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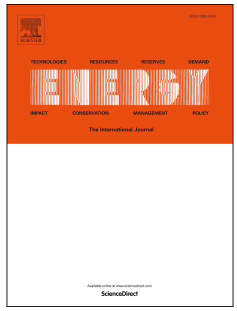

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Network design and technology management for waste to energy production: an integrated optimization framework under the principles of circular economy

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Abstract

The design of waste to bioenergy supply chains (W-BESC) is critically important for meeting the circular economy (CE) goals, whilst also ensuring environmental sustainability in the planning and operation of energy systems. This study develops a novel optimization methodology to aid sustainable design and planning of W-BESC that comprise multiple technologies as well as multiple product and feedstock types. The methodology identifies the optimum supply chain configuration and plans the logistics operations in a given region to meet the energy demand of specified nodes. A scenario based fuzzy multi objective modelling approach is proposed and utilized to capture the economic and environmental sustainability aspects in the same framework. We test the proposed model using the entire West Midlands (WM) region from the United Kingdom (UK) as a case study. In this scope, a comprehensive regional supply chain is designed to meet the energy and biofertilizer demand of specific nodes considering available waste and crop type biomass in the region. Further analysis is conducted to reveal the impacts of main economic and technological parameters on the supply chain performance indicators.

Keywords: Waste to energy supply chains; Network design; Technology management; Mathematical modelling; Fuzzy multi objective decision making

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1. Introduction

CE fundamentally lies on the idea of transforming products, production systems and supply chains in order to establish workable relationships between ecological systems and economic growth, pushing also the frontiers of environmental sustainability. The focus is on the creation of self-sustaining production systems in which materials are used over and over again (Genovese et al., 2015). Incorporating these CE principles into the supply chain planning and management strategies for energy systems, is important for minimizing material flows and for reducing unintended negative consequences of production processes (Srivastava, 2007).

The establishment of W-BESC as district energy systems for communities, supports the “win-win” philosophy, on which circular economy concept is based, that a prosper economy and healthy environment can co-exist (Tukker, 2013; Pan et al., 2015). In addition, W-BESC provide the circular relationship between greening and economic growth for facing existing environmental problems along with resource scarcity by increasing the resource utilization efficiency in energy production and in the use of renewable energies.

Various W-BESC are operated throughout the world, consisting of different biomass production systems, pre-processing and conversion operations, as well as transportation methods for raw materials and bio-based fuels. However, the wide use of biomass based energy systems has resulted in new challenges, such as: long-distance transport (e.g. from biomass production areas to energy producing facilities) and therefore additional logistics costs, energy consumption and ultimately higher greenhouse gas (GHG) emissions compared to small-scale utilisation. In many cases feedstock location, processing sites and product destinations have profound implications for the profitability and environmental impacts of the overall supply chain (Sharifzadeh et al., 2015). Hence, large capacity bioenergy plants require robust and integrated supply chain and logistics systems in place.

To overcome these challenges, proper methodologies need to be developed to select the most favourable supply chain configuration and logistics options and to identify cost-efficient bioenergy supply chain designs with minimal carbon footprint. There are a few prior studies in the literature (e.g. Aviso et al., 2011; Li and Hu, 2014; Sharifzadeh et al., 2015) that develop design methodologies by simultaneously considering sustainability and uncertainty aspects, but most of them capture these aspects by using separate methods after the design phase. In other words, after deciding on the recommended supply chain, uncertain parameters are only then considered in the scenario and/or sensitivity analysis phase. Most of them neither consider nor include the uncertainties in the optimization procedure in the design phase. We argue that it is important to develop and use an effective optimization methodology to capture both sustainability aspects and uncertainties in the system parameters in the same optimization framework in the design phase. Furthermore, there is no study in the literature that includes CE principles in design and planning of W-BESC by considering the utilization of useful by-products of the energy system in the supply chain.

This study develops a novel methodology, which could optimize multi waste supply chains including multiple types of production technologies considering circular economy principles, for the strategic and tactical decision making in waste biomass based energy production system investments. The proposed methodology finds the optimal supply chain configuration, selects the most appropriate production technologies and plans production/distribution activities that enables to meet the demand of multiple types of bio-products in a region considering a diversified set of available waste feedstocks and technology options. Useful by-products of the system are also considered to be utilized in the supply chain.

The proposed approach enhances the capital investment and technology management decisions for planning a waste biomass based system and could be used in two ways: 1) To identify the optimal configuration of the supply chain and plan the logistics operations in the development of new investments, 2) To monitor the main economic and environmental performance indicators of the existing supply chains taking the necessary actions to improve the performance.

To explore the viability of the proposed model, computational experiments are performed using the UK region of WM as a case study. Scenario and economic sensitivity analyses are conducted to provide deeper understanding of the proposed methodology and how changing parameters affect the optimum supply chain configuration and performance indicators. The effects of changes in the biofuel to energy conversion rate in bioenergy plants on the main revenue and cost components are also investigated.

The rest of the paper is organized as follows. Section 2 provides a literature review on the studies that develop optimization models for sustainable design of bioenergy supply chains identifying also the research gaps as well as the expected contributions of this research. Section 3 presents the problem description, formulation of the optimization model and the solution approach. In Section 4, the case study setting is explained where the proposed optimization approach is applied to the region of WM. Section 5 proposes the results, further analyses and discussion of the results. Section 6 discusses the conclusions along with future research directions.

2. Literature Review

In recent years, the integration of CE principles into the planning of waste to energy supply chains is gaining attention. Pan et al. (2015) analysed several waste to energy technologies including combustion, gasification and anaerobic digestion to provide portfolio options of technologies for different types of waste to energy supply chains for creating a CE system. In a similar vein, Nasir et al. (2016) used a case study from the construction industry to demonstrate and compare the environmental gains that can be achieved through the adoption of CE principles in comparison to the traditional linear production systems. Ahn et al. (2015) developed a deterministic mathematical programming model for strategic planning design of a biomass-to-biodiesel supply chain network from feedstock fields to end users that simultaneously satisfies resource constraints, demand constraints, and technology over a long-term planning horizon. Chabaane et al. (2011) presented a methodology to address sustainable supply chain design problems where carbon emissions and total logistics costs, including suppliers and sub-contractors selection, technology acquisition and the choice of transportation modes, are considered in the design phase. Wang et al. (2013) utilized to analyze bioethanol production from waste papers. Bioethanol supply chain is modelled by simulation to compare the selling price of bioethanol produced from waste paper with petrol price. Genovese et al. (2015) compared the performances of traditional and circular production systems across a range of indicators using two case studies from chemical and waste food (waste cooking oil to biodiesel) supply chains. They concluded that the integration of CE principles into sustainable supply chain management practices provides clear environmental advantages. Calderon et al. (2017) proposed a general optimisation framework based on a multiperiod mixed integer linear programming model to address the strategic design of waste to synthetic natural gas supply chains. The framework considers procurement of feedstocks, plantation of energy crops, and different modes for transportation of feedstocks and final products and allows researches and policy makers to investigate scenarios that promote the development of synthetic natural gas supply chains. The research by Mayerle et al. (2016) presented a methodology to design an animal waste to biogas supply chain which maximizes contribution and minimizes gas loss when biomass energy feedstock providers are small farms without on-site bio-digestion units.

The table in Appendix A presents a summary of our literature review on studies that develop optimization models to design bioenergy supply chains considering economic and environmental sustainability. The table depicts the type of the model developed, a brief description of the proposed study and limitations of each of the studies. The review of literature suggests that the vast majority of the supply chain design models in the literature focuses only on single type of waste (e.g. Woo et al., 2016; Marufuzzaman et al., 2016) and single type of end product (e.g. Roni et al., 2014). However, in real world applications bioenergy, which is obtained from multiple sources of waste biomass, is either used in transport applications or converted into electrical and thermal energy by power engines. Thus, these studies do not have the end user application in scope. In addition, none of the prior researches considers utilization of the by-product of the system along with the main products. In real world applications the useful by-products of the systems are often sold besides the main bio-products to increase the profitability of the systems and decrease the investment rate of return. Previous contributions have focused on single type conversion technology/process (thermochemical or biochemical), which makes them problem specific. Multiple types of conversion technologies may support a longer term supply, and reduce the effects of seasonal fluctuations and price instabilities as well as technological uncertainties on the supply chain performance. A good biomass to energy conversion rate strongly depends on supply and a balanced mix of biomass. This diversified system is also more applicable to real cases, which have a mix of biomass resources to utilise to meet energy needs.

To the best of our knowledge, none of the methodologies in the literature integrate the strategic decisions related to location, capacity and technology selection for both bioenergy plants and pre-processing facilities with tactical level decisions on production and distribution of bioenergy and biomass. Also, there is no study in the literature that captures sustainability and uncertainty aspects in the supply chain design phase by developing a design methodology to capture system uncertainties and optimize multiple objectives simultaneously. To address these gaps in the literature, this paper pro poses a comprehensive methodology to design waste biomass based supply chains for production of multiple types of bio-products (bioenergy and biofertilizer as by-product of the system) in a sustainable manner. The methodology is developed to aid strategic and tactical design of biomass based production chains in an uncertain decision environment considering also the tradeoffs between capital investment costs, profit, and GHG emissions in the supply chain. A fuzzy multi objective programming based procedure is used to obtain the optimum configuration and corresponding optimum values of supply chain performance indicators. Fuzzy multi objective programming is a rarely used method in bioenergy supply chain design studies, although it is one of the most effective solution approaches to solve multiobjective optimization problems considering inherent uncertainties and allowing prioritization of different objectives according to decision makers' preferences to provide economic and environmental insights. This method reflects the characteristics of the problem on hand and computational experiments show that it is able to provide high quality solutions in a reasonable amount of time.

The main contributions of this study are summarized in the following:

1. It proposes a novel optimization methodology combining mathematical modelling and fuzzy multi-objective decision making for the strategic and tactical decision making in biomass based energy production system investments.
2. The developed methodology integrates sustainability and uncertainty aspects in the supply chain design phase by capturing system uncertainties and optimizing economic and environmental objectives simultaneously.
3. The developed model covers multiple types of biomass, biomass to energy conversion technologies, biomass pre-processing facilities and bio-products. On that sense, the model is generalizable, the decision makers can utilize our model for different cases with only updating the data set.
4. The proposed methodology finds the optimal supply chain configuration and production/distribution planning that enables to meet the demand of multiple types of bio-products in a region considering a diversified set of available biomass feedstocks in the region. Useful by-products of the system are also considered to be utilized in the supply chain to promote circular economy.

Another contribution of this study is that the validity of the developed methodology is explored on a case study of WM, UK, which is the first attempt to design a comprehensive bioenergy production chain in this region. In addition further scenario and economic sensitivity analyses are conducted to provide managerial insights to aid companies and policy makers in making supply chain decisions.

3. Problem Description and Formulation of the Methodology

In this section, we describe the integrated supply chain configuration, technology selection, and production-distribution planning problem to produce bioenergy in a sustainable way. We also present our optimization methodology, which integrates mathematical modelling and fuzzy multi objective decision making, and outline the solution approach used to generate the optimum solution.

The methodology integrates all activities from feedstock supply to product distribution and consumption, and all elements of the chain from biomass source sites to demand nodes. The methodology integrates mathematical modelling and a scenario based fuzzy multi objective programming approach to involve objectives related to the economic and environmental performance of the supply chain and capture the trade-offs between the objectives as well as system specific uncertainties effectively.

3.1. Problem Description

This paper focuses on designing an optimized supply chain and distribution network for biomass based energy production considering sustainability aspects under problem specific uncertainties. The supply chain in consideration consists of following elements;

1. The biomass source sites to supply multiple types of biomass
2. Facilities for pre-treatment of biomass before conversion process
3. Facilities for collection of biomass before conversion process
4. Biomass to biofuel (liquid & gaseous) conversion plants
5. Combined Heat and Power (CHP) plants to convert biofuel into bioenergy
6. Product, by-product, energy demand nodes

In this scope, we developed a mathematical optimization model that capture economic, and environmental considerations by a multiobjective structure. The model aims to design the biomass based energy production chain by making decisions corresponding to; (1) configuration of the supply chain network with related locations, technologies and capacities; (2) procurement and allocation of the biomass resources; and (3) inventory, production and distribution planning, while meeting the energy demand of a particular area. More specifically, the decisions made by the model are;

1. Numbers, locations and capacities of facilities, bioenergy plants and CHP units,
2. Types of facilities for biomass treatment and technologies for bioenergy plants,
3. Amount of biofuel, by-product and energy produced in each energy plant,
4. Amount of biomass, biofuel and by-product distributed between biomass source sites, facilities, plants and demand nodes,
5. Amount of biomass treated/stored in facilities,
6. Amount of auxiliary material consumed in energy conversion plants.

The model determines the optimal configuration of the supply chain considering the tradeoffs between capital investment costs, profit and GHG emissions associated with production and transportation activities in the supply chain. To be more precise, to increase the profitability of the system, we have to produce more product which means at the same time constructing more plants/pre-processing facilities and increasing the capital investment costs. Also producing more product leads to increased biomass transportation and conversion activities which result in increased level of GHG emissions. Hence, it is important to capture the tradeoffs between conflicting objectives.

3.2. Formulation of the Mathematical Model

In this section, the mathematical formulation of the optimization model is proposed. The notations of the mathematical formulations are presented in Table 1.

Table 1. Notations used in the model

The model includes three environmental and economic objectives. The objectives are: (1) maximization of monthly total profit; (2) minimization of total capital investment cost and (3) minimization of GHG emissions (CO_2 eq) related to production and transportation.

Maximization of supply chain profit can be calculated as follows;

Eq. 1 represents the first objective function;

$$
\begin{aligned}
Max\ Profit = & \left[\left(\sum_{k=1}^{K} \sum_{l=1}^{L} \sum_{t=1}^{T} \sum_{u=1}^{U} SP_{tu}^{kl} \cdot P_{ut} \right) + \left(\sum_{k=1}^{K} \sum_{l=1}^{L} \sum_{t=1}^{T} \sum_{f=1}^{U} SBP_{tf}^{kl} \cdot P_{ft} \right) + \left(\sum_{k=1}^{K} \sum_{l=1}^{L} \sum_{n=1}^{N} SE_{n}^{kl} \cdot P_{nt} \right) \right] \\
& - \left[\begin{aligned} & \left(\sum_{j=1}^{J} \sum_{e=1}^{E} \sum_{c=1}^{C} VO_{ec} \cdot \left(\sum_{i=1}^{I} \sum_{b=1}^{B} S_{cb}^{ij} \right) \right) + \left(\sum_{k=1}^{K} \sum_{p=1}^{P} \sum_{t=1}^{T} VO_{pt} \cdot \left(\sum_{j=1}^{J} \sum_{b=1}^{B} S_{tb}^{jk} \right) \right) \\ & + \left(\sum_{q=1}^{Q} \sum_{t=1}^{T} VOCHP_{q} \cdot \left(\sum_{k=1}^{K} \sum_{n=1}^{N} E_{tn}^{k} \right) \right) \end{aligned} \right] \\
& - \left[\begin{aligned} & \left(\sum_{j=1}^{J} \sum_{e=1}^{E} \sum_{c=1}^{C} FO_{ec} \cdot C2_{ec} \cdot B_{jec} \right) + \left(\sum_{k=1}^{K} \sum_{p=1}^{P} \sum_{t=1}^{T} FO_{pt} \cdot C1_{pt} \cdot A_{kpt} \right) \\ & + \left(\sum_{k=1}^{K} \sum_{q=1}^{Q} \sum_{n=1}^{N} FOCHP_{q} \cdot CE_{qn} \cdot CHP_{q}^{k} \right) \end{aligned} \right] \\
& - \left[\begin{aligned} & \sum_{b=1}^{B} TV_{b} \cdot \left(\sum_{i=1}^{I} \sum_{j=1}^{J} d^{ij} \cdot \left(\sum_{c=1}^{C} S_{cb}^{ij} \right) \right) \\ & + \sum_{b=1}^{B} TV_{b} \cdot \left(\sum_{j=1}^{J} \sum_{k=1}^{K} d^{jk} \cdot \left(\sum_{t=1}^{T} S_{tb}^{jk} \right) \right) + \sum_{f=1}^{F} TV_{f} \cdot \left(\sum_{k=1}^{K} \sum_{l=1}^{L} d^{kl} \cdot \left(\sum_{t=1}^{T} SBP_{tf}^{kl} \right) \right) \\ & + \sum_{b=1}^{B} TF_{b} \cdot \left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{c=1}^{C} S_{cb}^{ij} \right) + \sum_{b=1}^{B} TF_{b} \cdot \left(\sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{t=1}^{T} S_{tb}^{jk} \right) \\ & + \sum_{f=1}^{F} TF_{f} \cdot \left(\sum_{k=1}^{K} \sum_{l=1}^{L} \sum_{t=1}^{T} SBP_{tf}^{kl} \right) \end{aligned} \right] \\
& - \left[\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{c=1}^{C} \sum_{b=1}^{B} P_{b} \cdot S_{cb}^{ij} \right] - \left(\sum_{k=1}^{K} W^{k} \cdot PW \right)
\end{aligned} \tag{1}
$$

Eq. 2 shows the second objective function, namely minimization of total capital investment cost of bioenergy plants and biomass pre-treatment facilities.

$$
\begin{aligned}
Min\ Total\ Investment\ Cost = & \left(\sum_{j=1}^{J} \sum_{e=1}^{E} \sum_{c=1}^{C} I_{ec} \cdot C_{ec} \cdot B_{jec} \right) + \left(\sum_{k=1}^{K} \sum_{p=1}^{P} \sum_{t=1}^{T} I_{pt} \cdot C_{pt} \cdot A_{kpt} \right) \\
& + \left(\sum_{k=1}^{K} \sum_{q=1}^{Q} ICHP_{q} \cdot CE_{qn} \cdot CHP_{q}^{k} \right)
\end{aligned} \tag{2}
$$

Eq. 3 shows the third objective function, namely minimization of GHG emissions associated with energy production, preprocessing and transportation activities. Transportation related GHG emissions include emissions caused by transportation vehicle and emissions caused by biomass sources.

$$Min\, GHG\, Emissions = \left(\sum_{k=1}^{K} \sum_{t=1}^{T} \left(\sum_{n=1}^{N} g_t \cdot E_{tn}^{k} \right) \right) + \left(\sum_{i=1}^{I} \sum_{j=1}^{J} \left(\sum_{c=1}^{C} \sum_{b=1}^{B} g_c \cdot S_{cb}^{ij} \cdot d_{bc} \right) \right)$$
$$+ \left(\left(g \cdot 2 \cdot d^{ij} \cdot \left(\sum_{c=1}^{C} \sum_{b=1}^{B} S_{cb}^{ij} / CT \right) \right) + \left(\sum_{b=1}^{B} gt_b \cdot \left(\left(\sum_{i=1}^{I} \sum_{j=1}^{J} d^{ij} \cdot \sum_{c=1}^{C} S_{cb}^{ij} \right) + \left(\sum_{j=1}^{J} \sum_{k=1}^{K} d^{jk} \cdot \sum_{t=1}^{T} S_{tb}^{jk} \right) \right) \right) \right) \quad (3)$$
$$+ \left(\left(g \cdot 2 \cdot d^{kl} \cdot \left(\sum_{t=1}^{T} \sum_{f=1}^{F} SBP_{tf}^{kl} / CT \right) \right) + \left(\sum_{f=1}^{F} gt_f \cdot \left(\sum_{k=1}^{K} \sum_{l=1}^{L} d^{kl} \cdot \sum_{t=1}^{T} SBP_{tf}^{kl} \right) \right) \right)$$

Eqs. 4-20 represent the constraints of the mathematical model.

$$\sum_{c=1}^{C} \sum_{j=1}^{J} S_{cb}^{ij} \le BS_b^i \quad \forall i = 1,..., I, \forall b = 1,..., B \quad (4)$$

$$\sum_{i=1}^{I} \sum_{c=1}^{C} S_{cb}^{ij} \cdot d_{bc} = \sum_{k=1}^{K} \sum_{t=1}^{T} S_{tb}^{jk} \quad \forall j = 1,..., J, \forall b = 1,..., B \quad (5)$$

$$\sum_{j=1}^{J} \sum_{b=1}^{B} S_{tb}^{jk} \le \sum_{p=1}^{P} A_{pt}^{k} \cdot C_{pt} \quad \forall k = 1,..., K, \forall t = 1,..., T \quad (6)$$

$$\sum_{i=1}^{I} \sum_{b=1}^{B} S_{cb}^{ij} \le \sum_{e=1}^{E} B_{ec}^{j} \cdot C_{ec} \quad \forall j = 1,..., J, \forall c = 1,..., C \quad (7)$$

$$\sum_{j=1}^{J} \sum_{b=1}^{B} S_{tb}^{jk} \cdot r_{but} = PR_{ut}^{k} \quad \forall k = 1,..., K, \forall u = 1,...,U, \forall t = 1,..., T \quad (8)$$

$$P_{ut}^{k} \cdot \left(1 - \sum_{n=1}^{N} y_{tun}^{k} \right) = \sum_{l=1}^{L} SP_{tu}^{kl} \quad \forall k = 1,..., K, \forall u = 1,...,U, \forall t = 1,..., T \quad (9)$$

$$\sum_{k=1}^{K} \sum_{t=1}^{T} SP_{tu}^{kl} \ge D_u^l \quad \forall l = 1,..., L, \forall u = 1,...,U \quad (10)$$

$$\sum_{j=1}^{J} \sum_{b=1}^{B} S_{tb}^{jk} \cdot r_{bft} = BP_{kft} \quad \forall k = 1,..., K, \forall f = 1,..., F, \forall t = 1,..., T \quad (11)$$

$$BP_{kft} = \sum_{l=1}^{L} SBP_{ft}^{kl} \quad \forall k = 1,..., K, \forall f = 1,..., F, \forall t = 1,..., T \quad (12)$$

$$\sum_{k=1}^{K} \sum_{t=1}^{T} SBP_{ft}^{kl} \le D_f^l \quad \forall l = 1,..., L, \forall f = 1,..., F \quad (13)$$

$$\sum_{t=1}^{T} \sum_{u=1}^{U} PR_{ut}^{k} \cdot y_{tun}^{k} \cdot e_{un} \cdot cv_n = E_{tn}^{k} \quad \forall k = 1,..., K, \forall n = 1,..., N \quad (14)$$

$$\sum_{t=1}^{T} E_{tn}^{k} \le \sum_{q=1}^{Q} CHP_q^k \cdot CE_{qn} \quad \forall k = 1,..., K, \forall n = 1,..., N \quad (15)$$

$$E_{tn}^{k} = \sum_{l=1}^{L} SE_{tn}^{kl} \quad \forall k = 1,...,K, \forall t = 1,...,T, \forall n = 1,...,N \tag{16}$$

$$\sum_{k=1}^{K} \sum_{t=1}^{T} SE_{n}^{kl} \geq D_{n}^{l} \quad \forall l = 1,...,L, \forall n = 1,...,N \tag{17}$$

$$\sum_{p=1}^{P} \sum_{t=1}^{T} A_{pt}^{k} \leq 1 \quad \forall k = 1,...,K \tag{18}$$

$$\sum_{e=1}^{E} \sum_{c=1}^{C} B_{ec}^{j} \leq 1 \quad \forall j = 1,...,J \tag{19}$$

$$\sum_{q=1}^{Q} CHPA_{q}^{k} \leq 1 \quad \forall k = 1,...,K \tag{20}$$

Eq. 4 restricts the biomass procurement amount from a supply region by the total available biomass in that region. Eq. 5 ensures the flow balance of the biomass supplied from biomass source site to pre-treatment/collection facility and from facility to biomass to biofuel conversion plant considering the conversion rate of biomass in the pre-treatment process. Eqs. 6 and 7 limit the amount of biomass transported to the facilities and plants to the maximum capacity of the corresponding capacity levels of plants/facilities. Eqs. 8 and 9 calculate the amount of biofuel produced in and distributed from the biomass conversion plants. Eq. 10 ensures that all the biofuel demand is met in the demand nodes. Eqs. 11 and 12 calculate the amount of byproduct produced in and distributed from the biomass conversion plants. Eq. 13 limits the byproduct distribution amount by the corresponding demand in the demand nodes (to eliminate the disposal of the excess byproduct). Eqs. 14 and 15 calculate the amount of energy produced in energy plants and restrict this amount to the maximum capacity of the corresponding capacity levels of these plants. Eqs. 16 and 17 ensure that all the energy demand is met in the demand nodes. Eqs. 18, 19 and 20 ensure that at most 1 facility, biomass to biofuel conversion plant and biofuel to energy conversion plant is constructed in each selected location.

3.3. Solution methodology

In this section, the solution methodology based on fuzzy multi-objective programming that is adapted to solve the developed multi-objective mathematical model is explained. The methodology combines fuzzy set theory and goal programming, which are rarely used methods in bioenergy supply chain design studies, although they are effective approaches to solve multi-objective optimization problems in an uncertain environment allowing prioritization of different objectives according to decision makers' preferences to provide economic and environmental insights. There are other widely used approaches to solve problems in an uncertain environment like Stochastic Programming (SP) or Robust Optimization (RO) (Quddus et al., 2018; Shabani and Sowlati, 2016; Azadeh et al., 2014; Zamar et al., 2015; Mohseni and Pishvaee, 2016). SP is an approach for modelling optimization problems when the parameters are uncertain, but assumed to lie in some given set of possible values following a probability distribution. SP models try to take advantage of the fact that probability distributions governing the data are known or can be estimated. These probability distributions can be estimated from data that have been collected over time, or in the absence of data from future periods. Using SP is meaningful only when a certain action can be repeated several times. However, due to special and dynamic characteristics of energy problems, in most cases there is not enough historical/objective data to model uncertain parameters within each scenario as random data. RO is a methodology to process optimization problems in which the data are uncertain and only known to belong to some uncertainty set. RO models the possible set of values, but nothing is said about their probabilities. By RO, the decision-maker constructs a solution that is admissible in some sense through a set of scenarios. RO can be especially suitable in absence of data, or when there is no need to give more importance to some values of the parameter than to others. This is generally not the case in energy problems, since data related to energy systems and supply chains is generally available however has a highly fluctuated nature. From that point onwards, fuzzy logic comes to the forefront to develop robust approaches for concept representation of energy systems with highly fluctuated and uncertain data. By fuzzy programming, uncertainty and vagueness is modelled using fuzzy numbers and fuzzy sets rather than discrete or continuous probability functions.

In design and management of complex problems like renewable energy systems it is important to incorporate different sustainability aspects to the decision making methodology by capturing multiple and usually conflicting objectives. Goal programming (GP) is one of the most widely used and well-organized techniques to handle the multi-objective structure of complex problems like renewable energy systems. However, the aspiration levels of objectives and constraints should be identified precisely for applying GP to practical problems, which is not always possible in most of the renewable energy cases due to the uncertainties in their complex nature. Fuzzy goal programming (FGP) can be employed in such situations, which allows the decision maker considering the vagueness in the aspiration levels of objectives and constraints as well as other uncertainty sources inherent in the system parameters and decision variables.

Especially in recent decades, decision makers dealing with energy problems have different priorities related to different sustainability aspects (economic, environmental and social). For example, for companies generally economic considerations are essential whereas environmental and social aspects become prominent for governments. Hence, for solving energy problems reliably, the relative importance of different objectives should be reflected besides uncertainty in data. To this aim, in this study, a modified version of Werners' *"fuzzy and"* operator (Werners, 1988) is applied. This version of Werners' *"fuzzy and"* operator was developed by Selim (2006) to reflect the relative importance of the objective functions by considering different weights for the objectives while handling problem specific uncertainties. For detailed information on FGP, Werners' *"fuzzy and"* operator and the modified version of Werners' *"fuzzy and"* operator used in this study, Yılmaz Balaman and Selim (2014) and Yılmaz Balaman and Selim (2015) can be referred. Figure 1 depicts the solution methodology in an algorithmic framework.

Figure 1. Solution methodology

In the second and third steps of the methodology, efficient extreme solutions for each objective are determined by solving the linear programming formulation of the problem developed in Section 3.1 (Eqs. 1-20) as a single objective problem considering each time only one objective. To this aim, a novel scenario based approach is utilized in this study dividing the problem into nine sub problems (SP). Scenarios represent the worst, best and expected situations for three objective functions, which are constructed by taking into consideration the lower, upper and expected values of the fuzzy price, cost and emission parameters. After constructing the scenarios, the model is solved according to one of the objectives (profit maximization, capital cost minimization or GHG emissions minimization) under three scenarios to determine the value for each function at each solution. Results can be used as starting points to specify the upper and lower limits for each objective. The pay-off table (Table 2) depicts the efficient extreme solutions that include maximum and minimum values of these results of each objective that is taken as the aspired level of achievement and the lowest acceptable level of achievement. In the fourth step of the methodology, the upper and lower limits for each objective can be chosen from the payoff table.

Table 2. The payoff table

In Table 1 Z_m $(m = 1,\ldots,M)$ and X^s represent the *m*th objective function and the optimal solution of the single objective problem handled in the *s*th situation $(s=1,\ldots,S)$, respectively. There are 3 objective functions and 27 situations (3 scenarios for each of the 9 sub problems). Entries Z_{sm} (m = 1,…,M), $(s=1,\ldots,S)$ in the payoff matrix can be calculated solving the problem with X^s for each objective. Each of the Z_{sm} (Z_{11}, Z_{12}, …, Z_{SM}) is called “efficient extreme solutions”. Upper and lower limits can be determined, as follows:

$$u_m = (Z_m)^{max} = \max_p (Z_{sm}) \quad p = 1,2,...,M \tag{21}$$

$$l_m = (Z_m)^{min} = \min_p (Z_{sm}) \quad p = 1,2,...,M \tag{22}$$

$$(Z_m)^{min} \le Z_m \le (Z_m)^{max} \tag{23}$$

In the fifth step of the methodology, the membership functions, which defines the degree of optimality the objective function, is calculated for each fuzzy goal. The following equations represent the membership function for the *m*th objective function, which is represented by $Z_m(x)$:

For “approximately less than or equal to”;

$$\mu_{Z_m}(x) = \begin{cases} 1 & ; \quad Z_m(x) \le l_m \\ \dfrac{u_m - Z_m(x)}{u_m - l_m} & ; \quad l_m < Z_m(x) \le u_m \\ 0 & ; \quad Z_m(x) > u_m \end{cases} \tag{24}$$

For “approximately greater than or equal to”;

$$\mu_{Z_k}(x) = \begin{cases} 1 & ; \quad Z_k(x) > u_k \\ \dfrac{Z_k(x) - l_k}{u_k - l_k} & ; \quad l_k < Z_k(x) \le u_k \\ 0 & ; \quad Z_k(x) < l_k \end{cases} \tag{25}$$

After calculating membership functions, the fuzzy model is transformed into a linear programming problem, represented by the following model, using Modified Version of Werners’ “Fuzzy and” operator;

$$\begin{aligned} &Maximize \quad \lambda + [(1-\gamma)(W_1\lambda_1 + W_2\lambda_2 + ... + W_m\lambda_m)] \\ &Subject\ to \quad \mu_1 \ge \lambda + \lambda_1 \\ &\qquad\qquad ... \\ &\qquad\qquad \mu_m \ge \lambda + \lambda_m \\ &\qquad\qquad \lambda, \gamma \in [0,1] \\ &and\ other\ system\ constraints \end{aligned} \tag{26}$$

where, $W_1,...W_m$ are the relative weights; $\mu_1,...,\mu_m$ are the membership functions; $\lambda_1,...,\lambda_m$ values are the λ values for the objectives. γ coefficient of compensation value. Determination of the relative weights of the objectives is not the focus of this paper. These values are assumed to be known. Part of the model defined by “and other system constraints” represents the constraint set formulated in Eqs. 4-20 in Section 3.1.

4. Case Study

4.1. Data Description

<u>Case study region, biomass sources and bioenergy demand:</u> The Nomenclature of Territorial Units for Statistics (NUTS) is a geographical classification that subdivides territories in the UK into regions at three different levels from larger to smaller territorial units (i.e. NUTS 1, 2 and 3 respectively). WM is a NUTS 2 level region and it is divided into seven NUTS 3 level territorial areas. The proposed approach is applied to all NUTS 3 level regions in the West Midlands (Birmingham, Coventry, Solihull, Sandwell, Walsall, Wolverhampton and Dudley) to design a comprehensive supply chain and transportation network in WM. Particular locations in the abovementioned NUTS 3 level regions are considered as bioenergy demand nodes (7 demand nodes, 1 node in each region), candidate locations for bioenergy plants (7 locations, 1 location in each region) and candidate locations for facilities (7

locations, 1 location in each region).

A diverse set of biomass feedstock resources is available in WM for biofuel and energy production. These resources are widely dispersed across the region and different types of feedstock tend to cluster in different locations. In this study, four types of biowaste (cattle manure, laying chicken manure, broiler chicken manure, waste wood) and one energy crop (maize) are assumed to be the potential biomass inputs. The existing yields and geographic distribution data on biowaste from husbandry are adopted from UK Department for Environment, Food & Rural Affairs (DEFRA) - farming statistics (2015) and aggregated at 5 cattle farms and 5 poultry farms around the region. Wood waste generated as part of the manufacturing processes and wood products disposed at end life are considered in the study. In this regard, data on packaging, industrial, construction, demolition and municipal wood waste potential in the WM came from Tolvik Ltd (2011) and concentrated at 3 wood waste production and recycle facilities around WM. Data on maize yields and geographical distribution of the maize fields are gathered from DEFRA - annual statistics on the structure of the agricultural industry (2015) and aggregated at 3 energy crop fields around the region.

We consider meeting the corresponding biomethane, electricity and heat demands in a particular area in each of the NUTS 3 regions in WM. The numbers of addresses in the area considered in each region are given in Table 3. Data on the demands came from DECC (2013) and DECC National Heat Map (2012).

Table 3. The numbers of addresses in the area considered in each region

The map of the case study region is depicted in Figure 2 with biomass source sites, demand nodes, and candidate locations for energy plants and facilities considered in this study.

Figure 2. Case study region map

<u>*Bioenergy plants and facilities:*</u> Anaerobic digestion (AD) and gasification (G) technologies are considered to convert biomass into biofuel. AD is utilized to produce biofuel (biomethane) from cattle manure, laying chicken manure, broiler chicken manure and maize, a proportion of which then be converted into electrical and thermal energy in CHP engines, since biomethane can either be used directly in the place of natural gas or converted into energy. Biofuel (syngas) produced from waste wood by G is assumed to be transformed into electrical and thermal energy entirely by CHP engines as syngas can not be used directly as a biofuel dissimilarly to biomethane. Collection (CO) and pre-treatment (PT) facilities to store, treat and distribute biomass are considered as pre-processing facilities. Cattle manure, laying chicken manure, broiler chicken manure and maize are collected and distributed via collection centres whereas pre-treatment facilities are used to treat waste wood to convert into wood pellet, which is a more efficient biomass, by drying process. The by-product of AD process (biofertilizer) is distributed to the energy crop fields from where maize is supplied to

bioenergy plants. The supply chain under consideration is illustrated in Figure 3.

Figure 3. An overview of the supply chain under consideration

The potential locations for energy plants and facilities are chosen based on UK renewable energy planning database, which is provided by DECC to track the progress of new renewable energy projects, from inception, to construction and to generation. Each month an extract of that database is provided. A total of 14 sites (7 for energy plants, 7 for facilities) are chosen as the candidate locations.

To ensure the efficiency of biomethane production process in the AD plants, the total solid content of biomass slurry in the fermentation tank should vary between 7% and 12%. To represent this technical limitation, Eq. 27 is included to the model as a case specific constraint;

$$7\% \leq \frac{\sum_{j=1}^{J}\sum_{b=1}^{B}\sum_{t=1}^{T} TS_b * S_{tb}^{jk}}{\left(\sum_{j=1}^{J}\sum_{b=1}^{B}\sum_{t=1}^{T} S_{tb}^{jk}\right) + W^k} \leq 12\% \quad \forall k \tag{27}$$

Where, TS_b is the total solid content of biomass b and W^k is the amount of water used to adjust the total solid content of the biomass mixture in the anaerobic digestion tank.

The electrical and thermal efficiency of the cogeneration units are taken as 33% and 43% (DECC, 2008). The conversion rate of wood to wood pellet is taken as 0.84 (Uslu et al.,2008). We assume in this case study that biofuel (biomethane) is only produced in AD whereas G plants are operated to produce only electrical and thermal energy. The generated electrical energy, thermal energy and biomethane are assumed to be fed into the national electricity grid, on-site heating system and natural gas pipeline network. Three capacity levels are considered for the pre-treatment facilities, biomass to biofuel conversion plants and CHP units. These capacity levels reported in Table 4.

Table 4. Capacity levels of the plants

Data on GHG emissions associated with wood pellet production in pre-treatment facilities and bioenergy production in plants are depicted in Table 5.

Table 5. Data on GHG emissions

Economics:

Energy prices and incentives: The European Union (EU) has adopted targets for the expanded use of renewable energies as one mean to achieve improved energy security, reduced GHG emissions, and improved competitiveness of the European economies. To promote the investments aimed at reaching these targets, two major different political support mechanisms are applied in EU 28 Member States at present, namely the feed-in tariff and the tradable green certificate (TGC) systems (Fouquet and Johansson, 2008). In conjunction with the EU targets, the UK Government has introduced a range of mechanisms to foster the development and deployment of low carbon energy technologies and markets. In the UK electricity market, since 2002, generators have been obliged to produce part of their electricity with renewable energy resources in accordance with the Renewable Obligation Order. The target for the proportion of renewables in the total energy production is 15% by 2020 (Clifford Chance, 2010). Since 2009, technology banding has been added, meaning that different technologies are rewarded with a different number of certificates (Gürkan and Langestraat, 2014).

There are mainly three incentive schemes for electricity, heat and fuel production from renewables in UK, namely feed-in tariff (FiT), Renewable Heat Incentive (RHI) and Renewables Obligation Certificate (ROC)[1]. Table 6 provides information on these schemes. For more detailed information on current values of incentives according to different renewable energy technologies, the references given in Table 6 can be utilized.

Table 6. Renewable energy support and incentive schemes in UK (Ang et al., 2016)

Considering the above mentioned incentives and the base prices, the ultimate prices for electricity, heat and biomethane are calculated for both AD and G. The data related to incentives are gathered from the sources depicted in Table and the base prices are derived from Digest of UK Energy Statistics (DUKES). Table 7 depicts the electricity, heat and biomethane prices calculated based on base prices and incentives.

Table 7. Current energy prices in UK

It is assumed that waste biomass is supplied at no charge by the local farms and companies. A gate fee is not considered in this study. The length of the time period used in our computational experiments is one month.

DECC (2012) is utilized to obtain the data on plant investment and operational costs. The unit investment costs are taken into account that they are lower in the plants with larger capacity because of economies of scale. The operational costs consist of fixed and variable costs, which are calculated based on the installed capacity and the amount biomass processed in the plants and facilities, respectively. The operational costs are computed based on the assumption that the plants operate in a three working shifts mode, which includes a total of 6188 operating hours. Working hours are calculated by setting 52 weeks per year, 5 days per week and 8 hours per day for one shift. One hour is needed from the entire week for the three shift working mode for the starting up and shutting down of a plant (Marufuzzaman et al., 2015). The unit investment and operational costs according to capacity levels are reported in Table 8. Unit costs are computed considering monthly biomass capacity of the

1. 2010 to 2015 government policy: low carbon technologies, DECC 2015, https://www.gov.uk/government/publications/2010-to-2015-government-policy-low-carbon-technologies/2010-to-2015-government-policy-low-carbon-technologies).

facilities and plants, and installed power of the CHP.

Table 8. Unit investment costs per installed capacity depending on capacity levels

Transportation: We consider that biomass feedstock is transported from source sites to facilities and from facilities to plants, and that biofertilizer is transported between plants and energy crop fields. Given the regional focus of our case study, a road network is assumed for transport using single trailer trucks with a capacity of 36 tons with average travelling speed of 60 km/hr. Currently, road transportation is the most common method for biomass delivery especially for distances <110 km (Searcy et al., 2007). Road transportation is favourable when flexibility is required and multiple forest and farm sited have to be accessed (Searcy et al., 2007).

Data on unit costs of transporting biomass and biofertilizer and on the GHG emissions associated with transportation are derived from the literature. The data related to cost and GHG emissions is updated for the local conditions regarding the data gathered from local logistics firms. Table 9 lists the unit fixed costs and variable costs of transportation, as well as the GHG emissions for transporting cattle manure, poultry manure, wood pellet, maize and biofertilizer by road transport. The data is assumed to be the same for all NUTS 3 level regions. GHG emissions from truck transportation is obtained as 0.692514 kg CO_2 eq/km from DEFRA Carbon Conversion Factors Dataset (2015d).

Table 9. Unit costs and GHG emissions for transportation

4.2. Results and Analyses

In this section, results of the case study are presented and analyzed. IBM ILOG CPLEX Optimization Studio, Version 12.2 is used to code and solve the proposed model on a desktop with Intel Core i5 3.50 GHz processor and 32 GB RAM. The model is composed of 493 constraints and 2965 variables (of which 105 are integer variables). The steps followed in solving the problem in the following sub-sections.

4.2.1. Efficient extreme solutions

Calculation of efficient extreme solutions is explained in “Section 3.3. Solution Methodology”. The sub problems and objective function values corresponding to 27 situations (as explained in Section 3.3 Solution Methodology) are reported in Appendix B. In the table, the values in bold depicts upper and lower bounds for total supply chain profit (€1,104,864/month and €-1,239,861/month), for total investment cost (€211,334,200 and €21,393,450) and for GHG emissions (4,314,202kg CO_2 eq and 2287 kg CO_2 eq). As the lower bound for the profit depicts the state of loss (under 0), it is taken as 0.

4.2.2. Membership functions

Calculation of membership functions is explained in "Section 3.3. Solution Methodology". The following equations represent the formulations of membership functions for each fuzzy objective.

$$\mu_{Profit} = \begin{cases} 1 & ; \quad Profit > 1{,}104{,}864 \\ \dfrac{Profit - 0}{1{,}104{,}864 - 0} & ; \quad 0 < Profit \le 1{,}104{,}864 \\ 0 & ; \quad Profit \le 0 \end{cases} \tag{28}$$

$$\mu_{Total\ Investment\ Cost} = \begin{cases} 1 & ; \quad Total\ Inv.Cost \le 21{,}393{,}450 \\ \dfrac{211{,}334{,}200 - Inv.Cost}{211{,}334{,}200 - 21{,}393{,}450} & ; \quad 21{,}393{,}450 < Total\ Inv.Cost \le 211{,}334{,}200 \\ 0 & ; \quad Total\ Inv.Cost > 211{,}334{,}200 \end{cases} \tag{29}$$

$$\mu_{GHG\ Emissions} = \begin{cases} 1 & ; \quad GHG\ Emissions \le 2287 \\ \dfrac{4{,}314{,}202 - GHG\ Emissions}{4{,}314{,}202 - 2287} & ; \quad 2287 < GHG\ Emissions \le 4{,}314{,}202 \\ 0 & ; \quad GHG\ Emissions > 4{,}314{,}202 \end{cases} \tag{30}$$

4.2.3. Fuzzy solutions

The fuzzy model is transformed into a linear programming problem, represented by the following model, taking into account the membership functions using Modified Version of Werners' "Fuzzy and" operator.

$$\begin{aligned} &Maximize \quad \lambda + [(1-\gamma)(W_{Profit}\lambda_1 + W_{Total\ Investment\ Cost}\lambda_2 + W_{GHG\ Emissions}\lambda_3)] \\ &Subject\ to \quad \mu_{Profit} \ge \lambda + \lambda_1 \\ &\qquad \mu_{Total\ Investment\ Cost} \ge \lambda + \lambda_2 \\ &\qquad \mu_{GHG\ Emissions} \ge \lambda + \lambda_3 \\ &\qquad \lambda, \gamma \in [0,1] \\ &and\ other\ system\ constraints \end{aligned} \tag{31}$$

where, W_{Profit}, $W_{Total\ Investment\ Cost}$ and $W_{GHG\ Emissions}$ are the relative weights; μ_{Profit}, $\mu_{Total\ Investment\ Cost}$ and $\mu_{GHG\ Emissions}$ are the membership functions; λ_1, λ_2 and λ_3 values are the λ values for the profit, total investment cost and GHG emissions objectives. γ coefficient of compensation value. As stated previously, part of the model defined by "other system constraints" represents the constraint set formulated in Eqs. 4-20 in Section 3.1.

Table 10 reports optimal solutions obtained by the proposed fuzzy solution procedure according to different γ (coefficient of compensation) values. At this stage, a sensitivity analysis is conducted to explore the impact of the γ on the results. In real life decision problems, relative importance of the objectives assigned by the decision makers may change according to decision maker or over time. To provide a broader decision spectrum to decision makers, the solutions are obtained by using four different combinations for the relative weights, i.e. four different weight structures (WS), for the objectives; (1) W_{Profit} =0.75, $W_{Total\ Investment\ Cost}$ =0.15 and $W_{GHG\ Emissions}$ =0.1 (WS_1), (2) W_{Profit} =0.5, $W_{Total\ Investment\ Cost}$ =0.3 and $W_{GHG\ Emissions}$ =0.2 (WS_2), (3) W_{Profit} =0.25, $W_{Total\ Investment\ Cost}$ =0.45 and $W_{GHG\ Emissions}$ =0.3 (WS_3), (4) W_{Profit} =0.1, $W_{Total\ Investment\ Cost}$ =0.3 and $W_{GHG\ Emissions}$ =0.6. This analysis enables to investigate the behavior of the developed model according to different weight combinations and validate the model.

WS_1 and WS_2 reflect the case that the most important performance indicator is the profitability of the supply chain for decision maker. In $WS_{1,}$ profit is significantly more important than the other objectives, whereas WS_2 explores the situation that the profit is relatively less important than it is in WS_1 but still more important than the other objectives. WS_3 reflects the decision maker's desire to minimize the total capital investment cost of the supply chain with priority. WS_4 can be adopted to the situations where the primary aim is to minimize the level of GHG emissions associated with energy production, biomass treatment and transportation activities in the supply chain. The first three weight structures ($WS_{1,}$ $WS_{2,}$ WS_3) are preferable especially for private investors/ companies, who put the economic considerations in the first place in design and operation of a supply chain. The last weight structure (WS_4) can be favorable by governmental and non-profit organizations, for which environmental considerations are more important than the economic ones.

The best values of the objectives are indicated in bold characters in Table 10. The average values of the objectives for each weight structure point out that the solution results offered by the developed fuzzy multi objective optimization approach change in parallel with the relative weight values. Each solution alternative offers a different supply chain configuration and distribution pattern resulting in different values of economic and environmental supply chain performance measures. Any of the solution alternatives can be selected as the best one depending on the priorities on different supply chain performance indicators. In this regard, tradeoffs among the alternative solutions need to be considered.

Table 10. Results of the model by "Fuzzy and" operator

If profitability is significantly more important than the total capital investment cost and amount of GHG emissions associated with the production and transportation activities in supply chain, 6th configuration alternative (WS_1, γ=0) can be treated as the best one. Configuring the supply chain according to this solution alternative results in a €476,332 monthly profit together with the highest levels of total investment cost and GHG emissions, which are €108,727,300 and 3,922,002 kg CO_2eq, respectively. However, changing the weight structure to WS_2 with the same γ value, which means that the profit is relatively less important than that of the WS_1, but still the most important performance factor, significant decreases in total investment cost (from €108,727,300 to €23,890,500, by 78%) and GHG emissions (from 3,922,002 to 7712 kg CO_2eq by 99.8%) can be attained with a decrease in profit by 37.8% (from €476,332 to €17,241).

The table reports that there are six solution alternatives (12th, 17th, 18th, 21st, 22nd, 23rd) offering the best configuration in terms of total investment cost with the value of €23,890,500 however they offers the least profitable options with monthly profit values of €17,241, €15,693, €17,467 and €13,776. Although they also suggest one of the best results in terms of GHG emission levels (2644, 2648 and 7712 kg CO_2eq), may not be a favourable options especially for private investors/ companies, who desire to get more profit. However, it would be the preferred option for investors who have a limited budget and cannot afford the initial investment expenses.

If the minimization of the level of GHG emissions associated with energy production, biomass treatment and transportation activities in the supply chain is the most important objective for the decision maker, then one of the 21st, 22nd or 23rd solution alternatives can be selected as the preferred supply chain configuration option. Construction of the supply chain according to these solution alternatives is possible with €23,890,500 capital investment cost and results in 2644 kg CO_2eq GHG emissions monthly. It should be noted that, these options offer the best values in terms of investment cost and GHG emissions however the profitability of the supply chain is not promising. Twenty-first and twenty-second alternatives result in €17,467 monthly profit, whereas 23rd solution alternative suggests the least profit value (€13,776) among all alternatives.

Comparing the results given in Table 10, we suppose that the decision makers consider the solution obtained by the model with the following γ and relative weight structure; W_{Profit}=0.5 , $W_{Total\ Investment\ Cost}$=0.3 and $W_{GHG\ Emissions}$=0.2 and γ=0.4 as the preferred solution. We performed a scenario analysis to investigate the effect of biomethane to energy conversion percentage on the supply chain performance indicators and configuration design. The core driver of this analysis is to explore the benefits from electricity and heat production in AD plants and providing an insight on the cases of utilizing AD plants for 1) both biomethane production and biomethane to energy conversion, and 2) only biomethane production in AD plants without energy conversion. To this aim, we present the results corresponding to the above mentioned weight structure considering two scenarios; 1) 80% of biomethane produced in the AD plants is converted into energy (base case), 2) less than 80% of biomethane produced in the AD plants is converted into energy.

As stated previously, the model focuses on strategic and tactical level decisions. Strategic level decisions have a long-term impact on the supply chain performance focusing on what the supply chain's configuration will be, how resources will be allocated, and what processes will be performed in each stage. Tactical level decisions on the other hand include medium term decisions (e.g. the supply, production and distribution amounts) that are repeated in each term of operation. The strategic and tactical level decisions on supply chain configuration design and production/ distribution planning made by the optimization model for the above mentioned scenarios are presented in the following sections.

4.2.4. Scenario 1 (base case)

In the first scenario, we assume that 80% of the biomethane produced in the AD plants is converted into energy and the remaining 20% is injected to the natural gas grid to meet the biomethane demand. The resulting configuration solution offers to construct 2 anaerobic digestion plants, 4 gasification plants, 2 collection centers and 1 pre-treatment facility in the case study region. In this case, the total monthly supply chain profit is €341,197, total capital investment cost is €90,331,000 and the total amount of GHG emissions associated with transportation, energy production and biomass treatment is 2,773,974 kgCO_2eq. Birmingham, Sandwell, Wolverhampton and Dudley are selected as gasification plant locations whereas anaerobic digestion plants are constructed in Walsall and Coventry. The model selected the same locations as AD plants for collection centers and constructed the pre-treatment facility in Birmingham, where a gasification plant is located at.

Figure 4 presents results on the strategic level decisions such as locations and capacities of bioenergy plants, CHP units, pre-treatment facilities and collection centers. The results reveal that, the model selected the first (minimum) capacity level for the bioenergy plants (6000 t/month for AD plants, 1500 t/month for G plant) and, the second (medium) and third (maximum) capacity levels for CHP units (3500 kWe and 5000 kWe). First (minimum) and third (maximum) capacity levels are selected for PT and CO facilities, respectively (1500 t/month for PT facility, 18,000 t/month for CO facilities).

Figure 4. Locations and capacities of bioenergy plants, CHP units, pre-treatment facilities and collection centers

Tactical level decisions about biofuel, energy and byproduct production in bioenergy plants, amount of biomass stored in collection centers and amount of biomass treated in pre-treatment center are depicted in Table 11. The material flow pattern is illustrated in Figure 5 and Figure 6. Figure 5 represents the biomass flow pattern between biomass source sites and facilities. Figure 6 illustrates the biomass flow pattern between facilities and plants.

Table 11. Tactical level decisions

Figure 5. Biomass flow pattern between biomass source sites and facilities

Figure 6. Biomass flow pattern between facilities and plants

4.2.5. Scenario 2

In the second scenario, it is assumed that less than 80% of biomethane produced in the AD plants is converted into energy. To explore the impact of the biomethane to energy conversion rate in AD plants on the supply chain performance indicators and configuration design, we analyzed the results obtained by using four different conversion percentages, 60%, 40% 20% and 0%. The resulting objective function values and configuration results are reported in Appendix C along with the results of the basic scenario (conversion percentage is 80%). Figures 7 a, b and c illustrate the change of objective function values with conversion percentage.

Figure 7a. Change of profit with biomethane conversion percentage

Figure 7b. Change of total investment cost with biomethane conversion percentage

Figure 7c. Change of GHG emissions with biomethane conversion percentage

It can be observed from Appendix C and Figure 7 that the total supply chain profit decreases with the decrease in the biomethane to energy conversion percentage in AD plants. The profit decreases dramatically with the reduction in the conversion percentage from 80% to 60%, by 13.6%. Decreasing the percentage from 60% to 40% and from 40% to 20% make the profit value reduce by 10.7% and 12.5%. However, profit decreases slightly (by 2.5%) when the conversion percentage changes from 20% to 0. The smallest profit is obtained in case of AD plants are only operated for biomethane production, in other words electricity and heat production is realized in only G plants

The table in Appendix C points out that, the highest total capital investment cost is obtained by converting 80% of biomethane into energy. The investment cost decreases dramatically with the change in the conversion percentage from 80% to 60%, by 11.6%, in parallel with the decrease in the total number of bioenergy plants. As seen from Table, if less than 80% of biomethane produced in AD plants is converted into energy, the number of AD plants decrease in the supply chain. The model constructs six bioenergy plants (2 AD and 4 G) in the first scenario (80% conversion percentage) around the region whereas it builds five plants (1 AD and 4 G) in all the other scenarios (conversion percentage lower than 80%). Further decreases in the conversion percentage make the investment cost decrease more slightly as can be observed from Figure 7(b).

The table also reports that the lowest amount of GHG emissions is obtained by converting 80% of biomethane into energy and it rises when the conversion percentage is changed to 60%. In this case, GHG emissions increase by 13.2%. Further decreases in conversion percentage effect the amount of GHG emissions to minor extent as observed from Figure 7(c).

The results suggest that if the profitability and/or the level of GHG emissions of the supply chain is the most important performance indicator for the decision maker, the first scenario should be considered where the 80% of the produced biomethane is converted into energy and the remaining part is used to meet the biomethane demand. However, it can be concluded that the case of utilizing AD plants for only biomethane production without any energy conversion process (0% conversion percentage) offers the minimum total investment cost with relatively lower profit and higher amount of GHG emissions in comparison with the first scenario. It can also be concluded that changing the conversion percentage from 80% to 60% effects the number, technology and location decisions for both bioenergy plants and facilities remarkably. A change in the conversion rate from 60% to 40% effects only location decisions whereas further changes below 40% have an insignificant effect on the configuration of the supply chain. The only difference is model does not construct CHP plant in Coventry since there is no need to convert biomethane into energy in AD plant at that location.

4.2.6. Economic analyses

<u>Revenue and cost analyses</u>

In this section, an economic sensitivity analysis is presented focusing on the main revenue and cost elements considered by the proposed supply chain design methodology. Table 12 reports the monthly revenues and costs of the entire supply chain network designed by the proposed model according to different biomethane to energy conversion rates. Table 12 also shows the proportion of individual revenue and cost components to total revenue and total cost, respectively. Each row of the table corresponds to a different configuration alternative, which are reported in Table 12.

Table 12. Revenue and cost components and their proportions in total revenue and total cost

The results reveal that both the total revenue and total cost decrease with the decrease in biomethane to energy conversion rate in AD plants and vice versa. The results also denote that, the changes in the proportions of the revenue and cost components to the total revenue and total cost are more significant in case of the conversion percentage is changed from 80% to 60% (from the first scenario to the second) than the changes in the proportions in the remaining conversion percentage change cases (among the conversion percentage values in scenario 2).

Revenue from electricity sales receives the biggest share of total income for all conversion percentages. It is followed by revenue from heat sales, fertilizer sales and biomethane sales, respectively. The percentage of electricity sales in total revenue is almost the same for all conversion percentages (62-63%), whereas the proportion of heat sales in the total revenue increases slightly in parallel with decrease in biomethane to energy conversion percentage. Revenue from biomethane sales is constant for all conversion levels in the second scenario (the conversion percentage values lower than or equal to 60%). As mentioned in the previous section, in the optimized supply chain configuration there are two AD plants for the first scenario (80% conversion percentage), whereas the model constructs one AD plant in the region for all conversion levels in the second scenario. Although the percentage of biomethane that is not converted into energy increases, as a result of the decrease in the number of AD plants, total biomethane production and sales decrease in the second scenario. In this case, AD plant produce biomethane to only meet the demand, which means there is no excess biomethane production. In addition, for higher values of conversion percentage, revenue from fertilizer sales are much higher than revenue from biomethane sales, however the difference is made up for lower conversion rates.

As a total cost component, share of operational cost of bioenergy plants and facilities in total monthly cost is significantly higher compared to the other cost components. Transportation cost is the second biggest cost component contributing to the total cost and followed by biomass purchasing cost and auxiliary material (water) cost. According to the results, for conversion percentages lower than or equal to 40%, biomass purchasing cost and auxiliary material cost is equal 0. In other words, in these configuration alternatives there is no need to purchase energy crop to convert into biomethane in AD plants, hence there is no cost of biomass since in our case study it is assumed that only energy crop is purchased, other (waste) types of biomass are supplied free of charge. The results also reveal that, in parallel with not using energy crop which has a relatively higher level of solid content than waste type biomass, for biomethane to energy conversion percentages lower than or equal to 40% there is no need to add water in the digester to adjust the total solid content. Appendix D illustrates the components of the total revenue and total cost according to different biomethane to energy conversion percentages.

5. Conclusions

This study focused on developing an optimization methodology to enhance the design and planning of multi waste biomass based supply chains to produce multiple types of bio-products via multiple technology types in the same supply chain integrating mathematical modelling and fuzzy multi objective decision making. The developed model constructs the supply chain identifying the optimum configuration and selecting the most appropriate biomass pre-processing and energy production technologies considering economic and environmental objectives. To explore the viability of the proposed model, a comprehensive case study was performed in the West Midlands region, UK.

The research investigated the impact of the percentage of biofuel to energy conversion by AD process on the profitability, total investment cost and GHG emissions. Also, a thorough revenue and cost analysis was performed to reveal the major components that impact the profitability. The major contribution of this study lies in the developed methodology, which can be generalized covering multiple types of waste biomass, biomass to energy conversion technologies, biomass pre-processing facilities and bio-products. Also the developed methodology optimizes the supply chain considering both sustainability and uncertainty aspects in the same optimization framework in the design phase. To this aim, the methodology simultaneously minimizes the total capital investment cost, maximizes the profitability of the supply chain and minimizes the harmful environmental impacts in terms of GHG emissions in an uncertain decision environment.

In our case study, a regional level design and planning problem is handled to guide overall targets on bio-product production scale for emerging waste based supply chains considering product demands and biomass supply limitations in the given region. However, the model can be readily extended to include additional, case-specific parameters and constraints required by the problem. Future research may apply the proposed methodology to different cases with additional, case-specific constraints and parameters. Furthermore, this research can be further extended to include a multi criteria decision making methodology so as to determine the relative weights of the objectives.

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Appendix A. Summary of the literature review

Reference	**Model type**	**Description of the study**	**Limitations**
Zhang and Wright (2014)	MINLP	Determines the optimal fast pyrolysis biorefinery supply chain structure with optimal plant sizes, locations, biomass supply, facility selection and product distributions for an integrated fast pyrolysis biorefinery.	Only cost consideration, Focuses only on biofuel production by single technology, No uncertainty consideration by the model,
Marvin et al. (2012)	MILP	Determines facility location, capacity and technology selection for biomass to biofuel supply chains as a network of biomass producers, conversion facilities, and markets.	Only cost consideration, Focuses only on biofuel production, No uncertainty consideration by the model,
Walther et al. (2012)	MILP	Proposes a multi-period MIP-model for integrated location, capacity and technology planning for the design of production networks for second generation synthetic bio-diesel.	Only cost consideration, No uncertainty consideration by the model.
Lee et al. (2014)	NLP	Synthesis of integrated pulp and paper biorefineries with maximum resource conservation considering the wastewater stream generated from system as a potential biomass.	Only profit consideration, Focuses only on biofuel production by single technology, No uncertainty consideration by the model,
Lin et al. (2014)	MILP	Developes a model to optimize biofuel supply chains includes a farm management module, a logistics planning module, a facility allocation module and an ethanol distribution module.	Only cost consideration, Focuses only on bioethanol production by single technology, No uncertainty consideration by the model,
Xie et al. (2014)	MILP	Plans a bioethanol supply chain considering seasonal yields of feedstock and demands. Locations and capacities of transshipment hubs, refineries and terminals are determined by the model along with seasonal feedstock/biofuel storage and shipment amounts.	Only cost consideration, Focuses only on cellulosic biofuel production, No uncertainty consideration by the model.
Roni et al. (2014)	MILP	Evaluates the feasibility of using biomass for co-fire for coal based power generation and developing a hub and spoke supply chain network to optimize the biomass delivery costs.	Only cost consideration, Focuses only on biomass co-firing in coal-fired power plants (single technology), No uncertainty consideration by the model.
De Meyer et al. (2015)	MILP	Develops a mathematical model, namely OPTIMASS to optimise strategic and tactical decisions in biomass-based supply chains. OPTIMASS evaluates changes in biomass characteristics due to handling operations. They performed scenario analysis to illustrate the impacts of different conditions on an existing supply chain.	No uncertainty consideration by the model.
Marufuzzaman et al. (2016)	MILP	Developed an optimization model to aid design and management of a logistics network for syngas production. The model identifies the	Focuses only on biomass to syngas supply chains with one type of product, biomass and technology

		optimal size and location of chipping terminals and biogasification facilities along with syngas production and transportation decisions.	
Bai et al. (2016)	Game theory, MIP	Designs a biofuel supply chain using a Stackelberg–Nash game model with a direct land-use constraint to capture farmland, food, and fuel market equilibrium. The effect of government regulations on farmland use is also considered to balance food and energy production in a competitive biofuel supply chain design framework.	Only profit consideration No uncertainty consideration by the model.
Woo et al. (2016)	MILP	Presented an optimization model for design and operation of a renewable hydrogen system considering various types of biomass. The model aids capital investment and energy import planning decisions.	Focuses only on biomass to hydrogen supply chains with one type of product and technology Only investment and operating cost consideration
Andersen et al. (2012)	MILP	Design and plan biodiesel supply chain representing all components of the supply chain such as crop fields, storages, production plants and distribution centers.	Only net present value consideration, Focuses only on biodiesel production, No uncertainty consideration by the model.
Zhang and Hu (2013)	MILP	Determines facility number, location, capacity and biofuel production decisions at operational level such as biomass collection, fuel production, fuel distribution and biomass/biofuel inventory control and allocation for a biofuel supply chain design.	Only cost consideration, Focuses only on cellulosic biomass to ethanol supply chains (single technology), No uncertainty consideration by the model.
Chen and Fan (2012)	MISP	Supports strategic planning of bioenergy supply chains and optimal feedstock allocation in considering potential future supply and demand uncertainties	Only cost consideration, Focuses only on cellulosic bioethanol supply chains (single technology).
Delivand, M. K., et al. (2015)	LP and MCA	Finds the optimal facility locations and scales for the bioenergy production from straw alone or integrated straw and pruning. The study consists of land availability and suitability analysis that an AHP-GIS approach is used to detect a number of appropriate locations, location allocation analysis that optimal plant locations were found for each scenario by minimizing the total transportation distance and logistics costs analysis and the corresponding life-cycle GHG emissions were estimated for each selected biomass plant.	Focuses only on biomass to electricity conversion by single technology, No uncertainty consideration.
Aviso et al. (2011)	FLP	Extends Tan, R. R., et al. (2009) to the case of multi-region systems that takes into account trade effects.	Only environmental (water footprint) consideration, No location decision
Lam et al. (2013)	MILP	Extends Čuček, L., et al. (2010) by applying P-graph method for design and modelling of open-structure biomass production supply	No uncertainty consideration

		networks. The model deals with the optimum selection of technologies, plants location, and the annual amount of biomass product considering the objective functions related to environmental impact, cost functions.	
Giarola, Zamboni, & Bezzo (2011)	MILP	Optimizes the environmental and financial performances of corn grain and stover based bioethanol supply chains simultaneously. Biomass type selection and supplier allocation, production technology, site selection, capacity assignment and production planning for bioethanol facilities, logistic distribution and transportation mode selection issues are taken into account simultaneously.	Focuses only on bioethanol supply chains, No uncertainty consideration.
Sharifzadeh et al. (2015)	MILP	Develops a model to determine the optimal supply chain design and operation under uncertainty. They studied the performance and commercial benefits of fast pyrolysis technology. They investigated both deterministic and uncertain scenarios.	Focuses only on biomass pyrolysis supply chains with one type of biomass and product Only cost consideration
Giarola et al. (2012)	MILP	Extends Giarola, Zamboni, & Bezzo (2011) to design bioethanol supply chains optimising the environmental and financial performances simultaneously by considering a wide set of alternative production technologies and specific geographical features. Production technologies are assessed according to their economic and environmental performances.	Focuses only on bioethanol supply chains, No uncertainty consideration .
Giarola, Shah and Bezzo (2012)	MILP	Extends Giarola, Zamboni, & Bezzo (2011) to address the long-term strategic design and planning of feasible and sustainable multi-echelon bioethanol supply chains by a aiming at the maximisation of the financial performance and complying with environmental sustainability criteria incorporating a carbon trading scheme.	Focuses only on bioethanol supply chains, No uncertainty consideration.
Bernardi et al. (2013)	MILP	Optimizes three conflicting objectives (economic, impact on global warming, and impact on water resources) based on the framework developed in Giarola et al. (2011), showing how the supply chain design may be affected by the prioritization of the different objectives and extending the model by adding different transportation options.	Focuses only on bioethanol supply chains, No uncertainty consideration
You and Wang (2011)	MILP	Addresses the optimal design and planning of biomass-to-liquids supply chains under economic and environmental criteria	Focuses only on biomass to liquids supply chains, No uncertainty consideration.

		represented by total annualized cost and life cycle greenhouse gas emissions. They proposed a model that takes into account diverse conversion pathways and technologies, feedstock seasonality, geographical diversity, biomass degradation, infrastructure compatibility, demand distribution, and government incentives.	
Santibanez-Aguilar et al. (2011)	MILP	Develops a model that simultaneously considers the profit maximization and the minimization of the environmental burdens for synthesis and planning of biorefineries, by determining optimal feedstock, processing technology and product combinations. The model is applied for planning the production of a biorefinery in Mexico considering 21 bioresources, 3 products and 10 different processing routes.	Focuses only on biofuel supply chains, No location and capacity decision, No uncertainty consideration
Li and Hu (2014)	MISP	Proposed a two stage stochastic supply chain design model for advanced biofuel production focusing on bio-oil gasification under uncertainty. They provided insights on the capital investment and logistics decisions.	Focuses only on advanced biofuel production supply chains with one type of biomass and product Only profit consideration

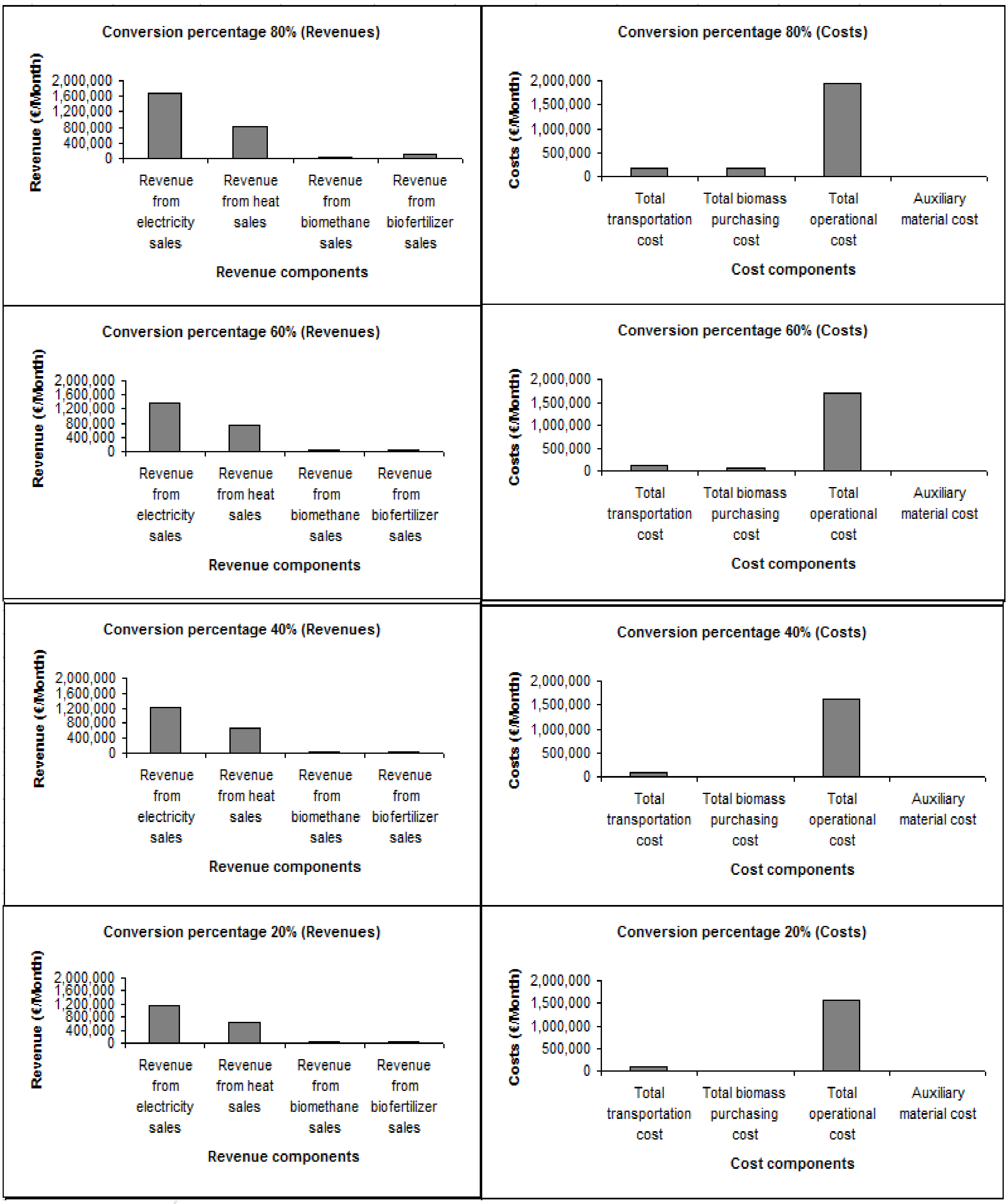
Appendix B. The sub problems and corresponding objective function values

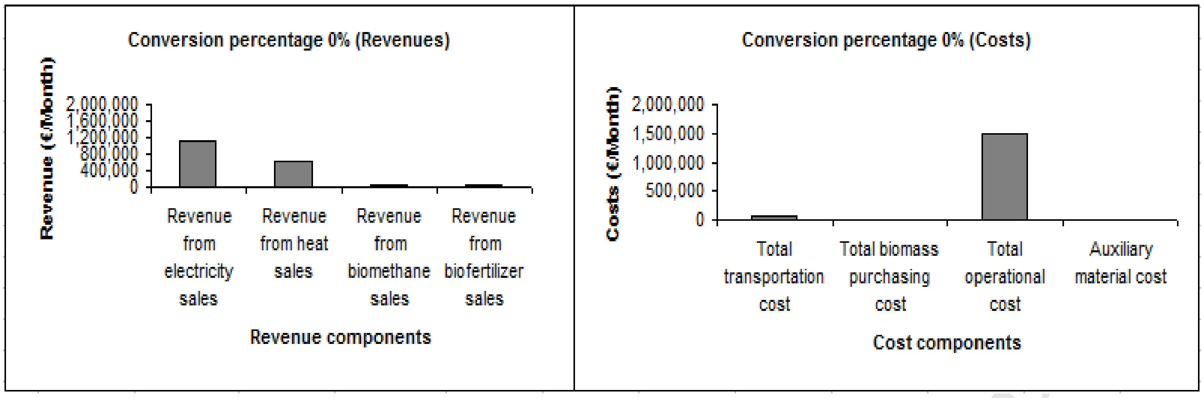
	Best scenario for monthly profit	Profit (€/Month)	Investment Cost (€)	GHG Emissions (kg CO_2 eq/Month)
SP 1	Lower bound of variable cost parameters, upper bound of revenue parameters			
	Max. Profit	**1,104,864**	109,080,800	3,922,566
	Min. Total Investment Cost	77,338	23,770,500	9276
	Min. GHG Emissions	-651,204	192,122,000	2542
	Expected scenario for monthly profit			
SP 2	Base values of variable cost and revenue parameters			
	Max. Profit	476,332	108,727,300	3,922,002
	Min. Total Investment Cost	-135,999	23,770,500	9276
	Min. GHG Emissions	-945,532	192,122,000	2542
	Worst scenario for monthly profit			
SP 3	Upper bound of variable cost parameters, Lower bound of revenue parameters			
	Max. Profit	-123,020	107,480,250	368,6575
	Min. Total Investment Cost	-349,336	23,770,500	9276
	Min. GHG Emissions	**-1,239,861**	192,122,000	2542
	Best scenario for total investment cost			
SP 4	Lower bound of investment cost parameters			
	Max. Profit	476,332	97,854,570	3,922,002
	Min. Total Investment Cost	-149,977	**21,393,450**	2542
	Min. GHG Emissions	-945,532	172,909,800	2542
	Expected scenario for total investment cost			
SP 5	Base values of investment cost parameters			
	Max. Profit	476,332	108727300	3,922,002
	Min. Total Investment Cost	-135,999	23,770,500	9276
	Min. GHG Emissions	-945,532	192,122,000	2542
	Worst scenario for total investment cost			
SP 6	Upper bound of investment cost parameters			
	Max. Profit	476,332	119,600,030	3,922,002
	Min. Total Investment Cost	-94,253	26,147,550	12993
	Min. GHG Emissions	-945,532	**211,334,200**	2542
	Best scenario for GHG emissions			
SP 7	Lower bound of emission parameters			
	Max. Profit	476,332	108,727,300	3,529,801
	Min. Total Investment Cost	-135,999	23,770,500	8348
	Min. GHG Emissions	-945,532	192,122,000	**2287**
	Expected scenario for GHG emissions			
SP 8	Base values of emission parameters			
	Max. Profit	476,332	108,727,300	3,922,002
	Min. Total Investment Cost	-135,999	23,770,500	9276
	Min. GHG Emissions	-945,532	192,122,000	2542
	Worst scenario for GHG emissions			
SP 9	Upper bound of emission parameters			
	Max. Profit	476,332	108,727,300	**4,314,202**
	Min. Total Investment Cost	-135,999	23,770,500	10,203
	Min. GHG Emissions	-945,532	192,122,000	2796

Appendix C. Results of the scenario analyses

Conversion percentage	Profit (€/Month)	Investment Cost (€)	GHG Emissions (kg CO_2 eq/Month)	Locations, Technologies and Capacities of Bioenergy Plants			Locations, Types and Capacities of Facilities		
				Location	Technology	Capacity	Location	Technology	Capacity
80%	341,197	90,331,000	2,773,974	Birmingham	G, CHP	1, 3	Birmingham	PT	3
				Coventry	AD, CHP	1, 2	Coventry	CO	1
				Dudley	G, CHP	1, 3	Walsall	CO	1
				Sandwell	G, CHP	1, 3			
				Walsall	AD, CHP	1, 3			
				Wolverhampton	G, CHP	1, 2			
				Location	Technology	Capacity	Location	Technology	Capacity
60%	294,620	79,796,550	3,140,180	Birmingham	G, CHP	1, 3	Birmingham	PT	3
				Solihull	AD, CHP	1, 2	Solihull	CO	1
				Dudley	G, CHP	1, 3	Walsall	PT	1
				Sandwell	G, CHP	1, 3			
				Walsall	G, CHP	1, 3			
				Location	Technology	Capacity	Location	Technology	Capacity
40%	263,041	79,304,500	3,135,579	Birmingham	G, CHP	1, 3	Birmingham	PT	3
				Solihull	G, CHP	1, 3	Solihull	PT	1
				Coventry	AD, CHP	1, 1	Coventry	CO	1
				Sandwell	G, CHP	1, 3			
				Walsall	G, CHP	1, 3			
				Location	Technology	Capacity	Location	Technology	Capacity
20%	230,116	79,304,050	3,135,314	Birmingham	G, CHP	1, 3	Birmingham	PT	3
				Solihull	G, CHP	1, 3	Solihull	PT	1
				Coventry	AD, CHP	1, 1	Coventry	CO	1
				Sandwell	G, CHP	1, 3			
				Walsall	G, CHP	1, 3			
				Location	Technology	Capacity	Location	Technology	Capacity
0%	224,346	78,330,050	3,135,155	Birmingham	G, CHP	1, 3	Birmingham	PT	3
				Solihull	G, CHP	1, 3	Solihull	PT	1
				Coventry	AD	1	Coventry	CO	1
				Sandwell	G, CHP	1, 3			
				Walsall	G, CHP	1, 3			

Appendix D. Revenue and cost components according to biomethane to energy conversion percentages





Conversion percentage 0% (Revenues)
Revenue (€/Month)
2,000,000
1,600,000
1,200,000
800,000
400,000
0
Revenue from electricity sales
Revenue from heat sales
Revenue from biomethane sales
Revenue from biofertilizer sales
Revenue components
Conversion percentage 0% (Costs)
Costs (€/Month)
2,000,000
1,500,000
1,000,000
500,000
0
Total transportation cost
Total biomass purchasing cost
Total operational cost
Auxiliary material cost
Cost components

Table 1. Notations used in the model

Indices	
i	*Biomass source sites*
j	*Candidate locations for facilities*
k	*Candidate locations for energy plants*
l	*Demand nodes*
b	*Biomass types*
u	*Product types*
f	*Byproduct types*
n	*Energy type*
p	*Biomass capacity levels for energy plants*
e	*Biomass capacity levels for facilities*
q	*Electrical energy production capacity levels of CHP units*
t	*Energy conversion technology*
c	*Facility type*
Decision Variables	
1. Binary variables	
A_{pt}^{k}	*1 if an energy plant of capacity p and technology t is located at k, 0 otherwise*
B_{ec}^{j}	*1 if a facility of capacity e and type c is located at j, 0 otherwise*
CHP_{q}^{k}	*1 if a CHP of capacity q is located in an energy plant at k, 0 otherwise*
2.Nonnegative variables	
S_{cb}^{ij}, S_{tb}^{jk}	*Amount of biomass b shipped from; biomass source site i to facility j with type c, facility j to energy plant k with technology t (ton)*
SP_{tu}^{kl}	*Amount of product u produced in energy plant k with technology t to meet demand of node l* (m^3)
SBP_{tf}^{kl}	*Amount of byproduct f distributed from energy plant k with technology t to demand node l (ton)*
SE_{tn}^{kl}	*Amount of energy n produced in plant k with technology t to meet demand of node l (kWh)*
PR_{tu}^{k}	*Amount of product u produced at energy plant k with technology t* (m^3)
BP_{tf}^{k}	*Amount of byproduct f produced at energy plant k with technology t (ton)*
E_{tn}^{k}	*Amount of energy n produced at plant k (kWh)*
W^{k}	*Amount of auxiliary material consumed at energy plant k (ton)*
Parameters	
1.Biomass supply and product demand	
$D_{u}^{l}, D_{f}^{l}, D_{n}^{l}$	*Amount of demand; of product u, byproduct f and energy n at demand node l* (m^3)
BS_{b}^{i}	*Amount of available biomass b at biomass source site i (ton)*
2. Capacities	
C_{pt}, C_{ec}	*Biomass capacity of; energy plant of capacity level p with technology t, facility of capacity level e with type c*
CE_{qn}	*Installed capacity of CHP of capacity level q for energy n (kWe/ kWth)*
3. Costs and prices	
$I_{pt}, I_{ec}, ICHP_{q}$	*Unit investment cost of; energy plant of capacity level p with technology t, facility of capacity level e with type c (€/ton), CHP of capacity level q (€/kWh)*
$VO_{pt}, VO_{ec}, VOCHP_{q}$	*Unit variable operational cost of; energy plant of capacity level p with technology t, facility of capacity level e with type c (€/ton), CHP of capacity level q (€/kWh)*

$FO_{pt}, FO_{ec}, FOCHP_q$	*Unit fixed operational cost of; energy plant of capacity level p with technology t, facility of capacity level e with type c (€/ton-month), CHP of capacity level q (€/kW-month)*
P_b, PW	*Unit cost of biomass b, auxiliary material (€/ton)*
P_{ut}, P_{ft}, P_{nt}	*Unit price of; product u (€/m³), byproduct f (€/ton), energy n produced by technology t (€/kWh)*
$TV_{b/f}$	*Unit fixed transportation cost of shipping biomass b, byproduct f (€/ton)*
$TF_{b/f}$	*Unit variable transportation cost of shipping biomass b, byproduct f (€/ton-km)*
4. Distances	
d^{ij}, d^{jk}, d^{kl}	*Distances from; biomass source site i to facility j, facility j to plant k, plant k to demand node l (km)*
5. Conversion rates	
r_{but}, r_{bft}	*Conversion rate of biomass b; to product u by plant technology t (m³/ton), to byproduct f by plant technology t (%)*
d_{bc}	*Conversion rate of raw biomass b into treated biomass in facility with type c (%)*
e_{un}	*Conversion rate of product u to energy n (kWh/m³)*
cv_n	*Conversion efficiency of cogeneration unit for energy n (%)*
y^k_{tun}	*Percentage of product u to be converted to energy n in plant k with technology t (%)*
6. Carbon Emissions	
g_t	*GHG emissions associated with energy production by plant with technology t* (kg CO_2 eq/kWh)
g_c	*GHG emissions associated with treatment by facility with technology c* (kg CO_2 eq/ton)
$gt_{b/f}$	*GHG emissions associated with biomass b, byproduct f transportation* (kg CO_2 eq/ ton-km)
g	*GHG emissions associated with transportation mode* (kg CO_2 eq/ km)
7. Other parameters	
DF	*Discounting factor*
CT	*Capacity of transportation vehicle (ton)*

Table 2. The payoff table

	Z_1	Z_2	…	Z_M
X^1	Z_{11}	Z_{12}	...	Z_{1M}
X^2	Z_{21}	Z_{22}	...	Z_{2M}
$\vdots$	...	...	...	...
X^S	Z_{S1}	Z_{S2}	...	Z_{SM}

Table 3. The numbers of addresses in the area considered in each region

Demand Node	**Number of addresses**
1. Birmingham	960 Residential
2. Solihull	180 Retail
3. Coventry	320 Residential
4. Dudley	1 Industrial user
5. Sandwell	1 Education
6. Walsall	6 Commercial Offices
7. Wolverhampton	39 Retail

Table 4. Capacity levels of the plants

Capacity Level	Total biomass capacity of G plants (t/month) (ukwin.org.uk)	Total biomass capacity of AD plants (t/month) (wrap.org.uk)	Installed capacity of cogeneration unit (kWe) (DECC, 2008)	Total biomass capacity of PT facilities (t/month) (ukwin.org.uk)	Total biomass capacity of CO facilities (t/month)
1 (Minimum Capacity)	1500	6000	2000	1500	6000
2 (Medium Capacity)	3000	12,000	3500	3000	12,000
3 (Maximum Capacity)	4500	18,000	5000	4500	18,000

Table 5. Data on GHG emissions

Source of GHG emissions	GHG emissions (kg CO_2 Eq/ kWh)	Reference
Conversion		
Biogas to energy	3.67×10^{-4} (kg CO_2 Eq/ kWh)	DEFRA Carbon Conversion Factors Dataset (2015)
Syngas to energy	0.18445 (kg CO_2 Eq/ kWh)	DEFRA Carbon Conversion Factors Dataset (2015)
Pre-treatment		
Pelletizing	1.47×10^{-4} (kg CO_2 Eq/ ton)	Cucek et al. (2010)

Table 6. Renewable energy support and incentive schemes in UK (Ang et al., 2016)

Year started	Name of policy	Brief description
2002	Renewables Obligation (RO)	The RO incentivises large-scale renewable electricity generation by requiring electricity suppliers to source a specified proportion of the electricity they provide from renewable sources. In exchange for purchasing renewable electricity, suppliers receive Renewables Obligation Certificates (ROCs). (DECC,2015a) Reference for incentive values http://www.epowerauctions.co.uk/erocrecord.htm
2010	Feed-in Tariffs (FiTs)	FiTs incentivises small-scale low carbon electricity generation by requiring energy suppliers to make payments to households and businesses with certified installations (DECC, 2015b). Reference for incentive values https://www.ofgem.gov.uk/system/files/docs/2016/04/01_april_2016_tariff_table.pdf
2011	Renewable Heat Incentive (RHI)	The RHI provides a tariff to businesses, the public sector and non-profit organisations for the installation of renewable heat technologies. Eligible technologies include solid biomass, ground-source or water-source heat pumps, deep geothermal, solar thermal collectors, biomethane injection and biogas combustion (DECC, 2015c). Reference for incentive values https://www.ofgem.gov.uk/environmental-programmes/non-domestic-renewable-heat-incentive-rhi/tariffs-apply-non-domestic-rhi-great-britain

Table 7. Current energy prices in UK

	Anaerobic Digestion			Gasification		
	Electricity	**Heat**	**Biomethane**	**Electricity**	**Heat**	**Biomethane**
Base Price (€/kWh)	0.057	0.04	0.0316	0.057	0.04	No production
FiT (€/kWh)						
Generation	0.0998	-	-	-	-	
Export	0.0628	-	-	-	-	
RHI (€/kWh)	-	0.026	0.0677	-	0.026	
ROC (€/kWh)	-	-	-	0.0957	-	
Total (€/kWh)	0.2196	0.066	0.0993	0.1527	0.066	

Table 8. Unit investment costs per installed capacity depending on capacity levels

Capacity Level	Unit investment cost of G plants (€/ton) *(DECC, 2012)*	Unit investment cost of AD plants (€/ton) *(DECC, 2012)*	Unit investment cost of CHP (€/kWe) *(DECC, 2012)*	Unit investment cost of PT facilities(€/ton) (Rentizelas et al., 2014)
1	9417	1652	487	842
2	8239	1446	419	739
3	7847	1377	352	709
Capacity Level	**Unit fixed and variable operational costs of G plants (€/ton) (DECC, 2012)**	**Unit fixed and variable operational costs of AD plants (€/ton) (DECC, 2012)**	**Unit fixed (€/kWe) and variable (€/kWh) operational costs of CHP (DECC, 2012)**	
1	55.33 -17.65	10.36 - 6.04	7 - 0.0072	
2	48.4 - 15.5	9.067 - 5.29	6.54 - 0.0064	
3	46.1 - 14.73	8.635 - 5.03	6 - 0.006	

Table 9. Unit costs and GHG emissions for transportation

	Fixed Cost (€/ton)	**Variable Cost (€/ton-km)**	**GHG emissions (kg CO_2 eq/ ton-km)**
Cattle Manure (liquid)	4.68 Parker et al. (2007)	0.043 Parker et al. (2007)	5.3×10^{-8} Cucek et al. (2010)
Broiler Hen Manure (Solid)	4.43 Parker et al. (2007)	0.048 Parker et al. (2007)	5.3×10^{-8} Cucek et al. (2010)
Layer Hen Manure (Liquid)	4.68 Parker et al. (2007)	0.043 Parker et al. (2007)	5.3×10^{-8} Cucek et al. (2010)
Waste Wood (Logging residues)	6.17 Perez-Verdin et al. (2007)	0.17 Perez-Verdin et al. (2007)	5.3×10^{-8} Cucek et al. (2010)
Wood pellet	3.2 Sokhansanj and Fenton (2006)	0.053 Sokhansanj and Fenton (2006)	2.4×10^{-7} Cucek et al. (2010)
Maize (Loose)	5.02 Kumar and Sokhansanj (2007)	0.24 Kumar and Sokhansanj (2007)	1.1×10^{-6} Cucek et al. (2010)
Fertilizer (liquid)	4.68 Parker et al. (2007)	0.043 Parker et al. (2007)	5.3×10^{-8} Cucek et al. (2010)

Table 10. Results of the model by "Fuzzy and" operator

W_{Profit}	$W_{Total\ Investment\ Cost}$	$W_{GHG\ Emissions}$	**Solution No.**	**γ**	**Profit (€/Month)**	**Investment Cost (€)**	**GHG Emissions (kg CO_2 eq/Month)**
	WS$_1$		1	1	344,284	91,888,550	2,970,575
0.75	0.15	0.1	2	0.8	344,368	91,888,550	2,970,245
			3	0.6	344,368	91,888,550	2,970,245
			4	0.4	341,214	91,948,550	2,982,557
			5	0.2	382,263	91,888,550	3,138,064
			6	0	**476,332**	108,727,300	3,922,002
			Average		372,138	94,705,008	3,158,948
	WS$_2$		7	1	344,284	91,888,550	2,970,575
0.5	0.3	0.2	8	0.8	344,284	91,888,550	2,970,575
			9	0.6	341,197	90,331,000	2,773,974
			10	0.4	341,197	90,331,000	2,773,974
			11	0.2	300,421	98,418,000	2,774,743
			12	0	17,241	23,890,500	7712
			Average		281,437	81,124,600	2,378,592
	WS$_3$		13	1	344,284	91,888,550	2,970,575
0.25	0.45	0.3	14	0.8	341,197	90,331,000	2,773,974
			15	0.6	341,197	90,331,000	2,773,974
			16	0.4	65,590	48,539,750	804,322
			17	0.2	17,241	**23,890,500**	7712
			18	0	15,693	23,950,500	2648
			Average		187,534	61,488,550	1,555,534
	WS$_4$		19	1	344,284	91,888,550	2,970,575
0.1	0.3	0.6	20	0.8	341,197	90,331,000	2,773,974
			21	0.6	17,467	23,890,500	**2644**
			22	0.4	17,467	23,890,500	2644
			23	0.2	13,776	23,890,500	2644
			24	0	15,693	23,950,500	2648
			Average		124,981	46,306,925	959,188

Table 11. Tactical level decisions

Plant Location	Electricity production (kWh/Month)	Heat production (kWh/Month)	Biofuel Production (m^3/month)	Byproduct (biofertilizer) production (ton/month)
1. Birmingham - G	1,845,727	2,400,000	1,026,430- Syngas	-
3. Coventry - AD	1,286,635	1,673,012	482,971- Biomethane	5397
4. Dudley - G	1,845,727	2,400,000	1,026,430- Syngas	-
5. Sandwell - G	1,845,727	2,400,000	1,026,430- Syngas	-
6. Walsall - AD	1,845,727	2,400,000	692,840 - Biomethane	4590
7. Wolverhampton - G	988,125	1,284,860	549,508- Syngas	-
Facility Location	**Collection/Pre-treatment Amount (ton/month)**			
1. Birmingham - PT	4500 – Waste wood			
3. Coventry - CO	5949 – Cattle Manure 49.52 – Broiler Manure			
6. Walsall - CO	2252 – Cattle Manure 3417 - Maize			

Table 12. Revenue and cost components and their proportions in total revenue and total cost

Conversion percentage	**Revenue from electricity sales**	**Revenue from heat sales**	**Revenue from biomethane sales**	**Revenue from biofertilizer sales**	**Total Revenue**
80%	1,684,281 - 63.8%	828,819 - 31.4%	23,351 - 9%	99,883 - 3.8%	2,636,334
60%	1,375,353 - 63.1%	730,511 - 33.5%	22,449 - 1%	52,213 - 2.4%	2,180,526
40%	1,237,584 - 62.5%	676,671 - 34.2%	22,449 - 1.13%	42,030 - 2.1%	1,978,734
20%	1,168,700 - 62.4%	649,751 - 34.7%	22,449 - 1.19%	31,432 - 1.6%	1,872,332
0%	1,127,370 - 62.3%	633,600 - 35%	22,449 - 1.25%	25,074 - 1.4%	1,808,493
Conversion percentage	**Total transportation cost**	**Total biomass purchasing cost**	**Total operational cost**	**Auxiliary material cost**	**Total monthly cost**
80%	172,081 - 7.5%	170,861 - 7.4%	1,946,742 - 85%	5452 - 0.2%	2,295,136
60%	117,133 - 6.2%	58,727 - 3.1%	1,708,404 - 90%	1641 - 0.08%	1,885,905
40%	97,636 - 5.7%	0	1,618,058 - 94.3%	0	1,715,694
20%	85,474 - 5.2%	0	1,556,743 - 94.7%	0	1,642,217
0%	78,192 - 4.9%	0	1,505,954 - 95%	0	1,584,146

1. Formulate the linear programming problem (see Section 3.1)
2. Solve the linear programming problem as a single objective problem considering each time only one objective
3. Obtain efficient extreme solutions
4. Find upper and lower bounds;

$$u_m = (Z_m)^{max} = \max_p(Z_{pm}) \quad p = 1,2,\ldots,M$$

$$l_m = (Z_m)^{min} = \min_p(Z_{pm}) \quad p = 1,2,\ldots,M$$

$$(Z_m)^{min} \le Z_m \le (Z_m)^{max}$$

5. Identify the membership function of each fuzzy objective and fuzzy constraint;

If the objective is minimization

Then $$\mu_{Z_m}(x) = \begin{cases} 1 & ; \quad Z_m(x) \le l_m \\ \dfrac{u_m - Z_m(x)}{u_m - l_m} & ; \quad l_m < Z_m(x) \le u_m \\ 0 & ; \quad Z_m(x) > u_m \end{cases}$$

Else $$\mu_{Z_k}(x) = \begin{cases} 1 & ; \quad Z_k(x) > u_k \\ \dfrac{Z_k(x) - l_k}{u_k - l_k} & ; \quad l_k < Z_k(x) \le u_k \\ 0 & ; \quad Z_k(x) < l_k \end{cases}$$

End If

6. Transform the fuzzy model into a linear model using "*fuzzy and*" operator;

$$\begin{aligned} &\text{Maximize} && \lambda + [(1-\gamma)(W_1\lambda_1 + W_2\lambda_2 + \ldots + W_m\lambda_m)] \\ &\text{Subject to} && \mu_1 \ge \lambda + \lambda_1 \\ & && \ldots \\ & && \mu_m \ge \lambda + \lambda_m \\ & && \lambda, \gamma \in [0,1] \end{aligned}$$

and other system constraints

7. Solve the model developed in Step 6
8. Find the optimal solution

Figure 1. Solution methodology

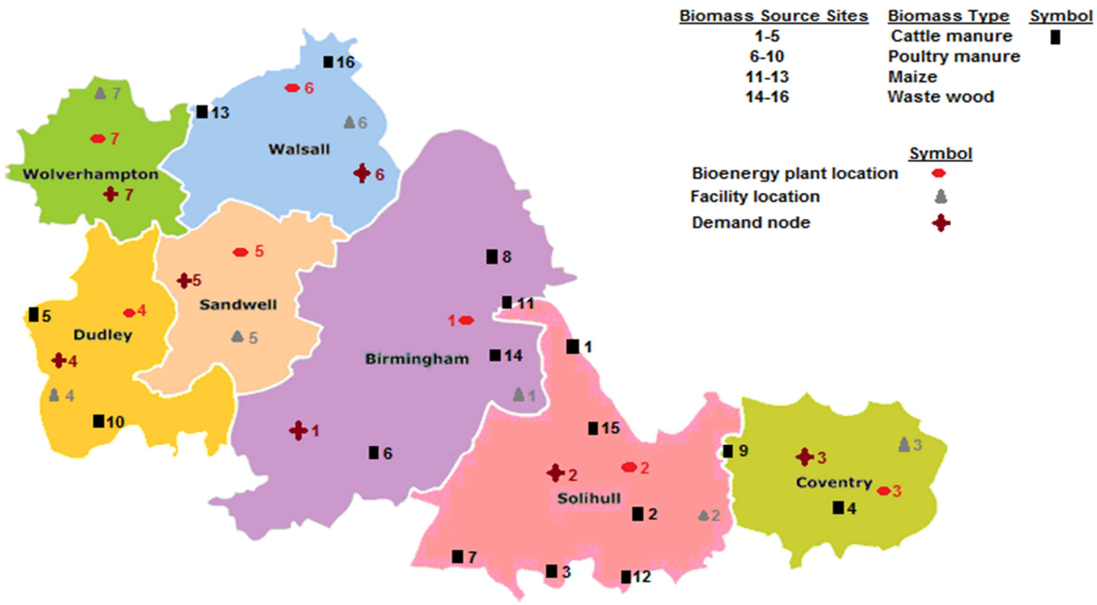


Figure 2. Case study region map

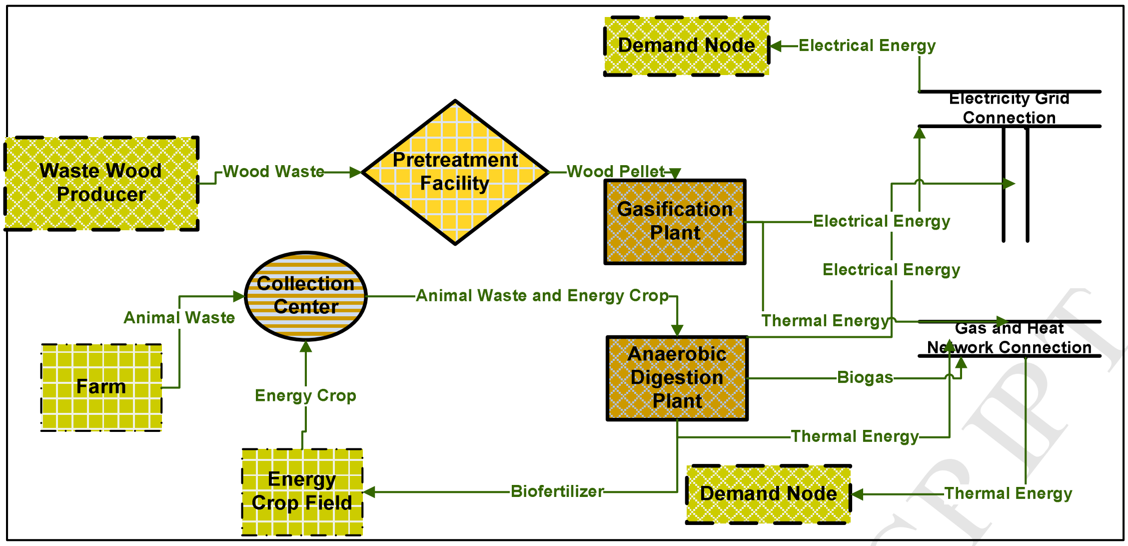


Figure 3. An overview of the supply chain under consideration

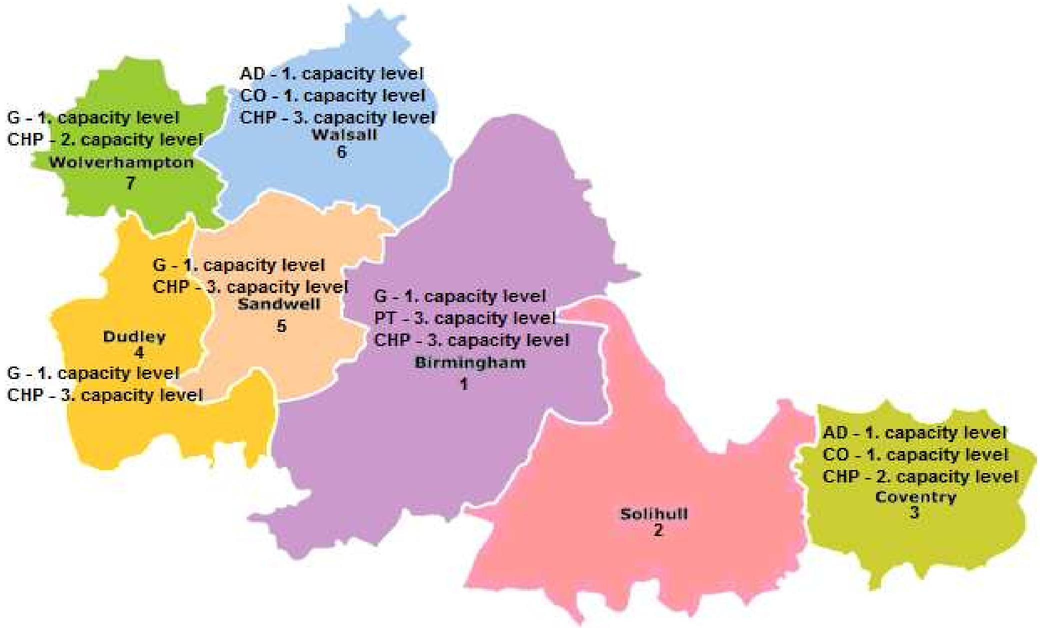


Figure 4. Locations and capacities of bioenergy plants, CHP units, pre-treatment facilities and collection centers

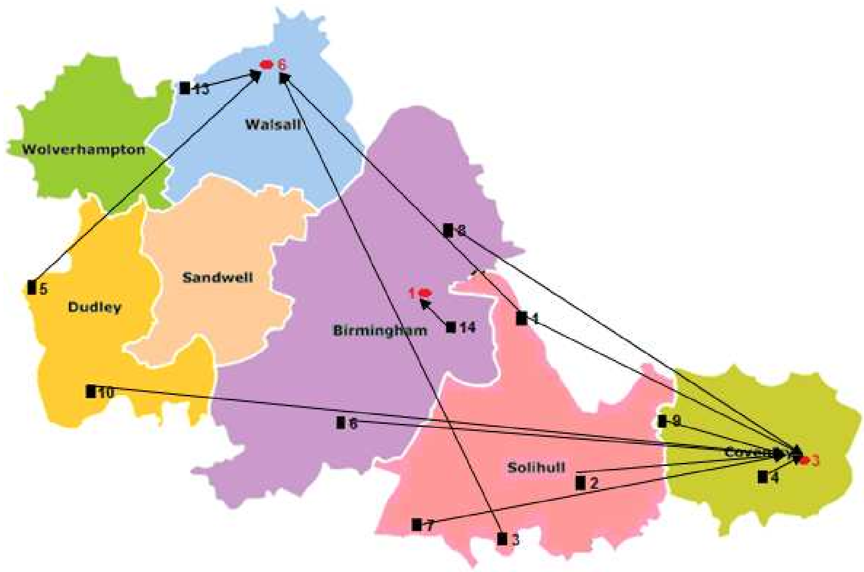


Figure 5. Biomass flow pattern between biomass source sites and facilities

Figure 6. Biomass flow pattern between facilities and plants

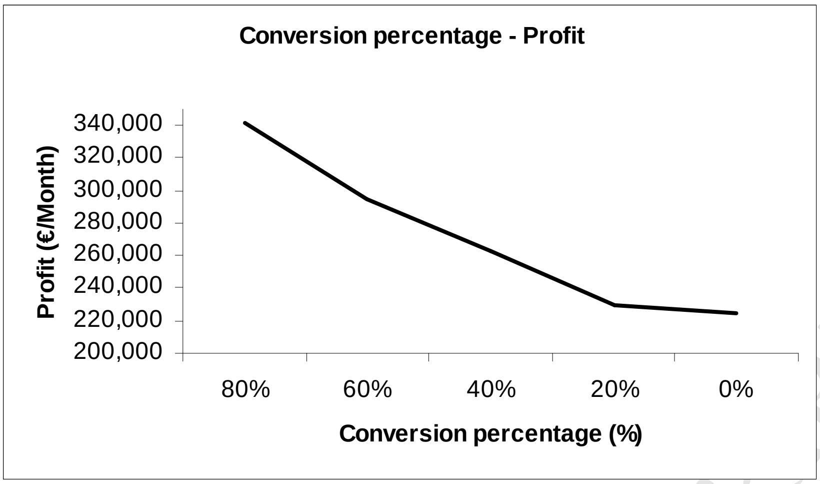


Figure 7a. Change of profit with biomethane conversion percentage

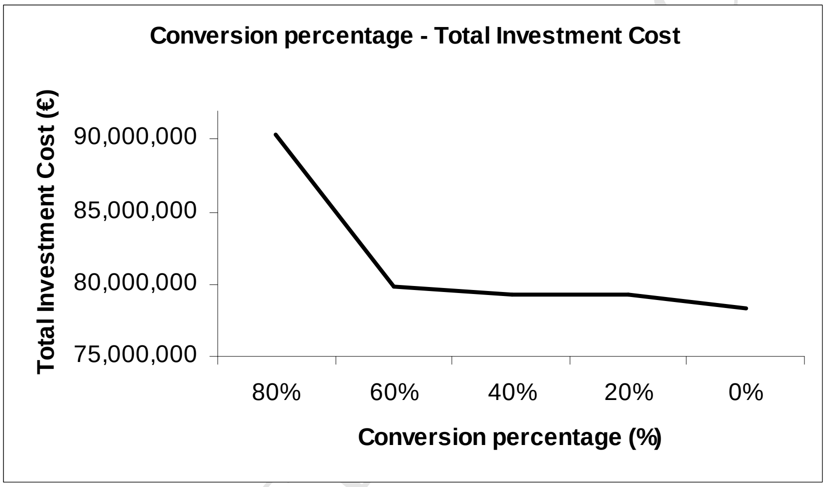


Figure 7b. Change of total investment cost with biomethane conversion percentage

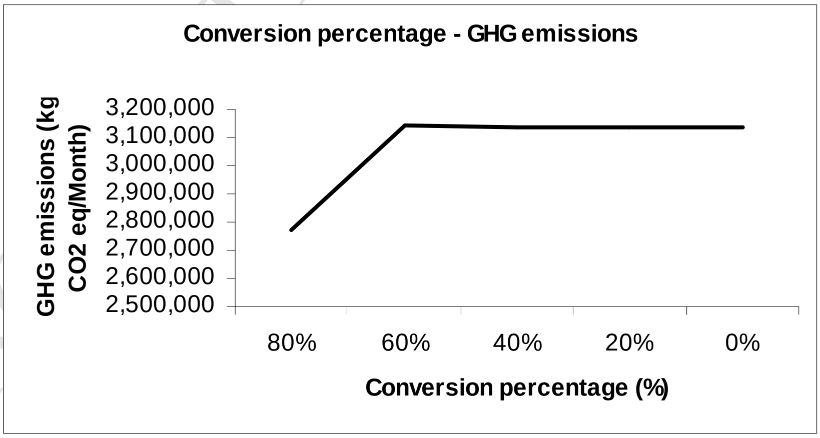


Figure 7c. Change of GHG emissions with biomethane conversion percentage

Highlights:

1. A methodology is developed to design multiple technology bioenergy supply chains.
2. The aim is to configure the supply chain and select the optimum technology.
3. The methodology captures sustainability aspects and uncertain parameters.
4. The methodology integrates mathematical modelling and fuzzy decision making.
5. The methodology is applied to a case study of West Midlands Region in the UK.