in the present year, $y = 1$, and $\text{CEPCI}_{y=1}$ and $\text{CEPCI}_{y=0}$ denotes the CEPCI value in year, $y = 1$ and $y = 0$, respectively.

A few constraints were set to ensure the model generated realistic results. The general requirement for the model to work was that the syngas demand, $S_{m,y}$, must be equaled to the syngas produced at the processing plant, $S_{m,y}$. This was achieved when the amount of biomass required to meet syngas demand, $F_{\text{B}, n_{j,k,m}, y}$ was satisfied (see Equation (16)). As a note, in the case where the availability of the main biomass was greater than $F_{\text{B}, n_{j,k,m}, y}$, the syngas production feedstock was purely supplied by the main biomass, $n$ ($F_{\text{B}, n_{j,k,m}, y}$) that was selected based on careful consideration of the suitability of the biomass for the conversion process and price consideration; otherwise, alternative biomass $n$ ($F_{\text{B}, n_{j,k,m}, y}$) or imported main biomass ($F_{\text{IMPORT}, n_{j,k,m}, y}$) were needed. The total amount of main biomass source and alternative biomass must be equalled to the total amount of biomass required for processing, $F_{\text{B}, n_{j,k,m}, y}$. This was to prevent unnecessary spendings to purchase the more expensive option of alternative biomass supply and only ensure that the alternative biomass supply is only opted for during shortage of the main biomass supply. Furthermore, in the case whereby the available main biomass supply, $F_{\text{B}, n_{j,k,m}, y}$ exceeded the amount of biomass required, $F_{\text{B}, n_{j,k,m}, y}$, the excess biomass will be stored for the use in the subsequent processing period ($m$, $y$) (see Equation (17)), where $F_{\text{B}, m,y}$ refers to the available amount of biomass at site $j$ during month $m$ and year $y$.

$$F_{\text{B}, n_{j,k,m}, y} = \sum_{j} F_{\text{B}, n_{j,k,m}, y} + \sum_{j} F_{\text{IMPORT}, n_{j,k,m}, y}$$

(16)

$$F_{\text{B}, m,y} = \sum_{y} F_{\text{B}, n_{j,k,m}, y} + \sum_{y} F_{\text{IMPORT}, n_{j,k,m}, y}$$

(17)

The drying of biomass was also a critical portion of developing the Monte Carlo Simulation model. The overall energy required for the drying of biomass can be calculated via Equation (18). The first part of the aforementioned equation described the heat energy required in heating the biomass to a specific temperature whereas the latter part describes the heat required in removing the water from the biomass.

$$\text{e}_{\text{drying}} = F_{\text{B}, m,y} \times \left[ (\Delta T \times c_{\text{B}}) + (w_{\text{water}} \times H_{\text{VAP}}) \right]$$

(18)

where $e_{\text{drying}}$ denotes energy required to dry the biomass, $c_{\text{B}}$ represents the specific heat capacity of the biomass, $w_{\text{water}}$ signifies the weight of water required to be removed (kg), and $H_{\text{VAP}}$ denotes the latent heat of vaporization of water.

Using a basis, $R_{\text{Basis}}$, of 1000 g (1 kg of water) for evaluation, $w_{\text{water}}$ can be calculated via Equation (19). The purpose of the equation was to calculate the amount of water to be removed during the drying process.

$$w_{\text{water}} = \frac{E_{\text{MC}} \times R_{\text{Basis}}}{R_{\text{Basis}} - (E_{\text{MC}} \times R_{\text{Basis}})}$$

(19)

where $E_{\text{MC}}$ denoted the desired moisture content, and $R_{\text{Basis}}$ signified the initial moisture content of the biomass to be input. The amount of coal required, $F_{\text{Coal}}$ was calculated via Equation (20) using $e_{\text{drying}}$ and $HV$ which denoted the heat value of coal (MJ/kg). The total drying cost for biomass was obtained via the multiplication of $F_{\text{Coal}}$ with the acquisition cost of coal, $C_{\text{coal}}$ (see Equation (21)).

$$F_{\text{Coal}} = \frac{e_{\text{drying}}}{HV}$$

(20)

$$C_{\text{coal}} = c_{\text{coal}} \times F_{\text{coal}}$$

(21)

It is noteworthy to summarize that randomized input values based on historical statistical data were used to represent the uncertainties studied in this work. The uncertainties included the initial moisture content of biomass ($E_{\text{MC}}$), transportation fuel price ($F_{\text{Coal}}$), fuel consumption rate of vehicles ($F_{\text{Coal}}$), biomass price ($C_{\text{coal}}$), coal acquisition price ($C_{\text{coal}}$), selling price of syngas ($S_{\text{coal}}$), biomass seasonal availability ($F_{\text{B}, n_{j,k,m}, y}$), and market demand of syngas ($S_{m,y}$). 10,000 iterative samples were generated in the model for each of the uncertainties. Subsequently, 10,000 different results for NPV and PP were obtained in this work. To note, the results obtained up to this stage are considered as the outcome of the base case.

### 3.4 Sensitivity analysis

Sensitivity analysis was performed to evaluate the impact of the mean value of each uncertainty on the resulting NPV outcome by evaluating the deviation of the resulting NPV as compared to the NPV obtained from the base case. If the mean value remains constant and standard deviation was varied instead, significant impact was towards the output standard deviation of the result, instead of the mean result (i.e., mean NPV). Thus, the deviation of the mean value would have a more significant impact on the mean NPV result as compared to the deviation of the standard deviation. The sensitivity analysis was achieved via deviation of the original mean of each uncertainty by 20% (i.e., $-20\%$ representing $\mu_{\text{lower}}$, and $+20\%$ representing $\mu_{\text{upper}}$). The new mean value, $\mu_{\text{lower}}$ and $\mu_{\text{upper}}$ were then entered into the Monte Carlo Simulation model while the new mean NPV outcome will then be extracted and benchmarked with that of the base case. The equations for performing sensitivity analysis were presented by Equation (22) to Equation (23). Subsequently, the resulting NPV at each deviated mean was recorded.
whereby, $\mu_{\text{Lower}}$ denotes the lower bound of the mean value of the uncertainty after deviation by $-20\%$ of the base value for a particular uncertainty, $\mu_{\text{Upper}}$, $\mu_{\text{Base}}$ signifies the upper bound of the mean value of the uncertainty after deviation by $+20\%$ of $\mu_{\text{Base}}$.

4. Illustrative case study

This section elaborated on the illustrative biomass gasification case study used to demonstrate the proposed methodology. Section 4.1 provided an overview of the case study while Section 4.2 described the development of the deterministic BELCA-P-graph model.

4.1. Overview of illustrative case study

An exemplative case study was presented to demonstrate the effectiveness of the methodology that was proposed in this study. The case study involved a 6 MW biomass gasification plant in Sarawak, Malaysia with two primary input feedstocks (EFB and PMF). Bau Palm Oil Mill Sdn. Bhd. (BAPOM) serves as the source for EFB whereas Serian Palm Oil Mill serves as the source for PMF (see Fig. 4). Other locally attainable biomass including paddy-based biomass was sourced from Joon Sing Rice Mill. When the availability of EFB and PMF was insufficient to cover the syngas demand, sourcing of alternative biomass such as paddy-based biomass or importation of main biomass, EFB were considered. The feedstock ratio data extracted from the BELCA-P-graph model (comprised of amount of main biomass, locally attainable biomass, and imported EFB) were then input into the Monte Carlo Simulation model. The model was performed on a monthly basis, with 360 operating days, 20 years, and an interest rate of 10%. Subsequently, the data for the identified alternative source of biomass (i.e., cost of biomass, transportation cost, and etc.) were input into the developed Monte Carlo Simulation model. All the input parameters and variables were summarized in Table S1 in Supplementary Materials. The monthly amount of FFB in Sarawak was obtained from Malaysian Palm Oil Board (2021b) and Malaysian Palm Oil Board (2021a). There were 82 FFB mills in Sarawak (Malaysian Palm Oil Board, 2021c). The maximum and minimum syngas demand was assumed to be at 100% and 80% of the production capacity of the gasification plant adopted from Mustafa et al. (2017). The agricultural land in Samarahan was 39,520 ha (Department of Agriculture Sarawak, 2021).

A total of six scenarios were evaluated in this case study as presented in Table S2 in Supplementary Materials. Scenario 1 depicted the simplest supply chain with two main sources of biomass (EFB and PMF) without the consideration of biomass shortage circumstances. Scenario 2 further complicated the scenario by imposing biomass shortage circumstances, while the importation of EFB was enabled to tackle the issue. Scenario 3 extended the supply chain network in Scenario 2 by considering other locally available biomass (i.e., PKS and RH). The main objective of the scenario was to investigate whether the inclusion of other locally available into the supply chain network can increase the overall mean NPV (by mitigating the need of importing expensive EFB from foreign regions). Scenario 4 was an extension from Scenario 3 to include the option to store the biomass for the use in subsequent periods. Scenario 4 evaluated different capacities of storage that are 400, 600, and 800 tonnes.

4.2. BELCA-P-graph model

The BELCA-P-graph model was developed and optimized under deterministic conditions. Thus, the uncertainties aforementioned were not evaluated using the BELCA-P-graph model. The main aim of the BELCA-P-graph model was to extract the feedstock ratio of the main biomass, other locally attainable biomass, and if necessary, importation of EFB or PMF from external locations. Fig. 5 illustrated the element acceptance range of the biomass gasification process. It is worth noting that this element acceptance range was after the drying process of biomass. In other words, the biomass that fits the element acceptance range was deemed suitable to be used as gasification feedstock without the need of additional drying. Generally, if the elemental properties of biomass were within the element acceptance range of the process (see Fig. 5a), the impact on the product quality and process performance could be assumed to be insignificant (Lim and Lam, 2016). The element acceptance range was plotted by introducing the element deviation factor (i.e., 5%) to literature data (adopted from Halim et al., 2020a, 2020b). On the other hand, the element radar chart of PMF and EFB was illustrated in Fig. 5. The elements considered in this study were important attributes of the biomass that needs to be taken into consideration in the gasification process (Abdul Malek et al., 2020).

In the BELCA-P-graph model, the mean acquisition cost for all locally available biomass and mean selling price of syngas were used as input (see Table S1 in Supplementary Materials) while the alternative biomass which was imported or attained from external sources was assumed at a higher rate of USD 50 per tonne (purchasing of alternative biomass from other locations on short notice may result in suppliers’ increasing the selling price of biomass). The transportation and handling cost for locally available biomass (EFB, PKS, PMF, and RH) was assumed to be USD 0.70/km/tonne of biomass (Lam et al., 2013). On the other hand, the transportation cost of the importation biomass was assumed to be twice that of locally available biomass, USD 1.40/km/tonne of biomass. The production scale was assumed to be the maximum demand that is 65,000 tonnes per year (see Table S1 in Supplementary Materials) was used as the demand constraint in the BELCA-P-graph model.

5. Result and discussion

5.1. BELCA-P-graph model

The monthly feedstock ratio for the main biomass, other locally attainable biomass, and possible importation of EFB were extracted from the BELCA-P-graph model and is summarized in Table 1. It is worthy to note that the aforementioned table presented results from January to March whereby the results for April to December can be obtained from...
supplementary materials (Table S3). It is observable from the aforementioned table that EFB is being utilized completely at 100% based on availability. When EFB’s availability or supply is lower, the percentage utilization of PKS is higher. This could be due to the similarity in their element radar chart as observed in Fig. 5, with the only significant difference observed in the moisture content. Under the current scenarios, the requirement to import is not required due to the wider range of considerations of locally available biomass. The percentage utilization extracted from the BELCA-P-graph model is then input into Monte Carlo Simulation model as an estimation of the amount of biomass required from each type of biomass required.

### 5.2. Stochastic economic evaluation

#### 5.2.1. CAPEX and OPEX of biomass gasification process

The operating cost and capital investment cost incorporated in the Monte Carlo Simulation model are listed in Table 2 and Table 3, respectively. The guidelines for the calculation of operating cost were extracted from the works of AlNouss et al. (2020) and Spath et al. (2005). The capital investment cost calculations were based on the calculation baseline extracted from the works of Aghabararnejad et al. (2015).

#### 5.2.2. Stochastic economic evaluation results and discussion

The Monte Carlo Simulation model was performed on a monthly basis for a period of 20 years. The uncertainties included in the Monte Carlo Simulation model are raw material acquisition price (i.e., EFB, PMF, PKS, RH, and coal), transportation-related components (i.e., transportation fuel price and fuel consumption rate of truck), monthly biomass availability, market demand of syngas, moisture content of biomass and the selling price of syngas. The variation in biomass moisture content will affect the drying cost of biomass. Subsequently, the probability density profile of NPV of the biomass gasification supply chain can be extracted from the Monte Carlo Simulation model as illustrated in Fig. 6 and Fig. 7.
Fixed operating cost (OPEX) of biomass gasification process.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Cost (USD)</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operating labour</td>
<td>360,000.00</td>
<td>USD 2,000/month/worker, 15 workers</td>
</tr>
<tr>
<td>Additional operating cost</td>
<td>90,000.00</td>
<td>29% of operating labor (AlNouss et al., 2020)</td>
</tr>
<tr>
<td>Maintenance and repairs</td>
<td>1,624,843.56</td>
<td>2% of total capital investment (Spath et al., 2005)</td>
</tr>
<tr>
<td>Plant overhead cost</td>
<td>992,421.78</td>
<td>50% of maintenance cost and operating labor cost (AlNouss et al., 2020)</td>
</tr>
<tr>
<td>Insurance and taxes</td>
<td>1,624,843.56</td>
<td>2% of total capital investment (Spath et al., 2005)</td>
</tr>
<tr>
<td>General administration cost</td>
<td>245,381.23</td>
<td>8% of the operational charges that include operating labor cost, plant overhead, maintenance cost, and operational charges (AlNouss et al., 2020)</td>
</tr>
<tr>
<td>Total Cost (USD)</td>
<td>5,388,373.89</td>
<td>-</td>
</tr>
</tbody>
</table>

The probability density profile illustrated in Fig. 6 highlights that the highest NPV range (curve leaned towards the right side of the graph) is observed in Scenario 1. The probability density profile is compressed into mean NPV and standard deviation. It is worthy to highlight that the standard deviation of the probability density profile can be used to evaluate the risk related to a particular investment (higher standard deviation would signify a higher risk of investment). Other than the calculation of standard deviation, the width of the probability profile could be used in evaluating the risk involved (larger width represents a higher tendency to deviate). The mean NPV and standard deviation for Scenario 1 is USD 111.84 million and USD 4.08 million, respectively. As there was no biomass shortage considered in this scenario, the two main biomass (EFB and PMF) is sufficient to meet the syngas demand.

Scenario 2 is presented as a scenario with biomass shortage and the main biomass could be imported from external locations with an assumption cost of USD 50 per tonne. This scenario has the second highest NPV range whereby the mean NPV and standard deviation is USD 110.29 million and USD 4.03 million, respectively. The additional cost required for the importation of main biomass from a further location have reduce the mean NPV by 1.39% from the previous scenario. When more fixed variable costing (assumptive cost of importation) were input into the developed model, the resulting standard deviation is observed to be lower as compared to the previous scenario.

Subsequently, Scenario 3 presents one of the lowest NPV range with the mean NPV and standard deviation of USD 99.54 million and USD 4.19 million, respectively. Comparatively, Scenario 3 has a lower mean NPV as compared to Scenario 1 and Scenario 2 due to the increase in supply chain components that leads to an increase in operating cost. The supply chain components implies the addition of two locally attainable biomass (RH and PKS) which included the acquisition site, transportation as well as the purchasing price. As the transportation-related variables and biomass pricing were considered as uncertainty in this study, the transportation and purchasing price of RH and PKS were input as an uncertainty variable in this scenario, thus, increasing the number of uncertainty variables. The increase in uncertainty variables...
considered in the model leads to an increase in the risk associated with the investment via evaluation of the output standard deviation. Other than that, biomass on its own is known for its cheaper selling price as compared to first generation biomass and fossil fuel (e.g., coal). For example, coal has a selling price of approximately USD 48.80 to USD 223.45 per tonne of coal (Trading Economics, 2021), whereas EFB has a selling price of USD 4.00 to USD 9.49 per tonne of EFB (see Table S1 in Supplementary Materials). However, amongst the type of biomass available such as EFB, PKS, PMF, and RH, the large differences observed in their respective pricing has an unfavorable outcome in the mean NPV observed. The cost of purchasing RH and PKS was approximately 15 and 13 times, respectively, higher than the cost of purchasing EFB. The multiple acquisition sites of biomass sources (EFB, PMF, PKS, and H) has increased the transportation cost and total operating cost of the supply chain. Thus, resulted in a significant decrease in mean NPV of approximately 9.75% from Scenario 2.

Scenario 4 was investigated as the extension of Scenario 3 with the consideration of storage tank for storing of excess biomass. Fig. 7 illustrates the probability density profile for Scenario 4 with biomass shortage and consideration of biomass storage system with the storing capacities of 400, 600, and 800 tonnes. The mean NPV for Scenario 4 with storage capacities of 400, 600, and 800 tonnes are USD 98.88 million, USD 98.58 million, and USD 98.18, respectively. The standard deviation for Scenario 4 with storage capacities of 400, 600, and 800 tonnes are USD 4.21 million, USD 4.18 million, and USD 4.18 million, respectively. The inclusion of biomass storage has led to the decrease in mean NPV which is due to the increase in CAPEX (to account for capital cost of storage tank). As the storage capacity increased from 400 tonnes to 800 tonnes, the mean NPV observed a further reduction of 0.71% given the higher capital cost required for the storage tank. The insight gathered from this scenario highlighted the implementation of biomass storage does not have a positive impact on the economic performance of the proposed supply chain. However, it is worthy to note that although biomass storage does not impact the economic performance of the biomass gasification plant positively, it could still be one of the redundancy required in reality. For instance, in the case of long-term biomass shortage (i.e., several months of biomass feedstock shortage), biomass storage may be critical in overcoming the biomass shortage problem.

The conventional fixed value input techno-economic analysis approach was performed as well for comparison by inputting the mean value for the uncertainty variables. The calculated NPV for Scenario 1, Scenario 2, and Scenario 3 are USD 112.39 million, USD 109.77 million, and USD 101.88 million, respectively. The results highlight that the conventional approach with fixed input variables leads to a higher calculated NPV whereas, in reality, the values of input variables will not be fixed. This could then result in an overestimation of financial performance of the proposed biomass supply chain.

On the other hand, the PP of the biomass gasification plant for Scenario 1, Scenario 2, and Scenario 3 is presented in Fig. 8. The overall results showed that Scenario 1 will have the highest probability (approximately 93%) to offset the capital investment in the fifth year of plant operations. Similarly, Scenario 2 has the probability of approximately 89% to achieve PP of five years. However, the probability of Scenario 3 to offset the capital investment in the fifth year of operations is relatively lower (approximately 40%). When looking at smaller timescale (monthly basis), Scenario 1 has the highest approximate probability of 16% to offset the capital investment in August of the fifth year of operation. Scenario 2 has the highest approximate probability of 15.5% to obtain the PP in the September of the fifth year of operation. Scenario 3 has a longer observable PP that is in December of the fifth year of operation with an approximate probability of 13%. The current PP results are aligned with the NPV results obtained whereby Scenario 1 offers the highest mean NPV value, which, therefore, requires a shorter PP as compared to that of Scenario 2 and Scenario 3. The PP of the biomass gasification plant for different storage capacities of Scenario 4 is presented in Fig. 9. It can be observed that when the storage capacity increases, the PP required also increases. This aligns with the NPV results obtained as when the mean NPV decreases, the PP will increases. The results highlight that the inclusion of biomass storage does not help in increasing the overall mean NPV or decreasing the PP. This is due to the additional cost required in purchasing the storage and higher transportation cost to cater for the excess biomass in the particular month. As in the current study, biomass is in excess in most of the

Fig. 7. Overall Probability Density of NPV in million USD for Scenario 4’s Storage Capacities (400, 600, and 800 tonnes).

Fig. 8. Probability of PP for biomass gasification plant for scenario 1, 2, and 3.
months, biomass storage did not play a significant role in the current study. However, biomass storage is still a redundancy required in reality (even though it decreases the mean NPV and increases the PP) when situations arise where months of biomass shortage may occur.

It is worthy to highlight that the economic results obtained (NPV, and PP) are both subjected to the current input values as shown Table S1 (Supplementary Materials), Table 2, and Table 3, where changes made to the values will lead to different outcomes. Under the current circumstances of input variables and values, Scenario 1 proves more profitable if the biomass supply from the main supply source can be assured. However, in the case of biomass shortage, the overall NPV outcome could face reduction up to 10.99% for the current input parameters and values. The current results provides an insight whereby it is observable that biomass shortage does indeed affect the profitability of the investment to a certain extent (up to 12.21% for the current study). Therefore, it is significant to consider biomass supply shortage during techno-economic evaluation to prevent underestimation or overestimation of the profitability of the project as it would require sourcing of alternative biomass supply that requires increase in unexpected expenses (i.e., transportation cost, higher biomass acquisition cost, and etc.). A sensitivity analysis is performed in the next section to further evaluate which uncertainty plays a larger role in influencing the NPV outcome.

5.3. Sensitivity analysis

The results of the sensitivity analysis for Scenario 1 to Scenario 3 are illustrated in Fig. 10, Fig. 11 to Fig. 12. The goal of the sensitivity analysis is to determine which uncertainty has a greater influence on the resulting mean NPV as compared to the mean NPV of their respective original case. The results find that the uncertainty that has the greatest influence on all three scenarios are syngas demand and syngas selling price that directly influence the profitability and cash in to the biomass gasification plant. A 20% lowered mean value for syngas demand results in a 43.31%, 42.68%, and 48.82% decrease in the mean NPV outcome for Scenario 1, Scenario 2, and Scenario 3, respectively. If the mean syngas demand were to increase 20%, the mean NPV outcome increases 43.00%, 40.99%, and 47.29% for Scenario 1, Scenario 2, and Scenario 3, respectively. When the mean syngas selling price deviated 20% lower than the base mean value, the mean NPV outcome is reduced by 44.14%, 44.81%, and 49.67% for Scenario 1, Scenario 2, and Scenario 3, respectively. Whereas, when the mean syngas selling price increased by 20%, the mean NPV outcomes are increased by 44.23%, 44.76%, and
49.63% for Scenario 1, Scenario 2, and Scenario 3, respectively. The other uncertainties such as raw material acquisition prices, biomass availability, and transportation fuel price does not have observable differences (i.e., the resulting mean NPV deviates in the range from 0.009% to 1.58%). Scenario 4 is used as the case in the sensitivity analysis and the results of the sensitivity analysis are presented in Fig. 13. Similar to the sensitivity analysis for the previous 3 scenarios, syngas demand and syngas selling price hold a more significant impact on the overall mean NPV outcome.

Based on the results obtained, one of the crucial insights that are obtained from the findings is the necessity to maintain the syngas selling price and syngas demand at a satisfactory range to avoid unnecessary losses. However, under current market situations, the fluctuations of syngas selling price and syngas demand are inevitable. In the case when syngas demand falls below the satisfactory demand range, one of the potential solutions will be to implement a proper syngas storage system during the construction phase. A proper storage system can prepare for an unexpected decrease in demand during low demand period. While storing during low demand period, alternative buyers or clients can be sourced out to ensure the cash in-flow into the business entity is not significantly affected. Aside from that, the engagement in supply and demand contracts (as proposed in Ngan et al. (2020)) that enables product sales for a fixed amount within a fixed duration under a fixed price was deemed an effective way to hedge the business risk. This preposition will also be able to curb the worrisome influence of the fluctuation of syngas selling price.

6. Conclusion

This research paper presented a proposed methodology that
integrated the use of BELCA-P-graph model with stochastic Monte Carlo simulation model to evaluate the economic impact of biomass shortage. The conclusion obtained upon arriving at the end of this study had found that the inclusion of biomass shortage scenario had led to a decrease in NPV compared to the scenario without biomass shortage. A reduction in the mean NPV ranging from 1.39% to 12.21% from Scenario 1 when biomass shortage scenario was included. On the other hand, the impact of sourcing alternative biomass that resulted into an increase in operating cost and ultimately, lowering of the overall NPV value was one of the findings in this research paper. Another finding of this study was that the storage of excess biomass did not play a significant role in increasing the overall mean NPV outcome. In fact, the increase in biomass storage size has lowered the overall mean NPV outcome in this study. However, it is worthy to note that, although implementation of biomass shortage lowered the overall mean NPV result, but it is a redundancy element required in reality to handle risk of unexpected long-term biomass shortage. The current study has biomass supply every month but in varying amount. However, in reality, when there is long term (i.e., more than 3 months) biomass shortage, the consideration of biomass storage may be useful. Apart from that, a sensitivity analysis has been performed, while two critical uncertainties that have a greater impact on the NPV outcome (i.e., syngas demand and syngas selling price) have been identified. Both of which are directly related to the profit gained by the biomass gasification plant. Therefore, this research paper had highlighted the significance of including biomass shortage during techno-economic analysis to avoid underestimation or overestimation of the economic profitability of the project. Although Scenario 1 had the highest profitability, however, it had not considered the consequences of biomass shortage that resulted in an overestimation of profit gain. This study can be further extended to consider multiple objectives that include environmental indices. For example, the carbon penalty associated with the supply chain can be factored into the model for a more accurate representation of the actual business model. Aside from that, an artificial intelligence (AI) model can also be developed to determine the feedstock ratio of each type of biomass available (locally and from external sources) during biomass feedstock shortage. This can provide more convenience to users as the developed AI model can determine combination of suitable biomass feedstock and their respective feedstock ratio. Apart from that, the current study can be extended further to evaluate the resiliency of the supply chain.

Credit Author

Shirleen Lee Yuen Lo: Methodology, Visualization, Writing – original draft Preparation; Chun Hsion Lim: Conceptualization, Writing – review & editing; Michael Francis D. Benjamin: Writing – review & editing; Hon Loong Lam: Supervision, Writing – review & editing; Jaka Sunarso: Supervision, Writing – review & editing; Bing Shen How: Supervision, Conceptualization, Writing – review & editing, Project administration, Funding acquisition

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This work was financially supported by Swinburne University of Technology Sarawak Campus via Full Fee-Waiver Studenship and Research Supervision Grant (2-5545 RSG). B.S. How would like to acknowledge the financial support given by the Ministry of Higher Education (MOHE), Malaysia under Fundamental Research Grant Scheme [grant number: FRGS/1/2020/TK0/SWIN/03/3].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.clet.2022.100554.

References
