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Process Synthesis of Biorefineries under Uncertain Feedstock Conditions based on Hurwicz Criterion

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Abstract

Climate change is a widespread issue posed by greenhouse gas (GHG) emission produced from human activities. As emission mitigation protocols increases in number, one way to comply with these protocols is by implementing biorefineries. A biorefinery converts biomass into biofuel, power and chemicals through a combination of processes. Due to the heterogeneous composition of biomass, various processing pathways are available for biomass conversion. This makes designing an optimal biorefinery process a difficult task. In addition, the inherent uncertainties in biomass feedstock supply would further complicate the decision-making process. To address these challenges, this work developed an optimisation model to synthesise an optimal biorefinery process design under uncertain feedstock conditions by adapting Hurwicz Criterion approach. The uncertainty in the feedstock supply is represented as scenarios in Hurwicsz Criterion approach. This approach allows the decision makers to input anticipated feedstock supply values into the criterion to choose the best alternative design. Hurwicz Criterion approach finds the intermediate area between total optimism and total pessimism criteria by including a coefficient of realism. The value for the coefficient of realism is subject to the decision makers' appetite towards risk. Based on the results from Hurwicz Criterion, biorefinery process design with best weighted average is selected. To illustrate the proposed methodology, a case study was solved. In the case study lignocellulosic biomass such as empty fruit bunch was used. The optimal biorefinery design with the best weighted average was the one sized at 8,000 kg/hr of biomass input. The products chosen for the biorefinery designs were bio-oil, pentanol and succinic acid. Following this, results from the Hurwicz Criterion is compared with results from a method that requires the use of historical data and probability.

Keywords: Biorefinery, Uncertainty, Hurwicz Criterion, Process Synthesis and Optimisation.

1 Introduction

In recent years, climate change has become a prominent topic of discussion. This is because climate change has the potential to cause irreversible risks that can jeopardise human health and life (Lin and Zhu 2019). Climate change is essentially an environmental issue caused by cumulated greenhouse gas emissions such as Carbon dioxide (CO_2) (Zhang and Xu 2018). In 2018, CO_2 emissions have increased by 2.0 % compared to 1.0 % increase in 2017 (Olivier and Peters 2020). Moreover, 89 % of the emissions originate from fossil fuel combustion to produce liquid and solid fuels (Olivier and Peters 2020). A study by IPCC showed that the industrial GHG emission must be reduced by 65 – 90 % in 2050 compared to 2010 levels in order to limit the global warming temperature to 1.5 ºC above pre-industrial level (IPCC 2018). Amid various emission mitigation protocols and agreements, the increasing trends in emissions become a hurdle in achieving mitigation goals. One potential solution to overcome this hurdle is to introduce biorefineries. The definition of biorefineries are depicted in many variations. The most established definition developed by National Renewable Energy Laboratory and agreed by Fernando et al. (2006) is: "*A biorefinery is a facility that integrates conversion processes and equipment to produce fuels, power, and chemicals from biomass*".

The abovementioned definition highlights the use of biomass as a feedstock for fuels, power and chemicals. IPCC proposed that biomass should be utilised as feedstock along with suitable technologies to achieve the GHG emission reduction goal before 2050 (IPCC 2018). According to Kamm and Kamm (2004) and Li et al. (2017), biomass is defined as an organic matter that can be obtained from organisms and used as feedstock to produce several products on a renewable basis. Biomass can be classified according to its originating source. There are currently four categories of feedstock; first generation (edible food crops), second generation (biodegradable lignocellulosic biomass), third generation (algae) and fourth generation (captured CO_2) feedstocks (Moncada et al. 2014). The four categories of biomass feedstocks indicate that there are several biomass options that can be used as feedstock to produce products. Each type contains a specific composition that is unique for further processing into fuels and chemicals. The biomass from these four categories tend to differ in terms of physical and chemical properties. This will impact the choice of processing units required to convert and fully utilise biomass into products (Cherubini 2010). Biomass can be processed using a variety of processes such as chemical, thermochemical, physical and biological processes (Gnansounou and Pandey 2017). These processes suggest that there is a large pool of potential processing pathways available for implementation. In this sense, the design of a biorefinery can be a complicated task. In addition, biorefineries face other issues too. For example, biorefineries experience challenges from uncertainties in biomass availability (i.e., seasonal variations), market price fluctuations, market demand and etc. These uncertainties also influence the way in which a biorefinery is designed. If designed incorrectly, the economic feasibility of a biorefinery can be called in question. To address the challenges mentioned above, Process Systems Engineering (PSE) offers several tools.

PSE is a research field that emphasises the development of systematic design methodologies (Grossmann and Westerberg 2000). This methodologies determines the ideal type, design, operation and interconnection of processing technologies in a process system (Nishida 1981). In PSE, there are several papers published on the topic of biorefinery design and optimisation. For instance, Kokossis et al. (2014) proposed a systems approach to consider the challenges in designing integrated biorefineries. Kokossis et al. (2014) combined process synthesis, process integration and flowsheeting methods from PSE to design biorefineries. Andiappan et al. (2015) used multiobjective optimisation approaches to synthesize a sustainable integrated biorefinery considering economic, environmental and energy performances. A novel Incremental Environmental Burden Assessment approach was also introduced in this work to evaluate the environmental impact of an integrated biorefinery (Andiappan et al. 2015). Meanwhile, Ng et al. (2015) developed a novel two-stage optimisation approach to design optimal biochemical products and synthesize optimum biomass conversion pathways in an integrated biorefinery. In this work, signature based molecular design techniques had been used to determine the optimal biochemical products whereas, superstructure mathematical optimisation approach had been used to synthesize the optimum biomass conversion pathways (Ng et al. 2015). Vikash and Shastri (2017) developed a model using an optimisation framework based on superstructure to synthesise a lignocellulosic biorefinery from alternative options in India to produce ethanol. This model considered aspects like multiple feedstock, the impact of biorefinery scale and the techno-economic feasibility. More recently, Aristizábal-Marulanda et al. (2019) presented an approach for the design and assessment of multiproduct biorefineries. This approach was developed based on 2-stage strategy; conceptual design and optimisation, where surrogate models were used to generate the superstructure. However, based on the contributions from the papers above, it is observed that the developed models did not consider uncertainties when optimising the biorefinery design. It is important to consider uncertainties in biorefinery design to account for variations in operations. Such uncertainties can be in the form of variations in biomass feedstock supply, composition of biomass, product prices, feedstock costs, etc. These uncertainties have a large impact on the economic performance of the optimal biorefinery design and it may even influence the feasibility of the design (Sy et al. 2018). Therefore, PSE methodologies can be used for optimisation under uncertainty using historical data (Grossmann et al. 2017).

Several studies have been conducted on design of biorefinery under uncertainty. For example, Tang et al. (2013) presented a robust optimisation method to synthesise an integrated biorefinery under various predefined uncertainties. Cheali et al. (2014a) presented a framework that uses Monte Carlo simulation to synthesise and design an optimal biorefinery process network under data uncertainty. They later developed a systematic framework (Cheali et al. 2014b) to synthesise and design a biorefinery network under market price uncertainty along with associated risks. Rizwan et al. (2015) proposed a systematic framework to optimise the processing pathways for a microalgae biorefinery considering technical data availability. Later, Giuliano et al. (2016) introduced a method to optimise a multiproduct biorefineries under uncertain biomass supply due to seasonality. This method involves linearisation of MINLP economic optimisation into a mixed integer linear program (MILP) to obtain an optimal solution. Kasivisvanathan et al. (2016) then developed a flexibility model to assess the ability of the plant to adapt to the fluctuating product demand. This model adopts the fuzzy optimisation approach to minimise cost while maximising the flexibility of the plant. Meanwhile, Gong et al. (2016) proposed a two-stage adaptive robust optimisation to optimise a bioconversion process network based on uncertainty. More recently, Caldeira et al. (2019) proposed a model to reduce cost and its changes in biodiesel production by incorporating operational and feedstock price uncertainty. A stochastic blending approach was incorporated to the models to address the uncertainty. Diehlmann et al. (2019) developed a hybrid simulation-optimisation approach to include uncertainties in the assessment of different utilisation pathways for rice straw in Thailand. This approach includes a Monte Carlo simulation and a two-stage stochastic programming model which accounts for uncertainties on the supply chain and system level. Dickson and Liu (2019) proposed a superstructure-based optimisation to obtain the economically and environmentally optimal pathway of biorefinery. A sensitivity analysis was also performed to consider uncertainties in process parameters (Dickson and Liu 2019). Cortes-Peña et al. (2020) used a process simulator to assess the prospects of design decision and scenarios for biorefineries under uncertainty. The process simulator used in Cortes-Peña et al. (2020) uses its swift and flexible framework to enable the design of biorefinery, simulation and techno-economic analysis under uncertainty. Palmeros Parada et al. (2020) adapted an approach that takes the stakeholder's values into account during the decision making for the design of a biorefinery. The approach by Palmeros Parada et al. (2020) considers the societal concerns and uncertainties resulting from sustainability controversies.

The tools developed in the reviewed works above can be used in the process design of a biorefinery. However, there are several areas noted for improvement;

- A portion of previous works that did not consider uncertainties were focused solely on optimising biorefinery to obtain the suitable processing technologies.
- Meanwhile, the rest of the previous works that did consider uncertainties, utilised stochastic programming approach to optimise the biorefinery design. Previous works assume that the historical data or probability distributions of uncertain parameters like feedstock seasonality are available to optimise the design under uncertainty. However, historical data and probabilities may not be available for newly established biorefineries.

As such, this work aims at fulfilling these research gaps. This work proposes a methodology to synthesise an optimal biorefinery process design under uncertain feedstock condition. In the past, several methods have been used for addressing uncertainty. For instance, Ling et al. (2018) proposed a systematic decision making framework for designing biomass CHP systems based on Maximax Criterion, Maximin Criterion and Minimax Regret Criterion respectively. The criterions presented in Ling et al. can be used when very limited historical data and probability distributions are available (Ling et al. 2018). Benito-Garzón et al. (2018) proposed a robust decision theory to be included as a guide to management decision on the translocation of tree population to compensate climate change. Benito-Garzón et al. (2018) also considered uncertainties on the climate scenarios by using Maximin, Maximax and Minimax decision criterion. Lastly, Park and Um (2018) developed an evaluative decision-making system framework to account for lack of information in strategic environmental assessment on dam plans. Park and Um (2018) used Maximax and Maximin criterion as one of the deficient information filling methods. However, Maximax, Maximin and Minimax criterion are used to obtain the best payoffs under the extremely best-case scenario, extremely worst-case scenario and with least regret scenario respectively. These criterions look at the most extreme ends of decision making which is unrealistic as it is uncommon for decision makers to be extremely optimistic or pessimistic (Liu 2018). On the other hand, Hurwicz Criterion is used to find the balance between optimistic and pessimistic decisions (Green and Weatherhead 2014). Hurwicz Criterion allows the decision makers (based on their experience and knowledge) to assign a percentage weight to optimism and the rest to pessimism (Pažek and Rozman 2009).

In this respect, the proposed methodology presents a mathematical model to determine the optimal biorefinery design with maximum gross profit. This methodology adapted an approach called Hurwicz Criterion to account for uncertainties when no historical data or probabilities are available. Hurwicz Criterion approach is used to recommend an optimal biorefinery process design under uncertainties based on the coefficient of realism.

2 Problem Statement

The task of designing an optimal biorefinery becomes increasingly complex due to the range of available processing routes. In addition, the complexity increases further when there is uncertainty in biomass feedstock supply. The design problem considered for this work is stated as follows: Biomass feedstock $b \in B$ consisting of components *i* (cellulose, hemicellulose, lignin and moisture content) with flow rates F_b and composition y_{ib} can be converted into intermediate products $p \in P$ by using technologies $t \in T$ with a fixed conversion factor ϕ_{itp}. The intermediate products with flow rates $F_{pt'}$ can then be converted into the final product $p' \in P'$ by using technologies $t' \in T'$ with a fixed conversion factor $\phi_{pt'p'}$. F_p and $F_{p'}$ represents the total flow rates of intermediate products *p* and final products *p'*. The objective function of this work is to maximise the gross profit *GP* of a biorefinery design. As mentioned earlier, seasonal nature of biomass results in uncertainty in biomass availability for biorefineries. The uncertainties in biorefinery design are mostly solved by using non-deterministic approaches that require probabilities. Data on probabilities heavily depend on historical data. Since biorefineries are still relatively new, historical data for certain feedstocks may not be readily available. In this respect, an approach that does not rely on historical data must be developed. Thus, the aim of this work is to develop an optimisation model to synthesise an optimal biorefinery process design under uncertain biomass supply, giving focus to lack of historical feedstock data.

The next section describes the methodology used to develop an optimisation model. The general superstructure developed for the biorefinery design is then explained. Based on the general superstructure, the mathematical model to optimise the biorefinery design is then formulated. Next, the Hurwicz Criterion approach is introduced for decision making under uncertainty. Lastly, a biorefinery case study is solved to illustrate the proposed methodology.

3 Methodology

Mathematical optimisation is one of the methods developed in the PSE (Grossmann and Daichendt 1996). It is a method that can be used to model substantial amount of processes and systems (Grossmann 1990). There are few steps involved in mathematical optimisation. The first step is to compile and present the details and data for all the possible process pathways and required processing units interconnected in a superstructure (Andiappan 2017). A superstructure is a network of interconnection of all possible process pathways (Ng et al. 2015). Hence, based on the collected data for the available process pathways and technologies, a general superstructure is constructed by interconnecting the technologies to represent a biorefinery as shown in **Fig. 1**.

As shown in **Fig. 1**, biomass $b \in B$ represents the available biomass feedstock with flow rates F_b. For instance, b = 1 may represent rice straw while b = 2 could denote wood wastes. Technology $t \in T$ can be used to convert

F_b into intermediate product $p \in P$. The final product $p' \in P'$ can be produced by converting the intermediate product $p \in P$ through technology $t' \in T'$. This general superstructure only contains technology *t* and *t'*. However, this superstructure can be extended for as many stages (e.g., technologies) as required. A mathematical model was then developed based on the general superstructure presented in **Fig. 1**. This is followed by the generation of the payoff table. In the payoff table, the *GP* of each scenario will be computed. The payoff table will then be used in the Hurwicz Criterion approach.

3.1 Mathematical Model

Next, the mathematical model can be developed based on the superstructure (in **Fig. 1**) to correlate variables and parameters of every technology considered in the design. An optimum design can be established by optimising the objective functions that are usually defined in the model along with the constraints. The mathematical optimisation of the biorefinery in this work considers its mass balance, capital (CAPEX), operating expenditure (OPEX) and gross profit. It should be noted that the italic notations indicate variables in the model while the non-italic notations refer to fixed parameters.

3.1.1 Mass balance

The mass balance for the biorefinery that utilises several types of biomass in different technologies are presented below. In Eq (1), y_{ib} is the user-defined composition of components *i* in biomass *b*. f_{ib} is the flow rate of components *i* in biomass *b*. Examples of components *i* in biomass *b* are cellulose, hemicellulose, lignin and moisture content. The available mass flow rate of biomass *b* is represented by F_b as shown in Eq (1).

$$f_{ib} = F_b y_{ib} \qquad \forall i \forall b \qquad (1)$$

F_{bt} in Eq (2) represents the distribution of every biomass *b* to technology *t*.

$$F_b = \sum_{t=1}^{T} F_{bt} \qquad \forall b \qquad (2)$$

f_{it} in Eq (3) represents the flow rates of components *i* of biomass *b* in technology *t*. Note, y_{ib} is included in Eq (3) because the composition will still be the same when there is a split/distribution. At every technology *t*, a fixed conversion or recovery factor of ϕ_{itp} is used to convert the components f_{it} of biomass *b* into intermediate product *p* with a total flow rate of F_p as shown in Eq (4).

$$f_{it} = \sum_{b=1}^{B} F_{bt} y_{ib} \qquad \forall i \forall t \qquad (3)$$

$$F_p = \sum_{b=1}^{B} \sum_{i=1}^{I} \phi_{itp} f_{it} \qquad \forall p \qquad (4)$$

Further conversion of intermediate product *p* into final product *p'* can be achieved by splitting F_p to technology *t'* as shown in Eq (5) below.

$$F_p = \sum_{t'=1}^{T'} F_{pt'} \qquad \forall p \qquad (5)$$

After the split, final product p with mass flow of $F_{p'}$ is produced from the conversion of intermediate product p with a constant conversion factor of $\phi_{pt'p'}$ at each technology t' as shown in Eq (6).

$$F_{p'} = \sum_{p=1}^{P}\sum_{t'=1}^{T'} \phi_{pt'p'} F_{pt'} \qquad \forall p' \tag{6}$$

3.1.2 Capital and operating cost

Capital expenditure (CAPEX) and operating expenditure (OPEX) for every potential technology t and t' makes up the total cost for a biorefinery. For a uniform payment of CAPEX, capital recovery factor (CRF) is used to annualise the CAPEX. CRF depends on the interest rate r and the payment duration, n (in years) for each technologies t and t' as shown in (7) and (8).

$$\mathrm{CRF}_t = \frac{\mathrm{r}_t\left(1+\mathrm{r}_t\right)^{\mathrm{n}_t}}{\left(1+\mathrm{r}_t\right)^{\mathrm{n}_t}-1} \qquad \forall t \tag{7}$$

$$\mathrm{CRF}_{t'} = \frac{\mathrm{r}_{t'}\left(1+\mathrm{r}_{t'}\right)^{\mathrm{n}_{t'}}}{\left(1+\mathrm{r}_{t'}\right)^{\mathrm{n}_{t'}}-1} \qquad \forall t' \tag{8}$$

Hence, the annualised CAPEX for technologies t and t' can be determined by using the Eq (9) and (10) where C_t^{CAPEX} and $C_{t'}^{CAPEX}$ is the capital cost of technologies t and t' respectively. From these equations, $\mathrm{x}_t^{\mathrm{CAPEX}}$ and $\mathrm{x}_{t'}^{\mathrm{CAPEX}}$ is the cost factor for CAPEX while $\mathrm{y}_t^{\mathrm{INST}}$ and $\mathrm{y}_{t'}^{\mathrm{INST}}$ are the installation cost associated with technologies t and t' respectively. I_t and $I_{t'}$ are binary variables, which means they only take values 0 or 1. These binaries are directly related to the installation cost. If the binary is 0, it indicates that the technology is not selected and hence, there will be no installation cost incurred. Whereas, if the binary is 1, this means that the technology is selected where its installation cost is incurred, and the variable cost will be determined based on the size of technology F. The binaries can be expressed using inequality constraints as shown in Eq (11) and (12) where M_t and $\mathrm{M}_{t'}$ are large arbitrary values which can sometime be the maximum capacity of the technologies and N_t and $\mathrm{N}_{t'}$ are minimum capacity of the technologies. The total annualised CAPEX can be obtained using Eq (13).

$$C_t^{\mathrm{CAPEX}} = \mathrm{CRF}_t\left(\sum_{b=1}^{B}\left(\mathrm{x}_t^{\mathrm{CAPEX}} F_{bt}\right) + \mathrm{y}_t^{\mathrm{INST}} I_t\right) \qquad \forall t \tag{9}$$

$$C_{t'}^{\mathrm{CAPEX}} = \mathrm{CRF}_{t'}\left(\sum_{p=1}^{P}\left(\mathrm{x}_{t'}^{\mathrm{CAPEX}} F_{pt'}\right) + \mathrm{y}_{t'}^{\mathrm{INST}} I_{t'}\right) \qquad \forall t' \tag{10}$$

$$\mathrm{N}_t I_t \le \sum_{b=1}^{B} F_{bt} \le \mathrm{M}_t I_t \qquad \forall t \tag{11}$$

$$\mathrm{N}_{t'} I_{t'} \le \sum_{p=1}^{P} F_{pt'} \le \mathrm{M}_{t'} I_{t'} \qquad \forall t' \tag{12}$$

$$C^{\mathrm{CAPEX}} = \sum_{t=1}^{T} C_t^{\mathrm{CAPEX}} + \sum_{t'=1}^{T'} C_{t'}^{\mathrm{CAPEX}} \tag{13}$$

The total OPEX of the biorefinery can be determined by using Eq (14) where $\mathrm{x}_b^{\mathrm{OPEX}}$ is the OPEX cost factor for biomass b.

$$C^{\mathrm{OPEX}} = \sum_{b=1}^{B} \mathrm{x}_b^{\mathrm{OPEX}} F_b \tag{14}$$

The potential revenue that can be obtained from biorefinery can be determined by using Eq (15) where $\mathrm{x}_{p'}^{\mathrm{REV}}$ is the price factor of product *p'*.

$$C^{\mathrm{REV}} = \sum_{p'=1}^{P'} \mathrm{x}_{p'}^{\mathrm{REV}} F_{p'} \tag{15}$$

Hence, the gross profit *GP* can be obtained for the designed biorefinery based on the calculated total CAPEX, OPEX and revenue as shown in Eq (16). This is then used in the next step – generating payoff table. Note that *GP* is important to determine the cash flow before calculating the net present value. Since the focus of this work is to determine a profitable biorefinery, *GP* is a sufficient economic evaluation at this stage. Thus, the NPV was not calculated in this work. However, the *GP* calculation can be easily extended to NPV should it be required.

$$GP = C^{REV} - \left(C^{CAPEX} + C^{OPEX}\right) \tag{16}$$

3.2 Hurwicz Criterion

To utilise the Hurwicz Criterion approach for uncertainty, a payoff table will be required. A payoff table is a table that represents the potential profits and losses that can be obtained during decision making. This table can be used to portray the possible gross profits generated from different scenarios that represents uncertainty in a biorefinery. The payoff table can be tabulated based on the mathematical model formulated in Section 3.3. Hence, the gross profits in the general scheme shown in Table 1 are generated based on the design plant size *E* and the available feed supply in scenario *F*. Feedstock supply *F* refers to the anticipated feedstock scenario. Meanwhile, plant size *E* refers to the biorefinery's design capacity sized based on the feedstock supply scenario. However, there are few crucial steps to take note of while generating the gross profits for the payoff table. Firstly, the values for F are determined based on the anticipated feedstock supply. For example, if a feedstock supply of 5,000 kg/hr is expected, then the possibility of sizing the plant to 5,000 kg/hr are analysed. Similarly, if 6,000 kg/hr of feedstock supply is anticipated, the possibility of sizing the plant to 6,000 kg/hr would be evaluated. This is repeated for all the other anticipated feedstock supply scenarios and corresponding plant sizes. This is how the values for E and F are populated. With this way, the decision maker will know whether a plant size that is larger could be useful to cater for all feedstock supply scenarios or a much lower size would be sufficient. Secondly, the developed mathematical model can be solved by fixing Eq (17) as the objective function to obtain the gross profits for the shaded cells in Table 1.

$$\text{Maximise}\, GP \tag{17}$$

The shaded cells in Table 1 represent the gross profits obtained when the designed biorefinery plant size is equal to the available feed supply. In other words, the available feedstock supply will be set as a constraint in the model. Whereas, the profits in the other cells of Table 1 are obtained when the designed plant size of the biorefinery is not equivalent to the available feed supply occurring in a particular scenario due to the seasonal nature of biomass.

Table 1 General payoff table

Design Plant Size E	Available Feed Supply F					GP_e^{max}	GP_e^{min}
	f = 1	f = 2	f = 3	⋯	f = F		
e = 1	GP_{11}	GP_{12}	GP_{13}	⋯	GP_{1F}	GP_1^{max} = Max (GP_{11}...GP_{1F})	GP_1^{min} = Min (GP_{11}...GP_{1F})
e = 2	GP_{21}	GP_{22}	GP_{23}	⋯	GP_{2F}	GP_2^{max} = Max (GP_{21}...GP_{2F})	GP_2^{min} = Min (GP_{21}...GP_{2F})
e = 3	GP_{31}	GP_{32}	GP_{33}	⋯	GP_{3F}	GP_3^{max} = Max (GP_{31}...GP_{3F})	GP_3^{min} = Min (GP_{31}...GP_{3F})
⋮	⋮	⋮	⋮	⋱	⋮	⋮	⋮
e = E	GP_{E1}	GP_{E2}	GP_{E3}	⋯	GP_{EF}	GP_E^{max} = Max (GP_{E1}...GP_{EF})	GP_E^{min} = Min (GP_{E1}...GP_{EF})
					Maximax →	Max (GP_1^{max}, ..., GP_E^{max})	-
					Maximin →	-	Max (GP_1^{min}, ..., GP_E^{min})

For example, assume that the biorefinery plant is designed at 50 kg/hr (i.e., e = 1). The gross profit in the shaded cell (i.e., GP_{11}) is obtained when the available feedstock supply f is also 50 kg/hr (i.e., f = 1). In other words, this would be the case where the feed supply is equal to the designed plant size. However, the gross profits in other cells (i.e., GP_{12}, GP_{13}) are obtained when the available feedstock supply f are 100 kg/hr and 150 kg/hr (i.e., f = 2, f = 3), which are larger (not equal) than the designed plant size 50 kg/hr (i.e., e = 1). In this case, there are few assumptions made while tabulating the gross profits in the payoff table. The assumptions are:

- If the available feedstock supply is lower than the designed biorefinery plant size, the gross profit would depend on the products produced from the available feedstock supply.
- If the available feedstock supply is higher than the designed biorefinery plant size, the gross profit would depend on the maximum capability of the designed plant size to produce products.

In the columns far right of Table 1, the maximum gross profit (GP_e^{max}) value and the minimum gross profit (GP_e^{min}) value for each row is determined. This is done by comparing GP values in each column for a given row (i.e., GP_{11}, GP_{12}, GP_{13}, ….GP_{1F}) and selecting the maximum and minimum value among them. As a result, each row will have a GP_e^{max} and GP_e^{min} value computed. These values will then be used in Maximax Criterion and Maximin Criterion respectively. Maximax Criterion and Maximin Criterion are criterion used during decision making under uncertainty. Maximax and Maximin criterion represent a decision maker's optimistic or pessimistic decision-making behaviour respectively (Pažek and Rozman 2009). Maximax Criterion is an approach where the decision maker is hoping for the best payoff based on the best scenario. In the case of Table 1, Maximax Criterion suggests selecting the design with the highest value among the GP_e^{max} values computed for each row. Meanwhile, Maximin Criterion is the opposite of the former where the decision maker hopes for the best payoff based on the worst scenario (Ling et al., 2018). In this respect, Maximin Criterion requires the selection of a design with the highest value among the GP_e^{min} values listed for each row.

Evidently, Maximax or Maximin Criterion forces the designers into approaching the design problem in an extremely optimistic or pessimistic way respectively (Hansson 2005). However, it is important to provide an alternative approach where decision-makers are not required to opt for such extreme decisions. In fact, it would be beneficial for designers of a biorefinery to consider a certain degree of optimism and pessimism while making important design decisions. In this sense, the Hurwicz Criterion is suitable to address such issue. While this work focused on the uncertain feedstock supply, the Hurwicz Criterion approach is applicable with other types of uncertainties. The payoff table can be updated to incorporate more scenarios to consider more types of uncertainties.

Hurwicz Criterion was founded by Leonid Hurwicz in 1951 (Hurwicz 1951). It was an approach developed to find the intermediate area between the Maximax and Maximin criteria (Fargier and Guillaume 2020). At present, there are no work done to consider uncertainty in biorefinery design using Hurwicz Criterion approach. Different methods have been used to account for uncertainties without historical data or probability distributions as reviewed at the end of Section 1. However, these methods are mainly used to determine the best payoffs at the most extreme ends of decision making, i.e. optimism or pessimism. Whereas, applying Hurwicz Criterion approach for uncertainties will allow the decision maker to find the balance between optimistic and pessimistic decisions since the latter decisions are unrealistic. Consequently, there are several works done using Hurwicz Criterion approach in different fields. For instance, Wen and Iwamura (2008) applied Hurwicz Criterion to model a facility location-allocation (FLA) problem. Jeantet and Spanjaard (2009) used Hurwicz Criterion to determine the optimal strategy in a decision tree endowed with imprecise probabilities. Sheng et al. (2013) used Hurwicz Criterion to formulate an uncertain optimal control model to learn the uncertain control system. Recently, Zhu et al. (2019) developed an uncertain Gaussian diffusion-Hurwicz criterion (UGHC) model to analyse the industry-air quality control (IAC) system in ecologically fragile coal-dependent cities.

Hurwicz Criterion approach is also known as the realism approach as it incorporates a coefficient of realism α. α essentially denotes the degree of optimism. α is pre-defined by the decision maker as a fraction to optimism and the rest to pessimism (Sheng et al. 2013). The value of the α depends on the decision maker's appetite towards risk. The α is also influenced by the decision maker's experience where it allows flexibility for the decision maker to make decision. The weighted average (*WA*) of each design can be calculated by using Eq (18) as shown below, note that $0 \leq \alpha \leq 1$.

$$WA_e = \alpha\left(GP_e^{\max}\right) + \left(1-\alpha\right)GP_e^{\min} \tag{18}$$

As can be seen from Eq (18) above, α is the degree of optimism whereas, $1 - \alpha$ represents the degree of pessimism. For each design plant size, the maximum gross profit of each row $GP_e^{\max}$ (from Table 1**)** is multiplied by the coefficient of realism α. Meanwhile, the minimum gross profit of a given row $GP_e^{\min}$ (from Table 1**)** is multiplied by the coefficient $1 - \alpha$. The sum of these results gives the weighted average *WA* of each design plant size. After calculating *WA* for each design plant size, the design plant size with highest *WA* should be selected as the chosen decision. In the following section, the proposed Hurwicz Criterion approach is demonstrated through a case study.

4 Hypothetical Case Study

Biomass feedstocks are generally abundant in nature. Among the different categories of biomass, the second generation feedstock (i.e., lignocellulosic biomass) is highly researched because its market growth is expected to increase by 50 % between 2014 – 2020 (UNCTAD 2016). In addition, second generation feedstocks reduce competition on land because they consist of unused parts of the plants (i.e., crop residues, wastes, etc.). Besides, about 50% of greenhouse gas emissions can be decreased by utilising crop residues in biorefineries (Cherubini and Ulgiati 2010). In Malaysia, around 168 million tonnes of biomass is produced per annum where 94 % of it is from palm oil waste (BE-Sustainable 2012). In 2018, 97.8 Million tonnes of fresh fruit bunches (FFB) were processed by a total of 451 mills in Malaysia to produce crude palm oil (CPO) and crude palm kernel oil (CPKO) (Malaysian Palm Oil Board 2019a,b). Empty fruit bunches (EFB) are the largest solid biomass waste from palm oil production; about 23 % of FFB processed (Onoja et al. 2018). This large amount of waste can be utilised in a biorefinery to produce valuable products rather than the usual way of burning the EFB or using them as fertilisers (Rosli et al. 2017).

EFB can be used in biorefineries to produce valuable products from their components. The typical composition of EFB is obtained from Akhtar et al. (2014) and is shown in Table 2. However, uncertainty in biomass supply exists due to several factors. Firstly, CPO is susceptible to fluctuations in production due to heavy productions in the previous years (Abdullah and Wahid 2011). These heavy productions induce stress to the palm trees hence fluctuations in EFB supply occurs. The uncertainty in EFB supply is also dependent on the rainfall and replanting programmes (Abdullah 2012). Therefore, a case study is carried out to demonstrate the methodology shown in Section 3 to select an optimal biorefinery design using Hurwicz Criterion. This case study incorporates uncertainty in EFB feedstock supply. This is done by considering scenarios where the available feedstock supplies are 4,000, 6,000, 8,000 and 10,000 kg/hr. Aside from this, this case study includes bio-oil, Fischer-Tropsch fuel (FT-fuel), bio-pentanol and succinic acid as potential products for the biorefinery. **Fig. 2** presents the superstructure of the biorefinery in this case study.

Table 2 Composition of empty fruit bunches (EFB)

Composition (wt%)					
Cellulose	Hemicellulose	Lignin	Moisture	Others	Total
44.2	33.5	20.4	1.9	-	100

In this case study, biomass *b* would be the empty fruit bunches (EFB). As can be seen from **Fig. 2**, there are four types of pre-treatment considered (i.e., torrefaction, organosolv, alkaline and microwave-alkali pre-treatment) to separate cellulose, hemicellulose and lignin from each other. Torrefaction, organosolv, alkaline and microwave-alkali pre-treatment recovers 97 %, 88 %, 62.1 % and 99.3 % of cellulose respectively. The complete recovery factors for all components are shown in Table 3.

Furthermore, there are two thermochemical pathways and one biological pathway considered in the biorefinery. Thermochemical pathway 1 consists of pyrolyser unit which directly converts 58 % of the biomass (without pre-treatment) into bio-oil. Meanwhile, in thermochemical pathway 2, the pre-treated biomass enters gasification unit to produce syngas and other gases that can be further converted to the final product. The CH_4 gas produced from gasifier is further converted to syngas through a steam methane reformer (SMR). Next, the syngas enters the Fischer-Tropsch reactor to produce the final product; FT-fuel. On the other hand, in biological pathway 1, the pre-treated biomass is converted into glucose via enzymatic hydrolysis reactor and this glucose enters the fermentation reactor to produce either carboxyl salts or calcium succinate. It should be noted that the pre-treated biomass can also enter the fermentation reactor without converting to glucose. The carboxyl salts are then converted to their respective ketones via ketonisation reactor. The ketones are converted into their respective alcohols which are then separated in a distillation unit to obtain bio-pentanol. Whereas, the calcium succinate is crystallised to remove the unwanted fermentation broth obtained from the fermentation reactor. The crystallised calcium succinate is hydrolysed to produce succinic acid which is then recovered via ion exchanger and reactive extraction unit. The conversion and recovery factors used in each technology are shown in Table 4 - 7. The data collected for the equipment cost estimation is also shown in Supporting Information: Table A. 1 & Table A. 2.

Table 3 Recovery factor of pre-treatment technologies

Technology	Recovery factor			
	Cellulose	Hemicellulose	Lignin	Moisture
Torrefaction	0.970	0.221	0.014	-
MW-Alkali	0.993	0.287	0.200	0.208
Organosolv	0.880	0.050	0.410	0.373
Alkaline	0.621	0.441	0.018	-

Table 4 Pyrolysis product yield from biomass

Technology	Yield		
	Bio-Oil	Char	Gases
Pyrolysis	0.58	0.26	0.16

Table 5 Conversion factor of enzymatic hydrolysis and gasifier

Technology	Conversion			
	Cellulose	Hemicellulose	Lignin	Moisture
Enzymatic hydrolysis	0.717	0.510	0.000	0.625
Gasifier	0.979	0.922	0.528	-

Table 6 Conversion factors of SMR and FT-reactor

Technology	Conversion			
	H_2	CO	CO_2	C_2H_4
SMR	0.0077	0.0394	0.0788	0.0004
FT-Reactor	-	0.896	0.252	-

Table 7 Other conversion/recovery factors

Technology	Conversion
Fermentation	1.000
Crystalliser	0.900
Hydrolysis	0.900
Reactive Extraction	0.997
Ion Exchange	0.710
Ketonisation	0.413
Hydrogenation	0.984
Alcohol recovery	0.195

It is important to note that although four types of products have been considered in this case study, the proposed methodology is flexible to consider as many products as possible. On top of this, the number of pathways and technologies required can also be extended in the superstructure to the desired level of the decision-maker. The proposed methodology can also be adaptable to multiple feedstocks.

For this case study, a mixed integer linear programming (MILP) model is developed following the general mathematical model formulation shown in Section 3. In addition to this, there were several assumptions made:

- It is assumed that the drying and grinding of the biomass are done together with the pre-treatments. Hence, the equipment cost of dryer and grinder are embedded into the cost of pre-treatment technologies.
- The annual operating time of the biorefinery is 8,000 hours.
- Only equipment cost is considered in the capital expenditure (CAPEX) estimation.
- The interest rate of 8 % is the same for every technology.
- The CAPEX is paid consistently every year for 15 years. Hence, the capital recovery factor (CFR) is 0.1019/year.
- Operating cost refers to the cost of the biomass feedstock.

4.1 Results for Case Study

The developed MILP model was solved under 1s with global solver via LINGO optimisation software version 17 using Apple MacBook Air with Intel Core i5 (1.6 GHz) processor and 8 GB 1600 MHz DDR3 memory. The developed model consists of 161 variables, 25 integers and 152 constraints for the case study.

The potential revenue, CAPEX and OPEX for each design plant size are shown in Table 8 below. The equipment cost of the technologies selected for each design plant size is shown in Table 9.

Table 8 Revenue, CAPEX and OPEX for each biorefinery design plant size using EFB

Design Plant Size (kg/hr)	4,000	6,000	8,000	10,000
Revenue ($/yr)	4,628,963	7,842,776	10,462,070	11,204,850
CAPEX ($/yr)	1,306,612	1,591,792	2,300,401	2,621,308
OPEX ($/yr)	960,000	1,440,000	1,920,000	2,400,000

Based on Table 9, it can be observed that at designed biorefinery plant size of 4,000 kg/hr and 6,000 kg/hr, pyrolyser, alkali reactor, fermentation reactor, ketonisation reactor, hydrogenation reactor and alcohol recovery unit technologies were selected as the optimal biorefinery design configuration with maximum gross profit. Meanwhile, these technologies were also selected for the plant sizes of 8,000 kg/hr and 10,000 kg/hr. On top of these technologies, additional technologies such as organosolv, enzymatic hydrolysis reactor, crystalliser, hydrolysis reactor and reactive extraction unit technologies were also selected. The optimal technology configurations for plant sizes of 4,000, 6,000, 8,000 and 10,000 kg/hr are shown in **Fig. 3** (a), (b), (c) and (d) respectively. Based on Table 8, the payoff table is tabulated (see Table 10). The gross profits in the payoff table are in terms of $/yr.

Table 9 Cost of equipment ($) for each design size in the case study

Technology	Design Plant Size (kg/hr)			
	4,000	6,000	8,000	10,000
Pyrolyser	6,350,679	9,150,679	9,107,841	9,394,300
Torrefier	-	-	-	-
Alkali	4,142,824	4,142,824	4,142,824	6,654,446
Microwave Alkali	-	-	-	-
Organosolv	-	-	2,680,679	2,861,177
Gasifier	-	-	-	-
Methane Steam Reformer	-	-	-	-
Fischer-Tropsch Reactor	-	-	-	-
Enzymatic Hydrolysis Reactor	-	-	1,914,950	1,940,233
Fermentation Reactor	935,900	935,900	2,850,850	2,936,436
Ketonisation Reactor	87,800	87,800	87,800	90,207
Hydrogenation Reactor	78,530	78,530	78,530	81,512
Alcohol Recovery Unit	1,233,051	1,233,051	1,233,051	1,285,668
Crystalliser	-	-	379,600	382,378
Hydrolysis Reactor	-	-	92,500	93,000
Ion Exchanger	-	-	-	-
Reactive Extraction	-	-	17,541	17,590
TOTAL CAPEX	12,828,784	15,628,784	22,586,167	25,736,947

The gross profits for the shaded cells in Table 10 were calculated by subtracting the capital cost of the designed biorefinery plant size and the operating cost of the available EFB feed supply from the potential revenue that can be obtained from available EFB feed supply.

Table 10 Payoff table for the case study (gross profits are in terms of $/yr)

Design Plant Size (kg/hr)	Available Feed Supply (kg/hr)				GP_e^{max}	GP_e^{min}
	4,000	6,000	8,000	10,000		
4,000	2,362,351	2,362,351	2,362,351	2,362,351	2,362,351	2,362,351
6,000	2,077,171	4,810,984	4,810,984	4,810,984	4,810,984	2,077,171
8,000	774,043	3,507,856	6,241,669	6,241,669	6,241,669	774,043
10,000	453,136	3,186,949	5,920,762	6,183,542	6,183,542	453,136
				Maximax →	6,241,669	-
				Maximin →	-	2,362,351

To calculate the gross profits for the cells aside from the shaded ones, the assumption stated in Section 3.4 is applied. If the available EFB feed supply is larger than the designed biorefinery plant size, the production of the product is restricted by the designed plant size. Hence, the gross profit will be constrained by the designed plant size. For instance, if the available feed supply is 6,000 kg/hr but the biorefinery plant size is designed for only 4,000 kg/hr, the biorefinery can only produce products based on the designed 4,000 kg/hr plant size. Thus, the gross profit would be the same as the gross profit obtained when the available feed supply was 4,000 kg/hr (i.e., $GP_{12} = GP_{11}$ = 2,362,351 $/yr). On the contrary, if the available EFB feed supply is smaller than the designed biorefinery plant size, the products are produced based on the available feed supply. Hence, the gross profit is obtained based on the available feed supply. This value would be lower since the designed plant size is capable of processing larger size than what is available. For example, if the available feed supply is 4,000 kg/hr but the biorefinery plant is designed for 6,000 kg/hr, the biorefinery can only produce products based on the available 4,000 kg/hr. Hence, the gross profit was calculated by subtracting the capital cost of the designed 6,000 kg/hr size and the operating cost of the available 4,000 kg/hr from the revenue obtained from the available 4,000 kg/hr feed supply as shown below. The capital cost, operating cost and the revenue required to calculate the gross profit can be found from Table 8.

$$
\begin{aligned}
GP_{21} &= 4,628,963 \text{ \$/yr} - 1,591,792 \text{ \$/yr} - 960,000 \text{ \$/yr} \\
&= 2,077,171 \text{ \$/yr}
\end{aligned}
$$

Once the payoff table is tabulated, values from Table 10 can be used to find the design plant size with the highest weighted average *WA* based on the Hurwicz Criterion approach. The results from Hurwicz Criterion approach is tabulated in Table 11 below for each design plant size considered for this case study.

Table 11 Results using the Hurwicz Criterion approach to determine the best *WA* for decision making

Design Plant Size (kg/hr)	Weighted Average *WA* (\$/yr) for each Design Plant Size using Coefficient of Realism α		
	When α = 0.1	When α = 0.5	When α = 0.9
4,000	2,362,351	2,362,351	2,362,351
6,000	2,350,552	3,444,078	4,537,603
8,000	1,320,805	3,507,856	5,694,906
10,000	1,026,176	3,318,339	5,610,501
Maximum Weighted Average WA^{max} (\$/yr)	2,362,351	3,507,856	**5,694,906**

When the coefficient of realism is 1 (i.e., α = 1), the Hurwicz Criterion reduces to Maximax Criterion (total optimist). Whereas, when the coefficient of realism is 0 (i.e., α = 0), the Hurwicz Criterion reduces to Maximin Criterion (total pessimist). Therefore, the coefficient of realism explored for this case study are 0.1 (highly pessimistic), 0.5 (neutral) and 0.9 (highly optimistic) as shown in Table 11. Aside from this, Table 11 shows the corresponding weighted average *WA* values for each design plant size. As mentioned previously, the weighted average *WA* for each designed plant size in Table 11 is calculated using the coefficient of realism along with GP^{max} and GP^{min} values in Table 10. For instance, the highest and lowest gross profit (i.e., GP^{max} and GP^{min}) for the designed plant size of 6,000 kg/hr in Table 10 is 4,810,984 \$/yr and 2,077,171 \$/yr respectively. In the case where the coefficient of realism of 0.1, it is used to determine the weighted average between these two values as shown below;

$$\begin{aligned} WA &= 0.1 \times (4,810,984) + (1 - 0.1) \times (2,077,171) \\ &= 2,350,552 \text{ \$/yr} \end{aligned}$$

This is then repeated for each designed plant size using the next coefficient of realism. The highest weighted average WA^{max} is then tabulated in the column far right of Table 11. From this column, the highest WA^{max} is then chosen as the design decision. In this case, the coefficient of realism of 0.9 gives the best WA^{max} of 5,694,906 \$/yr (i.e., shown in bold in Table 11). Based on this, the plant size of 8,000 kg/hr is the chosen design plant size.

4.2 Analysis of Results

Results from the case study indicate that two and/or more products are produced in each plant size design. Consequently, different technology configurations were selected between the scenarios. At 4,000 kg/hr and 6,000 kg/hr design size, the same configuration was selected. This configuration includes the pre-treatment unit (alkaline reactor), pyrolysis pathway which consists of only one technology (pyrolyser) to produce bio-oil and alcohol pathway to produce pentanol. Whereas the 8,000 kg/hr and 10,000 kg/hr design size had the same configuration with two pre-treatment units (alkaline reactor and organosolv), pyrolysis pathway to produce bio-oil, alcohol pathway to produce pentanol and dicarboxylic acid to produce to succinic acid. The larger design plant sizes 8,000 kg/hr and 10,000 kg/hr chose to produce 3 products (i.e., bio-oil, pentanol and succinic acid) compared to the smaller design plant sizes of 4,000 kg/hr and 6,000 kg/hr which only produces 2 products (i.e., bio-oil and pentanol). This might be due to the larger feed supply which might exceed the capacity of the smaller technologies in the bio-oil and pentanol pathways, therefore, to accommodate the rest of the feed supply, the model selects another pathway to produce an extra product with the remaining feed supply. It can be observed that the chosen plant design size using the Hurwicz Criterion approach is 8,000 kg/hr. The configuration with this design size produces bio-oil, pentanol and succinic acid. This is because at a coefficient of realism of 0.9, 8,000 kg/hr has the best weighted average among the other scenarios.

Apart from this, a sensitivity analysis was conducted to determine the tipping point at which the design decision changes in this case study. Table 12 shows the results generated for every α between 0 until 1 with an interval of 0.05. From this table, a graph of maximum weighted average against the coefficient of realism α was plotted as shown in **Fig. 4**. From **Fig. 4**, it can be seen that there are 2 tipping points. The first point is when α is 0.1, whereby if $\alpha \leq 0.1$ 4,000 kg/hr design size is chosen. The second tipping point is when α is 0.5. If α falls between $0.1 \leq \alpha \leq 0.5$, the 6,000 kg/hr design size is consistently chosen. However, if $\alpha \geq 0.5$, the 8,000 kg/hr size is consistently be favoured. From this analysis, it is clear that the plant size of 8,000 kg/hr is the profitable design choice. This is because of two reasons. The first reason is evidently due to its high gross profit. From **Fig. 5**, it can be observed that the plant size 8,000 kg/hr and 10,000 kg/hr have the highest gross profits compared to the rest. The CAPEX of the plant size 10,000 kg/hr is higher than plant size 8,000 kg/hr even though both the designs are using the same technologies. This is because the former requires higher capacity technologies to accommodate the larger feed supply than the latter plant size. The differences in the CAPEX and the technology configurations of both the designs can be seen in Table 9 and **Fig. 3** (c) and (d) respectively. Due to this, the gross profit of plant size 8,000 kg/hr is greater than plant size 10,000 kg/hr by about 50,000 $/yr. The second reason is because the plant size of 8,000 kg/hr covers the widest range of α as compared to the other two sizes as shown in **Fig. 4**. This essentially means that if the decision maker projects optimistic behaviour, the 8,000 kg/hr design size would be the recommended size for the biorefinery.

Table 12 Sensitivity analysis of the coefficient of realism α on the decision of design plant size

The coefficient of realism α	Weighted Average WA ($/yr)				WA^{max} ($/yr)
	4,000 kg/hr	6,000 kg/hr	8,000 kg/hr	10,000 kg/hr	
0.00	2,362,351	2,077,171	774,043	453,136	2,362,351
0.05	2,362,351	2,213,862	1,047,424	739,656	2,362,351
0.10	2,362,351	2,350,552	1,320,805	1,026,176	2,362,351
0.15	2,362,351	2,487,243	1,594,187	1,312,697	2,487,243
0.20	2,362,351	2,623,934	1,867,568	1,599,217	2,623,934
0.25	2,362,351	2,760,624	2,140,949	1,885,737	2,760,624
0.30	2,362,351	2,897,315	2,414,331	2,172,258	2,897,315
0.35	2,362,351	3,034,006	2,687,712	2,458,778	3,034,006
0.40	2,362,351	3,170,696	2,961,093	2,745,298	3,170,696
0.45	2,362,351	3,307,387	3,234,474	3,031,818	3,307,387
0.50	2,362,351	3,444,078	3,507,856	3,318,339	3,507,856
0.55	2,362,351	3,580,768	3,781,237	3,604,859	3,781,237
0.60	2,362,351	3,717,459	4,054,618	3,891,379	4,054,618
0.65	2,362,351	3,854,150	4,328,000	4,177,900	4,328,000
0.70	2,362,351	3,990,840	4,601,381	4,464,420	4,601,381
0.75	2,362,351	4,127,531	4,874,762	4,750,940	4,874,762
0.80	2,362,351	4,264,222	5,148,144	5,037,461	5,148,144
0.85	2,362,351	4,400,912	5,421,525	5,323,981	5,421,525
0.90	2,362,351	4,537,603	5,694,906	5,610,501	5,694,906
0.95	2,362,351	4,674,294	5,968,288	5,897,022	5,968,288
1.00	2,362,351	4,810,984	6,241,669	6,183,542	6,241,669

4.3 Comparison with Method Using Historical Data

From the hypothetical case study, the Hurwicz Criterion was applied to account for uncertainties without historical data or probability distributions in the design of biorefineries. However, the hypothetical case study in this work used empty fruit bunches, which is a biomass that readily has established historical data. This provides an opportunity for the results generated from Hurwicz Criterion to be compared with methods that require the use of historical data. In this respect, a comparison between the Hurwicz Criterion and an approach that requires probability distributions and historical data was conducted. The approach used for comparison is the Expected Opportunity Loss (EOL) approach. The EOL approach uses the same set of steps as Hurwicz Criterion until the payoff table. Hence, the EOL approach was conducted starting from the payoff table shown in Table 10. From here, a regret table with the probability distributions of each anticipated available feedstock supply was generated. The regret table is shown in Table 13 below. For more details on the regret table, readers are directed to Ling et al. (2018). The EOL value for each design size is the summation of regret value of each feed supply multiplied by its respective probability value. The EOL values calculated from each design size was then minimised to obtain the design decision. The minimum value of EOL was selected as the design decision since the regret/opportunity loss values were used in the calculations. It can be observed from Table 13 that the plant size of 6,000 kg/hr was chosen as the design decision from the EOL approach.

Table 13 Regret Table with the Expected Opportunity Loss (EOL)

Design Plant Size (kg/hr)	Available Feed Supply (kg/hr)				Expected Opportunity Loss (EOL)
	4,000	6,000	8,000	10,000	
4,000	0	2,448,633	3,879,318	3,821,191	2,308,526
6,000	285,180	0	1,430,685	1,372,558	543,346
8,000	1,588,309	1,303,128	0	58,127	944,891
10,000	1,909,216	1,624,035	320,907	0	1,234,212
Probability	0.25	0.42	0.25	0.08	-
				Minimum EOL	543,346

The design decision from the EOL approach differs from the decision obtained by using the Hurwicz Criterion approach. The decision from these approaches are compared in Table 14 below. It is noticeable that the decision from Hurwicz Criterion approach choses design size 8,000 kg/hr while the decision from the EOL approach choses 6,000 kg/hr size. However, it is worth noting that in the case study, an optimistic value of α was used. This is different from the EOL approach, which works on the principle of conservative decision-making. In this sense, it would only be fair to compare Hurwicz Criterion which uses a more conservative value for α. In the Hurwicz Criterion approach, the design decision of 6,000 kg/hr was consistently chosen in the sensitivity analysis when the α value falls between $0.1 \leq \alpha \leq 0.5$. When the decision maker choses an α value between $0.1 \leq \alpha \leq 0.5$, the decision maker is exhibiting a conservative or risk-neutral behaviour. Likewise, the EOL approach is also a conservative or risk-neutral approach. Therefore, the conservative or risk-neutral design decision favoured from both the approaches are the same, i.e. 6,000 kg/hr. The decision made by the decision maker while being conservative using the Hurwicz Criterion approach will match the decision from the approach that requires probability distribution or historical data. Meanwhile, the decision made by the decision maker while being optimistic using Hurwicz Criterion will differ from the other approach.

Table 14 Comparison of the design decision made from using Hurwicz Criterion and EOL approach

Design decision from Hurwicz Criterion approach	Design decision from Expected Opportunity Loss approach
8,000 kg/hr	6,000 kg/hr

5 Conclusions and Future Recommendations

In this work, a methodology was proposed to synthesise an optimal biorefinery process design under uncertain feedstock conditions. The proposed methodology adapted Hurwicz Criterion approach to account for the uncertainty in feedstock supply. The Hurwicz Criterion allows decision-makers to establish design decisions when there is a lack of historical data available on feedstock supply. The proposed methodology was illustrated using a biorefinery case study where it utilised empty fruit bunches (EFB) as the feedstock. For the case study, the optimal biorefinery design was determined based on the highest weighted average in Hurwicz Criterion. This optimal design had a configuration sized at 8,000 kg/hr of biomass input and corresponding coefficient of realism α of 0.9. The products chosen for the selected biorefinery design were bio-oil, pentanol and succinic acid. A sensitivity analysis was carried out to determine the tipping points at which changes in the optimal design plant size occurs. From this analysis, it can be confirmed that there are two tipping points: $\alpha \leq 0.1$ and $0.1 \leq \alpha \leq 0.5$. At $\alpha \leq 0.1$, the optimal design size was 4,000 kg/hr while at $0.1 \leq \alpha \leq 0.5$ it was 6,000 kg/hr design size. If $\alpha \geq 0.5$, the optimal design size was 8,000 kg/hr. Future work can be extended further towards incorporating multiple objectives. Other objectives such as environmental impact and safety may provide more unique biorefinery designs which should be included into the Hurwicz Criterion for holistic decision-making.

Compliance with Ethical Standards

Conflict of Interest - the authors declare that they have no conflicts of interest.

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Nomenclature

Sets

$b \in B$	Available biomass feedstock
$p \in P$	Intermediate product
$p' \in P'$	Final product
$t \in T$	Technology converting biomass into intermediate product
$t' \in T'$	Technology converting intermediate product into final product
i	Components of biomass

Variables

f_{ib}	Flowrates of components *i* in biomass *b*

y_{ib}	Composition of components *i* in biomass *b*
F_b	Flow rate of biomass *b*
F_{bt}	Flow rate of biomass *b* distributed to technology *t*
f_{it}	Flow rate of components *i* of biomass *b* in technology *t*
F_p	Flow rate of intermediate product *p*
$F_{pt'}$	Flow rate of intermediate product *p* distributed to technology *t'*
$F_{p'}$	Flow rate of final product *p'*
C_t^{CAPEX} / $C_{t'}^{CAPEX}$	Capital cost of technologies *t* / *t'* ($)
I_t / $I_{t'}$	Binaries for technologies *t* / *t'*
C^{CAPEX}	Total annualised capital cost ($/yr)
C^{OPEX}	Total operating cost ($/yr)
C^{REV}	Revenue ($/yr)
GP	Gross profit ($/yr)
E	Design plant size (kg/hr)
F	Available feed supply (kg/hr)
WA_e	Weighted average of each design plant size ($/yr)

Parameters

ϕ_{itp} / $\phi_{pt'p'}$	Fixed conversion or recovery factor
r	interest rate
n	payment duration in years
CRF_t / $\mathrm{CRF}_{t'}$	Capital recovery factor of technologies *t* / *t'*
x_t^{CAPEX} / $x_{t'}^{CAPEX}$	Capital cost factor for technologies *t* / *t'*
y_t^{CAPEX} / $y_{t'}^{CAPEX}$	Installation cost of technologies *t* / *t'*
N_t / $N_{t'}$	Minimum capacity of technologies *t* / *t'*
M_t / $\mathrm{M}_{t'}$	Maximum capacity of technologies *t* / *t'*
x_b^{OPEX}	Operating cost factor of biomass *b*
$x_{p'}^{REV}$	Price factor of product *p'*
α	Coefficient of realism

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