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Abstract

In this paper we propose a model to design the supply chain for densified biomass. Rail is typically used for long-haul, high-volume shipment of densified biomass. This is the reason why a hub-and-spoke network structure is used to model this supply chain. The model is formulated as a multi-objective, mixed-integer programing problem under economic, environmental, and social criteria. The goal is to identify the feasibility of meeting the Renewable Fuel Standard (RFS) by using biomass for production of cellulosic ethanol. The focus is not just on the costs associated with meeting these standards, but also exploring the social and environmental benefits that biomass production and processing offers by creating new jobs and reducing greenhouse gas (GHG) emissions. We develop an augmented ϵ-constraint method to find the exact Pareto solution to this optimization problem. We develop a case study using data from the Mid-West. The model identifies the number, capacity and location of biorefineries needed to make use of the biomass available in the region. The model estimates the delivery cost of cellulosic ethanol under different scenario, the number new jobs created and the GHG emission reductions in the supply chain.

Keywords
Multi-objective, Hub-and-spoke, Densified biomass, Augmented ϵ-constraint method, Rail transportation

1. Introduction
Fossil fuels, such as oil, coal and natural gas currently represent the prime energy sources in the world. However, an increasing energy demand, coupled with increasing concerns over global warming, have resulted in an increased interest in a variety of renewable energy resources (RES) such as biomass, solar, and wind. A variety of biomass feedstocks are presently used to produce biofuel and electricity. According to EIA, biomass contributes nearly 3.9 quadrillion British thermal units (BTU) and accounts for more than 4% of total U.S. primary energy consumption (EIA [1]). Over the last 30 years, the share of biomass in the total primary energy consumption has averaged less than 3.5% (EIA [1]). The US federal government passed the Energy Independence and Security Act [2] to increase the share of biomass in the total energy production. The Renewable Fuels Standard, part of the Energy Independence and Security Act of 2007, especially calls for US production of 16 billion gallons of cellulosic biofuel by 2022 out of a 21 billion gallons of advanced biofuels (National Biofuels Action Plan [3]; Biomass Program Multi-Year Program Plan [3]). As a result of these policies and incentives, it is expected that the number of biorefineries in the USA will increase. Due to the nature of biomass (biomass is bulky, fungible and difficult to transport), biorefinery logistics costs can be high. To minimize transportation costs, currently biorefineries are generally located within 50 miles radius of their supply (Aden et al.[5]).This is the reason why most of the ethanol produced in the USA comes from small sized biorefineries located close to corn farms. Therefore, traditional biorefineries do not benefit from the economics of the scale associated with high production volumes (Searcy and Flynn [6]). This in return impacts the cost of biofuels, which for the moment are not cost competitive with fossil fuels.

Recent reports published by the Idaho National Laboratory (INL) propose a commodity-based, advanced biomass supply chain design concept to support the large-scale production of biofuels (Hess et al. [7]). This system relies on densifying biomass at local preprocessing facilities before delivering to a biorefinery and before long distance transportation. Thus, under these advanced supply system designs, using high capacity transportation for long-hauls becomes an option worth investigating. Depending on the distance traveled, rail or trucks can be used to deliver densified biomass to a biorefinery (Hess et al., [6]). We use an extension of the hub-and-spoke network design problem (Aykin,[8]) to model this biomass supply system. The hub-and-spoke biomass supply system relies on using the existing high-capacity infrastructure that is in place for transport of products that have similar physical properties to densified biomass, such as, grain and wood chips. In-bound shipments of biomass from nearby suppliers rely on truck transportation. Suppliers located further away use unit train shipments. Hubs serve as transshipment points where shipments are consolidated and disseminated, and transportation modes are changed. In the hub-and-spoke model proposed, the first hub is a depot, and the second hub is a biorefinery. It is assumed that biorefinery will have rail access. We consider that unit trains are used for high-volume shipments between hubs.

Although traditionally the main objective of models developed and analyzed in the area of supply chain optimization, logistics management and transportation systems analysis has been minimizing costs, there has been growing interest to incorporate other objectives to biomass supply chain model. Typically those are environments and social objectives. Since the activities that occur in the densified biomass-biorefinery supply chains can result in multiple GHG emissions, environmental objective is incorporated with economic objective to evaluate the design alternatives and operation activities from an environmental perspective. In this work, the environmental objective is to minimize the total annual GHG emission due to CO_2 emission. Two types of emission are considered in this study. They are: emission due to transportation and biorefinery operation .Similarly the activities that occur in the densified biomass-biorefinery supply chains increase the local employment which can be measured by the number of accrued local jobs. The more local jobs that are created, the higher the social benefit has brought to the regional economy by the densified biomass- biorefinery supply chain.

In this paper, we address biomass-to-biorefinery supply chain using rail for long-haul, and high-volume shipment of densified biomass under economic, environmental, and social criteria. In that case in addition to identifying hub location, the model will identify the number, capacity and location of biorefineries needed to make use of the biomass available in the region. The economic objective minimizes the transportation cost, hub location cost and biorefinery investment and operations cost, environment objective minimizes the CO_2 emissions and social objective maximizes the social benefit measured by the number of accrued local jobs resulting from the activities of the densified biomass-biorefinery supply chain. The multi objective framework establishes the tradeoff among the economic, environmental and social performance. Pareto-optimal solutions are generated to reveal the tradeoff among the three objectives. Two case studies are performed to illustrate the proposed optimization approach. We use this model in order to: (a) estimate the delivery cost of c-ethanol produced from densifed biomass; (b) get insights about the different cost components of c-ethanol delivery cost; (c) percentage of RFS goal can be met by c-ethanol from the studied region.

2. Literature review

The models we propose are in line with the research on biomass supply chain and logistics management. Specific literature of this area is discussed by Roni et.al [9]. The mathematical model presented in this paper is an extension of the hub-and-spoke network design problem. The hub-and-spoke design problem is conventionally called hub location problem. Hub location model identifies the location hub nodes, and then, allocates non-hub nodes to hubs (Campbell [10]). A number of extensions of the hub location problem are found in the literature. These extensions are a reflection of issues that arise when managing this supply chain, such as, non-linear economies of scale, traffic management, transportation mode selection, and congestion. For an extensive review see Alumur and Kara [11],Tunc et al. [12]. Most of the literature on biomass supply chain considers the use of truck transportation for biomass shipments. This is mainly motivated by the design of traditional biomass supply chain which locates biorefineries within 50-miles radius of biomass supply. Some studies, such as Mahmudi and Flynn [14] investigate biomass transportation by rail. Other studies, such as the one by Ekşioğlu et al. [15], investigate the idea of locating a biorefinery nearby an intermodal facility. Such a sitting of a biorefinery would facilitate the long-haul and high-volume biomass transportation and could improve the performance of the biomass supply chain. While the work presented in this paper was inspired by the work of Ekşioğlu et al. [15], it extends the research by increasing the scope of the application, exploring a different use for biomass, and using a hub-and-spoke network design model.Multi-objective optimization during modeling biomass-to-biorefinery supply chain is studied by Zamboni et al. [16], Perimenis et al.[17], You and Wang [18] and You et al. [19].Both exact (Jozefowiez et al.[20]; Abounacer et al. [21]; Mavrotas [22]) and heuristics solution approach (Yuan and Wang [23]; Laumanns et al.[24]); Köksalan and Lokman [25]) have appeared in the literature to solve the multi-objective integer linear programs.

The analysis presented in this chapter is unique. We are not aware of hub-and-spoke supply chain models for in-bound biomass supply chains that considered economic, environmental and social factors. The work by You et al. [19] is closely related to this paper. Different from You et al. [19] this paper uses a hub-and-spoke supply chain structure to deliver biomass using high-volume transportation modes, such as rail to a broad region.

3. The Hub-and-Spoke Supply Chain Design

Figure 1 presents the hub-and-spoke model for a supply chain consisting of four local preprocessing facilities, two depots, one biorefinery, one terminal for biofuel blending and storage facilities and two customer .The depots represent the first hubs and the biorefinery represent the second hubs in this supply chain. The preprocessing facilities send truck shipments of densified biomass to a depot where shipments are consolidated. If the preprocessing facilities are located within 75 miles of a biorefinery, preprocessing facilities can send truck shipments to the biorefinery. It is assumed that the biorefinery will have railways access. The c-ethanol from a biorefinery is distributed to the customer through either a bulk terminal or a redistribution bulk terminal. This bulk terminal is typically a blending facility where it is stored until it is blended with gasoline. C-ethanol is shipped from the biorefinery by either truck or rail car depending on distance. It is assumed that if the distance between a biorefinery and bulk terminal is greater than 75 miles, rail car will be used. Once at the bulk terminal, the c-ethanol is broken down into smaller quantities, usually transports truck loads, and delivered to the customer.

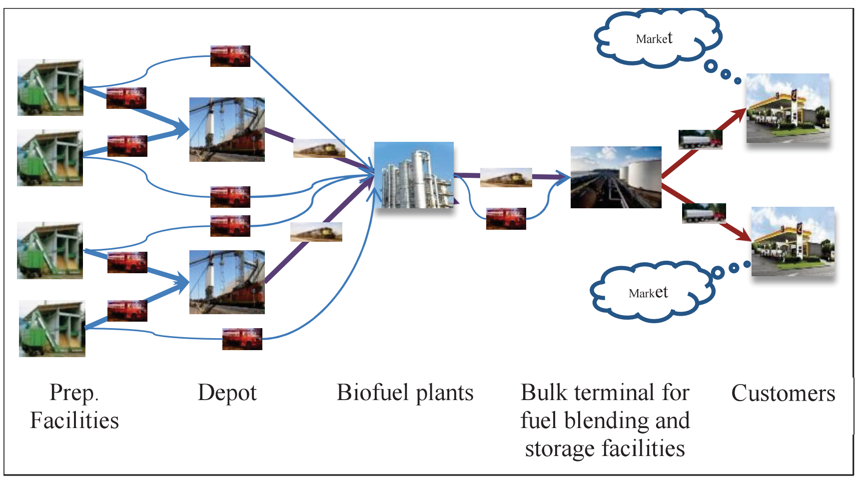

Fig.1: Supply chain network structure for Hub-and-spoke model to design densified biomass-to-biorefinery supply chain. Low-volume and short-distance transportation of biomass is done by trucks.

We model this supply chain design and management problem using a mixed integer linear programming (MILP) model. This model is also a facility location model since it identifies locations for depots, biorefinery. Let $G(N, A)$ denote the supply chain network, where, N represents the set of nodes and A represents the set of arcs. Set N consists of subset P which represents the set of preprocessing facilities, subset D which represents the set of depot, subset B which represents the set of biorefinery locations, subset L which represents set of bulk terminal (also known as blending and storage facilities) and subset C which represents set of customers. Set A consists of subset T_1 which represents the set of arcs that connect preprocessing facilities to depot, T_2 which represents the set of arcs that connect preprocessing facilities to biorefinery, subset T_3 which represents the set of arcs that connect biorefinery to the bulk terminal, subset T_4 which represents the set of arcs that connect bulk terminal to the customer, subset R_1 which represents the set of arcs that connect depots to biorefineries and subset R_2 which represents the set of arcs that connect biorefineries to the bulk terminal . Let $T = \{T_1 \cup T_2 \cup T_3 \cup T_4\}$ and $R = \{R_1 \cup R_2\}$. The transportation mode along arc T and R are truck and rail respectively.

The cost along arcs in T_1 ,T_2, T_3 ,T_4 is linear, and there are no upper bounds on the amount shipped using these arcs. The selection of such a function type reflects the practice. Low-volume and short-distance transportation of biomass is done by trucks. Typically, a fixed price per mile and per ton is charged. Thus, the distance traveled along arc (i, j), d_{ij}, is considered when calculating c_{ij}. We calculatec_{ij} by $c_{ij} = \vartheta^T + \theta^T * d_{ij}$, where $(i, j) \in T$ .Here ϑ^T is distance fixed cost per ton for truck and θ^T cost per mile per ton for truck. This is typically the case when transportation distance is relatively short. The transportation cost structure of arcs in R is a multiple-setup fixed charge type, which is described using Eq.(1).

$$f(x_{ij}) = \begin{cases} 0 & if \quad X_{ij} = 0 \\ \Psi_{ij} + c_{ij}X_{ij} & if \quad 0 < X_{ij} \leq \; V_{ij} \\ 2 * \Psi_{ij} + c_{ij}X_{ij} & if \quad V < \; X_{ij} \leq 2 * \; V_{ij} \\ \vdots & \\ \mathrm{n} * \Psi_{ij} + c_{ij}X_{ij} & if \quad (n-1) * V < \; X_{ij} \leq n * \; V_{ij} \end{cases} \qquad (1)$$

In this function, Ψ_{ij} reflects a fixed cost for loading/unloading a unit train. The variable cost (c_{ij}) charged per ton shipped and it depends on the distance traveled along arc (i, j). This is a piecewise linear cost function. In order to incorporate this function within the objective function of the MILP model presented below, we introduce the integer variables Z_{ij} .These variables represent the number of unit trains moving from depot i to biorefinery j. Then $f_{ij}(X_{ij}) = \Psi_{ij}Z_{ij} + c_{ij}X_{ij}$ .As a result total transportation cost this supply chain
$T_RC = \sum_{(i,j)\in T} c_{ij}X_{ij} + \sum_{(i,j)\in R}(c_{ij}X_{ij} + \Psi_{ij}Z_{ij})$

The hub location costs are the investment costs necessary to build the infrastructure in support of loading/unloading unit trains at a depot. Let W_i be a binary variable which takes the value 1 when node $i \in D$ is used as a depot, and takes the value 0 otherwise. Let ς_i the fixed investment cost at node $i \in D$. Thus, total hub location costs are HC = $\sum_{i\in D} \varsigma_i w_i$. Let ϱ_{ik} be the fixed investment cost at node $i \in B, k \in K$. Let β_{ik} be a binary variable which takes the value 1 when node $i \in B$ is used as a biorefinery location with capacity $\in K$, and takes the value 0 otherwise. Thus, total biorefinery location costs are BC = $\sum_{k\epsilon K} \sum_{i\epsilon B} \varrho_{ik}\beta_{ik}$.

Other parameters we use in order to build our model are: π_i represent demand shortage at customer i; α_i represents the penalty cost at customer i; s_i represents the supply of biomass at a pre-processing facility; v_{ij} represents the maximum capacity of a unit train for $(i, j) \in R$; u_j represents the storage capacity of depot j.

CO_2 emissions results from the combustion of the biofuel during transportation of biomass and biofuel in the supply chain. CO_2 emissions also results from the biorefinery construction and operation, and hub operation. The emission along arcs in T , R is linear, and there are no upper bounds on the amount shipped using these arcs. Emission parameters e_{ij} represents CO_2 emission per ton per mile in arc set$(i, j) \in A$. CO_2 emissions from a biorefinery are proportional to the size of the biorefinery. CO_2 emissions from hub operations are proportional to its capacity. Let ϵ_{ik} represents CO_2 emission per ton from biorefinery $i \in B$ and o_i represents CO_2 emission for establishing a hub at node $i \in D$.

Social benefit is measured by the number of accrued local jobs. Job results from the transportation activities of biomass and biofuel in the supply chain, biorefinery construction and operation, and hub operation. The number of job along arcs in T is linear and depends on the distance traveled and shipped amount. The numbers of job along arc R is linear and depend on number of unit train and distance. The number of job created due biorefinery operation and construction is a function of biorefinery size. Number of job created due to hub operation is assumed to be fixed. p_{ij}^T represents number of jobs created per ton due to transportation activities in arc $(i, j) \in A$, p_i^D represents number of job created due to locating depot $i \in D$ and p_{ik}^B represents number of job created for biorefinery $i \in B, k\epsilon K$.

The economic objective function minimizes the total of transportation cost, hub location costs, and penalty costs necessary to meet demand. The penalty costs occur when the needs for biofuels at a customer are not satisfied using biomass, but gasoline instead. Such a penalty serves in fact as a threshold price for delivering biomass. If the delivery price for biomass is higher than this threshold, then other sources will be used to meet supply requirements. The economic objective is defined as follows

$$\min\ TC \sum\nolimits_{(i,j)\in T} c_{ij}X_{ij} + \sum\nolimits_{(i,j)\in R_1} \left(c_{ij}X_{ij} + \Psi_{ij}Z_{ij}\right) + \sum\nolimits_{(i,j)\in R_2} \left(c_{ij}X_{ij} + \lambda_{ij}Y_{ij}\right) + \sum\nolimits_{i\in D} \varsigma_i W_i + \sum\nolimits_{k\in k} \sum\nolimits_{i\in B} \varrho_{ik}\beta_{ik} + + \sum_{i\in C} \alpha_i \Pi_i \qquad (2)$$

The environment objective function minimizes the total of CO_2 emissions due to transportation of densified biomass and operations of biorefinery. The environmental objective is defined as follows

$$Min\ TE = \sum\nolimits_{(i,j)\in T,R} e_{ij}X_{ij} + \sum\nolimits_{i\in D} \mu_i W_i + \sum\nolimits_{k\in K} \sum\nolimits_{i\in D} \epsilon_{ik}\,\beta_{ik} \qquad (3)$$

The social objective function maximizes the total number of jobs created due to transportation of densified biomass and operations of biorefinery. The social objective is defined as follows

$$\max SB = \sum\nolimits_{(i,j)\in T} p_{ij}^T X_{ij} + \sum\nolimits_{(i,j)\in R_1} p_{ij}^T Z_{ij} + \sum\nolimits_{(i,j)\in R_2} p_{ij}^T Y_{ij} + \sum\nolimits_{i\in D} p_i^D W_i + \sum\nolimits_{k\in K} \sum\nolimits_{i\in D} p_{ik}^B\,\beta_{ik} \qquad (4)$$

The following is the MILP formulation of the problem:

$$Minimize: (TC(X, Z, Y, \beta, W, \Pi), TE(X, \beta, W, \Pi))$$
$$Maximize: (SB(X, Z, Y, \beta, W, \Pi))$$
$$s.t \sum_{j\in D\,\cup\, C} X_{ij} \le s_i \quad \forall\, i \in P \qquad (5)$$
$$\sum_{i\in P} X_{ij} - \sum_{i\in B} X_{ji} = 0 \ \ \forall\, j \in D \qquad (6)$$
$$\sum_{i\in P\cup D} X_{ij} - \sum_{i\in L} X_{ji} = 0 \ \ \forall\, j \in B \qquad (7)$$
$$\sum_{i\in B} X_{ij} - \sum_{i\in C} X_{ji} = 0 \ \ \forall\, j \in L \qquad (8)$$
$$\sum_{i\in L} X_{ij} + \Pi_j = g_i \ \forall\, j \in C \qquad (9)$$
$$X_{ij} - v_{ij}Z_{ij} \le 0 \qquad \forall\, (i,j) \in R_1 \qquad (10)$$
$$X_{ij} - \ \tau_{ij}Y_{ij} \le 0 \qquad \forall\, (i,j) \in R_2 \qquad (11)$$
$$\sum_{i\in P} X_{ij} - u_j W_j \le 0 \qquad \forall\, j \in D \qquad (12)$$
$$\sum_{j\in P\,\cup\, D} X_{ji} - \sum_{k\in K} q_{ik}\beta_{ik} \le q_{ik} \ \ \forall\, i \in B \qquad (13)$$
$$\sum_{k\in K} \beta_{ik} \le 1 \ \ \forall\, i \in B \qquad (14)$$
$$X_{ij} \in R^n \ \forall\, (i,j) \in A \qquad (15)$$
$$\pi_i \in R^n \quad \forall\, i \in C \qquad (16)$$
$$W_i \in \{0,1\}, \quad \forall\, i \in D \qquad (17)$$
$$\beta_{ik} \in \{0,1\}, \ \ \forall\, i \in B, k \in K \qquad (18)$$
$$Z_{ij} \in Z^+ \ \ \forall\, (i,j) \in R_1 \qquad (19)$$
$$Z_{ij} \in Z^+ \ \ \forall\, (i,j) \in R_2 \qquad (20)$$

Constraints (5) indicate that the amount of biomass shipped from a preprocessing facility is limited by its availability. Constraints (6)-(8) are the flow balance constraints at depot, biorefinery site and bulk terminal respectively. Constraints (9) indicate that customer demand is satisfied by either by using biofuel shipments or by using other products (such as, gasoline). Constraints (10) and (11) set an upper limit on the amount of biomass shipped using unit trains and single car. Constraints (12) set a limit on the storage capacity of a hub. Constraints (13) set a limit on the capacity of a biorefinery. Constraints (14) set a limit on number of biorefinery at any location. Constraints (15) and (16) are the non-negativity constraints. Constraints (17) and (18) are binary constraints. Constraints (19) and (20) are the integrity constraints.

4. Solution approach

The MILP considers three objectives: the economic, environmental, and social. Typically, there does not exist a single solution that simultaneously optimizes each objective. Therefore we will produce Pareto optimal solutions that reveal the tradeoffs among the three objectives. In this paper we apply a novel version of ε- constraint method known as the augmented ε- constraint method (Mavrotas and Florios [22]; Mavrotas [26]) to find the Pareto optimal solutions. In this method the range of ε_1 and ε_2 is calculated by Lexicographic optimization method and efficient solution is guaranteed by reformulating the ε- constraint formulation with appropriate slack or surplus variable.

4.1 Lexicographic optimization to obtain the range of ε_1 and ε_2

In Lexicographic optimization method, we first optimize $\min TC(X,Z,Y,\beta,W,\Pi)$ s.t (5)-(20) and obtain $f_1 = TC(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$ .Then we optimize $\min TE(X,Z,Y,\beta,W,\Pi)$ s.t (5)-(20) by adding constraints $f_1 = TC(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$ in order to keep previous optimal solutions and obtain $f_2 = TE(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$. Finally we optimize $Max\ SB(X,Z,Y,\beta,W,\Pi)$ s.t (5)-(20) by adding constraints $f_1 = TC(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$ and $f_2 = TE(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$, and obtain $f_3 = SB(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$. At the end of Lexicographic optimization method we construct a payoff table shown in Table 2.

Table 2: Payoff table generated by Lexicographic optimization

Objective function	f_1	f_2	f_3
$\min TC(X,Z,Y,\beta,W,\Pi)$	$TC(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$	$TE'(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$	$SB'(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$.
$\min TE(X,\beta,W,\Pi)$	$TC(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$	$TE(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$.	$SB'(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$
$\max SB(X,\beta,Z,W,\Pi)$	$TC(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$	$TE(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$	$SB(X^*,Z^*,Y^*,\beta^*,W^*,\Pi^*)$.

After the calculation of the payoff table we divide the ranges of f_2 and f_3 into equal intervals and obtain grid points as the values of ε_1 and ε_2. The benefit of using Lexicographic optimization method is that it provides the range of ε_1 and ε_2 for efficient solution and provides a much more dense representation of the efficient set.

4.2 Reformulate the ε- constraint method with appropriate slack or surplus variable

The problem of generating weakly efficient solution from the ε- constraint method is overcome by incorporating the appropriate slack or surplus variables. These slack or surplus variables are used as a second term (with lower priority in a lexicographic manner) in the objective function, forcing the program to produce only efficient solutions. The new problem becomes:

Problem RMMILP
$\min TC(X,Z,Y,\beta,W,\Pi) + \delta(S_1 + S_2)$
$s.t\ TE(X,Z,Y,\beta,W,\Pi) + S_1 = \varepsilon_1$ (23)
$\mathrm{SB}(X,Z,Y,\beta,W,\Pi) - S_2 = \varepsilon_2$(24)
$S_1, S_1 \in R^+$(25)
and (5)-(20)

where δ is an adequately small number (usually between $10^{\wedge-3}$and $10^{\wedge-6}$ .The above formulation (RMMILP) of the ε- constraint method avoids the generation of weakly efficient solutions and produces only efficient solution(proof is given by Mavrotas, [26]). A procedure for the augmented ε- constraint method is given Fig. 3

Step 1	Apply Lexicographic optimization method to create payoff table Calculate the range of ε_1 and ε_2 from the payoff table Set number of interval k and compute step size by $\Delta\,\varepsilon_1 = \frac{\varepsilon_1^{max}-\varepsilon_1^{min}}{k}$, $\Delta\,\varepsilon_2 = \frac{\varepsilon_2^{max}-\varepsilon_2^{min}}{k}$ Pareto optimal set $\Lambda = \emptyset$
Step 2	for *i*=0 to *i*=k do $\varepsilon_1 = \varepsilon_1^{max} - \Delta\,\varepsilon_1$

		for j=0 to j=k do
		$\varepsilon_2 = \varepsilon_2^{min} + \Delta\, \varepsilon_2$
		Update RMMILP with modified ε_1 and ε_2
		Solve RMMILP
		If RMMILP feasible Then
		Add solution to Λ
		next j
		else
		Break

	Next *i*	

5. Case Study and Result

This case study is designed on the fact that production of large scale production biofuels in the West will be dependent on the biomass in the Midwest. We have selected nine states from the Midwest and West for case study. The selected states for biomass supply are: Iowa, Nebraska, Kansas, South Dakota, California, New Mexico, Nevada, and Arizona. Biomass availability data by state and county was extracted from the Knowledge Discovery Framework (KDF) [27] database, an outcome of the US Billion Ton Study led by the Oak Ridge National Laboratory. This data was further processed by INL to identify potential locations for depots and the corresponding amount of densified biomass available. Biofuel demand data at a county is estimated based on population of county, population of state and gasoline consumed by the state (EIA [28]. The data about the US railway network structure was provided by Oak Ridge National Lab [29].Truck transportation cost of biomass is estimated based on Searcy et al. [30]. Rail transportation costs of densified biomass are estimated based on Roni.[31] .You et al. [19] provided investment cost and operating cost for 45 MGY ethanol productions with simultaneous scarification and fermentation technology. We use this study to estimate the biorefinery investment cost. CO_2 emission is estimated based on GHG Protocol, [32]. Emission data from biorefinery operation is calculated on based Argo et al. [34]. The number of accrued local jobs for biorefinery construction and operations is calculated from the Jobs and Economic Development Impact (JEDI) model [33] developed by NREL. The number of job created due truck transportation is estimated on travel distance and amount of biomass shipped annual. The number of job created due to rail transportation is calculated based on distance traveled at each route and number of unit train operating every two weeks.

We perform two case studies to analyze the hub and spoke model. First case study focused on minimizing the total the cost and performs detail cost analysis. Second case study captures the hub and spoke model under economic, environmental, and social objectives; and presented Pareto optimal solutions. IBM CPLEX 12.5.1 was used to solve the MILP. Augmented ϵ-constraint method have been implemented in C++ with IBM CPLEX Concert Technology.

Table 1: Number of biorefinery, size, and percentage of utilization of biorefinery, delivered biofuel at each scenario

Scenario	Number of biorefinery with size (MGY)			Total capacity(MGY)	Utilization	Delivered Biofuel (MGY)	Percentage of RFS goal
	60	90	120				
1	2	2	7	1140	95.69%	1091	6.82%
2	1	2	8	1200	92.86%	1114	6.96%
3	1	3	7	1170	99.21%	1161	7.25%

Table 2: Average delivery cost of c-ethanol

Scenario	Trans. Cost ($/Gal.)	Hub Loc. Cost($/Gal)	Biorefin. Inv., prod. and Op. Cost($/Gal.)	Total delivery Cost ($/Gal.)
1	0.601	0.002	2.782	3.38
2	0.563	0.001	2.827	3.39
3	0.609	0.002	2.670	3.28

We solved the MILP model under three different scenarios. Each scenario was generated based on the maximum allowable travel distance between a preprocessing facility and a depot (Table 1). In Scenarios 1, 2 and 3, the travel distance is 10, 30 and 50 miles respectively. The number of biorefinery, total capacity and percentage of utilization varies from scenario 1 to 3(Table 1). The number of biorefinery with capacity, utilization and delivered c-ethanol for each scenario is showed in Table 1. Max. 1160 MGY c-ethanol can be delivered from the studied region. Moreover, 6.82%-7.25% of RFS goal can be met by c-ethanol from the studied region. Table 2 shows the average delivery cost of c-ethanol. Delivery cost varies from $3.28 to $3.39 per gallon.
Fig. 1 represents the number of biorefinery and its size based on scenario 3.If we examine the scenario 3 , we can observe that most of the biorefineries are located close to supply side such as Iowa, Kansas, Nebraska. There are two biorefineries located in Colorado which are influenced by customer demand. Biorefineries located in Colorado and Kansas use rail transportation to meet the biomass demand. Biorefinery located in South Dakota, Nebraska, and Reno County in Kansas use single car rail shipment to distribute c-ethanol.

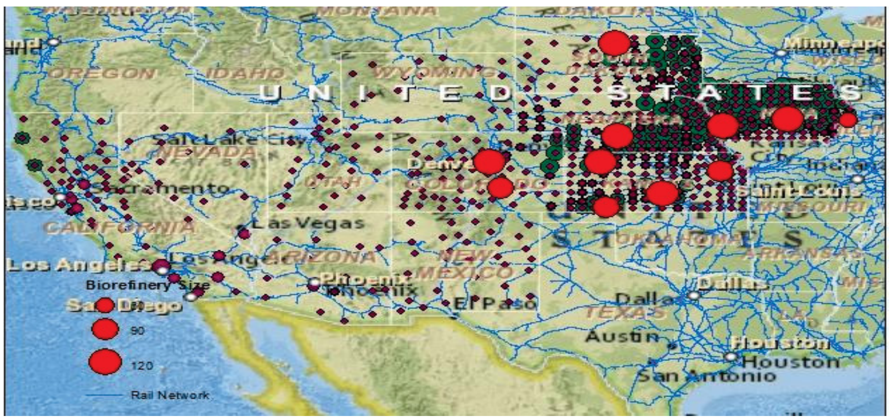

Figure 1: Number of biorefinery and its size based at scenario 3 presented with biomass supply and biofuel demand

Table 3 Pareto optimal solutions for scenario-1

Delivery cost	Delivered c-ethanol	CO_2 Emission	Total number of job	Number of biorefinery			Total number of biorefinery	Number of hub	% of inbound biomss shipped by rail	% of outbound biofuel shipped by rail	% RFS
($/Gal.)	Mill. Gal	Kil.Tonne		60	90	120					
3.07	987	2836	3153	1	1	7	9	52	48.08%	38.60%	6.17%
3.10	1058	3146	3411	0	0	9	9	66	62.06%	31.63%	6.61%
3.13	1015	2980	3442	1	4	5	10	31	33.20%	43.80%	6.34%
3.16	973	2778	2951	1	1	7	9	67	65.49%	21.20%	6.08%
3.18	1057	3133	3470	1	2	7	10	60	52.02%	26.76%	6.60%
3.20	957	2745	3168	2	4	4	10	34	45.48%	30.92%	5.98%
3.23	812	2393	2604	2	0	6	8	58	44.00%	15.14%	5.08%
3.26	984	2842	3346	3	5	3	11	34	38.28%	29.94%	6.15%
3.28	1039	3046	3589	5	3	4	12	29	35.56%	32.28%	6.50%
3.32	755	2179	2409	2	2	4	8	60	55.95%	10.66%	4.72%
3.36	845	2525	2754	2	2	5	9	52	46.04%	16.41%	5.28%
3.37	788	2413	2606	2	0	6	8	59	62.93%	12.94%	4.92%
3.41	991	3070	3566	2	4	5	11	38	37.25%	33.65%	6.20%
3.44	677	2168	2377	2	0	5	7	40	67.45%	9.22%	4.23%
3.45	1092	3466	3777	0	2	9	11	90	77.57%	51.48%	6.82%
3.49	666	2158	2357	2	0	5	7	41	69.33%	9.25%	4.16%
3.55	796	2591	2868	3	1	5	9	45	54.59%	7.55%	4.97%
3.60	905	2864	3256	3	4	4	11	39	44.08%	22.56%	5.66%
3.68	615	2047	2197	2	0	5	7	42	67.84%	11.46%	3.84%
3.76	733	2455	2680	3	1	5	9	38	50.14%	11.44%	4.58%
3.79	955	3566	3670	0	0	10	10	10	14.42%	0.00%	5.97%
3.81	594	2081	2222	2	0	5	7	31	59.07%	9.39%	3.71%
3.88	981	3566	3618	1	0	10	11	26	33.39%	0.00%	6.13%
3.90	971	3566	3671	1	0	10	11	26	33.96%	5.13%	6.07%
4.20	956	3466	3598	0	1	11	12	83	81.77%	54.70%	5.97%
4.35	918	3216	3627	4	4	6	14	89	80.71%	51.86%	5.74%

Economic, environmental and social objective are considered in the second case study. We first consider the tradeoff among economic, environmental and social objectives. Table 3 shows the Pareto optimal solutions for scenario-1. From scenerio-1 (Table 3) we can observe that as the annual CO_2 emission range from 1906 Kil. tonne to 3566 Kil.tonne, and annual number of job changes from 2124 to 3850 , delivery cost range \$3.07 to \$4.35. In scenerio1 depending on CO_2 emission number and number of job, delivered c-ethanol from biorefinery ranges from 557 MGY to 1118 MGY per year, number of biorefinery in studied region varies from 7-14, number of hub varies from 10-90, percentage of inbound biomass shipped by rail varies from 14.42% to 81.77%, percentage of outbound biofuel shipped by rail can be up to 54.7% and percentage of RFS goal varies from 3.48% to 6.99%.

6. Conclusion

In this paper, we address biomass-to-biorefinery supply chain using rail for long-haul, and high-volume shipment of densified biomass under economic, environmental, and social criteria. In that case in addition to identifying hub location, we identify the number, capacity and location of biorefineries needed to make use of the biomass available in the region. The economic objective minimizes the transportation cost, hub location cost and biorefinery investment and operations cost, environment objective minimizes the CO_2 emissions and social objective maximizes the social benefit measured by the number of accrued local jobs resulting from the construction and operation of the densified biomass biorefinery supply chain. An augmented ϵ-constraint method is used to find the exact Pareto set. Multi-objective tradeoffs among the economic, environmental, and social aspects are studied through the generation of Pareto Solutions. We evaluate the total amount of biomass that can be delivered to biorefinery based on four major class 1 rail and estimates the corresponding transportation cost for different scenario. Max. 1091-1161 MGY c-ethanol can be delivered. 6.82%-7.25% of RFS goal can be met by c-ethanol from the studied region. We estimated that transportation cost varies from \$0.563-\$0.609 per gallon. Delivery cost varies from \$3.2-\$3.39 per gallon. Scenario 3 results indicate that biorefinery location decisions are impacted by both biomass supply and demand. Finally, we presented Pareto optimal solutions for scenario 1.Pareto optimal solutions for scenario 1 shows as the annual CO_2 emission range from 1906 Kil. Tonne to 3566 Kil. Tonne, and annual number of job changes from 2124 to 3850, the delivery cost range \$3.07 to \$4.35.

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