Hybrid Approach for Carbon-constrained Planning of Bioenergy Supply Chain Network

Huini Leong a, Huiyi Leong a, Dominic C. Y. Foo b, Lik Yin Ng a, Viknesh Andiappan a,∗

aSchool of Engineering and Physical Sciences, Heriot-Watt University Malaysia, 62200, Putrajaya, Wilayah Persekutuan Putrajaya, Malaysia

bDepartment of Chemical and Environmental Engineering/Centre of Excellence for Green Technologies, The University of Nottingham Malaysia, Jalan Broga Road, 43500 Semenyih, Selangor, Malaysia

Abstract

With increasing emphasis on sustainable development, developing countries are required to adapt more sustainable approaches to energy policy-making. Bioenergy supply chain planning methodologies can provide viable frameworks for policy-making. However, current methodologies lack the ability to simultaneously consider CO2 emission reduction targets while design a bioenergy supply chain. As such, the objective of this work is to present a hybrid methodology that combines both carbon emission pinch analysis with superstructure-based optimisation technique. The proposed methodology was demonstrated via a palm-based case study, focused on the state of Selangor, Malaysia. The case study was broken into two scenarios. The first scenario accounted for an output-driven energy policy, whereby the electricity output of the bioenergy supply chain network (BSCN) is prioritised and the corresponding emission reduction is analysed. Results from the first scenario suggests that the optimised BSCN with 5,040 TJ output could reduce CO2 emission intensity by 9.71%. The second scenario focused on an emission-driven policy. Emission-driven policy establishes the emission reduction targets first and then determines the corresponding BSCN to achieve it. Results from this scenario indicate all oil palm plantations could afford to operate on low growth factors of up to 0.8 to avoid sharp drops in possible CO2 reductions for the BSCN. This policy was explored further by conducting sensitivity analysis on the agricultural growth and biomass export factors respectively. The analyses found that the optimised BSCN experience minimal change in costs when plantations have growth factors beyond 1.1. Lastly, analysis was performed to evaluate the range of technologies chosen based on the electricity output. The analysis found that power plant technologies were favoured more as compared to combined heat and power systems.

Keywords: carbon emission pinch analysis, superstructural optimisation, output-driven, emission-driven, process integration, palm biomass.

CEPA: Carbon emission pinch analysis; ATM: Automated targeting model; BSCN: bioenergy supply chain network; EFB: empty fruit bunch; PKS: palm kernel shell; PMF: palm mesocarp fiber; POME: palm oil mill effluent; CHP: combined heat and power; PP: power plant
*Corresponding Emails: huinileong@gmail.com (Huini Leong); huivileong285@gmail.com (Huiyi Leong); dominic.foo@nottingham.edu.my (D. C. Y. Foo); l.ng@hw.ac.uk (L. Y. Ng); v.murugappan@hw.ac.uk (V. Andiappan).
1 Introduction

In December of 2015, governments of the world made history in Paris by pledging to stop climate change at the 21st Conference of Parties (COP21). After two weeks of negotiations, the Paris Agreement was adopted by all participating nations (UN Framework Convention on Climate Change, 2015a). Since the Paris Agreement, many countries have been developing sector-specific plans and policies to achieve their emissions reduction commitments (UN Framework Convention on Climate Change, 2018). In fact, leaders of many countries recently met at the 24th Conference of Parties (COP24) to set out a global climate agreement on how to implement the Paris Agreement (UN Framework Convention on Climate Change, 2018). For many countries, renewable electricity plays an important role and many countries have either set targets or started along this path (UN Framework Convention on Climate Change, 2015b). Plans for renewable energy deployment requires consideration of many short- and long-term actions. These decisions would be a big departure from typical governmental decisions and policy-makers must rely on various types of analysis tools for additional insights and to explore trade-offs involved. However, specific analysis tools are required for developing countries. Developing countries face hurdles in keeping carbon reductions commitments due to lack of financial resources (UN Framework Convention on Climate Change, 2017). This in turn, would deter developing countries to consider capital intensive projects for renewable energy deployment. Therefore, it is imperative to set up decision-making tools that is not only suited for developed countries but also for developing countries.

Among the various developed tools, carbon emissions pinch analysis (CEPA) has gained good attention since its inception (Tan and Foo, 2007). CEPA is a planning tool developed for macro level energy planning based on carbon emission reduction targets, built on the same principles of the well-established pinch analysis and process integration tools (Klemeš, 2013; Linnhoff et al., 1982). In their seminal work, Tan and Foo (2007) proposed a graphical tool known as energy planning pinch diagram to determine the minimum renewable energy resources, while maximising the conventional fossil fuels. The main limitation of this early work is that, renewable energy has been assumed with zero carbon intensity. This limitation was later overcome in their latter work (Lee et al., 2009), where the energy planning pinch diagram was revised for renewable energy sources with low carbon intensity. To overcome the cumbersomeness of graphical techniques, algebraic technique (Sahu et al., 2014) and automated targeting model (ATM) (Lee et al., 2009) have also been proposed. For the latter, CEPA concept was incorporated into an optimisation framework and the ATM was solved to determine required the renewable energy resources. Since then, CEPA has been used for energy planning in both developed and developing countries. Examples of CEPA approaches
for developed countries include New Zealand (Atkins et al., 2010) and Ireland (Crilly and Zhelev, 2010) while examples for developing countries include China (Jia et al., 2010) and India (Priya and Bandyopadhyay, 2013). Tan et al. (2016) then extended the CEPA approach to consider near-optimal solutions and alternative network solutions using process graph method. More recently, Lim et al. (2018) presented a CEPA approach for the power sector in the United Arab Emirates. Following this, Baležentis et al. (2019) developed a CEPA approach that is based on ecological footprint and applied it on the power sector in Baltic States.

The mentioned CEPA approaches provide useful insights on planning for a given energy sector at the regional scale. Whilst regional scale planning can provide interesting insights to allocate renewable energy resources, it is important to consider the optimisation of renewable energy resource supply chains as well. Several contributions have been developed in the past for the optimisation of renewable energy resource supply chain. These contributions often based their work on mathematical programming approaches. For instance, Dunnett et al. (2008) adapted a model previously developed by Almansoori and Shah (2009) for a biomass-to-ethanol supply chain. In this model, full spatial representations are utilised with the aid of echelons to investigate the trade-offs between centralised and decentralised pre-processing of biomass. Echelons were used to break biomass supply chain stages into several levels. Later, Čuček et al. (2010) developed a biomass supply chain model which uses a multi-echelon structure. This model was then extended by Čuček et al. (2014) to consider 12 one-month periods, seasonality, purchase of raw materials and intermediate storage (with losses). Čuček et al. (2012) presented a multi-objective optimisation model for regional biomass supply chains, where economic performance, environmental and social footprints were considered. Results from this model suggested that biomass energy required more water, transportation and chemical input as compared to fossil energy. On the other hand, How et al. (2016) developed a transportation decision-making tool to optimise biomass supply chains with vehicle capacity constraints such as weight and volume. Ng and Maravelias (2017) proposed a multi-period model based on mixed integer linear programming (MILP) for the design and operational planning of cellulosic biofuel supply chains in the United States. In this work, the MILP model considers multi-year horizons for biomass selection and allocation, technology selection and capacity planning at regional depots and biorefineries (Ng and Maravelias, 2017). Meanwhile, Zore et al. (2017) developed a new metric for multi-criteria evaluation of sustainable supply networks, known as sustainability profit. Sustainability profit is composed of economic, environmental and social indicators whereby environmental and social indicators are measured based on its monetary unit equivalence. More recently, How and Lam (2018) presented a debottlenecking approach using Principal Component Analysis to identify sustainability
bottlenecks in a biomass supply chain and subsequently removing them. Zulkafli and Kopanos (2018) developed a general spatial optimisation framework based on a modified state-task network representation to design energy supply chain networks. Meanwhile, Gonela (2018) presented a stochastic mixed integer linear optimisation approach for hybrid electricity supply chains with special attention towards carbon emission schemes. Campanella et al. (2018) developed a modelling framework for forest supply chains. The framework considered the location and size of each production facility, the amounts of products and residues to be generated, and all the material flows within the network.

The abovementioned papers consider carbon-constrained planning and biomass supply chain planning as separate tasks, independent of each other. In reality, the decisions made in carbon emission reductions planning would affect decisions in biomass supply chain planning. It is worth noting that some biomass supply chain approaches have considered minimising environmental impacts. This however, fails to capture how much carbon emissions were reduced. Essentially, renewable energy resource supply chains play an important role in materialising the carbon reduction targets set by CEPA. In this sense, Li et al. (2016) developed a combined CEPA and biomass supply chain network synthesis approach to minimise carbon footprint in China. However, Li et al. (2016) only considered biomass collection efficiency for the biomass supply chain synthesis. More recently, an input-output analysis approach was incorporated into CEPA by Tan et al. (2018). This contribution analysed fixed industrial sectors via input-output analysis and its corresponding carbon emissions via CEPA.

The approaches that combined CEPA and biomass supply chain planning prove to be useful tools. However, there is room for improvement. For instance, these approaches are generic and assume that capital is an infinite resource for a given nation. In reality, developing nations face major challenges in securing capital to mobilise a nation-wide bioenergy supply chain to meet carbon emission reduction targets. Alongside this, it was observed that the level of decisions in supply chain planning for carbon emission reduction remains an area which needs further attention. Supply chain decisions are divided into three levels; strategic, tactical and operational (De Meyer et al., 2014). A vast majority of the papers discussed focused on either strategic or tactical decisions but not both simultaneously. In the context of supply chain planning for carbon emission reduction, it is imperative to consider strategic and tactical decisions simultaneously.

As such, the objective of this paper is to present a methodology that is able to simultaneously plan carbon emission reduction targets and bioenergy supply chain networks (BSCN) via the combined use of CEPA and superstructural optimisation. Essentially, the methodology proposed
in this paper offers two approaches. The first is known as \textit{output-driven} approach, which prioritises the output of the BSCN via superstructural optimisation and its corresponding emission reduction is determined through CEPA. The output-driven approach is particularly suited for developing countries with limited resources and are looking to take a cautious approach towards renewable energy. On the other hand, the second approach, otherwise known as \textit{emission-driven} approach focuses on targeting emission reductions via CEPA and subsequently establishing a cost effective BSCN through superstructural optimisation. The emission-driven approach caters for developed countries that have healthier financial positions and are able to invest in capital intensive renewable energy deployment. Note also that both output-driven and emission-driven approaches address strategic and tactical supply chain planning decisions.

The outline of this paper is as follows: a formal problem statement is provided in the next section to describe the problem addressed. Following this, a detailed account of the proposed methodology is provided. Subsequently, two case studies are solved to show applicability of the proposed methodology. Results from these two case studies are extensively analysed and key insights are discussed. Finally, implications, conclusions and future research works are provided at the end of the paper.

2 Problem Statement

As mentioned previously, developing countries face hurdles to adhere to carbon reductions commitments because of lack of financial resources (UN Framework Convention on Climate Change, 2017). Thus, it is important to develop decision-making tools that are not only applicable to developed countries but also for developing countries. For developed countries, it is easier to analyse the required renewable energy output needed to achieve carbon emission reductions agreed at the international stage. Meanwhile, developing countries would rather take a cautious approach towards capital investment to honour carbon emission reduction commitments. To do address these problems, this work proposes a methodology that considers the following;

- For developed countries: determination of required renewable energy output and corresponding BSCN based on emission reduction target.
- For developing countries: determination of corresponding carbon emission reductions based on optimal BSCN with minimised cost.

The following section describes the methodology proposed in this work.
The proposed methodology is shown in Figure 1.

As shown in Figure 1, the hybrid methodology proposed in this work is generally made up of two techniques, i.e., CEPA and superstructural optimisation. CEPA is implemented through the automated targeting model (ATM), where the minimum renewable energy target is determined through an optimisation framework (Lee et al., 2009). Even though ATM identifies the same target as the energy planning pinch diagram (Tan and Foo, 2007), it overcomes the cumbersomeness of the latter, and allows interaction with other optimisation techniques, such as superstructural optimisation (Foo and Tan, 2016). Superstructural optimisation is used in this work to enumerate several potential technological pathways that convert raw materials to products and/or energy (Andiappan, 2017). These pathways are then modelled by a mathematical model with the aim of determining an optimal pathway. Superstructural optimisation has been widely used in areas such as design of utility systems (Yeomans and Grossmann, 1999), eco-industrial parks (Andiappan et al., 2016) and biorefineries (Ng et al., 2015).
The proposed methodology in Figure 1 contains two approaches to design a BSCN, i.e. *emission-driven* and *output-driven*. The choice of approach would depend on the intended objective. The emission-driven approach begins by targeting a desired percentage reduction in CO\textsubscript{2} emissions via ATM. Based on the targeted emission reduction, the required electricity output is calculated. This required electricity output is then exported to the superstructure model to screen and select an optimal BSCN with minimum cost. If the cost of the optimal BSCN is within an acceptable range, it can be accepted for recommendation. Otherwise, the emission reduction must be revised to a more lenient target. This approach is particularly suitable for developed countries with substantial capital, looking to analyse several carbon emission scenarios and their corresponding impact on the optimal BSCN design.

Alternatively, the output–driven approach may be adopted. In this case, it is imperative to decide a suitable electricity output target accounting the number of participating biomass sources (i.e., plantations, suppliers). Following this, the superstructural approach determines an optimal BSCN based on the targeted electricity output at minimum cost. Next, the targeted electricity output is exported to ATM to obtain the corresponding percentage of CO\textsubscript{2} reduction. If reductions are deemed unacceptable, the BSCN optimisation must be revisited. In this case, a lower electricity output should be defined. This approach is suitable for developing countries with limited financial resources.

It is also worth noting that this methodology considers strategic and tactical planning decisions within the BSCN. Specifically, the strategic decision variables considered are flow of biomass within the BSCN, capital and operating costs, technology and capacity selection, biomass availability and emission reductions. Meanwhile, tactical decision variables considered are biomass production via growth factors, biomass export factors and the selection of biomass utilisation technologies.

Following sub-sections outline details for both techniques, i.e. ATM and superstructure optimisation.

### 3.1 Model Nomenclature

#### Indices

- $k$ Index for levels
- $s$ Index for supply
- $D$ Index for demand
Index for resources

Index for plantations

Index for biomass

Index for facility/export

Index for energy system/export

Index for energy

Parameters

Energy supply

Energy demand

Area of plantation $g$ planted with resource $b$

Yield of resource $b$ from plantation $g$

Growth factor of resource $b$ from plantation $g$

Available amount of resource $b$ from plantation $g$

Fraction of the available resources $b$ intended for export from plantation $g$

Conversion of resource $b$ to biomass $i$

Fraction of the produced biomass $i$ intended for export from technology $j$

Conversion of biomass $i$ to energy $e$

Variable cost for energy system $j$ per unit energy produced

Capital recovery factor for energy system $j$

Fixed cost for energy system $j$ per unit energy produced

Cost per unit flow of resource $b$ transported from plantation $g$ to facility $f$

Cost per unit flow of biomass $i$ transported to energy system $j$

Distance to transport resource $b$ transported from plantation $g$ to facility $f$
distance to transport resource $i$ transported to energy system $j$

Minimum operating capacity for a given energy system $j$

Maximum operating capacity for a given energy system $j$

**Variables**

Minimum renewable energy target

Residual energy at each emission level $k$

Residual load at each emission level $k$

Flow of resource $b$ transported from plantation $g$ to facility $f$

Flow of resource $b$ exported from plantation $g$

Flow of biomass $i$ produced

Flow of biomass $i$ transported to energy system $j$

Flow of biomass $i$ exported from facility $f$

Amount of energy $e$ produced at energy system $j$

Integer denoting existence of energy system $j$ in the supply chain

Annualised capital costs of the supply chain

Operational costs of the supply chain

**3.2 CEPA**

In order to determine the minimum renewable energy target for a carbon-constrained energy planning scenario, CEPA may be utilised. As discussed earlier, CEPA may be implemented through energy planning pinch diagram or ATM. For better interactions with the superstructural approach, ATM is utilised here. The basic framework of the ATM is given in Figure 2(a). First step of the procedure is to arrange emission factors ($C_k$) in an ascending order, with all energy demands ($E_{D}$) and supplies ($E_{S}$) located at their respective levels $k$. The main objective is to determine the minimum renewable energy target ($E_{RE}$), as given in Eq. (1):
Minimum = $E_{RE}$ (1)

In the energy cascade, the residual energy that leaves an emission level $k$ ($\delta_k$) is given by the summation of the residual energy from previous level with the net energy at each level:

$$\delta_k = \delta_{k-1} + (\sum_i E_S - \sum_j E_D)_k \quad \forall k$$ (2)

In the CO$_2$ load cascade, the residual load at each level $k$ ($\varepsilon_k$) is given by the product of the residual energy of previous level ($\delta_{k-1}$) with the difference of its adjacent levels:

$$\varepsilon_k = \varepsilon_{k-1} + \delta_{k-1} (C_k - C_{k-1}) \quad \forall k$$ (3)

Figure 2 CEPA tools: (a) Generic framework of ATM; (b) energy planning pinch diagram

Note that the energy sources entering the first level (i.e. $\delta_0 = E_{RE}$), as well as that leaving the last level must take positive values:

$$\delta_k \geq 0$$ \quad $k = 0, n$ (4)

Note also that the CO$_2$ emission loads for all levels should take non-negative values:
\[ \varepsilon_1 = 0, \varepsilon_k \geq 0 \quad k = 2, 3, \ldots n \] (5)

The above formulation is a linear problem (LP). \( E_{RE} \) can be determined by solving Eq. (1), subject to the constraints in Eqs. (2) – (5).

One may also display the results of ATM in the graphical tool of CEPA, i.e. energy planning pinch diagram. A generic form of the latter is given in Figure 2 (b). As shown, the opening of the left of the energy planning pinch diagram corresponds to the minimum renewable energy target as identified by the ATM, i.e. \( E_{RE} \), while that on the right corresponds to excess fossil fuels, which cannot be utilised due to CO\(_2\) emission constraint.

### 3.3 Superstructure Optimisation

In this section, the generic framework for superstructure optimisation is discussed. In the case of emission-driven approach, superstructure optimisation is used to screen and select an optimal bioenergy supply chain network (BSCN) with minimum cost, while targeting the minimum renewable energy (\( E_{RE} \)) determined by ATM. As for the output-driven approach, superstructure optimisation is used to determine the BSCN with minimum cost, followed by determining the corresponding CO\(_2\) emission reduction via ATM.

![Figure 3 Generic Superstructure for Bioenergy Supply Chain](image-url)
The generic superstructure in Figure 3 starts with plantations $g \in G$. In plantations $g \in G$, resources $b$ are planted with an area $A_{gh}$. The available amount of resource $b$, $F_{gh}^{\text{Res, Av}}$ is produced at a yield of $Y_{gh}$ and growth factor $G_{gh}$ as shown in Eq. (6). Growth factor $G_{gh}$ represents the potential increase or decrease in yearly yield for resources $b$. Note that the values set for $G_{gh}$ would depend on the plantation performance. If there are possibilities of disruption (e.g., the water crisis, droughts), the growth factor can be set below 1. On the other hand, if the plantations yield higher amounts of resource $b$ (than its prior period), the growth factor can be set to more than 1.

$$F_{gh}^{\text{Res, Av}} = A_{gh} Y_{gh} G_{gh} \quad \forall g \forall h \quad (6)$$

The available resource $b$ can be transported to another facility to undergo conversion or exported for further use as shown in Eq. (7). The total flow of resource $b$ transported to facility $f$ is given by $F_{ghf}^{\text{Trans}}$. Meanwhile, the flow of resource $b$ exported is denoted by $F_{ghf}^{\text{Exp}}$.

$$F_{ghf}^{\text{Res, Av}} \geq \sum_{f=1}^{F} F_{ghf}^{\text{Trans}} + \sum_{f=1}^{F} F_{ghf}^{\text{Exp}} \quad \forall g \forall h \quad (7)$$

$F_{ghf}^{\text{Exp}}$ is determined by Eq. (8). As shown, $F_{ghf}^{\text{Exp}}$ is computed based on the fraction ($a_{ghf}$) of the available resources $b$ intended for export from plantation $g$.

$$F_{ghf}^{\text{Exp}} = a_{ghf} F_{ghf}^{\text{Res, Av}} \quad \forall g \forall h, \forall f' = \text{Export} \quad (8)$$

The flow of resource $b$ transported to facility $f$ is then converted to biomass $i$ as shown in Eq. (9). The conversion of resource $b$ to biomass $i$ is given by $V_{bfi}$. The flow of biomass $i$ produced at facility $f$ is represented by $F_{i}^{\text{Bio}}$.

$$\sum_{g=1}^{G} \sum_{f=1}^{F} F_{ghf}^{\text{Trans}} V_{bfi} = F_{i}^{\text{Bio}} \quad \forall i \forall h \quad (9)$$

Following this, Eq. (10) then shows the split of $F_{i}^{\text{Bio}}$ further downstream. As shown, the flow $F_{i}^{\text{Bio}}$ can be split for transport to an energy system $j$ (i.e., CHP: combined heat and power; $PP = \text{power plant}$) $F_{ij}^{\text{CHP/PP}}$ or for export, $F_{ij}^{\text{Exp}}$. 

$$\text{...}$$
\[ F_i^{\text{Bio}} \geq \sum_{j=1}^J F_{ij}^{\text{CHP/PP}} + \sum_{j=1}^J F_{ij}^{\text{Exp}} \quad \forall i \] (10)

Similar to Eq. (8), \( F_{ij}^{\text{Exp}} \) is determined in Eq. (11), where \( \alpha_{ij} \) is the fraction of the produced biomass \( i \) intended for export from facility \( j \).

\[ F_{ij}^{\text{Exp}} = \alpha_{ij} F_i^{\text{Bio}} \quad \forall i, \forall j = \text{Export} \] (11)

The flow of biomass \( i \) transported to energy system \( j \) is then converted to energy \( e \) as shown in Eq. (12). The conversion of biomass \( i \) to energy \( e \) is given by \( V_{ij}^{\text{je}} \). The amount of energy \( e \) produced at energy system \( j \) is given by \( F_{je}^{\text{Energy}} \).

\[ \sum_{j=1}^J F_{ij}^{\text{CHP/PP}} V_{ij}^{\text{je}} = F_{je}^{\text{Energy}} \quad \forall e, \forall j \] (12)

It is important to note that the sum of \( F_{je}^{\text{Energy}} \) is the total renewable energy produced by the BSCN. In this respect, the sum of \( F_{je}^{\text{Energy}} \) is equal to \( E_{\text{RE}} \) from the ATM as shown in Eq. (13). Eq. (13) represents the linkage between ATM and the superstructure optimisation.

\[ E_{\text{RE}} = \sum_{j=1}^J \sum_{e=1}^E F_{je}^{\text{Energy}} \] (13)

The annualised capital costs of the supply chain (\( CAP \)) is computed using Eq. (14). \( CAP \) is determined based on the capacity of energy system \( j \), which is calculated using the energy produced \( F_{je}^{\text{Energy}} \) and the variable cost per unit energy produced \( VC_j \). \( CRF_j \) is the capital recovery factor for energy system \( j \). Meanwhile, the fixed cost (\( FC \)) is activated using a binary integer \( b_j \) which denotes the existence of energy system \( j \) in the supply chain. \( b_j \) is governed by the following Eq. (15), which shows the upper and lower capacities for a given energy system \( j \).

\[ CAP = \sum_{j=1}^J \sum_{e=1}^E (F_{je}^{\text{Energy}} VC_j + b_j \times FC_j) \times CRF_j \] (14)

\[ F_{ij}^{\text{CHP/PP, min}} \times b_j \leq F_{ij}^{\text{CHP/PP}} \leq F_{ij}^{\text{CHP/PP, max}} \times b_j \] (15)
Aside from this, the operational costs of the supply chain (OPEX) is computed using Eq. (16). OPEX is determined based on the transportation costs, which is calculated using the flow transported $F_{ghf}^{Trans}$ and $F_{ij}^{CHP/PP}$. The cost per unit flow transported is given by OFC$_{ghf}$ and OFC$_{ij}$.

\[
OPEX = \sum_{g=1}^{G} \sum_{h=1}^{H} \sum_{f=1}^{F} (F_{ghf}^{Trans} \cdot \text{OFC}_{ghf} \cdot d_{ghf}) + \sum_{i=1}^{I} \sum_{j=1}^{J} (F_{ij}^{CHP/PP} \cdot \text{OFC}_{ij} \cdot d_{ij})
\]

(16)

The total annualised cost (TAC) is given by the summation of CAPEX and OPEX, given as in Eq. (17).

\[
TAC = \text{CAP} + \text{OPEX}
\]

(17)

Note that the superstructure model in Equations (6)-(16) is a mixed integer linear program (MILP). It is also important note that Eq. (13) is a key constraint in linking both ATM and superstructure optimisation.

Following this, the proposed methodology in Figure 1 and formulations shown Sections 3.2 – 3.3 are demonstrated in the following section using a case study based in Malaysia.

4 Case Study

During COP21, the Malaysian government pledged to reduce its greenhouse gases emission intensity per unit gross domestic product from levels in year 2005, by 45% in 2030 (Begum, 2017). Assuming a gross domestic product growth rate of 4% every year, the country would need to achieve a reduction in 85 Million t of greenhouse gas emission per year for a sustainable low carbon future (Yap, 2017). In the effort of promoting green technology, then Ministry of Energy, Green Technology and Water launched the National Renewable Energy Policy and Action Plan 2010 (SEDA, 2018). This policy aimed to enhance national electricity supply security by increasing effective use of renewable resources. The Malaysian government targeted to achieve a green energy feed-in rate of 37,440 TJ by 2020. However, the outcome of general elections in 2018 brought change in Malaysian government agencies and policy-makers. During this transition period, many projects are being re-evaluated and/or kept on hold. Nevertheless, carbon intensity reduction and the future of the renewable energy sector in Malaysia remains a key focus as stated in an official address by the newly appointed Minister of Energy, Technology, Science, Climate Change and Environment (Brown, 2018). Among the available clean energy resources, oil palm biomass is abundantly found in Malaysia. Since 2017, the oil palm industry in Malaysia holds 5.81 million hectares of plantation land. From here, it is worth noting that this industry is a major
contributor to the gross domestic product of the Malaysian agricultural sector (Ministry of Foreign Affairs, 2018). In fact, Malaysia accounts for around 39% of world oil palm production and this figure was expected to rise by 3% in 2018 (MPOC, 2018). Crude palm oil is extracted from fresh fruit bunches via palm oil milling processes. During this process, huge amount of biomass wastes is produced. These wastes comprise of empty fruit bunches (EFB), palm kernel shell (PKS), palm mesocarp fiber (PMF), and wastewater with high pollution load, known as palm oil mill effluent (POME). Besides, oil palm trunk (OPT) and oil palm fronds (OPF) are also part of the biomass wastes during the replanting of oil palm tree (Sadhukhan et al., 2018).

This case study focuses planning renewable energy resources for Selangor, a densely populated state in the Malaysian Peninsular. In fact, Selangor has an urbanisation rate of 91.4% since 2010. Thus, it is imperative that the state of Selangor considers a sustainable strategy for its energy sector (Ministry of Natural Resources and Environment Malaysia, 2015).

In this case study, 7 palm oil mills, their plantations and one substation were considered. The locations of these sites are shown in Table 1 and are illustrated in Figure 4. As mentioned previously, these palm oil mills and plantations generate biomass as waste from their operations. The amount of biomass wastes generated by each plantation is summarised in Table 2 (Ministry of Natural Resources and Environment Malaysia, 2015). Note that the area of plantations and amount of biomass correspond to parameters $A_i$ and $F_i^{Bio}$ respectively. Also, the distance to substation is represented by the parameter $d_{ij}$.

### Table 1 GPS Coordinates and Distances of Mills and Plantations from TNB substation

<table>
<thead>
<tr>
<th>Mills and Plantations</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Distance to substation (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jugra</td>
<td>2.845557</td>
<td>101.467958</td>
<td>28</td>
</tr>
<tr>
<td>Eng Hong</td>
<td>2.860081</td>
<td>101.476569</td>
<td>30</td>
</tr>
<tr>
<td>Sime Darby East</td>
<td>2.883333</td>
<td>101.436136</td>
<td>24</td>
</tr>
<tr>
<td>Banting</td>
<td>2.728394</td>
<td>101.494616</td>
<td>50</td>
</tr>
<tr>
<td>Kampung Kuantan</td>
<td>3.344463</td>
<td>101.290602</td>
<td>77</td>
</tr>
<tr>
<td>Tuan Mee</td>
<td>3.265013</td>
<td>101.463790</td>
<td>42</td>
</tr>
<tr>
<td>Seri Ulu Langat</td>
<td>2.851192</td>
<td>101.650403</td>
<td>32</td>
</tr>
<tr>
<td>TNB Substation</td>
<td>2.9365</td>
<td>101.58014</td>
<td>-</td>
</tr>
</tbody>
</table>
The aim of this case study is to design an optimal bioenergy supply chain network (BSCN) to produce electricity from biomass, considering costs and CO$_2$ emission reductions. Within the BSCN, this case study assumes that a centralised energy system needs to be installed near the substation in Figure 4. The electricity generated from the centralised system will then be transmitted to the substation via a feed-in tariff scheme with the national grid. Figure 5 (a) and (b) show the superstructures developed based on the mills and plantations considered in Figure 4. Figure 5 (b) considers the decision of investing in includes different electricity generation systems.
i.e., power plants (PPs) and combined heat and power (CHP) systems. The following is a summary of the six biomass utilisation pathways considered in Figure 5;

**EFB Pathway:** The highest amount of biomass waste from mills is EFB. EFB contains high moisture content which would subsequently affect its calorific value. As such, several pre-treatment technologies such as hot air drying, superheated steam drying, and size reduction are evaluated. The dried EFB emerging from the selected technologies are then directed into a gasifier to produce syngas. Syngas is then utilised in a PP system to generate electricity or in a fluidised bed boiler (CHP system) to generate steam and electricity. To minimise the operating cost and to ensure the technologies are self-sustained, it is assumed that part of the electricity and steam generated is recycled to the dryer for the drying process.

**PKS Pathway:** The other biomass product exiting the palm oil mill comprises PKS. PKS is considered the most effective biomass fuel due to its high calorific value. In Figure 5(b), PKS may be utilised in PP system that converts it into syngas through a gasifier and later fed into a gas turbine for electricity. Alternatively, PKS can be combusted in a fluidised bed boiler for steam generation in a CHP system.

**PMF Pathway:** Similarly, PMF will undergo the same process route as PKS to generate electricity in a PP or steam and electricity in a CHP. However, it is less efficient for PMF to be used as a biomass fuel compared to PKS. This is because its low calorific value is relatively lower compared to PKS.

**POME Pathway:** This is a pathway where highly polluting wastewater emerging from the mill, POME is treated in a digester pond to produce value added methane gas. This methane gas is then combusted either in a gasifier (PP system) or a fluidised bed boiler (CHP system) for production of electricity and/or steam respectively.

**OPT Pathway:** OPT is biomass waste from oil palm plantations. It is obtained directly from plantations without processing in palm oil mills. This feedstock is available in abundance but possess very high density to be transported. In Figure 5(b), OPT can follow similar paths to both PKS and PMF to produce electricity and steam through PP or CHP systems respectively.

**OPF Pathway:** Similar to OPT, OPF is also a biomass waste directly obtained from the plantation. Research has shown that OPF contains large amount of sugar, proposing it to be a perfect feedstock to a gasifier (Roslan et al., 2014). This syngas generated would then be directed into a PP or a CHP for the generation of electricity and/or steam respectively.
Export: This path is allocated to accommodate the biomass waste products from each plantation for export markets such as Japan, South Korea, China, Thailand and Europe. This is represented by export factors $\alpha_{iy}$ and $\alpha_y$ in the proposed methodology.
Figure 5 (a) Superstructure of Bioenergy Supply Chain

Figure 5 (b) Superstructure of Centralised Energy System in Bioenergy Supply Chain
Tables 3 and 4 show other technical considerations considered in this case study;

### Table 3 Technical Considerations for Technologies in Scenario 1

<table>
<thead>
<tr>
<th>Technology</th>
<th>Data</th>
<th>Ref</th>
</tr>
</thead>
</table>
| Hot Air Drying                 | • Moisture content of EFB before and after the dryer are 60% and 10% respectively  
                                | • Efficiency of 85.93% ($V_{90}$)                                        | (Aziz et al., 2011)      |
|                                | • Requires 2.31 MJ/kg biomass from PP or CHP                          |                          |
| Superheated Steam Drying       | • Moisture content of EFB before and after the dryer are 60% and 10% respectively  
                                | • Efficiency of 86.72% ($V_{90}$)                                        | (Aziz et al., 2011)      |
|                                | • Requires 2.18 MJ/kg biomass from PP or CHP                          |                          |
| PP                             | • Efficiency is 40% ($V_{90}$)                                        | (Loh, 2017)              |
|                                | • Maximum power produced by the PP is 419.4 TJ ($F_{CHP\text{PP}, \text{max}}^g$) |                          |
| CHP                            | • Efficiency is 48.9% (with 26.5% for heat and 22.4% for electricity) ($V_{90}$) | (Loh, 2017)              |
|                                | • Maximum power produced by the PP is 1175.94 TJ ($F_{CHP\text{PP}, \text{max}}^g$) |                          |
| Gasifier                       | • Maximum weight of biomass waste handled is 1,612 t ($F_{CHP\text{PP}, \text{max}}^g$) | (Forbes International Co. LTD, 2018). |

### Table 4 Technical Considerations for Supply Chain in Scenario 1

<table>
<thead>
<tr>
<th>Factor</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Growth factors ($G_{gh}$)</td>
<td>1 for all plantations</td>
</tr>
<tr>
<td>Export factors ($x_{ghf}$ and $x_{ij}$)</td>
<td>0 for all plantations and mills</td>
</tr>
<tr>
<td>Biomass transportation costs ($OFC_{ghf}$ and $OFC_{ij}$)</td>
<td>0.23 USD t km$^{-1}$ travelled (Zafar, 2018)</td>
</tr>
<tr>
<td>CO$_2$ emission factor for Selangor ($C_i$)</td>
<td>66 million t per TJ (Loh, 2017)</td>
</tr>
</tbody>
</table>

Calorific values of each biomass considered in the model are given in Table 5. It is important to note that the calorific value considered in the MILP model takes into account of the efficiency of equipment are used. The model also includes cost of equipment used for each pathway (Table 6). The fixed cost indicate the capital and installation cost of the equipments, while variable cost includes operating and maintenance cost.
Table 5 Calorific Value of Biomass before and after Incorporating Equipment Efficiency.

<table>
<thead>
<tr>
<th>Pathway</th>
<th>Actual CV (MJ/kg)</th>
<th>Heat loss for drying (MJ/kg)</th>
<th>Final CV for PP <strong>(MJ/kg)</strong></th>
<th>Final CV for CHP &quot;(MJ/kg or MJ/m³)&quot;</th>
<th>Ref</th>
</tr>
</thead>
<tbody>
<tr>
<td>EFB (Hot Air Drying)</td>
<td>17.81</td>
<td>2.31</td>
<td>4.814</td>
<td>3.99</td>
<td>(Aziz et al., 2011)</td>
</tr>
<tr>
<td>EFB (Superheated Steam Drying)</td>
<td>17.81</td>
<td>2.18</td>
<td>4.944</td>
<td>3.99</td>
<td>(Aziz et al., 2011)</td>
</tr>
<tr>
<td>EFB (Size Reduction)</td>
<td>16.5</td>
<td>-</td>
<td>6.6</td>
<td>3.70</td>
<td>(EPA, 2018)</td>
</tr>
<tr>
<td>PKS</td>
<td>20.09</td>
<td>-</td>
<td>8.036</td>
<td>4.50</td>
<td>(Paul et al., 2015)</td>
</tr>
<tr>
<td>PMF</td>
<td>14.51</td>
<td>-</td>
<td>5.804</td>
<td>3.25</td>
<td>(Sarawak Energy, 2018)</td>
</tr>
<tr>
<td>POME</td>
<td>22</td>
<td>-</td>
<td>8.8</td>
<td>4.93</td>
<td>(Onoja et al., 2018)</td>
</tr>
<tr>
<td>OPT</td>
<td>17.47</td>
<td>-</td>
<td>6.988</td>
<td>3.91</td>
<td>(Rashid et al., 2017)</td>
</tr>
<tr>
<td>OPF</td>
<td>5.15</td>
<td>-</td>
<td>2.06</td>
<td>1.15</td>
<td>(EPA, 2018)</td>
</tr>
</tbody>
</table>

*CV – Calorific value, **corresponds to Vije

Table 6 Equipment Cost for Each Pathway.

<table>
<thead>
<tr>
<th>Pathway</th>
<th>Fixed cost, FC, (USD)</th>
<th>Variable cost, VC, (USD/ton or USD/kW)</th>
<th>Ref</th>
</tr>
</thead>
<tbody>
<tr>
<td>EFB (Hot Air Drying)</td>
<td>446,455.75</td>
<td>0.0245</td>
<td>(IRENA, 2013)</td>
</tr>
<tr>
<td>EFB (Superheated Steam Drying)</td>
<td>446,455.75</td>
<td>0.0245</td>
<td>(IRENA, 2013)</td>
</tr>
<tr>
<td>EFB (Size Reduction)</td>
<td>674,000</td>
<td>20</td>
<td>(IRENA, 2013)</td>
</tr>
<tr>
<td>PKS</td>
<td>14,250,000</td>
<td>3700</td>
<td>(Forbes International Co. LTD, 2018)</td>
</tr>
<tr>
<td>PMF</td>
<td>14,250,000</td>
<td>3700</td>
<td>(Forbes International Co. LTD, 2018)</td>
</tr>
<tr>
<td>POME</td>
<td>451,655</td>
<td>4350</td>
<td>(MP Energy, 2018)</td>
</tr>
<tr>
<td>OPT</td>
<td>14,250,000</td>
<td>3700</td>
<td>(MP Energy, 2018)</td>
</tr>
<tr>
<td>OPF</td>
<td>14,250,000</td>
<td>3700</td>
<td>(MP Energy, 2018)</td>
</tr>
<tr>
<td>PP</td>
<td>18,000,000</td>
<td>211.6</td>
<td>(Loh, 2017)</td>
</tr>
<tr>
<td>CHP</td>
<td>11,780,000</td>
<td>7670</td>
<td>(Loh, 2017)</td>
</tr>
</tbody>
</table>
For this case study, the formulated MILP model was solved in two scenarios. As entailed in Figure 1, the first scenario goes deeper into the output-driven approach. Meanwhile, the second scenario focuses on emission-driven approach. A detailed discussion of these two scenarios is provided in the following sub-sections.

4.1 Scenario 1 – Output-Driven Approach

Objective for Scenario 1 is to determine the optimal BSCN with minimum cost for a targeted electricity output via superstructure optimisation. Following this, the corresponding carbon emission reduction of the BSCN is determined via ATM.

Using the proposed framework in Figure 1 and Section 3, a mixed integer linear programming (MILP) model was formulated. Note that the MILP model was formulated based on the pathways shown in Figures 5 (a) and (b) in a optimisation software (i.e., LINGO version 17.0) on Acer Laptop with 4 GB RAM and Intel Core i5@ 1.70 GHz Processor. The MILP model consists of 231 variables, 30 integers and 250 constraints. The MILP model was solved by minimising the TAC in Eq. (17), subject to the constraints in Eqs. (1) – (16). Results from minimising Eq. (17) computed a BSCN with a minimum cost of 7.2 trillion USD. The corresponding \( E_{\text{RE}} \) computed for this optimal BSCN was 5040 TJ. The computed 5040 TJ electricity output was then exported to CEPA to determine the subsequent \( \text{CO}_2 \) emission reduction. Results of CEPA are shown in ATM (Figure 6) and the energy planning pinch diagram (Figure 7). It is also important to note that Figure 6 and 7 both indicate 5040 TJ equivalent amount of electricity generated using coal may be reduced, leading to lower \( \text{CO}_2 \) emissions (solid lines in Figure 7). The energy planning pinch diagram in Figure 7 shows that \( \text{CO}_2 \) emission is reduced from 5.5 to 4.9 Mt/y; the latter corresponds to an intensity of 59.6 t/TJ (= 4,916 kt/82,490 TJ). This means that with the aforementioned BSCN could reduce the current carbon intensity from 66.0 to 59.6 t \( \text{CO}_2 \)/TJ, which is a 9.71% reduction from the original status quo.

Table 7 shows the optimal flows of biomass transported from the plantations to the centralised energy system within the BSCN. As shown in Table 7, EFb and OPF are the most utilised biomass. Most notably, it can be seen that OPT was only utilised from one plantation. OPT is heavy to transport. In this respect, the model chose the shortest and cheapest OPT transportation route; Sime Darby East plantation to the centralised energy system. The optimal flow of biomas transported was then allocated to several technologies within the centralised energy system (as illustrated in Figure 8). In Figure 8, it can be seen that all EFB is sent to the PP system. Moreover, Figure 8 shows that the distribution of EFB and PKS to PP systems was higher as
compared to the CHP systems. However, the capacity constraint of the PP systems inhibited them from receiving more biomass. As a result, the remaining biomass (i.e., PMF, OPF and OPT) were directed to CHP systems to produce more electricity. Note that the total electricity output in Figure 8 is from biomass. The remaining 194.42 TJ electricity output comes from the POME source at the each palm oil mill.

It is important to note that the growth factor for all plantations were fixed at 1 and the export factor for all plantations are set to 0. However, these assumptions made are very unlikely in reality, especially with respect to a developing nation like Malaysia. The effect of varying both parameters will be discussed in the next section using the emission-driven approach.

<table>
<thead>
<tr>
<th>Emission Factor (t CO₂/TJ)</th>
<th>Supply (S)/Demand (D)</th>
<th>Energy Cascade (TJ)</th>
<th>CO₂ Load Cascade (t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>S_renewable = 5,040</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>51.6</td>
<td>S_natural gas = 60,176</td>
<td>5,040</td>
<td>260,064</td>
</tr>
<tr>
<td>66.0</td>
<td>D_current demand = -82,491</td>
<td>65,216</td>
<td>783,736</td>
</tr>
<tr>
<td>105.0</td>
<td>S_coal = 22,314</td>
<td>5,040</td>
<td>(Pinch)</td>
</tr>
</tbody>
</table>

Figure 6 Results of ATM for BSCN in Scenario 1
Table 7 Amount of Biomass Utilised from each Source in Scenario 1

<table>
<thead>
<tr>
<th>Source</th>
<th>EFB (/h)</th>
<th>PKS (t/h)</th>
<th>PMF (t/h)</th>
<th>POME (m³/h)</th>
<th>OPT (t/h)</th>
<th>OPF (t/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jugra</td>
<td>9.9</td>
<td>2.5</td>
<td>5.9</td>
<td>0.029</td>
<td>0.0</td>
<td>70.4</td>
</tr>
<tr>
<td>Eng Hong</td>
<td>9.9</td>
<td>2.5</td>
<td>5.9</td>
<td>0.029</td>
<td>0.0</td>
<td>70.4</td>
</tr>
<tr>
<td>Sime Darby East</td>
<td>8.8</td>
<td>2.2</td>
<td>5.2</td>
<td>0.026</td>
<td>62.8</td>
<td>62.6</td>
</tr>
<tr>
<td>Banting</td>
<td>11.0</td>
<td>2.8</td>
<td>6.5</td>
<td>0.033</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Kampung Kuantan</td>
<td>4.4</td>
<td>1.1</td>
<td>2.4</td>
<td>0.013</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Tuan Mee</td>
<td>5.9</td>
<td>1.5</td>
<td>3.5</td>
<td>0.018</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Seri Ulu Langat</td>
<td>9.9</td>
<td>2.5</td>
<td>5.9</td>
<td>0.029</td>
<td>0.0</td>
<td>10.3</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>59.8</strong></td>
<td><strong>14.9</strong></td>
<td><strong>35.3</strong></td>
<td><strong>0.177</strong></td>
<td><strong>62.8</strong></td>
<td><strong>213.7</strong></td>
</tr>
</tbody>
</table>
Figure 7 Pinch Analysis for base case (dotted lines) and Scenario 1 (solid lines).
Figure 8 Optimal Allocation of Biomass within Centralised Energy System in Scenario 1
4.2 Scenario 2 – Emission-Driven Approach

The oil palm industry in Malaysia faces many difficulties; one of those being the limitation in increasing fresh fruit bunch yields in plantations. This limitation may be related to the effect of drastic weather conditions (i.e., drought, haze, etc.), disease attacks and poor water quality at plantations. Fresh fruit bunch yields are crucial as they influence the amount of biomass generated at the POM process. As such, Scenario 2 analyses various growth factors to determine its impact on the decisions with regards to BSCN design. Note that growth factors below 1 are set to consider possibilities of disruption (e.g., the water crisis that is common in Malaysia). On the other hand, growth factor that is more than 1 indicates that the plantations are yielding higher crops than its previous period.

The growth factors considered for Scenario 2 are shown in Table 8. In Case 1, the growth factor for Seri Ulu Langat plantation is varied within the range of 0.6 – 0.8. Case 2, on the other hand varied growth factors in the same range, but for two plantations, i.e. Seri Ulu Langat and Tuan Mee. In Case 3, the same range of growth factors were varied for three plantations i.e. Seri Ulu Langat, Tuan Mee and Kampung Kuantan.

<table>
<thead>
<tr>
<th></th>
<th>Jugra</th>
<th>Eng Hong</th>
<th>Sime Darby East</th>
<th>Banting</th>
<th>Kampung Kuantan</th>
<th>Tuan Mee</th>
<th>Seri Ulu Langat</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Case 1</strong></td>
<td>1</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.6</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.6</td>
<td>0.8</td>
</tr>
<tr>
<td><strong>Case 2</strong></td>
<td>1</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td><strong>Case 3</strong></td>
<td>1</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
</tbody>
</table>

Following this, the energy planning pinch diagram and ATM is used to determine the required bioenergy to achieve a given CO₂ emission reduction target. Once the required bioenergy is determined, it is exported to the superstructure model where constraints in Eqs. (1)-(16) are solved by minimising the TAC in Eq. (17). This was procedure repeated for growth factors in the aforementioned Cases 1 – 3. Note that the model formulated here was also solved in the same optimisation software (i.e., LINGO version 17.0) on Acer Laptop with 4 GB RAM and Intel Core
i5@ 1.70 GHz Processor. Like in Scenario 1, the MILP model consists of 231 variables, 30 integers and 250 constraints.

Results for Cases 1–3 are shown in Figures 9 – 11. Figure 9 shows the energy planning pinch diagram particularly for Case 3 in Scenario 2, where the growth factor is 0.6 for three plantations. The energy planning pinch diagram shows that CO₂ emissions were reduced from 5.45 to 4.96 Mt/y. The latter corresponds to an intensity of 60.1 t/TJ (= 4,960 kt/82,490 TJ). The electricity output required to achieve this CO₂ emission reduction is 4,644 TJ. Subsequently, the optimal BSCN with minimum TAC was determined for the 4,644 TJ electricity output. Figure 10 (a)-(c) indicate the results obtained for the BSCNs in Case 1- 3 respectively. In Figure 10 (a), it is found that the lowest CO₂ reduction achieved is 9.26% when the growth factor of one plantation in the BSCN is 0.6. The lowest CO₂ reduction of 9.16% is obtained in Figure 10 (b) when growth factors of two plantations are 0.6. When three plantations in the BSCN have growth factors of 0.6, the lowest attainable CO₂ reduction is 8.95% (Figure 10 (c)).

Figure 9 Pinch Analysis for base case (dotted lines) and Scenario 2 (solid lines).
Growth Factor for One Plantation in Case 1

Growth Factor for Two Plantations in Case 2

Growth Factor for Three Plantations in Case 2
Figure 10 Electricity Output and CO$_2$ Reduction from the Status Quo using Varied Growth Factors for; (a) Case 1 – One Plantation, (b) Case 2 – Two Plantations, (c) Case 3 – Three Plantations

Meanwhile, Figure 11 shows a comparison of electricity outputs across all three cases according to growth factors. As shown, a decreasing trend in electricity output was observed from Case 1 to 3. This is because the number of plantations with varied growth factors increase from Case 1 to 3. This would subsequently reduce the amount of biomass available for utilisation and electricity generation. Moreover, it was observed that there was a significant drop in electricity output between instances where three plantations have growth factors of 0.8 and 0.7 (as indicated in Figure 11). This significant drop provides insight on the level to which the BSCN can tolerate in terms of reduction in growth factors. Essentially, Figure 11 suggests that in the case where three plantations were to experience reduced growth factors, the lowest tolerable growth factor without experiencing a significant drop in electricity output is 0.8. Aside from this, the distance between 0.7 and 0.6 lines are relatively closer. This indicates a low difference in electricity produced and reduction in CO$_2$ between the two cases. In general, the electricity outputs obtained in all three cases are lower than Scenario 1 (5040 TJ). This is because Scenario 1 considered growth factors of 1 for all plantations. In addition, it can be concluded that the electricity output and CO$_2$ reductions decrease when growth factors decreases.

Figure 11 Comparison of Electricity Output between Cases 1, 2 and 3
4.2.1 Sensitivity Analysis – Growth Factor

To evaluate the effect of the growth factors on the BSCN, sensitive analysis is carried out.

The sensitivity analysis used similar growth factors ranging between 0.7 – 1.3 for all plantations.

Results of the sensitivity analysis are shown in Figures 12 and 13. As shown, the lowest possible reduction in carbon dioxide emission is 8.7%. This corresponds to an electricity output of 4500 TJ, as shown in Figure 13. Aside from this, growth factors of up to 1.3 was analysed to study its impact on the cost of the BSCN. According to Figure 12, the cost approaches a constant trend when growth factors increase beyond 1.1. This shows that there BSCN is able to experience an increase in growth factors from 1.1 to 1.3 in all plantations without a steep increase in costs. However, the increase in CO₂ reduction becomes less obvious from growth factors of 1.1 onwards. This might be due to the less obvious increase in electricity output starting from growth factor 1.1 (indicated in Figure 13). The constraint here is the capacity of equipment. Besides this, CHP systems were not prioritised because of their relatively lower electricity generation efficiency. But when PP systems reach their maximum capacity, CHP systems are required to supply the remaining portion of electricity output targets.

Figure 12 Further Analysis of Cost and Percentage of CO₂ Reduction on Different Growth Factor.
4.2.2 Sensitivity Analysis – Export Factor

Apart from growth factors, a sensitivity analysis was performed on export factors of biomass. Among all the biomass included in the model, PKS is identified to be the highest exportation quantity of biomass waste. This is because PKS has low weight and relatively high calorific value, which allows transportation of high energy content per t of biomass. Malaysia exports up to 135,000 t of PKS (which is 32% of Malaysia’s annual PKS export) annually to the world (Zainul, 2017). Besides, The Edge Financial Daily also reported that Malaysia is currently holding 54% of market share for PKS in Japan, and companies still intend to increase the annual output to Japan (Laohalidanond, 2011). As the export quantity increases significantly, the electricity produced by PP or CHP would be crucially affected. This would directly impact the Malaysian government’s aim to reduce its CO₂ emissions per gross domestic product. The analysis on export factor of PKS from no export (0) to fully export (1) is shown in Figure 14. As observed in Figure 14, CO₂ reductions experience a drop between export factors 0.3–0.5. This provides insight on the range of biomass export that Selangor should avoid if the aim is to generate large amounts of electricity. The amount of electricity produced is also relatively lower after the export factor of 0.5 as shown in Figure 14.
In addition to this, export factors were analysed further via five sub-cases. These five sub-cases were analysed to better understand the effect of exporting individual biomass on the electricity output of the BSCN. The first case shown in Table 9 is carried out to study the importance of OPT and OPF. OPT and OPF are less favourable as they are too heavy to be transported even though they are available abundantly. The low calorific value of OPF contributes to this decision too. Furthermore, the weight of OPT, constraints on size and cost of equipment, also add to the low feasibility of investing in OPT path. The outcome of base case as displayed in Table 5 comply with this insight. Hence, OPT and OPF has the lowest priority in the model. Results in Table 10 further supports this insight. It is observed that as the export for OPT and OPF increases, the effect on electricity output is minimal. In this sense, it would be sensible to direct OPT and OPF residues for other uses.

The second and third sub-cases are then compared together. The result demonstrated that when the amount of exported PKS increases to 0.3, the electricity output will decrease (as shown in Case 3 of Table 10). This holds true as the calorific value for PKS is the highest among all biomass available in the palm oil industry. However, in terms of electricity output, the difference between both cases are minimal. This is because the huge amount of EFB and PMF was available to compensate for the loss caused by high PKS export. Proceeding to the Cases 4 and 5, both electricity outputs were similar. This is because the loss from PKS was compensated by PMF and
EFB here as well. This strengthens the conclusion that quantity of PMF and EFB was favoured over PKS since it was highly exported in these scenarios.

**Table 9 Export Factor of Different Cases.**

<table>
<thead>
<tr>
<th>Case</th>
<th>EFB</th>
<th>PKS</th>
<th>PMF</th>
<th>OPF</th>
<th>OPT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>Case 2</td>
<td>0.3</td>
<td>0.2</td>
<td>0.3</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Case 3</td>
<td>0.2</td>
<td>0.3</td>
<td>0.2</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Case 4</td>
<td>0.3</td>
<td>0.3</td>
<td>0.2</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Case 5</td>
<td>0.2</td>
<td>0.2</td>
<td>0.3</td>
<td>0.1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

**Table 10 Result for Different Cases.**

<table>
<thead>
<tr>
<th>Electricity Output (TJ)</th>
<th>Reduction in CO₂ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>4698</td>
</tr>
<tr>
<td>Case 2</td>
<td>4626</td>
</tr>
<tr>
<td>Case 3</td>
<td>4554</td>
</tr>
<tr>
<td>Case 4</td>
<td>4590</td>
</tr>
<tr>
<td>Case 5</td>
<td>4608</td>
</tr>
</tbody>
</table>

4.2.3 *Technology Analysis*

Lastly, the technologies chosen for the BSCN were analysed in detail. This is to list the possible technologies and to analyse the trend of technologies selected when electricity output is increased. The pathways chosen at different targeted electricity output are shown in Figure 15. In Figure 15, superheated steam drying and size reduction technologies utilising EFB can be considered as the “must invest” technology. This is because of the huge amount of EFB that emerged from the palm oil mills and its relatively high calorific value as shown in Table 3 and Table 5 respectively. Aside from this, Figure 14 shows that the technology chosen increases with the targeted electricity produced. Besides, PKS and POME utilisation technologies are also considered among the primary technologies used. The technology of OPT and OPF are least encouraged as the volume produced increases the difficulty in transportation and the necessity to invest in more equipment. In fact, PP systems were prioritised over CHP systems since the intended output of this particular model is electricity rather than steam. However, when CHP
systems are selected, PKS was prioritised as fuel due to its highest calorific value and light weight. This is evident when the electricity produced exceeds the 2160 TJ interval shown in Figure 15.

Figure 15 Analysis of Technologies Chosen based on Different Electricity Output.

Summary of Insights:

- With output of 5040 TJ, the BSCN is able to reduce carbon emission intensity of the state of Selangor by 9.71%, given no export of biomass and a stagnant growth factor for plantations.
All plantations are able to cope with reduced growth factors up to 0.8, without experiencing a significant drop in electricity output. In other words, 0.8 is the minimum growth factor in which all plantations can afford to operate at.

BSCN is able to manage up to 30% increase in yield for all plantations starting from growth factor of 1.1 without steep increase in cost.

CO₂ reductions experience a steep drop between export factors 0.3–0.5. This the range of biomass export that Selangor should consider avoiding if the aim is to generate large amounts of electricity.

When export for OPT and OPF increases, the effect on electricity output is minimal. It would be logical to direct OPT and OPF residues for other uses.

When amount of exported PKS increases, the electricity output will decrease. The calorific value for both PKS is the highest among all biomass available. However, the difference in electricity output between both cases are minimal because the huge amount of EFB and PMF available compensates for the loss in calorific value caused by high PKS export.

OPT and OPF technologies were the least encouraged as the volume produced increases the difficulty in transportation and requires high investment costs.

PP technologies are prioritised over CHP technologies as the main output is electricity instead of steam. However, if the CHP system is utilised, PKS is prioritised as fuel due to its highest calorific value and light weight. This is evident when the electricity produced exceeds 2160 TJ.

5 Implications

As a whole, the methodology presented in this work provides policy-makers a systematic tool to analyse potential CO₂ intensity reduction strategies and policies to meet commitments made in the Paris Agreement. Fundamentally, the presented methodology provides tailored approaches for both developed and developing countries to analyse CO₂ intensity reduction and BSCN planning.

Key results from both scenarios could provide several policy implications. For instance, results from Scenario 1 suggests that oil palm plantations in the state of Selangor could provide a CO₂ intensity reduction of 9.71%, given that that growth factors are stagnant at 1 and export factors are kept to 0. It is worth noting that Selangor is just one of 14 federal states in Malaysia. This 9.71% provides policy-makers insight on the potential carbon reduction that could be
achieved when a BSCN is implemented in a state rather than exporting its biomass to other
countries. Aside from this, Scenario 2 provided further insights on lowest possible growth factors
that each plantation can tolerate to achieve acceptable CO₂ intensity reductions. Essentially, such
insight allows policy-makers to determine the likelihood of poor growth rates in oil palm
plantations by comparing to historical data that is readily available.

Alongside this, the technology analysis provided information on technologies frequently
selected for a given range of electricity output. Such insight allows policy-makers to determine the
promising technologies worth investing in either via investment and/or research. On top of this,
policy-makers can make more informed decisions on formulating incentive packages, subsidies
and grants to encourage local investment in such technologies.
6 Conclusion

In conclusion, this work presented a hybrid planning methodology to consider CO$_2$ emission reduction target while simultaneously optimising a bioenergy supply chain network (BSCN). This methodology made a combined use of carbon emission pinch analysis (CEPA) and superstructural optimisation to analyse two distinctive policy scenarios. The first scenario is the output-driven approach, which prioritised the output of the bioenergy supply chain network (BSCN) and followed by its corresponding emission reduction. The second approach, which emission-driven targeted emission reductions first and subsequently determined the BSCN with minimum cost. Sensitivity analyses were also conducted in the second scenario, where the impact of both growth factors of agricultural plantations and export factors of the biomass were analysed. Finally, technology analysis was performed to analyse the range of technologies chosen based on the electricity output. Results from the two scenario solved and analyses conducted, provided several key findings and insights. Firstly, an optimised BSCN with 5,040 TJ output could reduce CO$_2$ emission intensity by 9.71%. Secondly, it was found that all oil palm plantations could afford to operate on low growth factors of up to 0.8 to avoid steep drops in CO$_2$ reduction performance in the BSCN. In addition, it was found that the optimised BSCN experiences minimal change in costs when plantations have growth factors beyond 1.1. Lastly, it is worth noting that power plant technologies were favoured more as compared to combined heat and power systems. The proposed methodology can be improved further to tackle biomass aggregators in the supply chain and uncertainties in biomass feedstock collection via Monte Carlo simulations. Moreover, proposed methodology can be directed towards additional tactical and operational supply chain planning decisions such as transport mode selection, optimal biomass delivery schedules and vehicle planning.

Acknowledgement

The authors would like to acknowledge LINDO Systems for providing academic licenses to conduct this research.

References


Brown, V., 2018. Yeo: You don’t need to know me, you need to know how - Nation. Star Online.


Zainul, E., 2017. FGV seeks to increase exports of palm kernel shell to Japan [WWW Document]. Edge Mark.
