Abstract—This paper presents a two-stage optimisation approach to regional energy planning with biomass utilisation. The aim of the first stage is to determine the optimal energy mix and the bioenergy target, which is to be fulfilled in the second stage when synthesising the optimal biomass supply chain network. The mathematical formulation of the two stages yields two linear models, for which global optimality is guaranteed if a solution exists. A literature case study is used to illustrate the proposed approach.

I. INTRODUCTION

The exploitation of fossil fuels such as coal and oil since the Industrial Revolution has caused serious pollution to the environment and the build-up of carbon dioxide (CO₂) in the atmosphere, with the latter being regarded as the most important long-lived “forcing” of climate change. Although not by the supply limits, especially with the breakthrough in hydraulic fracturing of non-conventional gas reserves, the use of fossil fuels will still be constrained by CO₂ emissions and does not appear to be capable of meeting the increasing energy demand in a sustainable manner. Therefore, it is necessary to seek alternative energy sources.

Global concern about the depletion of energy resources, climate change and environmental emissions are amongst the key drivers of sustainable development. Reducing greenhouse gas (GHG) emissions and mitigating global warming are becoming socially and economically pressing for nations all over the world. Effective measures to mitigate and adapt to climate change include the use of renewable energy (RE) sources (e.g. solar, wind and biomass), which provide clean and sustainable energy production and serve as a promising alternative to conventional sources. According to Energy Technology Perspectives 2016 [1], carbon capture and storage (CCS), renewables and end-use energy efficiency are key technologies to achieve the 2°C Scenario, expected to contribute more than 80% of the total CO₂ emission reduction required in 2050. In particular, bioenergy is the single largest RE source today, providing 10% (50 EJ) of world total primary energy supply, and thus plays a crucial role in many developing countries.

Carbon-constrained energy planning (CCEP) is a relatively new area of research aiming to address carbon emission reduction issues in a systematic manner [2]. Several techniques were developed under the framework of carbon emission pinch analysis (CEPA). Tan and Foo [3] presented the first graphical targeting tool known as energy planning composite curves to determine the optimal allocation of fossil energy whilst minimising the use of carbon-neutral energy sources. The concept of CEPA was later extended to scenarios involving land [4] and water footprints [5], as well as segregated targeting with regions based on unique sets of energy sources [6,7], using graphical, algebraic and optimisation tools. For cases with multi-footprint constraints, a superstructure-based mathematical approach was developed by Pękala et al. [8]. Also, there have been several applications of the developed tools in energy planning for Ireland [9,10], New Zealand [11-13], California [14] and China [15].

CCEP was later extended to address the problem of CCS deployment in the power generation sector, focusing on the implications of retrofitting power plants for carbon capture (CC). Graphical [16], algebraic [17] and optimisation-based techniques [2,18,19] have been used to account for the interplay between carbon emission reduction and power losses, which then necessitate compensatory power to be either imported from adjoining regions, or otherwise generated from new, low-carbon power plants. Planning of power generation systems considering CCS to be one of the low-carbon options has also been demonstrated by Elkamel et al. [20]. These proposed methods can, on a static (i.e. single-period) basis, determine the minimum extent of CC retrofitting in a fleet of power plants (hence minimised power losses and compensatory power) to meet the energy demand and emission limit. Ooi et al. [21] later extended the previously developed techniques [2,16] to the multi-period problem for Malaysia’s energy sector planning.

Recently, CCEP has been applied by Li et al. [22] to identify the biomass electricity target in the context of regional energy planning. This target is then fulfilled by synthesising a biomass supply chain network that minimises the carbon footprint. The latter part of their work is similar to those presented earlier by Lam et al. [23,24]. In this paper, an alternative two-stage optimisation approach to the integrated planning of biomass-based power generation is developed. The mathematical formulation not only captures all the concepts of the original approach [22], but is also capable of handling more details and complexities that may not be easily or effectively done with graphical techniques. Specifically, the optimisation model allows for non-uniform biomass collection rates and road factors, and considers the selection of optimal site(s) for building power plants. A case study is presented to illustrate and validate the proposed approach.

II. PROBLEM STATEMENT

The problem addressed in this paper can be formally stated as follows. Given:
• A set of energy demands (regions) \( j \in J \). Each region has an energy demand \( D_j \) and is subject to a carbon emission limit \( E_j \).

• A set of energy sources \( i \in I \), including biomass, used to satisfy the demands. Each source has a maximum amount of energy supply \( P_i \), and is characterised by a carbon emission factor \( C_i \).

The objective is first to determine the optimal energy mix for the region(s), and thus the target for bioenergy, in such a way that the use of low-carbon sources (e.g. biomass and CCS plants) is minimised for cost and feasibility considerations. It is then to synthesise the optimal bioenergy supply network(s). In this case, each region is divided into a set of zones \( k \in K \). The site(s) for biomass energy conversion is selected from the zones so that the carbon emissions associated with biomass transport is minimised.

III. MODEL FORMULATION

The overall approach to regional energy planning with biomass utilisation involves two successive stages. In the first stage, the optimal energy mix that meets the energy demand as well as the emission limit for the region(s) is determined, and the target for bioenergy is identified. This target is then passed to the second stage, in which the optimal biomass supply chain network that fulfils the target is synthesised. The mathematical formulation of the two stages is presented below. Notation used is given in the Appendix.

A. Stage 1: Identification of the Bioenergy Target

Similar to those presented by Tan and Foo [3] and Pękala et al. [8], based on the general source-sink superstructure (as shown in Fig. 1), the model for determining the optimal energy mix in the context of regional bioenergy planning is presented as follows.

Energy balance for each source:
\[
\sum_i f_{ij} \leq P_i \quad \forall i \in I
\]
where \( f_{ij} \) is the energy supplied from source \( i \) to demand \( j \), and \( P_i \) is the potential electricity of source \( i \).

Energy balance for each demand (region):
\[
\sum_j f_{ij} \geq D_j \quad \forall j \in J
\]
where \( D_j \) is the energy demand of region \( j \).

Aggregate carbon emission limit:
\[
\sum_i \sum_j f_{ij} C_i \leq \sum_j E_j
\]
where \( C_i \) is the carbon emission factor of source \( i \), and \( E_j \) is the carbon emission limit for region \( j \).

The objective function for stage 1 is to minimise the use of low-carbon energy sources \((i' \in I^{BE})\), i.e.
\[
\min \phi_1 = \sum_i \sum_j f_{ij}
\]

B. Stage 2: Synthesis of the Bioenergy Supply Network

Equation (5) limits the number of biomass power plants to be built to a maximum of \( N \), and (6) defines unsuitable \((S_k = 0)\) and suitable sites \((S_k = 1)\).

\[
\sum_k z_k \leq N \quad \text{(5)}
\]
\[
z_k \leq S_k \quad \forall k \in K \quad \text{(6)}
\]

where \( z_k \) is a binary variable indicating if a power plant is built in zone \( k \), while \( S_k \) is a binary parameter denoting if zone \( k \) is suitable for a power plant.

Equation (7) describes the mass balance for the biomass transported from zone \( k \) to zone \( k' \) if no plant is built there.

\[
\sum_k m_{kk'} \leq \lambda_k M_k \quad \forall k \in K \quad \text{(7)}
\]
where \( m_{kk'} \) is the amount of biomass transported from zone \( k \) to zone \( k' \), \( \lambda_k \) is the biomass collection rate in zone \( k \), and \( M_k \) is the potential biomass in zone \( k \).

The target for bioenergy \((D^BE = \sum_{i' \in biomass} f_{i'j})\) to be identified in stage 1 is to be met. This is given in (9):

\[
\sum_k \sum_{k'} \eta_k LHV_k m_{kk'} \geq D^BE \quad \text{(9)}
\]
where \( \eta \) is the thermal efficiency of the power plant, and \( LHV_k \) is the lower heating value of the biomass from zone \( k \).

Figure 1. Generic source-sink representation.
The objective function for stage 2 is to minimise the carbon emissions from biomass transport, i.e.,
\[
\min \phi_2 = \sum_k \sum_{k'} m_{kk'} \delta_{kk'} R_{kk'} C^{T}
\]
(10)
where \(\delta_{kk'}\) is the distance between zones \(k\) and \(k'\), \(R_{kk'}\) is the road (distance correction) factor, and \(C^{T}\) is the carbon footprint of biomass transport.

With the presence of binary variables, (5)–(10) constitute a mixed integer linear programming (MILP) model, for which global optimality is guaranteed. Furthermore, no significant computational difficulties are expected in solving this model for cases of typical size.

IV. CASE STUDY

In this section, a case study taken from Li et al. [22] is used to illustrate the proposed approach. The developed models are implemented and solved in the GAMS environment [25] on a Core i5-4340, 2.90 GHz processor, utilising CPLEX as the LP and MILP solver. All solutions were found with negligible processing time (< 0.2 CPU s).

This case study considers energy planning in Laixi, the northernmost part of Qingdao, China. Laixi is divided into 15 zones, of which the locations and potential biomass are given in Table I. Note that the heating values vary from zone to zone because of the difference in biomass resources. With different willingness of the rural residents to collect biomass, Li et al. [22] considered three simplified scenarios with different mean collection rates: 100%, 80% and 40%, assuming fixed thermal efficiency of 30% for power generation.

Table II presents the data required to determine the optimal generation mix for Laixi. It is estimated that Laixi’s electricity demand in 2020 will be 2500 GWh, while the emission limit is set to 1260 ktCO\(_2\) [22], which corresponds to 80% of the 2012 level. In addition, the electricity from biomass is limited to a feasible maximum of 30% of the total supply, according to the 2003-2020 urban master plan of Laixi. Once the electricity target for biomass is identified, the optimal biomass supply chain network can be synthesised. For simplicity, a common road factor of 1.2 is assumed in this case study to estimate the distance between two zones. It is further assumed that the biomass power plant is to be built in either zone 2 or zone 13, based on the government’s intention. The emission factor of biomass transport is set to 0.04 kgCO\(_2\)/t/km.

### A. Model Application and Validation

Solving the LP ((1)–(4)) and MILP ((5)–(10)) models for all three scenarios gives consistent results with those reported in the original work [22], as summarised in Table III for the optimal electricity mix, and Table IV for the optimal biomass supply chain network. With only minor rounding differences in energy supplies (for scenario 3) and carbon footprints, the validity of the proposed models is confirmed.

### B. Relaxation of Simplifying Assumptions

The foregoing results are based on the assumption that the biomass energy conversion plant is only to be built in either zone 2 or zone 13, and thus may not be the true optimum in terms of the carbon footprint. Therefore, it is assumed in this work that the plant may be built in any of the zones. Assuming also \(\lambda = 80\%\) as in scenario 2, hence the same bioenergy target, solving the MILP model gives the minimum carbon footprint of 460.47 t, which corresponds to a 7.3% reduction from the original result (496.92 t). Fig. 2 shows the resulting biomass supply chain network, where the plant is built in zone 4.

### TABLE I. LOCATIONS OF ZONES

<table>
<thead>
<tr>
<th>Zone</th>
<th>Location (km,km)</th>
<th>Potential Biomass (t/y)</th>
<th>Lower Heating Value (GJ/t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(16,16)</td>
<td>39,136</td>
<td>15.23</td>
</tr>
<tr>
<td>2</td>
<td>(16,22)</td>
<td>29,007</td>
<td>15.28</td>
</tr>
<tr>
<td>3</td>
<td>(18,28)</td>
<td>31,968</td>
<td>15.22</td>
</tr>
<tr>
<td>4</td>
<td>(3,21)</td>
<td>43,625</td>
<td>15.17</td>
</tr>
<tr>
<td>5</td>
<td>(8,10)</td>
<td>28,540</td>
<td>15.29</td>
</tr>
<tr>
<td>6</td>
<td>(16,2)</td>
<td>76,320</td>
<td>15.19</td>
</tr>
<tr>
<td>7</td>
<td>(10,1)</td>
<td>65,147</td>
<td>15.14</td>
</tr>
<tr>
<td>8</td>
<td>(0,10)</td>
<td>33,885</td>
<td>15.16</td>
</tr>
<tr>
<td>9</td>
<td>(1,30)</td>
<td>65,349</td>
<td>15.17</td>
</tr>
<tr>
<td>10</td>
<td>(1,40)</td>
<td>48,717</td>
<td>15.22</td>
</tr>
<tr>
<td>11</td>
<td>(15,38)</td>
<td>57,614</td>
<td>15.26</td>
</tr>
<tr>
<td>12</td>
<td>(0,0)</td>
<td>33,357</td>
<td>15.28</td>
</tr>
<tr>
<td>13</td>
<td>(20,0)</td>
<td>63,669</td>
<td>15.17</td>
</tr>
<tr>
<td>14</td>
<td>(0,20)</td>
<td>58,026</td>
<td>15.22</td>
</tr>
<tr>
<td>15</td>
<td>(5,42)</td>
<td>73,036</td>
<td>15.28</td>
</tr>
</tbody>
</table>

### TABLE II. ENERGY SOURCE DATA

<table>
<thead>
<tr>
<th>Energy source</th>
<th>Emission Factor (kt CO(_2)-eq)</th>
<th>Electricity for 2020 (GWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal</td>
<td>1</td>
<td>To be determined</td>
</tr>
<tr>
<td>Coal with CCS</td>
<td>0.2</td>
<td>To be determined</td>
</tr>
<tr>
<td>Oil</td>
<td>0.8</td>
<td>0</td>
</tr>
<tr>
<td>Natural gas</td>
<td>0.5</td>
<td>180</td>
</tr>
<tr>
<td>Biomass</td>
<td>0</td>
<td>To be determined</td>
</tr>
</tbody>
</table>

### TABLE III. OPTIMAL ELECTRICITY MIX

<table>
<thead>
<tr>
<th>Energy Source</th>
<th>Electricity for 2020 (GWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1 ((\lambda = 100%))</td>
<td>Scenario 2 ((\lambda = 80%))</td>
</tr>
<tr>
<td>Coal</td>
<td>1070</td>
</tr>
<tr>
<td>Coal with CCS</td>
<td>500</td>
</tr>
<tr>
<td>Natural gas</td>
<td>180</td>
</tr>
<tr>
<td>Biomass</td>
<td>750</td>
</tr>
<tr>
<td>Total</td>
<td>2500</td>
</tr>
</tbody>
</table>
TABLE IV. OPTIMAL BIOMASS SUPPLY

<table>
<thead>
<tr>
<th>Power plant location</th>
<th>Zone 2</th>
<th>Zone 2</th>
<th>Zone 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biomass transported (t/y):</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zone 1 to zone 2</td>
<td>39136</td>
<td>31308.8</td>
<td>15654.4</td>
</tr>
<tr>
<td>Zone 2 to zone 2</td>
<td>29007</td>
<td>23205.6</td>
<td>11602.8</td>
</tr>
<tr>
<td>Zone 3 to zone 2</td>
<td>31968</td>
<td>25574.4</td>
<td>12787.2</td>
</tr>
<tr>
<td>Zone 4 to zone 2</td>
<td>43625</td>
<td>34900</td>
<td>17450</td>
</tr>
<tr>
<td>Zone 5 to zone 2</td>
<td>28540</td>
<td>22832</td>
<td>11416</td>
</tr>
<tr>
<td>Zone 6 to zone 2</td>
<td>76320</td>
<td>61056</td>
<td>30528</td>
</tr>
<tr>
<td>Zone 7 to zone 2</td>
<td>65147</td>
<td>52117.6</td>
<td>26058.8</td>
</tr>
<tr>
<td>Zone 8 to zone 2</td>
<td>33885</td>
<td>27108</td>
<td>13554</td>
</tr>
<tr>
<td>Zone 9 to zone 2</td>
<td>65349</td>
<td>52279.2</td>
<td>26139.6</td>
</tr>
<tr>
<td>Zone 10 to zone 2</td>
<td>0</td>
<td>38973.6</td>
<td>19486.8</td>
</tr>
<tr>
<td>Zone 11 to zone 2</td>
<td>57614</td>
<td>46912.1</td>
<td>23045.6</td>
</tr>
<tr>
<td>Zone 12 to zone 2</td>
<td>0</td>
<td>20401.92</td>
<td>13342.8</td>
</tr>
<tr>
<td>Zone 13 to zone 2</td>
<td>63480.44</td>
<td>50935.2</td>
<td>25476.7</td>
</tr>
<tr>
<td>Zone 14 to zone 2</td>
<td>58026</td>
<td>46420.8</td>
<td>23210.4</td>
</tr>
<tr>
<td>Zone 15 to zone 2</td>
<td>0</td>
<td>58428.8</td>
<td>29214.4</td>
</tr>
<tr>
<td>Total carbon footprint (tCO₂)</td>
<td>452.83</td>
<td>496.92</td>
<td>252.56</td>
</tr>
</tbody>
</table>

The impact of decentralising biomass energy conversion on the carbon footprint is further analysed. Assuming \( \lambda = 80\% \) and that up to two plants may be built, solving the MILP model gives the optimal sites in zone 6 and zone 9, with the minimum carbon footprint of 265.72 t. This corresponds to a significant further reduction of 39.2%. Fig. 3 shows the resulting biomass supply chain network. It can be seen that decentralised energy conversion with two plants shortens the distance of transport and thus reduces the associated carbon emissions. However, building more plants of smaller size could increase the cost, suggesting a trade-off between the number of plants and the carbon footprint.

![Figure 2. Optimal biomass supply network for one power plant.](image)

![Figure 3. Optimal biomass supply network for two power plants.](image)

V. CONCLUSION

A two-stage mathematical optimisation approach to integrated planning of biomass-based power generation has been developed in this paper. The proposed approach eliminates the repetitive calculations involved in the procedure of Li et al. [22], and takes into account further complexities in biomass supply network synthesis, such as multiple sites and plants. As can be seen in the case study results, the carbon footprint of biomass transport can be significantly reduced (~46.5%) when decentralised biomass energy conversion is allowed. Future work will consider the extension to detailed supply chain synthesis, down to the technology level with differentiated energy demands and biomass sources.

APPENDIX

Notation used in the model formulation is as follows:

**Indices and sets**

\( i \in I \) = energy sources

\( j \in J \) = low-carbon sources

\( j \in J \) = energy demands (regions)

\( k \in K \) = zones

**Parameters**

\( C_i \) = carbon footprint of biomass transport

\( C_j \) = carbon emission factor of source \( i \)

\( D_{BE} \) = bioenergy target

\( D_i \) = energy demand of region \( j \)

\( E_j \) = carbon emission limit for region \( j \)

\( LHV_k \) = lower heating value of the biomass from zone \( k \)

\( M_k \) = potential biomass in zone \( k \)

\( N \) = maximum number of biomass power plants

\( P_i \) = potential electricity of source \( i \)
\( R_{kk'} \) = road factor for the distance between zones \( k \) and \( k' \)
\( S_k \) = binary denoting if zone \( k \) is suitable for a power plant
\( \delta_{kk'} \) = distance between zones \( k \) and \( k' \)
\( \lambda_k \) = biomass collection rate in zone \( k \)
\( \eta \) = thermal efficiency of the power plant

**Variables**

\( f_i \) = energy supplied from source \( i \) to demand \( j \)
\( m_{kk'} \) = biomass transported from zone \( k \) to zone \( k' \)
\( z_k \) = binary indicating if a power plant is built in zone \( k \)

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**REFERENCES**


