Journal of Cleaner Production 172 (2018) 2594–2617

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Integrated optimization of sustainable supply chains and transportation networks for multi technology bio-based production: A decision support system based on fuzzy ε-constraint method

Şebnem Yılmaz Balaman [a, *], Aristides Matopoulos [b], Daniel G. Wright [c], James Scott [c]

[a] Department of Industrial Engineering, Dokuz Eylül University, Tınaztepe Campus, 35160, İzmir, Turkey
[b] Engineering Systems & Management Group, School of Engineering & Applied Science, Aston University, Aston Triangle, Birmingham, B4 7ET, UK
[c] European Bioenergy Research Institute (EBRI), Aston University, Aston Triangle, Birmingham, B4 7ET, UK

A R T I C L E I N F O

Article history:
Received 20 December 2016
Received in revised form
17 November 2017
Accepted 19 November 2017
Available online 21 November 2017

Keywords:
Bi-level decision support system
Supply chain design
Transportation network design
Sustainable energy production
Fuzzy ε-constraint method

A B S T R A C T

Developing and employing effective design methodologies can significantly improve the economic and environmental viability of renewable production processes. This study contributes by presenting a novel bi-level decision support system (DSS) to aid modelling and optimization of multi technology, multi product supply chains and co-modal transportation networks for biomass based (bio-based) production combining two multi-objective mathematical models. Considering the supply chain configuration optimized by the first level of the DSS, in the second level, the transportation network is designed specifying the most appropriate transportation mode and related transportation option under transfer station availability limitations. A hybrid solution methodology that integrates fuzzy set theory and ε-constraint method is proposed. This methodology handles the system specific uncertainties addressing the economic and environmental sustainability aspects by capturing trade-offs between conflicting objectives in the same framework. To explore the viability of the proposed models and solution methodology, a regional supply chain and transportation network is designed using the entire West Midlands (WM) region of the UK as a testing ground. Additionally, scenario and sensitivity analyses are conducted to provide further insights into design and optimization of the biomass based supply chains.

1. Introduction

Bio-products are considered as a part of solution to the world wide increasing resource depletion problem as they are alternative resources to traditional non-renewable sources for material and energy production. Bio-products derived from bio-resources can replace much of the energy, fuels, chemicals, plastics etc. that are currently derived from fossil fuel based sources (Ramaswamy et al., 2007). In many cases for the supply of bio-resources, long-distance transport may be necessary which results in additional logistics costs, energy consumption and ultimately higher GHG emissions compared to small-scale utilization. The International Energy Agency states that almost 25% of the energy related CO_2 emissions worldwide result from transportation activities (IEA, 2009). As transport distance and mode plays a major role in energetic and environmental performance of the supply chain, the associated logistics network must be designed so as to ensure the best compromise between cost and environmental impact (Galvez et al., 2015). To ensure sustainability in a bio-based supply chain, usually multiple conflicting objectives have to be considered by a systematic engineering design approach. In addition, these systems are exposed to a number of system specific uncertainties and technological instabilities. Considering different technologies and processes that have the ability to produce common bio-products in the same supply chain can minimize the impact of these instabilities and provides enhanced fulfilment of consumers' demand for bio-products.

This study focuses on developing proper and effective optimization methodologies to select the most favourable supply chain configuration and design the transportation network to identify cost-efficient bio-based supply chain with a small environmental impact. The methodology integrates all supply chain activities from feedstock supply to product distribution and consumption, and all elements of the chain from biomass source sites to demand nodes.

* Corresponding author.
E-mail address: s.yilmaz@deu.edu.tr (Ş.Y. Balaman).

https://doi.org/10.1016/j.jclepro.2017.11.150
0959-6526/

To this aim, a bi-level DSS is developed to optimize multi biomass based supply chains and transportation networks under co-modality considerations to produce multiple types of bioproducts by different technology options in the same supply chain. The first level identifies the optimum structure of the supply chain and selects the most appropriate production technologies under demand and feedstock availability limitations. In the second stage, based on the output from the first stage related to locations of nodes and the delivery amounts between the nodes, a model is developed to decide how optimally route the material flows from its origin to destination.

Both models integrate objectives related to the economic, environmental and service level performance of the supply chain. To obtain optimized solutions, a hybrid algorithm is proposed combining fuzzy set theory and ε-constraint method in a novel way to capture both sustainability aspects by considering the trade-offs between different objectives and system specific uncertainties within the same framework. This hybrid method reflects the characteristics of the problem and computational experiments show that it is able to provide high quality solutions in a reasonable amount of time. To explore the viability of the proposed DSS, computational experiments are performed on a case study of WM Region in the UK, which is the first attempt to design a comprehensive biomass based supply chain and transportation network in this region. In addition economic, environmental and sensitivity analyses are conducted to provide deeper understanding of the proposed DSS and how changing parameters effect the optimum supply chain design and performance indicators.

The rest of the paper is organized as follows. Section 2 provides a literature review on the studies that develop optimization models for bio-product supply chains and related it to our study. In section 2, the research gaps in the current literature are revealed and the contributions of this study to fulfil these gaps are stated. Section 3 presents the problem description, formulation of the optimization models and the solution approach. In Section 4, the case study setting is described where the proposed DSS is applied to the region of WM, the results, further analyses and discussion of the results are explained. Section 5 discusses the conclusions along with future research directions.

2. Literature review

Table in Supplementary Material 1 presents a literature review on studies that develop optimization models to design bio-based supply chains and/or transportation networks considering economic and environmental sustainability. In the table, the studies are classified according to the type of the model developed, a brief description of the proposed study and limitations of each of the studies.

Review of literature suggest that there are a few studies that feature any multimodal transportation in the design of biomass based supply chains (e.g. Poudel et al., 2016; Marufuzzaman et al., 2014a, b, c) and of these studies none have a comprehensive transportation network model, which selects both the optimum transportation mode/option and the most appropriate transfer stations.

In the literature, studies in the supply chain design field that develop methodologies by considering sustainability and uncertainty aspects can be investigated into two broad categories; studies that consider sustainability aspects and uncertainty by separate methods such as scenario and sensitivity analyses after the design phase (e.g. Aviso et al., 2011) and studies that capture both sustainability aspects and uncertainties by the same framework (e.g. Giarola et al., 2012a, b; Gonela et al., 2015a,b; Marufuzzaman et al., 2014b). However, most of the studies in the latter category utilize Stochastic Programming to represent uncertain system parameters. Stochastic Programming 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. Stochastic Programming models take the advantage of 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 Stochastic Programming is meaningful only when a certain action can be repeated several times. However, due to special and dynamic characteristics of energy problems, in some cases there may not be enough historical/objective data to model uncertain parameters within each scenario as random data. From that point onwards, fuzzy logic comes to the forefront to develop robust approaches for concept representation of energy systems and supply chains 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 addition, very few among these studies handle sustainability issue representing each economic, environmental and social aspect of sustainability by an objective function using a multi-objective modelling framework.

Also, the vast majority of the biomass supply chain design researches focus on biorefinery concept that biofuel (eg. bioethanol, biodiesel) is produced especially for transportation purposes without considering energy conversion or utilization of useful by-products of the system (e.g. Andersen et al., 2012; Zhang and Hu, 2013; Chen and Fan, 2012; Xie et al., 2014). In these systems, final biofuel to energy conversion are much less important and these systems are different in the supply chain structures from the systems that biomass is used for energy purposes, i.e. the key point is that a refinery is not a power station and accordingly the related markets, business operations, and technologies are different. Differently from these studies that handle biomass based supply chains for biofuel production for transportation sector, this study specifically deals with conversion of multiple sources of biomass into biofuels, for the purpose of generating energy in terms of heat and power in bioenergy plants by power engines. Although there are a few studies that focus on biomass to energy conversion (e.g. Cucek et al., 2010), there is still a need to develop a comprehensive optimization methodology to design both supply chain configuration and transportation networks including transfer stations to produce and distribute multiple types of bio-products (e.g. biofuel and bioenergy) and useful by-products (e.g. bio-fertilizer). In addition, most of the models developed so far capture one type of biomass and one type of conversion technology/process. However, real-world bio-based supply chains often have diversified feedstock types and sources, and multiple technologies. A modelling approach that can accommodate this diversification will be more resilient and may support longer term supply, and reduce the effects of seasonal fluctuations and price instabilities as well as technological uncertainties on the supply chain performance. In addition, the representation of typical biomass supply chains capturing different sorts of products, operations and attributes would result in a holistic approach that is capable of addressing different types of problems for different types of biomass-based supply chains and different optimization models (De Meyer et al., 2016).

To address these gaps in the literature, this paper proposes a new mathematical programming based optimization approach to design sustainable supply chains along with logistics networks. To obtain optimized solutions from the optimization models, a hybrid solution algorithm is proposed combining fuzzy set theory and ε-constraint method in a novel way. The major contributions and novelties of this study are;

1. The developed methodology optimizes the supply chain configuration and transportation network considering both sustainability aspects by representing each aspect by a different objective in a multi objective structure and uncertainty in system parameters in the same optimization framework in design phase.
2. Instead of focusing on one type of product/technology, the developed methodology covers multiple types of feedstock, technologies, transportation modes/options and bio-products in one supply chain. Useful by-products of the system are also considered to be utilized in the supply chain to promote circular economy.
3. A novel transportation network design model is developed to select the optimum stations for material transfer among available options, along with the optimum mode and option for biomass and bio-product transportation under co-modality principles.
4. This study presents a hybrid methodology to solve multi-objective mathematical models. The methodology combines fuzzy set theory and ε-constraint method by capturing the problem specific uncertainties and sustainability aspects simultaneously.

3. Problem description and formulation of the models

In this section, we describe the integrated supply chain configuration, technology selection, production-distribution planning and transportation network design problem for bio-based production in a sustainable way. We also present our bi-level DSS and outline the solution approach used to generate the optimum solution for multi-objective optimization models consisting the DSS.

3.1. Problem description

This paper focuses on designing an optimized supply chain and transportation network for biomass based 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 feedstock
2. Facilities for pre-processing of biomass prior to conversion process
3. Facilities for storage of biomass prior to conversion process
4. Biomass conversion plants
5. Energy production units
6. Demand nodes

We developed two MILP models that capture economic, environmental and service level considerations by a multi-objective structure, which are consecutively executed in the same framework to optimize the supply chain configuration and transportation network simultaneously. The first model, the supply chain configuration design model (CDM), aims to design the biomass based supply chain by making decisions corresponding to; (1) configuration of the supply chain network; (2) procurement and allocation of the biomass resources; and (3) inventory, production and distribution planning, while meeting the bio-product demand of a particular area. The model determines the optimum configuration of the supply chain considering the trade-offs between total supply chain profit and GHG emissions associated with production activities. To be more precise, to increase the profitability of the supply chain, we have to increase the production yield which at the same time means increasing the production related GHG emissions. Hence, it is important to capture the trade-offs between these two conflicting objectives. Transportation costs and GHG emissions associated with transportation activities are not included in CDM since they are included and optimized by the second model, which has the aim of optimizing the transportation network. However, considering the fact that the optimum supply chain structure is highly impacted by decisions related to biomass and product distribution pattern between the locations, a third objective function for the minimization of total ton-kilometres (ton-kms) is included in the model besides the maximization of total supply chain profit and minimization of production related GHG emissions. The decisions made by the CDM are; (1) Numbers, locations and capacities of facilities and conversion plants, (2) Types of facilities and technologies for conversion plants, (3) Amount of bio-product produced in each plant, (4) Amounts biomass and bio-product distributed between biomass sites, facilities, plants and demand nodes, (5) Amount of biomass treated/stored in facilities, (6) Amount of auxiliary material consumed in conversion plants.

The outputs of CDM related to locations, capacities and technologies of facilities and plants as well as the transportation amounts between the selected locations are passed to the second model, the transportation network optimization model (TNM). The configuration decisions (represented by decision variables with notations $A^k_{pt}B^j_{ec}$ and CHP^k_q in CDM) determine the optimum locations of plants and facilities, conversion technology/facility types and capacities of plants and facilities. The transportation related decisions are made by the TNM considering the distances and material flow amounts between these specified locations. The total amounts of biomass and biofertilizer that is transported between locations (represented by ST^{ij}, ST^{jk} and ST^{kl} in the TNM model) are obtained by summing $S^{ij}_{cb}, S^{jk}_{tb}SF^{kl}_{tf}$ values that are derived from CDM model. The TNM aims to optimize the biomass and bio-product distribution network and transportation mode considering available single mode and multimodal transportation options. The model includes three objectives to capture the trade-offs between the costs, GHG emissions and service level obtained by each transportation option. The decisions made by the TNM are;

1. Selection of the optimum transportation mode (single mode or multimodal) to transport biomass and bio-product between biomass source sites, facilities, plants and demand nodes,
   i. If single mode is selected; determination of the optimum transportation option among the available options (rail, road, sea … etc.),
   ii. If multimodal is selected; determination the optimum combination of modes among the available options (rail-road, road-rail, road-sea, rail-sea … etc.),
   iii. If multimodal is selected; determination the optimum station for transfer of material from one vehicle to another.
2. Amount of biomass and bio-product transported by each mode between biomass source sites, facilities, plants and demand nodes,

The proposed DSS is illustrated in Fig. 1.

3.2. Formulation of the models

In this section, the mathematical formulations of the two optimization models are proposed. The notations of the mathematical formulations are presented in Appendix A.

3.2.1. Supply chain configuration design model

The model includes three environmental and economic objectives. The objectives are: (1) maximization of total profit; and (2) minimization of GHG emissions (CO_2 eq) related to production in the supply chain and (3) minimization of total transportation distance.

The first objective function, namely maximization of supply chain profit, can be calculated as follows;

Total Profit = Total Revenue- (Discounted Investment Costs + Variable Operational Costs + Fixed Operational Costs + Biomass Purchasing Cost + Auxiliary Material Cost).

Eq. (1) represents the first objective function;

Eq. (2) shows the second objective function, namely minimization of GHG emissions associated with energy production and pre-processing activities.

$$Min\ z = \left(\sum_{k=1}^{K}\sum_{t=1}^{T}\left(\sum_{n=1}^{N} g_t \cdot E_{tn}^{k}\right)\right) + \left(\sum_{i=1}^{I}\sum_{j=1}^{J}\left(\sum_{c=1}^{C}\sum_{b=1}^{B} g_c \cdot S_{cb}^{ij} \cdot d_{bc}\right)\right) \tag{2}$$

$$\begin{aligned} Max\ z = {} & \left[\left(\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{u=1}^{U} SP_{tu}^{kl} \cdot P_{ut}\right) + \left(\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{f=1}^{U} SF_{tf}^{kl} \cdot P_{ft}\right) + \left(\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{n=1}^{N} SE_{n}^{kl} \cdot P_{nt}\right)\right] - DF \cdot \left[\left(\sum_{j=1}^{J}\sum_{e=1}^{E}\sum_{c=1}^{C} I_{ec} \cdot C_{ec} \cdot B_{jec}\right)\right. \\ & \left. + \left(\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T} I_{pt} \cdot C_{pt} \cdot A_{kpt}\right) + \left(\sum_{k=1}^{K}\sum_{q=1}^{Q} ICHP_q \cdot CE_q \cdot CHP_q^k\right)\right] \\ & - \left[\begin{array}{l} \left(\sum_{j=1}^{J}\sum_{e=1}^{E}\sum_{c=1}^{C} VO_{ec} \cdot \left(\sum_{i=1}^{I}\sum_{b=1}^{B} S_{cb}^{ij}\right)\right) + \left(\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T} VO_{pt} \cdot \left(\sum_{j=1}^{J}\sum_{b=1}^{B} S_{tb}^{jk}\right)\right) \\ + \left(\sum_{q=1}^{Q}\sum_{t=1}^{T} VOCHP_q \cdot \left(\sum_{k=1}^{K}\sum_{n=1}^{N} E_{tn}^{k}\right)\right) \end{array}\right] \\ & - \left[\begin{array}{l} \left(\sum_{j=1}^{J}\sum_{e=1}^{E}\sum_{c=1}^{C} FO_{ec} \cdot C2_{ec} \cdot B_{jec}\right) + \left(\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T} FO_{pt} \cdot C1_{pt} \cdot A_{kpt}\right) \\ + \left(\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{n=1}^{N} FOCHP_q \cdot CE_{qn} \cdot CHP_q^k\right) \end{array}\right] - \left[\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{c=1}^{C}\sum_{b=1}^{B} PB_b \cdot SB_{cb}^{ij}\right] - \left(\sum_{k=1}^{K} W^k \cdot PW\right) \end{aligned} \tag{1}$$

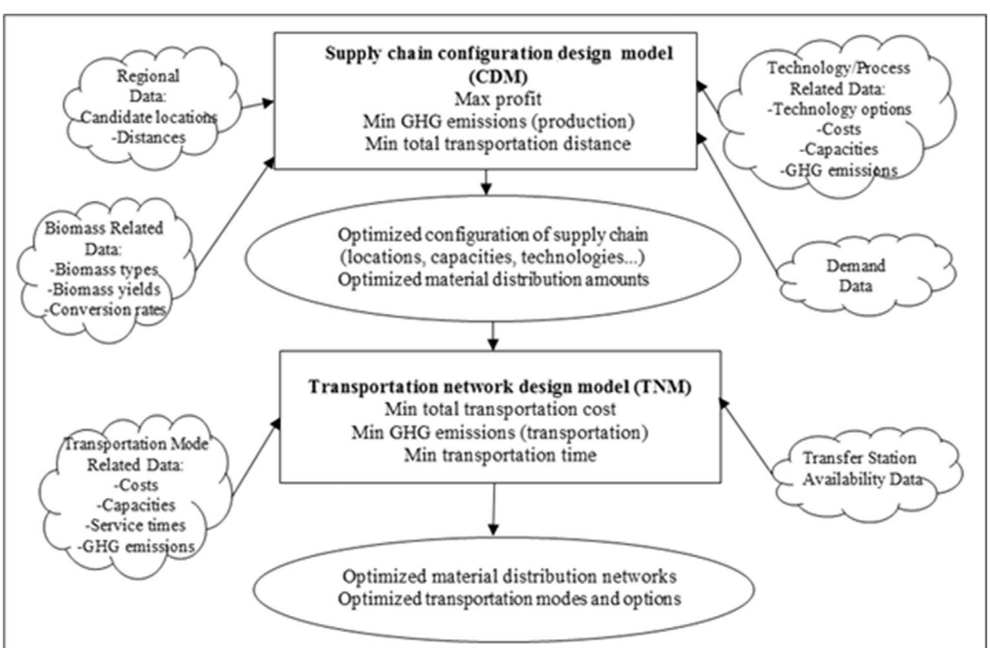

Fig. 1. Description of the DSS

Eq. (3) depicts the third objective function, minimization of total ton-kms, which represents the sum product of the distances and transportation amounts between biomass source sites, facilities and plants. The aim of this objective is to configure the supply chain so as to minimize the supply of biomass from and distribution of bio-fertilizer to relatively long distances.

$$\begin{aligned} Min\ \ z = & \left(\sum_{i=1}^{I}\sum_{j=1}^{J} d^{ij}\cdot\left(\sum_{c=1}^{C}\sum_{b=1}^{B} S_{cb}^{ij}\right)\right) \\ & + \left(\sum_{j=1}^{J}\sum_{k=1}^{K} d^{jk}\cdot\left(\sum_{t=1}^{T}\sum_{b=1}^{B} S_{tb}^{jk}\right)\right) \\ & + \left(\sum_{k=1}^{K}\sum_{l=1}^{L} d^{kl}\cdot\left(\sum_{t=1}^{T}\sum_{f=1}^{F} SF_{tf}^{kl}\right)\right) \end{aligned} \tag{3}$$

Eqs. (4)–(20) represent the constraints of the CDM model.

$$\sum_{c=1}^{C}\sum_{j=1}^{J} S_{cb}^{ij} \le BS_b^i \quad \forall i, \forall b \tag{4}$$

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

$$\sum_{j=1}^{J}\sum_{b=1}^{B} S_{tb}^{jk} \le \sum_{p=1}^{P} A_{pt}^{k}\cdot C_{pt}\ \forall k, \forall t \tag{6}$$

$$\sum_{i=1}^{I}\sum_{b=1}^{B} S_{cb}^{ij} \le \sum_{e=1}^{E} B_{ec}^{j}\bullet C_{ec} \quad \forall j,\ \forall c \tag{7}$$

$$\sum_{j=1}^{J}\sum_{b=1}^{B} S_{tb}^{jk}\cdot r_{but} = PR_{ut}^{k}\ \forall k, \forall u, \forall t \tag{8}$$

$$PR_{ut}^{k}\cdot\left(1-\sum_{n=1}^{N} y_{tun}^{k}\right) = \sum_{l=1}^{L} SP_{tu}^{kl}\ \forall k, \forall u, \forall t \tag{9}$$

$$\sum_{k=1}^{K}\sum_{t=1}^{T} SP_{tu}^{kl} \ge D_u^l\ \ \forall l, \forall u \tag{10}$$

$$\sum_{j=1}^{J}\sum_{b=1}^{B} S_{tb}^{jk}\cdot r_{bft} = F_{kft}\ \forall k, \forall f, \forall t \tag{11}$$

$$F_{kft} = \sum_{l=1}^{L} SF_{ft}^{kl}\ \forall k, \forall f, \forall t \tag{12}$$

$$\sum_{k=1}^{K}\sum_{t=1}^{T} SF_{ft}^{kl} \le D_f^l\ \forall l, \forall f \tag{13}$$

$$\sum_{t=1}^{T}\sum_{u=1}^{U} PR_{ut}^{k}\cdot y_{tun}^{k}\cdot e_{un}\cdot cv_n = E_n^k\ \forall k, \forall n \tag{14}$$

$$E_n^k \le \sum_{q=1}^{Q} CHP_q^k\cdot CE_{qn}\ \forall k, \forall n \tag{15}$$

$$E_n^k = \sum_{l=1}^{L} SE_n^{kl} \quad \forall k, \forall n \tag{16}$$

$$\sum_{k=1}^{K} SE_n^{kl} \ge D_n^l\ \forall l, \forall n \tag{17}$$

$$\sum_{p=1}^{P}\sum_{t=1}^{T} A_{pt}^{k} \le 1\ \forall k \tag{18}$$

$$\sum_{e=1}^{E}\sum_{c=1}^{C} B_{ec}^{j} \le\ 1 \quad \forall j \tag{19}$$

$$\sum_{q=1}^{Q} CHPA_q^k \le 1\ \forall k \tag{20}$$

Eq. (4) restricts the biomass procurement amount from a supply site by the total available biomass amount in that site. Eq. (5) ensures the flow balance of the biomass supplied from biomass source site to facility and from facility to biomass conversion plant considering the material loss in the biomass after the pre-treatment process (if the facility is for storage of biomass, the conversion rate d_{bc} is 1, which means no loss). 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 by-product produced in and distributed from the biomass conversion plants. Eq. (13) limits the by-product distribution amount by the corresponding demand in the demand nodes (to eliminate the disposal of the excess by-product). Eqs. (14) and (15) calculate the amount of energy produced in energy production units and restrict this amount to the maximum capacity of the corresponding capacity levels of plants. Eqs. (16) and (17) ensure that all the energy demand is met in the demand nodes. Eqs. (18)–(20) ensure that at most 1 facility, 1 biomass conversion plant and energy production unit is constructed in each selected location.

3.2.2. Transportation network design

The model includes three objectives related to environmental, economic and service level performances of the supply chain. The objectives are: (1) minimization of total transportation cost; and (2) minimization of GHG emissions (CO_2 eq) related to transportation in the supply chain and (3) minimization of total transportation time.

The first two objective functions are structured similarly, including the Eqs. (21)–(24);

$$Term\ 1 = \left(\left(\sum_{i=1}^{I}\sum_{j=1}^{J} d1^{ij}\cdot M1^{ij}_{\alpha b}\right) + \left(\sum_{j=1}^{J}\sum_{k=1}^{K} d1^{jk}\cdot M1^{jk}_{\alpha b}\right) + \left(\sum_{k=1}^{K}\sum_{l=1}^{L} d1^{ki}\cdot M1^{kl}_{\alpha f}\right) + \left(\sum_{i=1}^{I}\sum_{g=1}^{G} d2^{ig}\cdot M2^{ig}_{\alpha b}\right) + \left(\sum_{j=1}^{J}\sum_{v=1}^{V} d2^{jv}\cdot M2^{jv}_{\alpha b}\right) + \left(\sum_{k=1}^{K}\sum_{z=1}^{Z} d2^{kz}\cdot M2^{kz}_{\alpha f}\right)\right) \tag{21}$$

$$Term\ 2 = \left(\left(\sum_{i=1}^{I}\sum_{j=1}^{J} M1^{ij}_{\alpha b}\right) + \left(\sum_{j=1}^{J}\sum_{k=1}^{K} M1^{jk}_{\alpha b}\right) + \left(\sum_{k=1}^{K}\sum_{l=1}^{L} M1^{kl}_{\alpha f}\right) + \left(\sum_{i=1}^{I}\sum_{g=1}^{G} M2^{ig}_{\alpha b}\right) + \left(\sum_{j=1}^{J}\sum_{v=1}^{V} M2^{jv}_{\alpha b}\right) + \left(\sum_{k=1}^{K}\sum_{z=1}^{Z} M2^{kz}_{\alpha f}\right)\right) \tag{22}$$

$$Term\ 3 = \left(\left(\sum_{g=1}^{G}\sum_{j=1}^{J} d3^{gj}\cdot M3^{gj}_{\beta b}\right) + \left(\sum_{v=1}^{V}\sum_{k=1}^{K} d3^{vk}\cdot M3^{vk}_{\beta b}\right) + \left(\sum_{z=1}^{Z}\sum_{l=1}^{L} d3^{zi}\cdot M3^{zl}_{\beta f}\right)\right) \tag{23}$$

$$Term\ 4 = \left(\left(\sum_{g=1}^{G}\sum_{j=1}^{J} M3^{gj}_{\beta b}\right) + \left(\sum_{v=1}^{V}\sum_{k=1}^{K} M3^{vk}_{\beta b}\right) + \left(\sum_{z=1}^{V}\sum_{l=1}^{L} M3^{zl}_{\beta f}\right)\right) \tag{24}$$

Eq. (25) represents the first objective function, minimization of total transportation cost. The formulation comprises the Distance Fixed Cost (DFC) and Distance Variable Cost (DVC) (Lu et al., 2015). DFC is independent of distance between the locations and covers the infrastructure costs (construction and maintenance costs of facilities such as piers and cranes), loading and unloading costs, as well as administration costs. DFC is an important factor to determine the competitive position between the modes (Lu et al., 2015). DVC includes the variable costs related to the distance between nodes, such as fuel, labour, maintenance and capital recovery and depreciation of the transportation equipment.

$$Min\ \ z = \left(\sum_{\alpha=1}^{A}\sum_{b=1}^{B}(TCvar_{\alpha b}\cdot Term\ 1)\right) + \left(\sum_{\alpha=1}^{A}\sum_{b=1}^{B}(TCfix_{\alpha b}\cdot Term\ 2)\right) + \left(\sum_{\beta=1}^{B}\sum_{b=1}^{B}\left(TCvar_{\beta b}\cdot Term\ 3\right)\right) + \left(\sum_{\beta=1}^{B}\sum_{b=1}^{B}\left(TCfix_{\beta b}\cdot Term\ 4\right)\right) \tag{25}$$

Eq. (26) formulates the objective of minimization of total GHG emissions associated with transportation. This objective function consists of distance fixed emissions (DFE) and distance variable emissions (DVE) similarly to the first objective function. GHG emissions from loading and unloading operations constitute the DFE, whereas DVE depends on the distance travelled.

$$Min\ z = \left(\sum_{\alpha=1}^{A}\sum_{b=1}^{B}(CEvar_{\alpha b}\cdot Term\ 1)\right) + \left(\sum_{\alpha=1}^{A}\sum_{b=1}^{B}(CEfix_{\alpha}\cdot Term\ 2)\right) + \left(\sum_{\beta=1}^{B}\sum_{b=1}^{B}\left(CEvar_{\beta b}\cdot Term\ 3\right)\right) + \left(\sum_{\beta=1}^{B}\sum_{b=1}^{B}\left(CEfix_{\beta}\cdot Term\ 4\right)\right) \tag{26}$$

Eq. (27) represents the third objective function, namely minimization of total transportation time, which is an indicator of the service level related to transportation activities in the supply chain. This objective comprises the travel time related to the distance travelled and time required to transfer the material from one vehicle to another.

$$Min\ z = \left(\sum_{\alpha=1}^{A}\left(TT_{\alpha}\cdot\left(\left(\sum_{i=1}^{I}\sum_{j=1}^{J} d1^{ij}\cdot X^{ij}_{\alpha}\right) + \left(\sum_{j=1}^{J}\sum_{k=1}^{K} d1^{jk}\cdot X^{jk}_{\alpha}\right) + \left(\sum_{k=1}^{K}\sum_{l=1}^{L} d1^{ki}\cdot X^{kl}_{\alpha}\right) + \left(\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{g=1}^{G}\sum_{\beta=1}^{B} d2^{ig}\cdot Y^{ijg}_{\alpha\beta}\right) + \left(\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{v=1}^{V}\sum_{\beta=1}^{B} d2^{jv}\cdot Y^{jkv}_{\alpha\beta}\right) + \left(\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{z=1}^{Z}\sum_{\beta=1}^{B} d2^{kz}\cdot Y^{klz}_{\alpha\beta}\right)\right)\right)\right) + \left(\sum_{\beta=1}^{B}\left(TT_{\beta}\cdot\left(\left(\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{g=1}^{G}\sum_{\alpha=1}^{A} d3^{gj}\cdot Y^{ijg}_{\alpha\beta}\right) + \left(\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{v=1}^{V}\sum_{\alpha=1}^{A} d3^{vk}\cdot Y^{jkv}_{\alpha\beta}\right) + \left(\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{z=1}^{Z}\sum_{\alpha=1}^{A} d3^{zl}\cdot Y^{klz}_{\alpha\beta}\right)\right)\right)\right) + \left(\sum_{\alpha=1}^{A}\sum_{\beta=1}^{B}\left(TRT_{\alpha\beta}\cdot\left(\sum_{l=1}^{L}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{g=1}^{G}\sum_{v=1}^{V}\sum_{z=1}^{Z} Y^{ijg}_{\alpha\beta} + Y^{jkv}_{\alpha\beta} + Y^{klz}_{\alpha\beta}\right)\right)\right) \tag{27}$$

Eqs. (28)–(33) represent the constraints of the second model.

$$\sum_{b=1/f=1}^{B/F} M1_{\alpha b/\alpha f}^{ij/jk/kl} \le TCap_a \cdot X_{\alpha}^{ij/jk/kl} \cdot AV1_{\alpha}^{ij/jk/kl} \quad \forall l, \forall j, \forall j, \forall k, \forall \alpha \tag{28}$$

$$\sum_{b=1/f=1}^{B/F} M2_{\alpha b/\alpha f}^{ig/j\upsilon/kz} \le TCap_a \cdot Y_{\alpha\beta}^{ijg/jk\upsilon/klz} \cdot AV2_{\alpha}^{ig/j\upsilon/kz} \cdot AVS_{g/\upsilon/z}^{ij/jk/kl}$$
$$\sum_{b=1/f=1}^{B/F} M3_{\beta b/\beta f}^{gj/\upsilon k/zl} \le TCap_\beta \cdot Y_{\alpha\beta}^{ijg/jk\upsilon/klz} \cdot AV3_{\beta}^{gj} \cdot AVS_{g/\upsilon/z}^{ij/jk/kl}$$
$$\forall l, \forall j, \forall k, \forall g, \forall \upsilon, \forall z, \forall \alpha, \forall \beta \ne \alpha \tag{29 –30}$$

$$\left(\sum_{\alpha=1}^{A} M1_{\alpha b/\alpha f}^{ij/jk/kl}\right) + \left(\sum_{\alpha=1}^{A} \sum_{g=1/\upsilon=1/z=1}^{G/V/Z} M2_{\alpha b/\alpha f}^{ig/j\upsilon/kz}\right) = ST_b^{ij/jk/kl} \quad \forall i, \forall j, \forall k, \forall l, \forall b, \forall f \tag{31}$$

$$M2_{\alpha b/\alpha f}^{ig/j\upsilon/kl} = M3_{\beta b/\alpha f}^{gj/\upsilon k/zl} \quad \forall i, \forall j, \forall k, \forall l, \forall g, \forall \upsilon, \forall z, \forall b, \forall f, \forall \alpha, \forall \beta \tag{32}$$

$$\left(\sum_{\alpha=1}^{A} X_{\alpha}^{ij/jk/kl}\right) + \left(\sum_{\alpha=1}^{A} \sum_{\beta=1}^{B} \sum_{g=1/\upsilon=1/z=1}^{G/V/Z} Y_{\alpha\beta}^{ijg/jk\upsilon/klz}\right) \le 1 \quad \forall i, \forall j, \forall k, \forall l \tag{33}$$

The constraint set represented by Eq. (28) is valid if single mode transportation is selected by the model to transport material from one node to another. This constraint set limits the amount of material (biomass and bio-product) shipped by a transportation mode between biomass source sites, facilities and plants, to the capacity and availability of this mode between considered locations. Eqs. (29) and (30) represent the constraint set that is valid if multimodal transportation is selected. Eq. (29) limits the amount of material shipped by a transportation mode from biomass source sites, facilities and plants to the transfer stations, to the capacity and availability of this mode between considered locations. Eq. (30) restricts the amount of material shipped by a transportation mode from transfer stations to the biomass source sites, facilities and plants, to the capacity and availability of this mode between considered locations. Eq. (31) ensures that the amount of material transported by either single mode or multimodal options between locations is equal to the amount determined by the CDM in the first stage of the DSS. Eq. (32) ensures that the transportation amounts from origin to station and from station to destination are equal. Finally, Eq. (33) ensures either single mode or multimodal transportation is selected between two nodes.

4. Solution methodology

The solution methodology combines fuzzy set theory and ε-constraint methods, more specifically ε-constraint method is extended by integrating fuzzy logic.

ε-constraint method is one of the most widely used and well-organized techniques to handle the multi-objective structure of complex problems (Haimes et al., 1971). The method is aimed to minimize only one objective function (commonly, it may be the most preferred or primary one) and to limit the others by some allowable values $\varepsilon_i, i \in \{1, \ldots, m\}$, and in this way, transforming the multi-objective optimization problem into a single-objective problem. For detailed information about the ε-constraint method and its advantages over other techniques to solve multi-objective problems, Reza Norouzi et al. (2014), Rezvani et al. (2015), Mavrotas (2009), Steuer (1986) and Miettinen (1999) cane be referred.

Assume the following MOMP problem is considered as problem P (Mavrotas, 2009):

$$\begin{aligned} & max/min \quad (f_1(x), f_2(x), \ldots f_m(x)) \\ & st \quad x \in S \end{aligned} \tag{34}$$

where x is the vector of decision variables, $(f_1(x), f_2(x), \ldots f_m(x))$ are the m objective functions and S is the feasible region.

In the ε-constraint method we optimize one of the objective functions using the other objective functions as constraints incorporating them in the constraint part of the model and converting problem P *to* P_0 as shown below (Chankong and Haimes, 1983);

$$\begin{aligned} & max\ /min \quad f_1(x) \\ & st \quad f_2(x) \ge \varepsilon_2 \ for\ max\ functions, \\ & \quad f_3(x) \le \varepsilon_3 \ for\ min\ functions, \\ & \quad \ldots \\ & \quad f_m(x) \ge \varepsilon_m, \\ & \quad x \in S. \end{aligned} \tag{35}$$

By introducing the ranges $\varepsilon_i, i \in \{1, \ldots, m\}$ of objective functions the efficient solutions of the problem are obtained.

Despite its advantages, it is emphasized in the literature that the ε-constraint method has two points that need attention in its implementation (Mavrotas, 2009; Ahmadi et al., 2014). The main advantage of the solution methodology developed in this study is that it tackles with these two issues. The first issue is with the calculation of the ranges of objective functions over the efficient sets. To overcome this deficit, the hybrid solution procedure developed in this study employs a fuzzy logic based procedure to determine the ranges more realistically considering the system uncertainties. The second problem with this technique is that the generated pareto optimal solutions using this method may be dominated or inefficient; therefore, it is necessary to select the most efficient one among them. Fuzzy decision making is utilized herein to eliminate this shortcoming.

In this paper a modified version of the ε-constraint method is used to address these issues by combining the method with fuzzy set theory. The modified ε-constraint method for the proposed problem is described as the following steps;

Step 1. Problem P in Section 2 can be transformed into problem P_0 according to the basic principles of the ε-constraint method. In P_0, the objective function is corresponding to f_1 of P, and f_2 and f_3 of P is dealt with as a constraint of P_0. Problem P_0 can be represented as follows:

$$\begin{aligned} & minf_1(x) \\ & st \quad f_2(x) \le \varepsilon_2, \\ & \quad f_3(x) \le \varepsilon_3, \\ & and\ other\ constraints \end{aligned} \tag{36}$$

Step 2. To solve problem P_0, we need to determine ε_2 and ε_3 (upper bound for the second and third objective functions) that is limited by the range of objective functions f_2 and f_3. To obtain the appropriate ranges of f_2 and f_3, multi objective model P in Section 2 is solved as a single objective problem using each time only one objective and ignore the others to specify the efficient solutions (i.e.

upper bound, expected value and lower bound) for f_2 and f_3. For this purpose, a fuzzy logic based procedure is utilized and the problem is divided into sub problems. Each time, one of the upper, lower and expected values of the fuzzy parameters are taken into consideration and sub problems are solved according to one of the objective functions. For this purpose, a novel scenario based approach is utilized in this study. The problem is divided into nine sub problems (SP) based on a scenario approach. Scenarios represent the best, expected and worst situations for three objective functions, which are constructed by taking into consideration the upper, lower and expected values of the fuzzy parameters. After constructing the scenarios, the model is solved according to one objectives under three scenarios and the corresponding value for each objective function at each solution is determined.

Step 3. Based on the findings from Step 2, the payoff table, which is an asymmetric matrix where the matrix elements represent the optimum values of the corresponding objective function, is constructed. The lower, upper and expected values of each objective function are determined based on the payoff table.

Step 4. Solve the problem P_0 with different values of ε_2 and ε_3 (i.e. upper, expected and lower values from the payoff table), and finally, obtain a set of pareto optimal solutions.

Step 5. After a set of pareto optimal solutions are obtained, a decision maker may wish to select a preferred one from them and may also want to know its degree of optimality. The fuzzy logic based approach (Esmaili et al., 2011) can both provide a most preferred solution and also indicate its degree of optimality. Therefore, in this paper, it is applied to assist in choosing a preferred solution. In the m-objective optimization problem with k pareto optimal solutions, the membership function μ_i^k indicates the degree of optimality for the *ith* objective function in the *kth* solution. It is defined as follows;

1. In the case of objective functions being minimized;

$$\mu_i^k = \begin{cases} 1 & ; \quad f_i^k(x) \le l_i \\ \dfrac{u_i - f_i^k(x)}{u_i - l_i} & ; \quad l_i < f_i^k(x) \le u_i \\ 0 & ; \quad f_i^k(x) > u_i \end{cases} \tag{37}$$

2. In the case of objective functions being maximized;

$$\mu_i^k = \begin{cases} 1 & ; \quad f_i^k(x) > u_i \\ \dfrac{f_i^k(x) - l_i}{u_i - l_i} & ; \quad l_i < f_i^k(x) \le u_i \\ 0 & ; \quad f_i^k(x) < l_i \end{cases} \tag{38}$$

where l_i and u_i denote the lower and upper limits of objective function f_i of P, respectively, and $f_i^k(x)$ represents the value of the *ith* objective function in the *kth* pareto optimal solution, such that $f_i^k(x) \in [l_i, u_i]$.

Step 6. If a decision maker offers a preferred weight vector, which represents the relative importance of each objective according to the decision maker's preferences, for the cost minimization and emission minimization objectives, for each solution k, the membership degree μ^k is calculated based on its individual membership functions by adding weight factors as follows:

$$\mu^k = \frac{\sum_{i=1}^{m} w_i \cdot \mu_i^k}{\sum_{i=1}^{m} w_i} \tag{39}$$

The solution with the maximum value of μ_i^k is selected as the most preferred solution.

5. Computational studies

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 NUTS 3 level regions in the WM (Birmingham, Coventry, Solihull, Sandwell, Walsall, Wolverhampton and Dudley) are used as the testing ground to design a comprehensive bio-based supply chain and transportation network in WM.

5.1. Input data

5.1.1. Biomass supply and bio-product demand

In this study, four types of bio-waste and one energy crop are assumed to be the potential feedstock for bio-based production systems; cattle manure, laying chicken manure, broiler chicken manure, waste wood and maize, which are available in WM and widely dispersed across the region. The existing yields and geographic distribution data on bio-waste from husbandry are adopted from DEFRA (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 Consulting 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 (2015) and aggregated at 3 energy crop fields around the region.

We consider meeting the corresponding bio-methane, electricity, heat and bio-fertilizer demands in a particular area in each of the NUTS 3 regions in WM. The numbers of addresses of which bio-methane and bioenergy demands are considered to be fulfilled in each region are given in Table 1. Regarding data on demands came fromDECC (2012a, b). Produced bio-fertilizer is assumed to be distributed to the crop fields from which maize is supplied to the conversion plants.

The map of the case study region is depicted in Fig. 2 with biomass source sites, demand nodes, and candidate locations for energy plants and facilities considered in this study. Distances between 16 specific biomass source sites, 7 plant locations, 7 facility locations and 7 demand nodes can be provided by the

Table 1
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

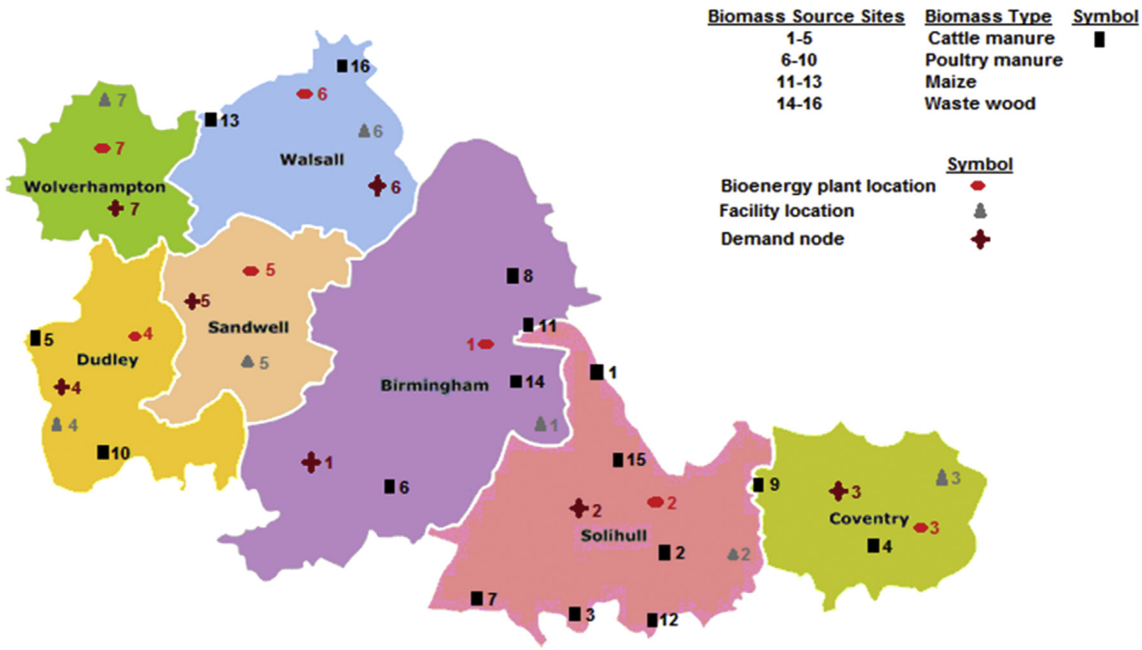

Fig. 2. Case study region map.

corresponding author along with related post codes upon special request.

5.1.2. Plants and facilities

In this case study, Anaerobic Digestion (AD) and Gasification (G) are considered as bio-based production technologies. AD is utilized to produce bio-methane, which is a combustible gas that can either be directly injected into natural gas grid or converted into useful forms of energy, from cattle manure, laying chicken manure, broiler chicken manure and maize. A proportion of produced bio-methane is converted into electrical and thermal energy in CHP engines. Biofuel (syngas) produced from wood pellet by G systems is assumed to be transformed into electrical and thermal energy entirely by CHP engines as syngas, differently from bio-methane, can not be used directly in the place of natural gas. There are two types of pre-processing facilities; collection and pre-treatment facilities to store, treat and distribute biomass. Collection centres are used as hub locations to collect cattle manure, laying chicken manure, broiler chicken manure and maize, and distribute them to plants. Waste wood is sent to pre-treatment facilities from supply regions to be converted into wood pellet, which is a more efficient biomass. The by-product of AD process, which can be utilized as high quality organic fertilizer (bio-fertilizer) in agricultural activities, is distributed to the energy crop fields from where maize is supplied to be converted into bio-product in plants. The supply chain under consideration is illustrated in Fig. 3.

The potential locations for the bio-based production plants and facilities are selected 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

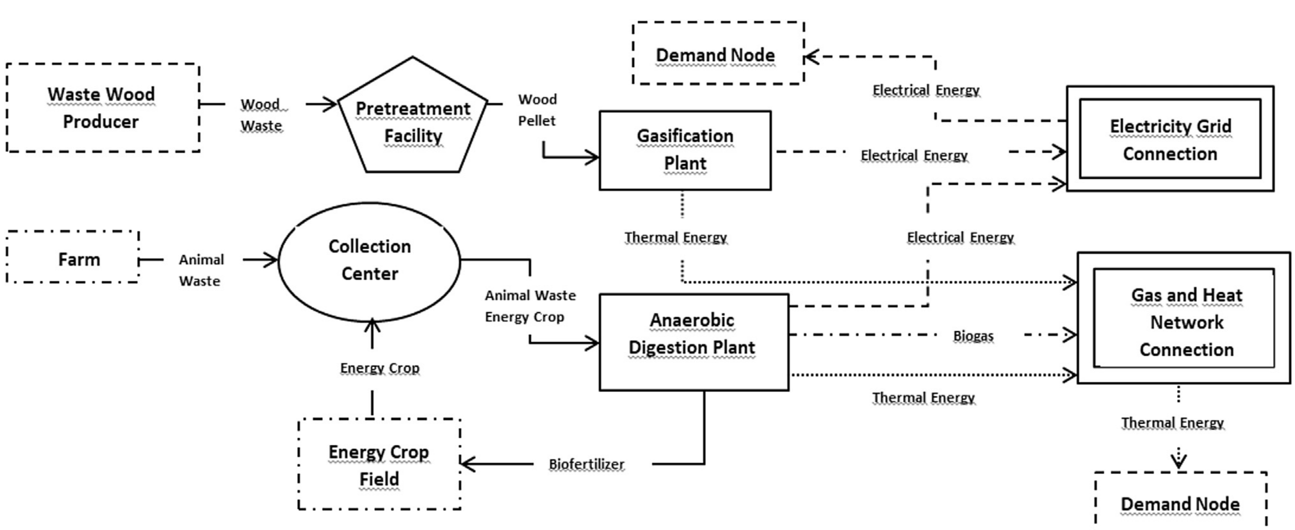

Fig. 3. An overview of the supply chain under consideration.

generation. A total of 14 sites (7 for the plants, 7 for the facilities) are chosen as the candidate locations.

To ensure the efficiency of bio-methane 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. (40) is included to the model as a case specific constraint;

$$7\% \leq \frac{\sum_{j=1}^{J}\sum_{b=1}^{B}\sum_{t=1}^{T} TS_b \cdot S_{tb}^{jk}}{\left(\sum_{j=1}^{J}\sum_{b=1}^{B}\sum_{t=1}^{T} S_{tb}^{jk}\right) + W^k} \leq 12\% \quad \forall k \tag{40}$$

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 upper and lower limit values are obtained by utilizing expert opinions and they may be different for various cases according to the specific conditions of the anaerobic digestion system considered in the case. Hence, they can be changed to be used in different cases.

We assume in this case study that biofuel (bio-methane) is only produced in AD whereas G plants are operated to produce only electrical and thermal energy. The generated electrical energy, thermal energy and bio-methane are assumed to be fed into the national electricity grid, on-site heating system and natural gas pipeline network. 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). Table 2 depicts the rates of conversion of biomass into biogas, syngas and bio-fertilizer as well as the rates of conversion of biogas and syngas into electrical and thermal energy. These values are obtained by utilizing expert opinions and they may be different for different cases according to the specific regional or environmental conditions. Hence, they can be changed and adaptable to different cases as the other parameter values used in our computational experiments.

Three capacity levels are considered for the pre-processing facilities, biomass to biofuel conversion plants and CHP units. These capacity levels reported in Table 3.

Data on GHG emissions associated with wood pellet production in pre-treatment facilities and bioenergy production in plants are depicted in Table 4.

5.1.3. Prices and costs

Considering the incentives that UK Government provides to promote the development and deployment of low carbon energy technologies and markets, and the base prices, the ultimate prices for electricity, heat and bio-methane are calculated for both AD and G. The base prices are derived from Digest of UK Energy Statistics (DUKES). Table 5 reports the electricity, heat and bio-methane prices calculated based on the base prices and incentives.

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 (2012a, b) is utilized to obtain the data on plant investment and operational costs. The investment costs are taken into consideration in a manner that they decrease with higher capacities because of economies of scale. The operational costs consist of the 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 an assumption that the plants operates 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 h per day for one shift. 1 h is needed from the entire week for a three shift working mode for the starting up and shutting down of a plant (Marufuzzaman et al., 2016). The unit investment and operational costs according to capacity levels are reported in Table 6. It should be noted that, unit costs are computed considering monthly biomass capacity of the facilities and plants, and installed power of the CHP.

Table 2
Conversion rates.

Biomass to Biofuel/Biofertilizer Conversion Rates			
Biomass Source	Biomass to Biogas Conversion Rate (kg/m^3)	Biomass to Syngas Conversion Rate (kg/m^3)	Biomass to Biofertilizer Conversion Rate
Cattle manure	80	–	0.9
Laying chicken manure	140	–	0.85
Broiler chicken manure	60	–	0.85
Waste wood	–	960	–
Maize	150	–	0.75
Biofuel to Energy Conversion Rates			
	Energy Type		
Biofuel Type	**Biofuel to Electricity Conversion Rate** (kwh/m^3)	**Biofuel to Thermal Energy Conversion Rate** (kwh/m^3)	
Biogas	10	5.4	
Syngas	10	5.4	

Table 3
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 4
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)	DECC Carbon Conversion Factors Dataset (2016)
Syngas to energy	0.18,445 (kg CO_2 Eq/kWh)	DECC Carbon Conversion Factors Dataset (2016)
Pretreatment		
Pelletizing	1.47×10^{-4} (kg CO_2 Eq/ton)	Cucek et al. (2010)

Table 5
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[a] (€/kWh)						
Generation	0.0998	–	–	–	–	
Export	0.0628	–	–	–	–	
RHI[b] (€/kWh)	–	0.026	0.0677	–	0.026	
ROC[c] (€/kWh)	–	–	–	0.0957	–	
Total (€/kWh)	0.2196	0.066	0.0993	0.1527	0.066	

[a] FiT (Feed-in Tariffs): FITs incentivises small-scale low carbon electricity generation by requiring energy suppliers to make payments to households and businesses with certified installations. (DECC, 2015a).
[b] RHI (Renewable Heat Incentive): The RHI provides a tariff to businesses, the public sector and non-profit organisations for the installation of renewable heat technologies. (DECC, 2015b).
[c] ROC (Renewables Obligation Certificate): 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. (DECC, 2015c).

Table 6
Unit investment costs per installed capacity depending on capacity levels.

Capacity Level	Unit investment cost of G plants (€/ton) (DECC, 2012a, b)	Unit investment cost of AD plants (€/ton) (DECC, 2012a, b)	Unit investment cost of CHP (€/kWe) (DECC, 2012a, b)	Unit investment cost of PT facilities (€/ton) (Rentzelas 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, 2012a, b)	Unit fixed and variable operational costs of AD plants (€/ton) (DECC, 2012a, b)	Unit fixed (€/kWe) and variable (€/kWh) operational costs of CHP (DECC, 2012a, b)
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

5.1.4. *Transportation*

In our case study, we consider biomass is transported upstream supply chain (from biomass source sites to facilities and from facilities to plants), and bio-fertilizer is transported downstream supply chain (from plants and maize fields).

Multimodal road-rail transport in particular has been the focus for the bio-based industry (Floden and Williamsson, 2016) and has been found to have less environmental impact than competing modes (Kreutzberger et al., 2003; Lindholm and Berg, 2005). Also it is the most sustainable transport option when considering all three pillars of sustainability (economic, societal, and environmental) (Floden and Williamsson, 2016). Considering these facts on multimodal road-rail transport and given the regional focus in our case study, road and rail are considered as the preferred transportation modes. Specifically two types of road and rail transport are captured: transportation by a single trailer truck with a load capacity of 32 tons with average travelling speed of 60 km/h and a unit train with a load capacity of 120 tons with average travelling speed of 100 km/h.

In this case study, unit costs of transporting biomass and bio-fertilizer are derived from the literature as well as the data on GHG emissions associated with transportation. The cost and GHG emissions data is adapted to the local conditions considering the data gathered from local logistics firms. Table 7 lists the unit fixed costs and variable costs of transportation, and GHG emissions for transporting cattle manure, poultry manure, wood pellet, maize and bio-fertilizer by road and rail transport. The data is assumed to be the same for all NUTS 3 level regions. GHG emissions from truck and rail transportation is obtained as 0.0845 kg CO_2 eq/ton-km (100% laden) and 0.02950 kg CO_2 eq/ton-km, respectively from DECC Carbon Conversion Factors Dataset (2016).

The data is assumed to be the same for all NUTS 3 level regions. 30 stations are considered throughout the region for transhipment of biomass and bio-fertilizer from one mode to another in case of using multimodal transportation. 22, 13 and 10 of them are available between biomass source sites and facilities, facilities and plants, and plants and energy crop fields, respectively.

5.1.5. *Uncertain parameters*

Biomass based production systems are exposed to a number of uncertainties that significantly effect the economic and environmental performance of the supply chain especially over the medium and longer term horizons. System parameters are affected by economic, social and environmental policies as well as the fluctuations in market conditions. To minimize the negative impacts of such uncertain conditions, the sources of these uncertainties need

Table 7
Unit costs and GHG emissions for transportation.

	Truck Transportation			Train Transportation		
	Fixed Cost (€/ton)	Variable Cost (€/ton-km)	GHG emissions (kg CO_2 eq/ton-km) Cucek et al. (2012)	Fixed Cost (€/ton)	Variable Cost (€/ton-km)	GHG emissions (kg CO_2 eq/ton-km) Cucek et al. (2012)
Cattle Manure (Semi-solid)	4.43 Tittmann et al. (2010)	0.02658 Tittmann et al. (2010)	5.3×10^{-8}	28.35 Tittmann et al. (2010)	0.0127 Tittmann et al. (2010)	–
Broiler Hen Manure (Solid)	4.43 Tittmann et al. (2010)	0.02658 Tittmann et al. (2010)	5.3×10^{-8}	28.35 Tittmann et al. (2010)	0.0127 Tittmann et al. (2010)	–
Layer Hen Manure (Semi-solid)	4.43 Tittmann et al. (2010)	0.02658 Tittmann et al. (2010)	5.3×10^{-8}	28.35 Tittmann et al. (2010)	0.0127 Tittmann et al. (2010)	–
Waste Wood	6.17 Perez-Verdin et al. (2007)	0.077 Perez-Verdin et al. (2007)	5.3×10^{-8}	28.35 Tittmann et al. (2010)	0.0127 Tittmann et al. (2010)	8×10^{-9}
Wood pellet	2.7 Lu et al. (2015)	0.078 Lu et al. (2015)	2.4×10^{-7}	15.86 Lu et al. (2015)	0.015 Lu et al. (2015)	8×10^{-9}
Maize (Loose)	5.05 Sokhansanj et al. (2009)	0.12 Sokhansanj et al. (2009)	1.1×10^{-6}	15.15 Sokhansanj et al. (2009)	0.0245 Sokhansanj et al. (2009)	8×10^{-9}
Fertilizer (Liquid)	3.89 Tittmann et al. (2010)	0.0198 Tittmann et al. (2010)	5.3×10^{-8}	20.07 Tittmann et al. (2010)	0.00913 Tittmann et al. (2010)	–

to be specified and considered in the design and investment planning phase. Considering this fact, uncertainties in the following parameters, of which values are highly impacted by governmental policies, competition between firms in the related market and natural conditions about weather, soil … etc. as well as technical and technological uncertainties, are handled and included to the methodology in this study; (1) Bio-product prices, (2) Cost of biomass and auxiliary material, (3) Investment and operational costs, (4) Transportation costs, (5) Level of GHG emissions, (6) Transportation time, (7) Biomass yields.

We define the coefficients in the model corresponding to each of the above mentioned parameters within a range. The lower and upper bounds for these coefficients are assumed to be 90% and 110% of their expected values in our computational experiments. These coefficients are utilized in the scenario based approach in the second step of the solution methodology (explained in Section 4-Solution Methodology) to establish nine sub problems each represent the best, expected and worst situations for three objective functions, which are constructed by taking into consideration the upper, lower and expected values of the fuzzy parameters. Different values of these coefficients can be considered in the same methodology in other applications with different problem specific objectives and constraints.

5.2. Results and analyses

This section presents and analyses the results of our computational experiments. The proposed DSS is programmed and solved using IBM ILOG CPLEX Optimization Studio, Version 12.2 on a desktop with Intel Core i5 3.50 GHz processor and 32 GB RAM. The problem is solved by the presented fuzzy multi objective programming approach taking the steps (see Section 4). The CDM model is composed of 1527 constraints and 3751 variables (of which 105 are integer variables). The size of the TNM is larger than CDM (137,537 constraints and 19,062 variables of which 2382 are integer) because of the large number of transfer stations (30 stations) considered around the region by the model. Both models are solved within approximately 5 s.

5.2.1. Results of CDM – the optimized supply chain configuration

This section describes the optimized supply chain configuration with related location, capacity and technology decisions determined by CDM. The payoff table is obtained as described in Section 3 (Steps 2 and 3). To this aim, three cases are derived, representing the best, expected and worst scenarios for each objective function. In each case, one of the upper, base or lower values of fuzzy parameters, are taken into consideration to determine the corresponding value of objective. For example, to derive the best case for profit, the lower bound of cost parameters, upper bound of revenue parameters and upper bound of biomass yield are considered, whereas the worst case for the same objective is established considering the upper bound of cost parameters, lower bound of revenue parameters and lower bound of biomass yield. Supplementary Material 2 depicts the payoff values corresponding to each objective function determined considering the upper, lower and expected values of the fuzzy parameters.

In this study, we consider profit as the objective function corresponding to f_1 of P, whereas GHG emissions and transportation distance are considered as f_2 and f_3 of P and dealt with as a constraint of P_0 (for detailed explanation regarding notations f_1, f_2, f_3, P and P_0 see Section 3.2.3). Supplementary Material 2 reports that there are five different values for ε_2 and seven different values for ε_3, which are depicted in bold characters in the Supplementary Material 2 also shows the upper and lower limits of objectives, which are emphasized with italic characters and notation l_i and u_i.

The CDM is solved considering 40 different combinations of ε_2 and ε_3, and a set of pareto optimal solutions is obtained. Supplementary Material 2 depicts the profit, GHG emissions and ton-kms values for each pareto optimal solution alternative according to each combination of ε_2 and ε_3 values (upper limit for GHG emissions and ton-kms). In addition, the table shows the corresponding membership function (μ^k) values for each solution alternative. The membership function values are calculated as described in Section 3.2.3 (Step 5), based on three different weight structures for the objective functions, to reflect the relative importance of the objectives and provide the DM for a more confident solution set;

(1) $w_{profit} = 0.6$, $w_{GHG\ Emissions} = 0.2$ and $w_{Ton\text{-}kms} = 0.2$ (WS_1),

(2) $w_{profit} = 0.2$, $w_{GHG\ Emissions} = 0.6$ and $w_{Ton\text{-}kms} = 0.2$ (WS_2),
(3) $w_{profit} = 0.2$, $w_{GHG\ Emissions} = 0.2$ and $w_{Ton\text{-}kms} = 0.6$ (WS_3).

Decision makers from different sectors and backgrounds (governmental units or private companies) can choose the best alternative according to their preferences related to objective functions considering the trade-offs between the objectives (i.e. economic vs. environmental).

The main results that can be obtained from Supplementary Material 3 are summarized in the following;

1. If maximization of total profit is the most important supply chain performance measure for a decision maker, it would be convenient to adopt the first weight structure (WS_1) ($w_{profit} = 0.6$, $w_{GHG\ Emissions} = 0.2$ and $w_{Ton\text{-}kms} = 0.2$). Hence, according to the solution methodology adopted in this study, the optimum solution should be selected as the solution with the highest μ^k value corresponding to this weight structure, which is 0.40 in our case. From Table 4, it can be observed that there are four solution alternatives with μ^k value equal to 0.4, however the 6th alternative has the highest profit value among them (€40,632/Month), which can be treated as the optimum solution in case of considering the supply chain profit as the most important performance criterion. The supply chain configured according to the decisions specified by the 6th solution alternative results in 2755 kg CO_2 eq GHG emissions and 314,093 ton-km. In this situation, 1 collection centre with 2nd (medium) capacity level is constructed in Solihull, whereas Birmingham and Solihull are selected for construction of 1 AD plant in each with the 1st (minimum) capacity level. Although there are higher profit values than €40,632/Month, such as €56,230/Month, €63,230/Month and €66,361/Month, the GHG emissions and ton-kms values corresponding to these alternatives are significantly higher than the 6th alternative, which makes the 6th alternative a rational option. If the 39th alternative is selected by decision maker, which is one of the solution alternatives that results in the highest profit value (€66,361/Month) with relatively better result in ton-kms (862,845 ton-km) in comparison with other solutions with the same profit value, the model suggests to construct 1 pre-treatment facility and 1 collection centre in Birmingham and Dudley, respectively, both with the 3rd (maximum) capacity level. In this case, 3 G plants are determined to be constructed in Birmingham, Walsall and Wolverhampton, whereas Coventry, Dudley and Sandwell are the selected counties for construction of AD plants. In this case the GHG emissions from the production and pre-processing activities in the supply chain is 2,354,048 kg CO_2 eq, which is one of the highest values offered by alternatives. However this alternative may be a preferable option for especially private companies for which the profitability is the first consideration when designing and planning a supply chain.

2. If the minimization of GHG emissions is the most important objective for the decision maker, then the second weight structure (WS_2) should be adopted ($w_{profit} = 0.2$, $w_{GHG\ Emissions} = 0.6$ and $w_{Ton\text{-}kms} = 0.2$). In this case, taking into account the highest μ^k value offered by this weight structure, 13th solution alternative can be treated as the best one, which offers 2542 kg CO_2 eq GHG emissions along with €4336/month profit and 270,767 ton-kms. The configuration results of 13th solution alternative are; 2 AD plants with the 1st capacity level are constructed in Birmingham and Walsall. Solihull and Walsall are the selected counties for construction of 2 collection centres with the 3rd capacity level. The table reports that there are other solution alternatives with the same emission value, however most of them offers less profit than the 13th solution, except for the 16th solution alternative, which offers more ton-kms than the 13th solution. With changing the supply chain design from the 13th to 16th alternative, an increase by €16,734/month in profit can be attained with an increase in ton-kms by 703,921 ton-km. Hence, trade-offs between profit and ton-kms objectives specify the alternative that can be adopted as the preferred solution.

3. If transportation distance is the most important consideration for a decision maker, the third weight structure (WS_3) should be adopted ($w_{profit} = 0.2$, $w_{GHG\ Emissions} = 0.2$ and $w_{Ton\text{-}kms} = 0.6$). It can be observed from Table 4 that the 5th solution alternative can be considered as the optimum solution for this situation, which offers 270,766 ton-km along with €34,256/month profit and 2648 kg CO_2 eq GHG emissions. However, there are alternatives which offer a better ton-kms value (78,468 ton-km) with a higher μ^k value. But configuration of the supply chain according to the decisions suggested by these alternatives results in a monthly loss by €-100,562. So, these alternatives may not be preferred by especially decision makers who cares also about profitability of the supply chain. The 6th alternative also offers a good solution in terms of ton-kms with a value of 314,093 ton-km. It also suggests a better profit value than the 5th alternative (€40,632), but a higher GHG emissions value (2755 kg CO_2 eq). Hence, it can be concluded that, changing the configuration decision from the 5th to 6th alternative, an increase by 18.6% in profit can be attained with an increase in GHG emissions by 4% and an increase in ton-kms by 16%. Since, the increase in profit is higher than the increase in ton-kms, the 6th alternative can be considered by the decision makers who also care about the profitability of the supply chain along with a well-designed and economic transportation network. 34th alternative also offers good values in terms of profit (€49,104) and ton-kms (294,911 ton-km), however GHG emissions from the supply chain configured considering this alternative is significantly higher than the 5th and 6th alternatives (2,352,021 kg CO_2 eq).

4. If we look from a more holistic point of view to select a configuration alternative which is good and reasonable in terms of all supply chain performance indicators, the 5th alternative is an appropriate option to adopt considering the average of the μ^k values corresponding to all three weight structures. This solution alternative offers the maximum average μ^k value (0.64), which means that it can be adopted if the decision maker has no strong preference regarding to the relative importance of any of the objectives.

In the following sections, a scenario analysis is conducted to reveal how the decision makers' preferences regarding to the importance of objectives impact the supply chain configuration and related supply chain performance indicators. To this aim, three scenarios, each of which represents the case of selecting one objective as the most important so as to reflect the three weight structures captured above, and are analysed.

5.2.1.1. Scenario 1. economic design with profit consideration. In the first scenario, considering the profit as the most important objective for the decision maker and adopting the first weight structure (WS_1), 39th alternative in Table 4, which is one of the solution alternatives that results in the highest profit, is specified as the preferred solution. This alternative offers €66,361 monthly profit, 2,354,048 kg CO_2 eq GHG emissions and 862,845 ton-kms. It should be noted that, all configuration alternatives with €66,361 profit value result in the same GHG emissions (2,354,048 kg CO_2 eq), hence 39th alternative is selected to adopt in the first scenario, which offers relatively better result in ton-kms (862,845 ton-km) in comparison with other solutions with the same profit value.

The resulting configuration solution offers to construct 3 AD plants, 3 G plants, 1 collection centre and 1 pre-treatment facility in the case study region. Collection centre and pre-treatment facility are constructed in Dudley and Birmingham, respectively. Birmingham, Walsall and Wolverhampton are selected as G plant

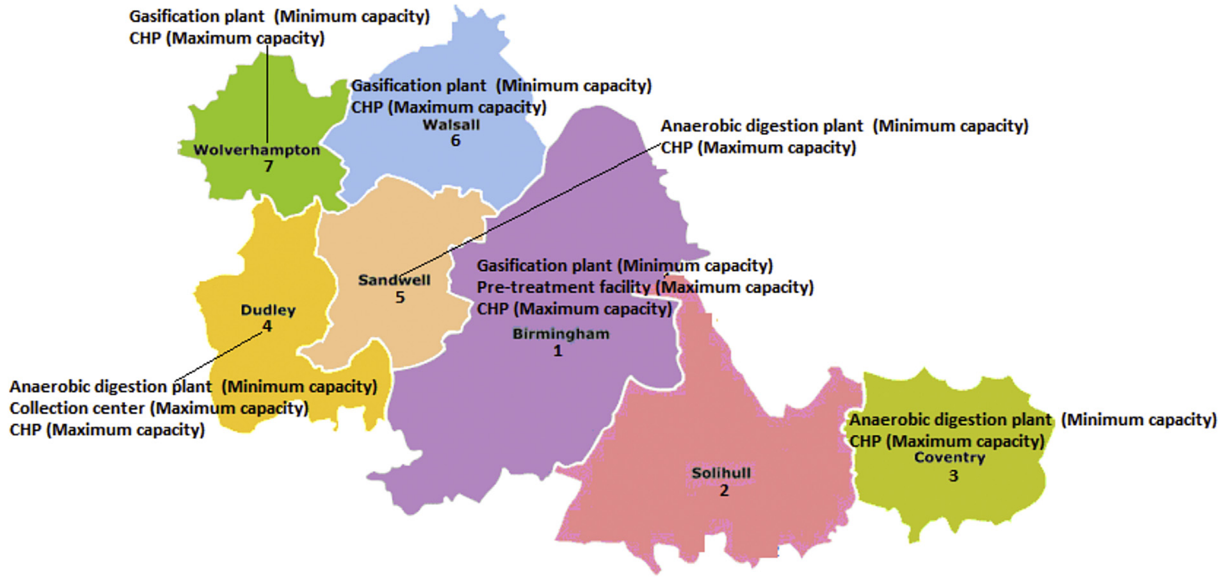

Fig. 4. Locations and capacities of bioenergy plants, CHP units, pretreatment facilities and storages.

locations, whereas AD plants are located in Coventry, Dudley and Sandwell.

Fig. 4 presents results on the configuration decisions such as locations and capacities of bioenergy plants, CHP units, pretreatment facilities and collection centres. The results reveal that, the model selects the first (minimum) capacity level for the bioenergy plants (6000 t/month for AD plants, 1500 t/month for G plant) and, the third (maximum) capacity levels for CHP units (5000 kWe). The third (maximum) capacity level is selected for both PT and CO facilities, respectively (4500 t/month for PT facility, 18,000 t/month for CO facilities).

Tactical level decisions about biofuel, energy and by-product production in bioenergy plants, amount of biomass stored in collection centres and amount of biomass treated in pre-treatment centre are depicted in Table 8. The material flow pattern is illustrated in Figs. 5–7. Fig. 5 represents the biomass flow pattern between biomass source sites and facilities, whereas Figs. 6 and 7 illustrate the biomass flow pattern between facilities and plants and bio-fertilizer flow pattern between plants and crop fields.

The amount of biomass distributed between biomass source sites, facilities and plants as well as the amount of bio-fertilizer distributed between plants and crop fields are specified in the first level by CDM and used as input parameters in the second level (TNM) of the DSS along with the configuration decisions made in the first level. Table 9 reports the biomass and bio-fertilizer distribution amounts between the nodes of the supply chain.

5.2.1.2. Scenario 2. environmental design with GHG consideration. In the environmental design scenario, the second weight structure (WS2) is assumed to be adopted by the decision maker. We suppose that the 16th solution alternative, which is one of the solutions that result in minimum environmental impact, is considered as the preferred option which offers 2542 kg CO_2 eq GHG emissions along with €21,070/month and 974,688 ton-km. This solution alternative offers the highest profit value among the alternatives that result in the same amount of GHG emissions. Adopting this solution alternative, the model determines to locate 2 AD plants in Coventry and Sandwell with the 1st capacity level (6000 t/month), 2 collection centres in Solihull and Wolverhampton with the 2nd capacity level (12,000 t/month) and 2 CHP units in Coventry and Sandwell with the 3rd capacity level (5000 kWe). The configuration of the supply chain along with the material flow pattern is illustrated in Figs. 8 and 9.

The supply chain configuration alternative offered by the second

Table 8
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	1,845,727	2,400,000	692,840 – Biomethane	4947
4. Dudley – AD	1,845,727	2,400,000	692,840 – Biomethane	4937
5. Sandwell – AD	1,845,727	2,400,000	692,840 – Biomethane	4657
6. Walsall – G	1,845,727	2,400,000	1,026,430- Syngas	–
7. Wolverhampton – G			1,026,430- Syngas	–
Facility Location	**Collection/Pretreatment Amount (ton/month)**			
1. Birmingham – PT	3818 – Waste wood			
4. Dudley- CO	8202 – Cattle manure 49.53 – Broiler manure 74.29 – Layer manure 9405 – Maize			

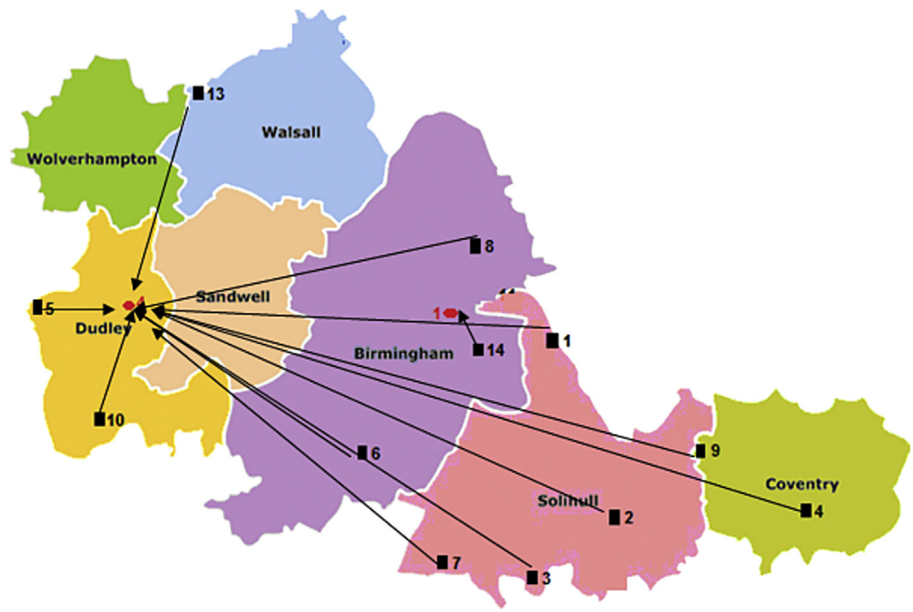

Fig. 5. Biomass flow pattern between biomass source sites and facilities.

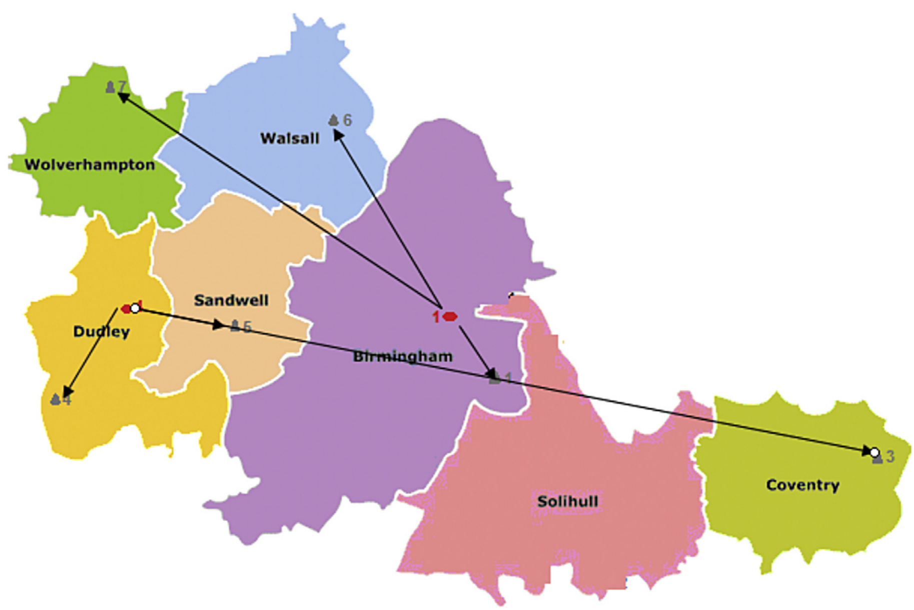

Fig. 6. Biomass flow pattern between facilities and plants.

scenario results in €42,291 lower profit than the design alternative offered by the first scenario. But the level of GHG emissions in the second scenario is significantly lower than that is offered by the first scenario, there is a difference by 2,351,506 kg CO_2 eq between scenarios. However, the second scenario suggests a less well designed configuration in terms of ton-kms, which is 111,843 ton-km more than the first scenario.

In comparison with the first scenario, there are fewer bioenergy plants constructed by the model in the second scenario, in order to make the energy production and biomass pre-treatment related GHG emissions lower as suggested by the weight structure. Constructing more bio-based plants means more bio-product production, which increases the revenues and profitability of the supply chain but results in higher GHG emissions. It should be noted that, in both scenarios the bio-product demand is met, which is ensured by the model constraints, however the difference between the excess biofuel and bioenergy production causes the difference in profit values of two scenarios. In addition, the model prefers to construct anaerobic digestion plants and collection centres instead of gasification plants and pre-treatment facilities, since the energy production via gasification and pre-treatment activities result in higher GHG emissions considering the data set related to unit emissions for these activities. Hence, the level of GHG emissions are decreased significantly in comparison with the emissions in the first scenario, in which energy production by gasification and pre-treatment activities takes place.

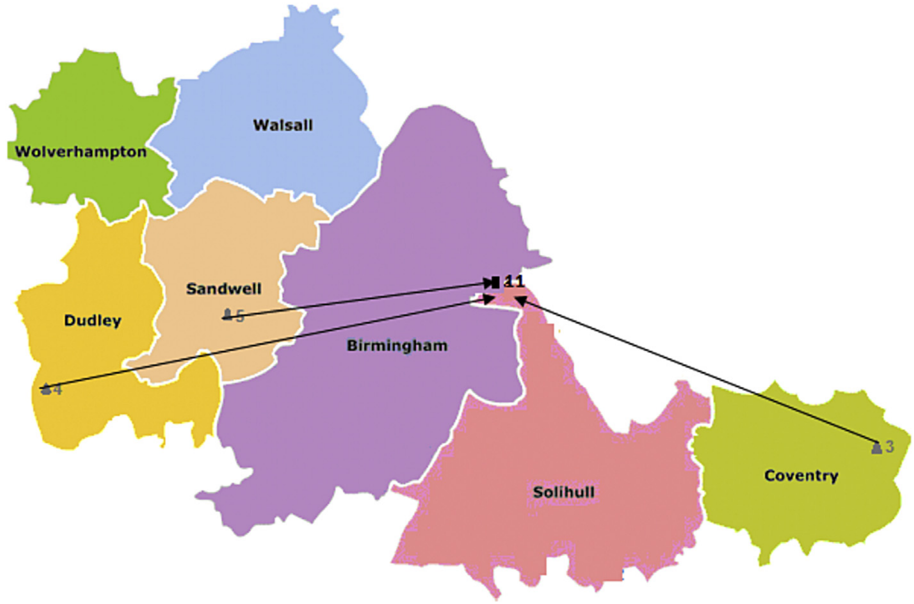

Fig. 7. Biofertilizer flow pattern between plants and crop field.

Table 9
Biomass and biofertilizer distribution amounts between the nodes of the supply chain.

Biomass Source Site	Facility	Biomass Type	Biomass Amount (ton)	Facility	Plant	Biomass Type	Biomass Amount (ton)
1	4	Cattle manure	2916	4	3	Cattle manure	2952
2	4	Cattle manure	2160	4	3	Broiler manure	49.5
3	4	Cattle manure	1116	4	3	Maize	2998
4	4	Cattle manure	1037	4	4	Cattle manure	2863
5	4	Cattle manure	973	4	4	Layer manure	74.3
6	4	Broiler manure	11.52	4	4	Maize	3061
6	4	Layer manure	17.28	4	5	Cattle manure	2387
7	4	Broiler manure	24.2	4	5	Maize	3345
7	4	Layer manure	36.3	1	1	Wood pellet	1069
8	4	Broiler manure	12.1	1	6	Wood pellet	1069
8	4	Layer manure	18.2	1	7	Wood pellet	1069
9	4	Broiler manure	0.43	**Plant**	**Crop Field**	**Biofertilizer Amount (ton)**	
9	4	Layer manure	0.64	3	11	4947	
10	4	Broiler manure	1.25	4	11	4947	
10	4	Layer manure	1.88	5	11	4947	
13	4	Maize	9405				
14	1	Waste wood	3818				

5.2.1.3. Scenario 3. proximity focused design with ton-kms consideration. In case of a well and economically designed transportation network is the first consideration of the decision maker in designing a bio-product supply chain, the third weight structure (WS3) should be adopted. In the third scenario, we assume that the 5th alternative is adopted, which offers one of the best configuration option in terms of ton-kms (270,766 ton-km) along with relatively better profit and emission values (€34,256 and 2648 kg CO_2 eq) than the other alternatives with the same ton-kms value. It should be noted that, the 5th alternative also offers the best solution from a holistic point of view according to the average μ^k values.

In this situation, the configuration results are; 2 collection centres and 2 AD plants with 1st capacity level (6000 t/month for both plants and facilities) are constructed in Solihull and Wolverhampton. 1 CHP is constructed in each of the both regions, in Solihull with the 2nd capacity level and in Wolverhampton with the 3rd capacity level. The configuration of the supply chain along with the material flow pattern is illustrated in Fig. 10. In the figure, the solid lines, dotted lines and dashed lines represent the biomass flow between biomass sites and facilities, biomass flow between facilities and plants and bio-fertilizer flow between plants and crop fields, respectively.

Fig. 10 reveals that there are remarkably less transportation activities in the supply chain designed in the third scenario which is conducted considering the third weight structure and the 5th solution alternative. In this situation, the model located the plants and facilities in the same regions so as to minimize the total ton-kms. In addition, as can be observed from the figure, the model designs the material distribution pattern in a way that enables more material to be supplied from nearer locations than distant locations in comparison with the first two scenarios. Although the collection centres are located in the same regions as in the second scenario (environmental design), the biomass flow pattern from biomass sites to facilities is remarkably different from the second scenario. It should be noted that, the weight of the ton-kms is far more less than the weight of the GHG emissions in the second scenario, hence the model configured the supply chain with less focus on the ton-kms. As a result, the material flow pattern is not

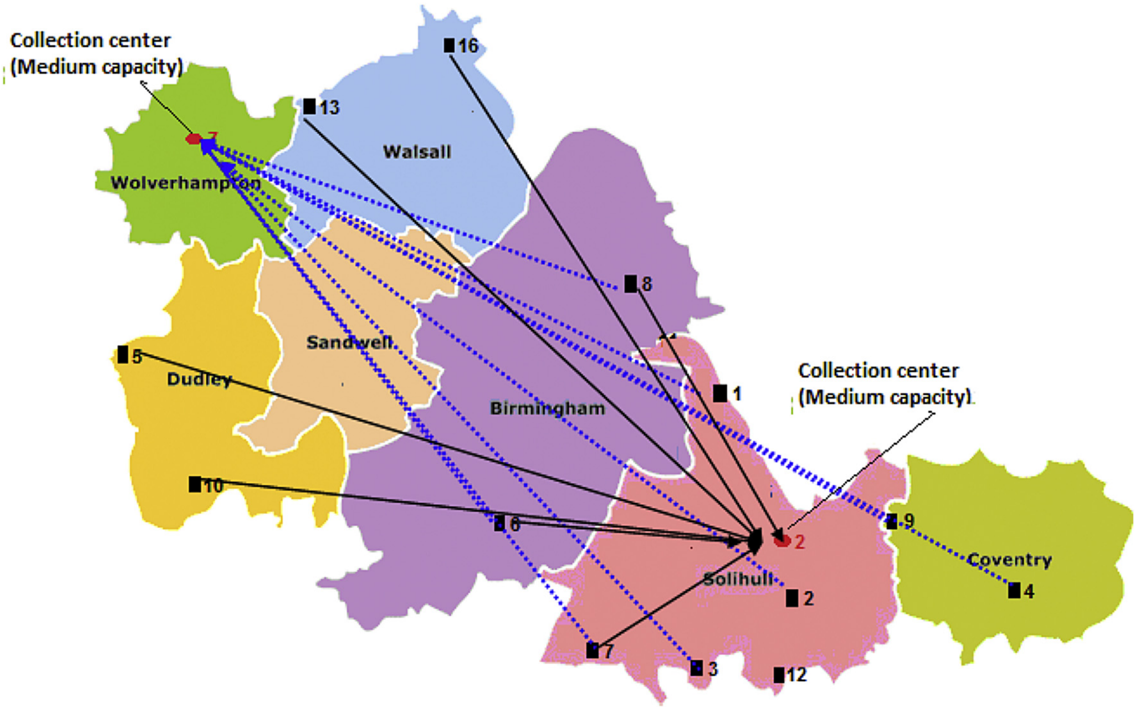

Fig. 8. Locations and capacities of collection centres and biomass flow pattern between collection centres and biomass sites.

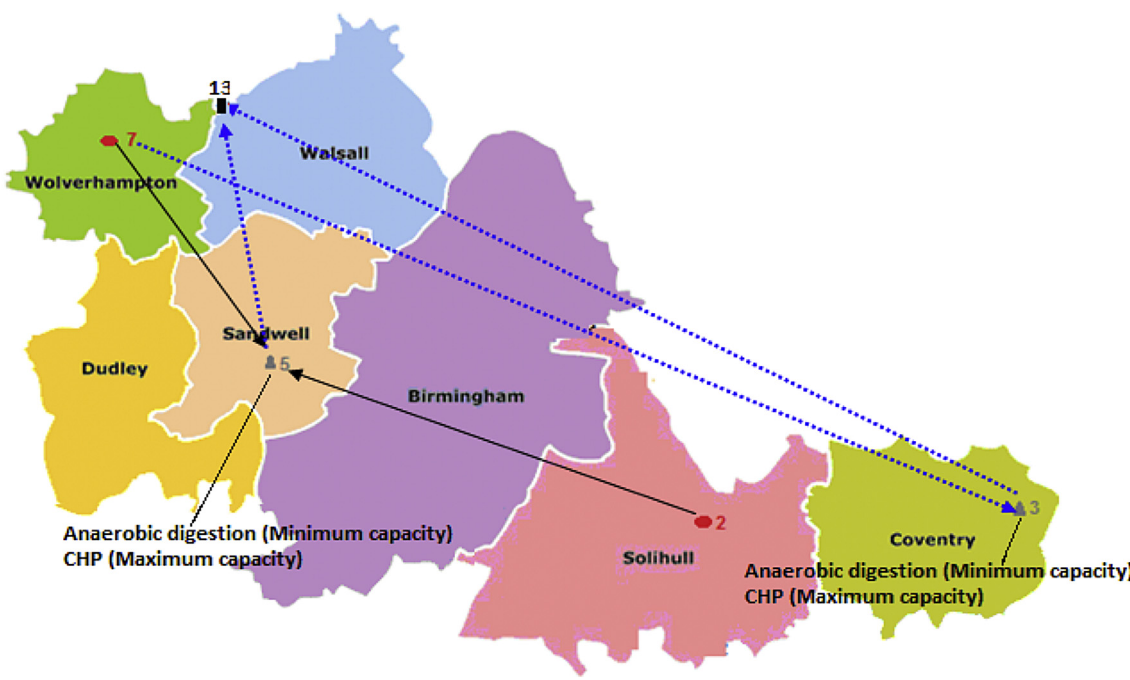

Fig. 9. Locations and capacities of plants and biomass flow pattern between collection centres and plants.

effectively designed, which means there are more material flows from distant regions than nearby. However, giving the ton-kms objective more weight in the third scenario, the model focuses on this objective, which results in a remarkably better designed flow pattern.

5.2.2. Results of TNM — the optimized transportation network

In the second level of the DSS, the transportation network is optimized considering the decisions regarding locations and distribution amounts given by CDM in the first level of DSS. In this phase of the DSS, the TNM aims to determine the optimum mode of transportation (single mode or multimodal); in case of single mode selection, the optimum option for single mode transportation among available options (road or rail); in case of multimodal selection, the optimum combination of modes among available options (road-rail or rail-road) and the optimum transfer stations

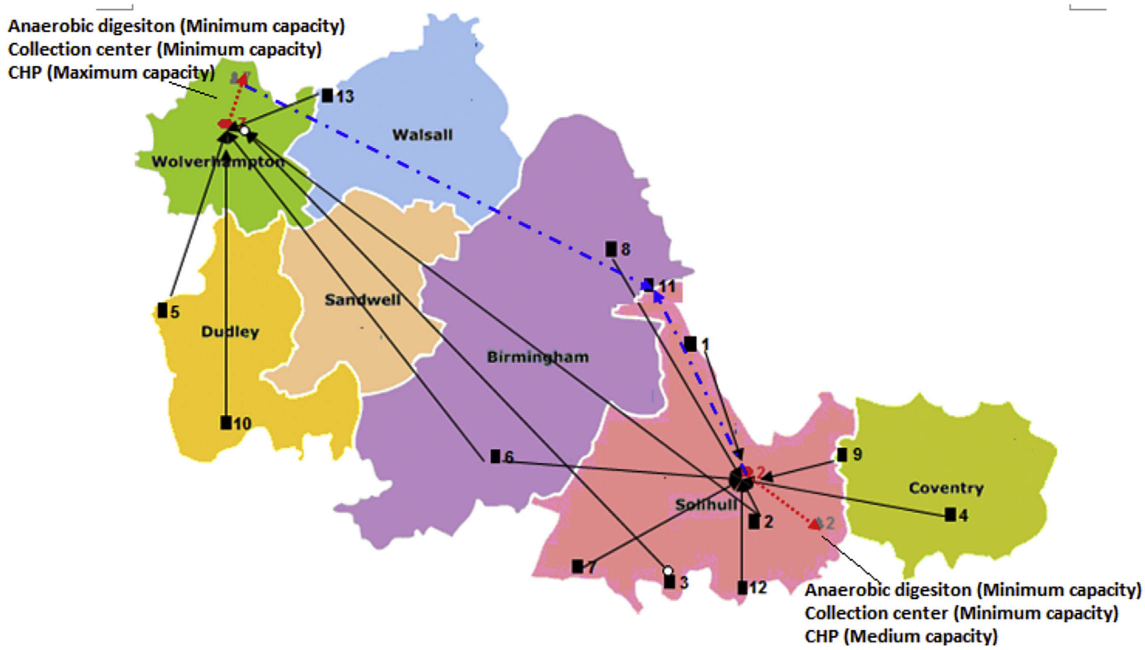

Fig. 10. Configuration of the supply chain along with the material flow patterns.

among a set of available stations between locations, considering the trade-offs between transportation cost, GHG emissions related to transportation and transportation time. As solution methodology, the modified ε-constraint method is used in the same way as it is used in the first level. In this section, based on the scenario analyses conducted in the previous section, the supply chain configuration suggested by the first scenario (economic design with profit consideration) is adopted and TNM is applied taking into account the decisions related to the location, capacity, technology and material flow pattern and amounts between locations, which are made by CDM. The reasons of choosing the configuration offered by the first scenario is twofold; 1. There are more plants constructed in the case study region in comparison with the third scenario and hence more material flows along with a higher ton-kms value specified by the CDM, so that the applicability of the TNM can be explored in more detail and reliably, 2. This scenario offers higher profit than the other two scenarios, which is the most important consideration in most of the practical applications. In addition, a sensitivity analysis is also conducted in this section, to investigate the impacts of different configuration decisions which are made in the above mentioned three scenarios, on the optimized transportation network.

The payoff table, which depicts the payoff values corresponding to each objective function, is represented by Supplementary Material 4. As in the first level of DSS, the upper, expected and lower bounds of parameters (in this case, unit transportation cost, transportation related GHG emissions and unit transportation time parameters) are taken into consideration to establish the best, expected and worst cases.

In this phase, we consider transportation cost as the objective function corresponding to f_1 of P, whereas GHG emissions and transportation time are considered as f_2 and f_3 of P and dealt with as a constraint of P_0. The table reveals that the results corresponding to the objective values that are obtained by minimization of transportation related GHG emissions and minimization of transportation time are the same in each case, which means optimization according to these two objectives result in the same supply chain configuration. This argument is reasonable because minimization of transportation time means minimization of the total transportation distance, which results in less transportation activities and hence less GHG emissions associated with transportation activities. Hence these two objectives change in parallel to each other.

Supplementary Material 4 reports that there are six different values for each of the ε_2 and ε_3, which are depicted in bold characters in the table, which also shows the upper and lower limits of objectives, which are emphasized with italic characters and notation l_i and u_i. Hence, the TNM is solved considering 36 different combinations of ε_2 and ε_3, and a set of pareto optimal solutions is obtained. Supplementary Material 5 depicts the cost, GHG emissions and transport time values for each pareto optimal solution alternative according to each combination of ε_2 and ε_3 values (upper limit for GHG emissions and transport time). In addition, the table shows the corresponding membership function (μ^k) values for each solution alternative. The membership function values are derived based on three different weight structures for the objective functions as in the first level of DSS. These weight structures reflect different preferences related to economic, environmental and service level objectives. These weight structures are given as follows;

1. $W_{cost} = 0.6$, $w_{GHG\ Emissions} = 0.2$ and $w_{Transport\ time} = 0.2$ (WS_1),
2. $W_{cost} = 0.2$, $w_{GHG\ Emissions} = 0.6$ and $w_{Transport\ time} = 0.2$ (WS_2),
3. $W_{cost} = 0.2$, $w_{GHG\ Emissions} = 0.2$ and $w_{Transport\ time} = 0.6$ (WS_3).

It should be noted that the total transportation distance, transportation amounts and the routes, which are specified in the first level of DSS by CDM, are the same for all of the alternatives. However, alternatives differentiate in the transportation modes and options selected by TNM in the second phase. In this phase of DSS, TNM specifies the most appropriate mode (single mode or multimodal) and option (road, rail, road+rail, rail+road) to transport biomass and bio-fertilizer between prespecified locations considering a set of available options between these locations in the case study region. The main implications that can be obtained from

Supplementary Material 5 are summarized in the following;

1. If minimization of transportation cost is the most important supply chain performance measure for a decision maker, it would be convenient to adopt the first weight structure (WS_1) ($w_{cost} = 0.6$, $w_{GHG\ Emissions} = 0.2$ and $w_{Time} = 0.2$). Hence, according to the solution methodology adopted in this study, the optimum solution should be selected as the solution with the highest μ^k value corresponding to this weight structure, which is 0.71 in our case. From Table 13, it can be observed that there are two pareto optimal solutions with μ^k value equal to 0.71, the 26th and 32nd solutions, both give the same cost, GHG emissions and time values. Configuring the transportation network according to these solutions result in €336,446 transportation cost, 118,346 kg CO_2 eq GHG emissions and 478 min transportation time.

2. If minimization of GHG emissions is the most important objective for the decision maker, then the second weight structure (WS_2) should be considered ($w_{profit} = 0.2$, $w_{GHG\ Emissions} = 0.6$ and $w_{Ton\text{-}kms} = 0.2$). In this case, taking into account the highest μ^k value offered by this weight structure, 20th solution alternative can be treated as the best one, which offers 105,266 kg CO_2 eq GHG emissions along with €448,748 cost and 448 min transport time. This alternative is followed by 14th solution option which offers 106,511 kg CO_2 eq GHG emissions along with €446,472 cost and 448 min transport time.

3. If transportation time is the most important consideration for a decision maker, the third weight structure (WS_3) should be selected ($w_{profit} = 0.2$, $w_{GHG\ Emissions} = 0.2$ and $w_{Ton\text{-}kms} = 0.6$). In this situation, giving the same time value (448 min), the 14th and 20th solutions offer the maximum μ^k value (0.73). However the 20th alternative results in a lower GHG emission with a higher cost value than the 14th option. The optimum solution can be chosen based on the preferences of the decision maker. Changing the configuration of the supply chain from the alternative offered by the 14th option to the 20th option results in a decrease in GHG emissions by 1245 kg CO_2 eq can be attained with €2276 increase in transportation cost.

4. According to the average of the μ^k values corresponding to all three weight structures, the 26th alternative can be selected as an appropriate option, if the aim of the decision maker is to select a configuration alternative which is good in terms of all supply chain performance indicators. This solution alternative offers the maximum average μ^k value (0.68), which means that it can be adopted if the decision maker has no strong preference regarding to the relative importance of any of the objectives.

According to the results given in Supplementary Material 5, we present the decisions on transportation network offered by the 26th (€336,446 transportation cost, 118,346 kg CO_2 eq GHG emissions and 478 min transport time) and the 20th (€448,748 cost, 105,266 kg CO_2 eq GHG emissions and 448 min transport time) alternatives to reflect the situations that; 1. the most important criterion for decision maker is cost and 2. the most important criteria for decision maker is GHG emissions and/or time. The transportation decisions described by these two alternatives are prescribed in Appendix B.

It can be observed from the tables that if transportation cost is the major consideration when designing the transportation network between the specified locations, the model selects single mode transportation with road option for all routes. However, in the cases that environmental impacts of transportation related activities and/or the service level in terms of total transportation time are the most important criteria for the decision maker, the model adopts single mode rail and multimodal (road+rail and rail+road) transportations, choosing the most appropriate mode and option considering the available options between the locations.

5.2.3. *Sensitivity analyses*

This section presents the results of the sensitivity analyses that are conducted to reveal the relationships between supply chain performance measures (supply chain profit, production related GHG emissions and ton-kms), configuration decisions (plant and facility numbers/locations/capacities) and transportation network performance measures (transportation cost, transportation related GHG emissions and transportation time). More specifically, the impacts of the changes in supply chain performance measures and configuration decisions on transportation network performance measures are analysed by the sensitivity analyses. To this aim, we have chosen 10 supply chain configuration results (depicted in the Table in Supplementary Material 6) made by CDM among 40 pareto optimal solutions in Supplementary Material 3 and ran the model considering the data set of these 10 options to get the results related to configuration of the supply chain as well as transportation network performance measures. Then, we have analysed the impact of the supply chain decisions on the transportation network performance measures to reveal the relationships between the supply chain objectives/performance measures and transportation network performance measures. Table in Supplementary Material 6 presents the results on the performance of the transportation network according to 10 different supply chain configuration options and corresponding supply chain performance measures derived from Supplementary Material 3. Fig. 1 in Supplementary Material 6 represents the change of transportation performance indicators by the changes in the supply chain performance measures.

It can be observed from the Fig. 1.1 that, the transportation cost decreases in parallel with the decrease in profitability of the supply chain, which means that the transportation networks optimized taking into account configurations that offer relatively less profitability will be less costly. Fig. 1.7 depicts that the total ton-kms of the supply chain also effects the transportation cost. Designing the transportation network considering the configuration options which result in less total ton-kms will be more cost effective, which is also the case for the practical applications. However, Fig. 1.4 reveals that there is no remarkable relationship pattern between GHG emissions associated with production activities and transportation cost that the configuration options which result in either low or high GHG emissions may offer lower transportation cost. The figure also reveals that, transportation related GHG emissions and transportation time do not have a strong relationship with both profitability and production related GHG emissions, which means that we cannot foresee the resulting transportation related GHG emissions and transport time corresponding to a transportation network which is designed taking into account a supply chain configuration with maximized profit or minimized production related GHG emissions. However, it can be concluded from Figs. 1.8 and 9 that the total ton-kms of the supply chain have a more remarkable effect on both transportation related GHG emissions and transportation time as well as transportation cost. This result also reveals that the proposed DSS is viable because the transportation focused configuration design in the first level results in better transportation network performance as it is expected in practical applications.

Fig. 2 in Supplementary Material 6 presents the results of the sensitivity analyses on the impact of the configuration decisions in terms plant numbers on the supply chain and transportation network performance measures. The results (Fig. 2.1) reveal that there is not a significant trend representing the relationship between profitability and total plant number, which means that we can not predict the profitability of a supply chain by only taking into account the total plant number or the configuration designed by economic considerations such as profit maximization does not necessarily result in a high number of plants. The same thing is true for the relationship between the total ton-kms and total plant number (Fig. 2.3). Configuring the supply chain focusing on minimization of transportation activities does not always result in decreased plant numbers. However, it can also be observed that there is a relationship between total plant number and production related GHG emissions (Fig. 2.2). Configuring the supply chain with environmental considerations result in a lower number of plants. Fig. 2.2 reveals that the configurations with total plant number less than or equal to 4 result in significantly lower GHG emissions and Fig. 2.8 reveals that the decrease in GHG emissions caused by the decrease in G plants. If we investigate the relationship between total plant number and transportation network performance, Fig. 2.4 offers that there is not an explicit relationship between transportation cost and plant number, similarly between transport time and plant number (Fig. 2.6), which means that total plant number does not have a strong impact on the transportation cost and time. However, there is a relationship between total plant number and transportation related GHG emissions (2.5), emissions decrease in parallel with the plant number to a certain extent and then plant number rises dramatically even though the emission value decreases, and then again emissions tends to decrease with plant number.

Looking the relationship between AD/G plant numbers and supply chain performance indicators (Fig. 2.7–2.12), reveals that AD plant number is not impacted significantly by any of the three performance measures, profit, production related GHG emissions or ton-kms, which means that the focus of the design process (economic, environmental or transportation) does not effect the number of AD plants, or correlatively the number of AD plants does not effect significantly any of the supply chain performance measures, it shows an almost constant trend whatever the value of the objectives are. However, number of G plants changes remarkably with the changes in supply chain performance indicators. There is not a pattern for profit and ton-kms that change obviously with number of G plants, however we can conclude that the production related GHG emissions is highly impacted by the number of G plants, the less G plants in the supply chain means less production related GHG emissions. Similarly the number of G plants in the supply chain effects the GHG emission level of the chain. If the effects of AD and G plant numbers on the transportation network performance are investigated, we can see that the transportation cost is significantly lower when there are no G plants in the supply chain. We cannot interpret the relationship between G plant number and transportation related GHG emissions and transport time as there is not a regular relationship between them. The same situation is true for AD plants since the number of AD plants does not change in parallel with the changes in transportation network performance measures.

6. Conclusions

The main focus of this study is developing mathematical modelling based optimization methodologies to design sustainable supply chains and transportation networks to produce bio-products by multiple technologies. To this aim, a bi-level DSS is developed comprising two interconnected models. Although these two levels of the DSS are related and interconnected to each other, they differentiate in the scope of decisions they adopt. The first level includes strategic level decisions which have long term impact and may need revisions after a long time period usually five or more years. It decides what the supply chain's configuration will be and how resources will be allocated, which are the decisions usually taken at the highest levels of management and carry higher levels of risk. The second level deals with tactical level decisions that are medium term decisions usually spanning between six months and one year (De Meyer et al., 2015). They are usually made by medium level management units within the constraints of the overarching strategic supply chain decisions. They can also be made by the supplier(s) of the company which outsource elements of the distribution and fulfilment services. For example, in our case a third-party logistics firm can make the second level decisions considering the first level decisions made by the management of their client company. The two optimization models can be used either together to design a comprehensive supply chain and transportation network or separately to configure the supply chain or given the configuration to plan the transportation network.

Future uncertainties caused by changes in governmental regulations, economic conditions, competition between firms in the energy market and environmental conditions as well as technological developments effect the economic and environmental performance of the supply chain especially over the medium and longer term horizons. Hence, medium and long term decisions related to supply chain configuration and material transportation should be revised and remade using a proper methodology after a specific time period to minimize the effect of possible uncertainties. In this study, a hybrid fuzzy multi-objective decision making method is proposed to handle problem specific uncertainties effectively. Computational experiments are performed to explore the viability of the proposed DSS. Three scenarios are analysed to provide a broader perspective from three different point of views, economic, environmental and proximity. In addition, the impacts of configuration design on the performance of transportation network is analysed by sensitivity analyses to reveal the interconnectivity between two levels of the DSS. The analyses provide managerial insights to aid companies and policy makers in making supply chain and transportation related decisions.

The proposed DSS integrate two comprehensive mathematical models and a novel fuzzy multi objective solution methodology. The mathematical models that are integrated to each other by DSS enable to make a wide range of decisions from the detailed configuration of the production chain to material flow amounts and transportation mode selection considering all supply chain activities from feedstock procurement to end use of products that are needed to be handled in designing and operating large scale supply chains. One of the most important advantage of the optimization procedure employed by DSS is that it handles both system specific uncertainties (through the fuzzy solution methodology) and different sustainability aspects (by the mathematical models) considering six objectives representing economic, environmental and service level perspectives. The proposed solution methodology overcomes two issues related to ε-constraint method by employing fuzzy logic; calculation of the ranges of objective functions and generating pareto optimal solutions and selecting the most efficient one among them as explained in Section 4. The proposed approach enhances the capital investment and technology management decisions along with production/distribution planning for comprehensive design of a bio-based system. The DSS can be utilized 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 and take the necessary actions to improve the performance.

The optimization models are generalizable and can be adapted to different design and planning scenarios using the same general framework. Our models can be utilized for various supply chain design problems with only updating the data set. Future research opportunities include applying the DSS to different cases with additional, case-specific constraints and parameters. Our case study handles a regional design problem to guide overall targets on bio-product supply chains, however it is also possible to apply the same methodology for use by a single company for strategic design and tactical planning of its own supply chain under similar production and supply targets. Future research can also include extending the methodology to a multi period structure to capture the fluctuations over time in the system parameters such as energy prices, biomass supply and energy demand. Furthermore, in this study three different weight structures are considered to reflect relative importance of the objectives in both models. In future research, different weights can be selected to represent perspectives of different decision makers. This research can also be further extended to include a multi criteria decision making methodology so as to determine the relative weights of the objectives to be used in the last step of the solution methodology.

Acknowledgements

This research is a part of Şebnem Yılmaz Balaman's post doctoral research project which is financially supported by TÜBITAK(The Scientific and Technological Research Council of Turkey) 2219-National Postdoctoral Research Scholarship Programme.

Appendix A. Notations of the indices, parameters and decision variables for CDM and TNM

A1. Notations for CDM

Indices	
i	*Biomass source sites*
j	*Candidate locations for facilities*
k	*Candidate locations for energy plants*
l	*Demand nodes*
b	*Biomass types*
u	*First Generation Product types*
f	*Byproduct types*
n	*Second Generation Product types*
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^k_{pt}	*1 if an energy plant of capacity p and technology t is located at k, 0 otherwise*
B^j_{ec}	*1 if a facility of capacity e and type c is located at j, 0 otherwise*
CHP^k_q	*1 if a CHP of capacity q is located in an energy plant at k, 0 otherwise*
2. Positive variables	
S^{ij}_{cb}, S^{jk}_{tb}	*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^{kl}_{tu}	*Amount of product u produced in energy plant k with technology t to meet demand of node l (m^3)*
SF^{kl}_{tf}	*Amount of byproduct f distributed from energy plant k with technology t to demand node l (ton)*
SE^{kl}_n	*Amount of energy n produced in plant k to meet demand of node l (kWh)*
PR^k_{tu}	*Amount of product u produced at energy plant k with technology t (m^3)*
F^k_{tf}	*Amount of byproduct f produced at energy plant k with technology t (ton)*
E^k_n	*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^l_u, D^l_f, D^l_n	*Amount of demand; of product u, byproduct f and energy n at demand node l (m^3)*
BS^i_b	*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	
$I_{pt}, I_{ec}, ICHP$	*Unit investment cost of; energy plant of capacity level p with technology t, facility of capacity level e with type c (€/ton), CHP (€/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)*
PB_b, PW	*Unit cost of biomass b, auxiliary material (€/ton)*
P_{ut}, P_{ft}, P_{nt}	*Unit price of; product u (€/m^3), byproduct f (€/ton), energy n produced by technology t (€/kWh)*
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}, d_{bc}	*Conversion rate of biomass b; to product u by plant technology t (m^3/ton), to byproduct f by plant technology t (%), in facility with type c (%)*
e_{un}	*Conversion rate of product u to energy n (kWh/m^3)*
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)
7. Other parameters	
DF	*Discounting factor*

A2. Notations for TNM

Indices	
i	*Biomass source sites*
j	*Locations of facilities*
k	*Locations of energy plants*
l	*Demand nodes*
b	*Biomass types*
g	*Transshipment stations between biomass source sites and facilities*
v	*Transshipment stations between facilities and energy plants*
z	*Transshipment stations between energy plants and biomass source sites*
α, β	*Transportation modes*

Decision Variables

1. Binary variables	
$X^{ij}_\alpha, X^{jk}_\alpha, X^{kl}_\alpha$	*1 if transportation mode α is used to transport; biomass from biomass source site i to facility j, biomass from facility j to plant k, byproduct form plant k to demand node l, (single mode transportation)0 otherwise*
$Y^{ijg}_{\alpha\beta}, Y^{jkv}_{\alpha\beta}, Y^{klz}_{\alpha\beta}$	*1 if biomass/byproduct is transshiped from transportation mode α to mode β; at station g between biomass source site i and facility j, at station v between facility j and plant k, at station z between plant k and demand node l, (multimodal transportation)0 otherwise*

(*continued*)

2. Positive variables	
$M1^{ij}_{\alpha b}, M1^{jk}_{\alpha b}, M1^{kl}_{\alpha f}$	*Amount of biomass b/byproduct f transported by transportation mode a from; biomass source site i to facility j, facility j to energy plant k, energy plant k to demand node l (single mode transportation) (ton)*
$M2^{ig}_{\alpha b}, M3^{gj}_{\alpha b}$	*Amount of biomass b transported by; transportation mode a from biomass source site i to transshipment station g, transportation mode b from transshipment station g to facility j (multimodal transportation between i and j) (ton)*
$M2^{jv}_{\alpha b}, M3^{vk}_{\beta b}$	*Amount of biomass b transported by; transportation mode a from facility j to transshipment station v, transportation mode b from transshipment station v to plant k (multimodal transportation between j and k) (ton)*
$M2^{kz}_{\alpha f}, M3^{zl}_{\beta f}$	*Amount of byproduct f transported by; transportation mode a from plant k to transshipment station z, transportation mode b from transshipment station z to demand node l (multimodal transportation between k and l) (ton)*
Parameters	
$TCvar_{\alpha b}$	*Variable cost of transportation of biomass b by mode a (€/ton-km)*
$TCfix_{ab}$	*Fixed cost of transportation by mode a (€/ton)*
TT_a	*Transportation time by transportation mode a (h/km)*
$TRT_{\alpha\beta}$	*Transshipment time from transportation mode a to transportation mode b (h)*
$TCap_a$	*Total transportation capacity of transportation mode a (ton)*
Distances	
$d1^{ij}, d1^{jk}, d1^{kl}$	*Distances from; biomass source site i to facility j, facility j to plant k, plant k to demand node l (km)*

(*continued*)

$d2^{ig}, d2^{jv}, d2^{kz}$	*Distances from; biomass source site i to station g, facility j to station v, plant k to station z (km)*
$d3^{gj}, d3^{vk}, d3^{zl}$	*Distances from; station g to facility j station v to plant k, station z to demand node l (km)*
Availability	
$AV1^{ij}_a, AV1^{jk}_a, AV1^{kl}_a$	*Availability of transportation mode a from; biomass source site i to facility j, facility j to energy plant k, energy plant k to demand node l (single mode transportation)*
$AV2^{ig}_a, AV3^{gj}_b$	*Availability of; transportation mode a from biomass source site i to transshipment station g, transportation mode b from transshipment station g to facility j (multimodal transportation between i and j)*
$AV2^{jv}_a, AV3^{vk}_b$	*Availability of; transportation mode a from facility j to transshipment station v, transportation mode b from transshipment station v to plant k (multimodal transportation between j and k)*
$AV2^{kz}_a, AV3^{zl}_b$	*Availability of; transportation mode a from plant k to transshipment station z, transportation mode b from transshipment station z to demand node l (multimodal transportation between k and l)*
Carbon Emissions	
$CEvar_{\alpha b}$	*Variable GHG emissions associated with transportation by mode a (*kg CO_2 eq/ton-km*)*
$CEfix_a$	*Fixed GHG emissions associated with transportation by mode a (*kg CO_2 eq/ton*)*
Other parameters	
$ST^{ij}, ST^{jk}, ST^{kl}$	*Total amount of biomass/byproduct shipped from; biomass source site i to facility j, facility j to energy plant k, energy plant k to demand node l (ton)*

Appendix B. Transportation decisions for the 26th and 20th solutions

Biomass source site	Facility	Biomass	Amount	26th solution alternative			20th solution alternative		
				Transportation mode	Transportation option	Transfer station	Transportation mode	Transportation option	Transfer station
1	4	Cattle manure	2916	Single	Road	–	Single	Road	–
2	4	Cattle manure	2160	Single	Road		Multi	Road+Rail	1 (Solihull)
3	4	Cattle manure	1116	Single	Road		Single	Road	–
4	4	Cattle manure	1037	Single	Road		Single	Road	–
5	4	Cattle manure	973	Single	Road		Multi	Road+Rail	17(Wolverhampton)
6	4	Broiler manure	11.52	Single	Road		Single	Road	–
6	4	Layer manure	17.28	Single	Road		Single	Road	–
7	4	Broiler manure	24.2	Single	Road		Single	Rail	–
7	4	Layer manure	36.3	Single	Road		Single	Rail	–
8	4	Broiler manure	12.1	Single	Road		Single	Road	–
8	4	Layer manure	18.2	Single	Road		Single	Road	–
9	4	Broiler manure	0.43	Single	Road		Single	Rail	–
9	4	Layer manure	0.64	Single	Road		Single	Rail	–
10	4	Broiler manure	1.25	Single	Road		Single	Road	–
10	4	Layer manure	1.88	Single	Road		Single	Road	–
13	4	Maize	9405	Single	Road		Single	Rail	–
14	1	Waste wood	3818	Single	Road		Single	Road	–

(*continued on next page*)

(*continued*)

Biomass source site	Facility	Biomass	Amount	26th solution alternative			20th solution alternative		
				Transportation mode	Transportation option	Transfer station	Transportation mode	Transportation option	Transfer station
Facility	Plant	Biomass	Amount	**26th solution alternative**			**20th solution alternative**		
				Transportation mode	Transportation option	Transfer station	Transportation mode	Transportation option	Transfer station
4	3	Cattle manure	2952	Single	Road	–	Single	Road	–
4	3	Broiler manure	49.5	Single	Road		Single	Road	–
4	3	Maize	2998	Single	Road		Single	Road	–
4	4	Cattle manure	2863	Single	Road		Single	Road	–
4	4	Layer manure	74.3	Single	Road		Single	Road	–
4	4	Maize	3061	Single	Road		Single	Road	–
4	5	Cattle manure	2387	Single	Road		Single	Rail	–
4	5	Maize	3345	Single	Road		Single	Rail	–
1	1	Wood pellet	1069	Single	Road		Single	Road	–
1	6	Wood pellet	1069	Single	Road		Multi	Rail+Road	12(Berkswell)
1	7	Wood pellet	1069	Single	Road		Multi	Rail+Road	6 (Marston Green)

Plant	Biomass Source Site (Crop Field)	Biofertilizer Amount (ton)	26th solution alternative			20th solution alternative		
			Transportation mode	Transportation option	Transfer station	Transportation mode	Transportation option	Transfer station
3	11	4947	Single	Road	–	Single	Road	–
4	11	4947	Single	Road		Single	Road	
5	11	4947	Single	Road		Single	Road	

Appendix C. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jclepro.2017.11.150.

References

Ahmadi, A., Ahmadi, M.R., Nezhad, A.E., 2014. A lexicographic optimization and augmented ε-constraint technique for short-term environmental/economic combined heat and power scheduling. Elect. Pow. Comp. Syst. 42 (9), 945–958.

Andersen, F., Iturmendi, F., Espinosa, S., Diaz, M.S., 2012. Optimal design and planning of biodiesel supply chain with land competition. Comput. Chem. Eng. 47, 170–182.

Aviso, K.B., Tan, R.R., Culaba, A.B., Cruz Jr., J.B., 2011. Fuzzy input–output model for optimizing eco-industrial supply chains under water footprint constraints. J. Clean. Prod. 19, 187–196.

Chankong, V., Haimes, Y.Y., 1983. Multiobjective Decision Making: Theory and Methodology (North-Holland, New York).

Chen, C., Fan, Y., 2012. Bioethanol supply chain system planning under supply and demand uncertainties. Transp. Res. Part E Logist. Transp. Rev. 48 (1), 150–164.

Čuček, L., Lam, H.L., Klemeš, J.J., Varbanov, P.S., Kravanja, Z., 2010. Synthesis of regional networks for the supply of energy and bio-products. Clean Technol. Environ. Policy 12, 635–645.

Čuček, L., Varbanov, P.S., Klemeš, J.J., Kravanja, Z., 2012. Total footprints-based multi-criteria optimisation of regional biomass energy supply chains. Energy 44 (1), 135–145.

De Meyer, A., Cattrysse, D., Van Orshoven, J., 2015. A generic mathematical model to optimise strategic and tactical decisions in biomass-based supply chains (OPTIMASS). Eur. J. Oper. Res. 245, 247–264.

De Meyer, A., Snoeck, M., Cattrysse, D., Van Orshoven, J., 2016. A reference data model to support biomass supply chain modelling and optimisation. Environ. Modell. Softw. 83, 1–11.

Esmaili, M., Amjady, N., Shayanfar, H.A., 2011. Multi-objective congestion management by modified augmented e-constraint method. Appl. Energy 88 (3), 755–756.

Flodén, J., Williamsson, J., 2016. Business models for sustainable biofuel transport: the potential for intermodal transport. J. Clean. Prod. 113, 426–437.

Galvez, D., Rakotondranaivo, A., Morel, L., Camargo, M., Fick, M., 2015. Reverse logistics network design for a biogas plant: an approach based on MILP optimization and Analytical Hierarchical Process (AHP). J. Manuf. Syst. 37, 616–623.

Giarola, S., Zamboni, A., Bezzo, F., 2012a. Environmentally conscious capacity planning and technology selection for bioethanol supply chains. Renew. Energy 43, 61–72.

Giarola, N., Shah, A., Bezzo, F., 2012b. A comprehensive approach to the design of ethanol supply chains including carbon trading effects. Biores. Technol. 107, 175–185.

Gonela, V., Zhang, J., Osmani, A., 2015a. Stochastic optimization of sustainable industrial symbiosis based hybrid generation bioethanol supply chain. Comput. Ind. Eng. 87, 40–65.

Gonela, V., Zhang, J., Osmani, A., Onyeaghala, R., 2015b. Stochastic optimization of sustainable hybrid generation bioethanol supply chains. Transp. Res. Part E Logist. Transp. Rev. 77, 1–28.

Haimes, Y.Y., Lasdon, L.S., Wismer, D.A., 1971. On a bicriterion formulation of the problems of integrated system identification and system optimization. IEEE Trans. Syst. Man. Cybern. SMC 1 (3), 296–297.

International Energy Agency, 2009. Transport, Energy and CO2: Moving toward Sustainability.

Kreutzberger, E., Macharis, C., Vereecken, L., Woxenius, J., 2003. Is intermodal freight transport more environmentally friendly than all-road freight transport: a review. In: Paper Presented at the NECTAR Conference No 7, Umeå, Sweden June 13–15.

Lindholm, E., Berg, S., 2005. Energy requirement and environmental impact in timber transport. Scand. J. For. Res. 20 (2), 184–191.

Lu, X., Withers, M.R., Seifkar, N., et al., 2015. Biomass logistics analysis for large scale biofuel production: case study of loblolly pine and switchgrass. Biores. Technol. 183, 1–9.

Marufuzzaman, M., Ekşioğlu, S.D., Hernandez, R., 2014a. Environmentally friendly supply chain planning and design for biodiesel production via wastewater sludge. Transp. Sci. 48 (4), 555–574.

Marufuzzaman, M., Ekşioğlu, S.D., Huang, Y., 2014b. Two-stage stochastic programming supply chain model for biodiesel production via wastewater treatment. Comput. Oper. Res. 49, 1–17.

Marufuzzaman, M., Ekşioğlu, S.D., Li, X., Wang, J., 2014c. Analyzing the impact of intermodal-related risk to the design and management of biofuel supply chain. Transp. Res. Part E Logist. Transp. Rev. 69, 122–145.

Marufuzzaman, M., Li, X., Yu, F., Zhou, F., 2016. Supply chain design and management for syngas production. ACS Sustain. Chem. Eng. 4 (3), 890–900.

Mavrotas, G., 2009. Effective implementation of the e-constraint method in Multi-Objective athematical Programming problems. Appl.Math. Comput. 213, 455–465.

Miettinen, K., 1999. Nonlinear Multiobjective Optimization. USA: Kluwer, Boston, MA.

Perez-Verdin, G.G., Grebner, D., Sun, C., Munn, I., Schultz, E., Matney, T., 2007. Woody biomass feedstock supplies and management for bioenergy in southwestern Mississippi. In: Proceedings of the 2007 Southern Forest Economics Workshop, San Antonio, Texas.

Poudel, S.R., Marufuzzaman, M., Bian, L., 2016. A hybrid decomposition algorithm for designing a multi-modal transportation network under biomass supply uncertainty. Transp. Res. Part E Logist. Transp. Rev. 94, 1–25.

Ramaswamy, S., Tschirner, U., Chen, Y., 2007. Transforming academic curricula: pulp

and paper to biobased products - providing education and research training for the conventional and emerging biobased products industry and the bio-economy. In: ACS Symposium Series Chapter 4, Section 1, Materials, Chemicals and Energy from Forest Biomass Ed. By Argyropoulos.
Rentizelas, A.A., Tolis, A.I., Tatsiopoulos, I.P., 2014. Optimisation and investment analysis of two biomass-to-heat supply chain structures. Biosyst. Eng. 120, 81–91.
Reza Norouzi, M., Ahmadi, A., Esmaeel Nezhad, A., Ghaedi, A., 2014. Mixed integer programming of multi-objective security constrained hydro/thermal unit commitment. Renew. Sustain. Energy Rev. 29 (0), 911–923.
Rezvani, A., Gandomkar, M., Izadbakhsh, M., Ahmadi, A., 2015. Environmental/economic scheduling of a micro-grid with renewable energy resources. J. Clean. Prod. 87 (0), 216–226.
Sokhansanj, S., Mani, S., Turhollow, S., et al., 2009. Large-scale production, harvest and logistics of switchgrass (Panicum virgatum L.) – current technology and envisioning a mature technology. Biofuel. Bioprod. Biorefin. 3 (2), 124–141.
Steuer, R.E., 1986. Multiple Criteria Optimization, Theory, Computation and Application. Krieger, Malabar, FL.
Tittmann, P.W., Parker, N.C., Hart, Q.J., Jenkins, B.M., 2010. A spatially explicit techno-economic model of bioenergy and biofuels production in California. J. Transp. Geog 18 (6), 715–728.
Tolvik Consulting Ltd, 2011. 2011 Briefing Report. The UK Waste Wood Market.
UK Department of Energy Climate Change, 2008. CHP Finance:A Detailed Guide for CHP Developers–Part 5.
UK Department of Energy Climate Change, 2012a. National Heat Map.
UK Department of Energy Climate Change, 2015a. 2010 to 2015 Government Policy: Low Carbon Technologies. Appendix 5: the Renewables Obligation (RO).
UK Department of Energy Climate Change, 2015b. 2010 to 2015 Government Policy: Low Carbon Technologies. Appendix 8: Feed-in Tariffs scheme.
UK Department of Energy Climate Change, 2015c. 2010 to 2015 Government Policy: Low Carbon Technologies. Appendix 6: Renewable Heat Incentive (RHI).
UK Department of Energy Climate Change, 2016. Greenhouse Gas Reporting - Conversion Factors 2015.
UK Department of Energy Climate Change, 2012b. Government Response to the Consultation on Proposals for the Levels of Banded Support under the Renewables Obligation for the Period 2013-17 and the Renewables Obligation Order 2012.
UK Department for Environment Food & Rural Affairs, 2015. Farming Statistics - Final Crop Areas, Yields, Livestock Populations and Agricultural Workforce.
Uslu, A., Faaij, A.P.C., Bergman, P.C.A., 2008. Pre-treatment technologies, and their effect on international bioenergy supply chain logistics. Techno-economic evaluation of torrefaction, fast pyrolysis and pelletisation. Energy 33, 1206–1223.
Xie, F., Huang, Y., Eksioglu, S., 2014. Integrating multimodal transport into cellulosic biofuel supply chain design under feedstock seasonality with a case study based on California. Biores. Technol. 152, 15–23.
Zhang, L., Hu, G., 2013. Supply chain design and operational planning models for biomass to drop-in fuel production. Biomass Bioenergy 58, 238–250.