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A Simulation-Based Robust Biofuel Facility Location Model for an Integrated Bio-Energy Logistics Network

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Abstract:

Purpose: The purpose of this paper is to propose a simulation-based robust biofuel facility location model for solving an integrated bio-energy logistics network (IBLN) problem, where biomass yield is often uncertain or difficult to determine.

Design/methodology/approach: The IBLN considered in this paper consists of four different facilities: farm or harvest site (HS), collection facility (CF), biorefinery (BR), and blending station (BS). Authors propose a mixed integer quadratic modeling approach to simultaneously determine the optimal CF and BR locations and corresponding biomass and bio-energy transportation plans. The authors randomly generate biomass yield of each HS and find the optimal locations of CFs and BRs for each generated biomass yield, and select the robust locations of CFs and BRs to show the effects of biomass yield uncertainty on the optimality of CF and BR locations. Case studies using data from the State of South Carolina in the United State are conducted to demonstrate the developed model's capability to better handle the impact of uncertainty of biomass yield.

Findings: The results illustrate that the robust location model for BRs and CFs works very well in terms of the total logistics costs. The proposed model would help decision-makers find the most robust locations for biorefineries and collection facilities, which usually require huge investments, and would assist potential investors in identifying the least cost or important facilities to invest in the biomass and bio-energy industry.

Originality/value: An optimal biofuel facility location model is formulated for the case of deterministic biomass yield. To improve the robustness of the model for cases with probabilistic biomass yield, the model is evaluated by a simulation approach using case studies. The proposed model and robustness concept would be a very useful tool that helps potential biofuel investors minimize their investment risk.

Keywords: bio-energy logistics network, robust biorefinery location, biomass yield, simulation approach

1. Introduction

Diverse and affordable energy is critical for the future of every country in the world. To reduce the dependence on foreign oil and also mitigate the environmental impacts (e.g., climate change, pollution) of using fossil fuel, a significant amount of research in the United States has recently been devoted to methods of producing biofuel. Less attention has been given to the cost of transporting bulky biomass feedstock to biorefinery plants. The biomass transportation cost is, however, significant compared to the biofuel production cost. For this reason, a majority of existing biorefinery plants in the United States are located in the Midwest where biomass, such as corn and soybean, is abundant.

With the soaring and unstable gasoline price and the increasing environmental concern, many other states in the U.S. are now seeking the opportunity to use biomass feedstocks, such as switchgrass, for producing biofuel. Also, under the Energy Independence and Security Act (EISA) of 2007, the United States Environmental Protection Agency (EPA) has developed a Renewable Fuel Standard Program (RFS) to ensure that gasoline in the U.S. contains a minimum percentage of renewable fuel. The latest RFS (2011) "w*ill increase the volume of renewable fuel required to be blended into gasoline from 9 billion gallons in 2008 to 36 billion gallons by 2022*." Therefore, there is an immediate demand for biomass transportation cost analysis model to help locate new biorefineries optimally.

Some federal agencies in the United States have taken major steps since 2006 to implement the Advanced Energy Initiative rolled out by the US Government. The U.S. Department of Energy has announced plans to invest nearly $1 billion in partnership with the private sector and academia to research, develop, and deploy advanced biofuel technologies by 2012. This includes up to $272 million for commercial-scale BRs, up to $240 million for demonstration scale BRs working on novel refining processes, and more than $400 million for bio-energy centers (2011).

The vast expansion in biofuels production and use mandated by EISA will require the development of new methods and equipment to collect, store, and pre-process biomass in a manner acceptable to biorefineries. These activities, which constitute as much as 20% of the current cost of finished cellulosic ethanol, are comprised of four main elements:

- Harvesters & collectors that remove feedstocks from cropland and out of forests.
- Storage facilities that provide a steady supply of biomass to the biorefinery, in a manner that prevents material spoilage.
- Preprocessing/grinding equipment that transforms feedstocks to the proper moisture content, bulk density, viscosity, and quality.
- Transportation of feedstocks and biofuels

In this study, we consider an integrated biomass and bio-energy logistics network consisting of four different types of facilities: a supply point - farm or harvest site (HS), a storage point - collection facility (CF), a production point - biorefinery (BR), and a demand point - blending station (BS). We assume that the locations of HS and BS are fixed and the demand of each BS is constant throughout the planning period. The logistics network structure is depicted in Figure 1. The inbound flows (solid arrows) in Figure 1 represent the collection, storage, and transportation of biomass, which can be of many types. The biomass collected at each HS is brought by trucks into a local CF. Smaller loads of biomass collected from the HS are temporarily stocked at the CF before they are consolidated and transported to a BR by large-capacity trucks for processing into biofuel. A CF is a potential site to store and preprocess (e.g., compress) biomass to a more valuable density and/or to pre-treat biomass to make a better quality biomass feedstock so that they can be transported in a more cost-effective way. In addition, a direct transportation of biomass from a HS to a BR is allowed and the resulting transportation cost is usually higher than going through the CF, since the direct shipping of biomass from a HS to the BR requires more space (due to the low biomass density) and more operations and preparation to be processed into biofuel. The outbound flows (dashed arrows) in Figure 1 show that biofuels are transported from BRs to BSs to be blended with fossil fuels before being distributed to gas stations. Given the locations of BSs and their demands, the transportation costs mainly depend on the proximity of BRs to BSs. In this logistics network, determining the locations of BRs and CFs will be the most important decision. This is because a BR usually requires several million dollars as the annualized construction and operation cost. Also, the use of CFs would affect the quality of biofuel that primarily depends upon the moisture content in the biomass (Dyken, Bakken & Skjelbred, 2010), letting alone the total transportation cost between HSs and BSs.

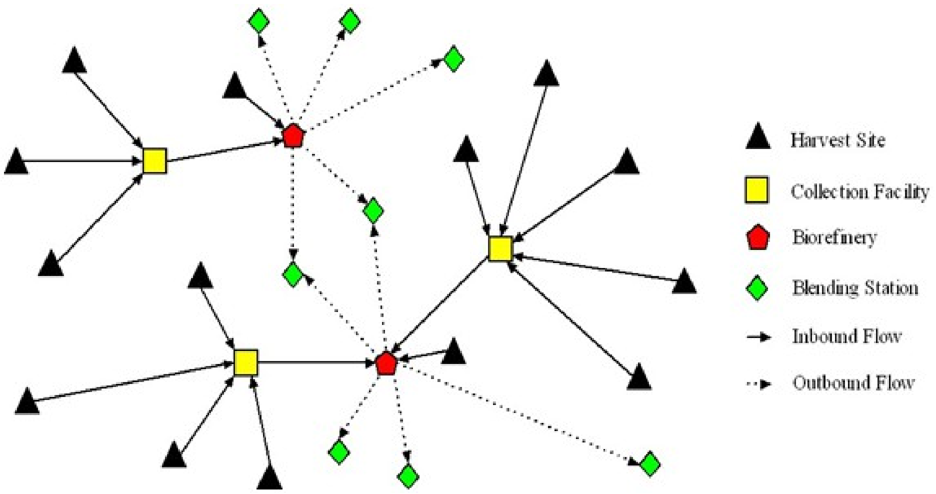

Figure 1. Schematic of Biomass/Bio-Energy Logistics Network

What complicates the decision of CF and BR locations is the uncertainty in biomass yield. Intuitively, different biomass yield scenarios will affect the optimality of a biofuel facility location plan. To develop a robust model, we first present a mixed integer quadratic program (MIQP) modeling approach to simultaneously determine the optimal locations of BRs and CFs and the transportation scheme for a given biomass yield scenario. We then investigate the effects of biomass yield on the optimality of the selected location by simulating the biomass yield of each HS, i.e., generating biomass yield for each HS using three probability distributions and finding the optimal locations of BRs and CFs for each yield scenario. Based on the simulation results, we identify the most frequently selected locations of BRs and CFs (referred to as 'robust locations',) for various biomass yields scenarios. By comparing the optimal solutions for the different biomass yield scenarios, a robust location is then identified.

2. Literature Review

Many existing studies have focused on bio-processing technologies to improve the biofuel yield and quality (Antonpoulou, Gavala, Skiadas, Angelopoulos & Lyberatos, 2008; Lee, Chou, Ham, Lee & Keasling, 2008; Ranganathan, Narasimhanm & Muthukumar, 2008; van Dyken, Bakken & Skjelbred, 2010; Weyens, Lelie, Taghavi, Newman & Vangronsveld, 2009). Although the cost of transporting bulky and unrefined biomass feedstock is also significant as compared to the total cost for producing biofuel, much less attention has been given to the understanding of biomass and bio-energy logistics systems and the reduction of biomass and bio-energy logistics costs.

In recent years, several biomass and bio-energy logistics studies have been conducted. Most of these existing studies focus either on the optimization of biorefinery locations (Celli, Ghiani, Loddo, Pilo & Pani, 2008; Graham, English & Noon, 2000; Panichelli & Gnansounou, 2008;

Perpiñá, Alfonso, Pérez-Navarro, Peñalvo, Vargas & Cárdenas, 2009; Steen, Kang, Bokinky, Hu, Schimer, McClure et al., 2010) or on the optimization and simulation of the biomass collection, storage, and transport operations (Frombo, Minciardi, Robba, Rosso & Sacile, 2009; Kumar & Sokhansanj, 2007; Rentizelas, Tolis & Tatsiopoulos, 2009; Sokhansanj, Kumar & Turhollow, 2006). Eksioglu, Acharya, Leightley and Arora (2009) investigate the integrated biomass and biofuel logistics network design, simultaneously taking into account the optimization of facility locations (e.g., collection facilities, biorefineries), transportation, and inventory control. In their paper, several critical issues are not adequately addressed: for instance, how the uncertainty in biomass yield affects the robustness and optimality of the logistics network design and how to develop efficient heuristic algorithms to solve the formulated logistics model, which typically is an NP-hard problem.

The remaining of the paper is organized as follows. Section 3 introduces an integrated facility location and transportation model in detail. Following the description of the model formulation, case studies are conducted and analysis for simulation results is presented in section 4. Section 5 summarizes the developed models and research findings. It also provides recommendations for future research directions.

3. Development of Integrated Optimization Model

We propose the integrated optimization mathematical model by modifying the model (Eksioglu et al., 2009). In our proposed model, we assume that CFs can be located at any HS and a biorefinery (BR) can only be built at candidate BR location, since BR locations must satisfy some realistic requirements. This is a reasonable assumption at the planning stage for the bio-energy logistics model. It may be difficult to decide potential CF locations which are not HSs, since the assignment of HSs to a CF is not known.

Let F be the set of all harvesting sites (HSs) and potential collection facility (CF) locations, indexed by f. Now, let J, I, and K respectively be the set of CFs, BRs, and BSs, indexed by j, i, and k. Also, let L and G respectively be the set of capacities of BR and CF, indexed by l and g. The parameters used in this formulation are the following: Ψ_{il}^{b} is amortized annual cost of constructing and operating a BR_i with the l^{th} size; Ψ_{jg}^{c} is amortized annual cost of constructing and operating a CF_j with the g^{th} size; C_l^b and C_g^c denote the actual capacity of l^{th} and g^{th} size of BR and CF, respectively; β_f and γ_f are conversion rates to bio-energy of biomass feedstock shipped from CF to BR and from HS to BR, respectively; S_f denotes the yield of biomass feedstock from HS_f; D_k is the demand of biofuel for BS_k; δ_i is the maximum number of HSs that ship biomass directly to Br_i; d_{fj}^{1}, d_{fi}^{2}, d_{ji}^{3} and d_{ik}^{4} are unit transportation cost (UTC) from HS_f to CF_j, from HS_f to BR_i, from CF_j to BR_i, and from BR_i to BS_k, respectively. In this study, we set

$d^2_{fi} = \alpha * d^1_{fj}$, $\alpha \geq 1$ to denote a higher unit transportation cost for shipping biomass from HS_f directly to BR_i.

The decision variables used in the mixed integer quadratic programming (MIQP) formulation are the following: x^b_{il} is a binary variable that equals 1 if a biorefinery of size *l* is located in site *i*, and 0 otherwise; x^c_{jg} is a binary variable that equals 1 if a collection facility of size *g* is located in site *j*, and 0 otherwise; y^1_{fj} is a binary variable that equals 1 if HS_f's yielded biomass shipped to CF_j and 0 otherwise; y^2_{fi} is a binary variable that equals 1 if HS_f ships biomass directly to BR_i, and 0 otherwise; y^3_{ji} is a binary variable that equals to 1 if CF_j is assigned to BR_i, and 0 otherwise; y^4_{ik} is the fraction of BR_i' produced biofuel shipped to BS_k; y^4_{mk} is the fraction of demand for BS_k that must be satisfied by a dummy BR_m, for the occurrence of shortage, that is, the total demand of all BSs cannot be met because the total supply from all BRs is not enough, and 0 otherwise.

Letting N_b and N_c denote the maximum number of BRs and CFs to be built, we formulate the following MIQP model that minimizes the total logistics cost (TLC), which is the sum of the annualized construction and operation cost for CFs and BRs and the transportation costs from HSs to CFs, HSs to BRs, CFs to BRs, and BRs to BSs:

$$\text{Minimize TLC} = \left[\sum_{i\in I}\sum_{l\in L}\psi^b_{il}x^b_{il} + \sum_{j\in J}\sum_{g\in G}\psi^c_{jg}x^c_{jg}\right] + \left[\sum_{j\in J}\sum_{f\in F}S_f d^1_{fj}y^1_{fj} + \sum_{i\in I}\sum_{f\in F}S_f d^2_{fi}y^2_{fi}\right] + \left[\sum_{i\in I}\sum_{j\in J}\left(\sum_{f\in F}S_f y^1_{fj}\right)d^3_{ji}y^3_{ji}\right] + \left[\sum_{i\in I}\sum_{k\in K}D_k d^4_{ik}y^4_{ik}\right] \quad (1)$$

$$X^b_i = \sum_{l\in L}x^b_{il},\ \forall i\in I \quad (2)$$

$$X^c_j = \sum_{g\in G}x^c_{jg},\ \forall j\in J \quad (3)$$

$$\sum_{i\in I}X^b_i \leq N_b, \quad (4)$$

$$\sum_{j\in J}X^c_j \leq N_c, \quad (5)$$

$$\sum_{j\in M}y^1_{fj} + \sum_{i\in I}y^2_{fi} = 1, \forall f\in F \quad (6)$$

$$X^c_j u_j \leq \sum_{f\in F}y^1_{fj} \leq X^c_j U_j,\ \forall j\in J \quad (7)$$

$$\sum_{f\in F}S_f y^1_{fj} \leq \sum_{g\in G}C^c_g x^c_{jg},\ \forall j\in J \quad (8)$$

$$\sum_{j\in J}\sum_{f\in F}\beta_f S_f y^1_{fj}y^3_{ji} + \sum_{f\in F}\gamma_f S_f y^2_{fi} \leq \sum_{l\in L}C^b_l x^b_{il},\ i\in I \quad (9)$$

$$\sum_{i \in I} y^3_{ji} = X^c_j, \quad \forall j \in M \tag{10}$$

$$\sum_{f \in F} y^2_{fi} \leq \sum_{l \in L} \delta_i x^b_{il}, \quad \forall i \in I, \tag{11}$$

$$\sum_{i \in I} \left(\sum_{j \in J} \sum_{f \in F} \beta_f S_f y^1_{fj} y^3_{ji} + \sum_{f \in F} \gamma_f S_f y^2_{fi} \right) \geq \sum_{k \in K} D_k \left(y^4_{ik} + y^4_{mk} \right), \tag{12}$$

$$\sum_{i \in I} y^4_{ik} + y^4_{mk} = 1, \quad \forall k \in K. \tag{13}$$

Constraints (2) and (3) ensure that a BR and a CF of size *l* and *g* are located in sites i and j. Constraints (4) and (5) require that at most N_b BRs and N_c CFs can be constructed. Constraints (6) ensure that each HS is assigned to a CF or a BR. Constraints (7) ensure that each selected CF should cover at least u_j and at most u_j HSs (set to 2 and 10 in this study). Constraints (8) are capacity constraint for CFs, that is, the amount of biomass a CF receives should not exceed its capacity. Constraints (9) are capacity constraint for BRs, that is, the amount of biofuel a BR can produce should not exceed its capacity. Constraints (10) ensure that a CF supplies biomass to the selected BR sites only. Constraints (11) ensure that at most δ_i HS is directly covered by BR_i. Constraints (12) and (13) ensure that the total amount of biofuel converted from biomass by all BRs is enough to satisfy the total demand of biofuel for all BSs. If not, a dummy biorefinery, BR_m, is added to satisfy the shortage.

To solve the above MIQP problem, letting $z_{fji} = y^1_{fj} y^3_{ji}$ to linearize the term $y^1_{fj} y^3_{ji}$ in Equations (1), (9) and (11), we add the following:

$$\text{Max}\left\{0,\ y^1_{fj} + y^3_{ji} - 1\right\} \leq z_{fji} \leq y^1_{fj}. \qquad \forall i \in I,\ \forall j \in J. \tag{14}$$

Hereafter, this newly introduced model given by Equations (1)-(14) is referred to as the Integrated Biofuel Facility Location (IBFL) model.

4. Case Study

We conduct a case study using the scenario illustrated in Figure 2 (EPA Tracked Sites in South Carolina with Biorefinery Facility Siting Potential, 2013). Fifteen (15) counties, whose biomass resources are classified 'good' or better as shown in Figure 2, are selected as the harvesting sites (HSs). Then, one city is chosen from each county using a centroid approach and is considered a candidate location for collection facility (CF). Five (5) locations and ten locations (10) throughout South Carolina are considered as candidate sites for BRs and blending stations (BSs), respectively, as shown in Figure 3. The potential locations for BRs are selected based upon low population density, easy access to interstate highways, etc.

Although not shown in Figure 3, the actual distances among cities representing HSs, CFs, BRs, and BFs, are calculated. Table 1a shows the demands (in thousand gallons) for all BSs. These demands are hypothetical values and can be readily replaced by true demand data for real-world applications. The values of the input parameters are summarized in Table 1b. Based on these input data, an Excel Spreadsheet model is developed. Excel Analytic Solver Platform with VBA (Visual Basic for Applications) is used to solve the proposed model.

To simulate the uncertainty in biomass yields, we randomly generate biomass yield for each HS using three popular probability distributions. The minimum and maximum biomass yield values for each HS are obtained from the ranges shown in Figure 2. The probability distributions considered in this paper are normal distribution, uniform distribution, and triangular distribution.

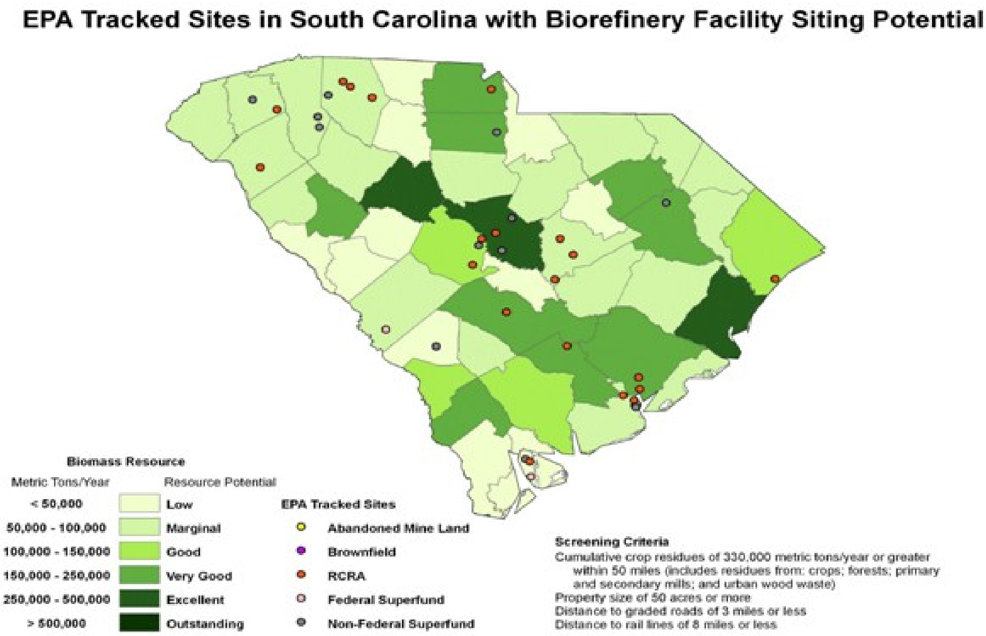

Figure 2. Candidate Harvesting Sites, Collection Facility, and Biorefinery

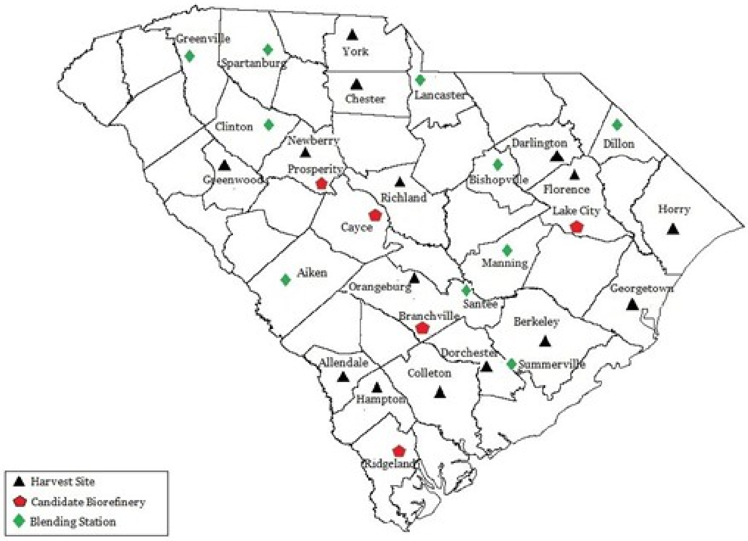

Figure 3. Candidate Biorefinery, Harvesting Sites, and Blending Stations

No.	Blending Station	Demand(in 1000 gallons)
1	Aiken	300
2	Bishopville	200
3	Clinton	300
4	Dillon	150
5	Greenville	150
6	Lancaster	200
7	Manning	250
8	Santee	150
9	Spartanburg	300
10	Summerville	200

Table 1a. Demand for Blending Station

Symbol	Meaning	Value
Ψ^b_{il}	Amortized annual cost of constructing and operating a BR_i with the l^{th} size	\$0.7M, \$0.8M, and \$1M for l=1, 2, 3.
Ψ^c_{jg}	Amortized annual cost of constructing and operating a CFj with the gth size	\$120K, \$150K, and \$200K for g=1, 2, 3.
C^b_l	Actual capacity of l^{th} size of BR	500K, 800K, 1M gallons for l=1, 2, 3.
C^c_g	Actual capacity of g^{th} size of CF	400K, 800K, 1M tons for g=1,2,3.
β_f	Conversion rates to bio-energy of biomass feedstock shipped from CF to BR	70%
γ_f	Conversion rates to bio-energy of biomass feedstock shipped from HS to BR	50%
δ_i	Maximum number of HSs that ship biomass directly to BR_i	1
N_b	Maximum number of BRs to be built	3
N_c	Maximum number of CFs to be built	6
d^1_{fj}	Unit transportation cost (UTC) from HS_f to CF_j	\$0.08/mile/K metric tons
d^2_{fi}	Unit transportation cost (UTC) from HS_f to BR	2* d^1_{fj}
d^3_{ji}	Unit transportation cost (UTC) from CF_j to BR_i	\$0.04/mile/K metric tons
d^4_{ik}	Unit transportation cost (UTC) from BR_i to BS_k	\$0.01/mile/K gallons

Table 1b. Input Data Used for Case Study

Case 1. Normal Distribution: in this case, the mean biomass yield at HS_f, μ_f, and its standard deviation, σ_f, are obtained from

$$\mu_f = (w_f + W_f)/2 \tag{15}$$

and

$$\sigma_f = (W_f - w_f)/6 \tag{16}$$

where w_f and W_f denote minimum and maximum amounts of biomass yield at HS_f shown in Figure 2. To derive Equation (16), we assume that w_f and W_f are located at three standard deviations on either side of its mean.

Case 2. Uniform Distribution: we use the minimum, w_f, and maximum value, W_f for the parameters of the uniform distribution.

Case 3. Triangular Distribution: two skewed distributions are considered for biomass yield. The first one is a right-skewed distribution. Its mode, $O_{(r)f}$, is located at

$$O_{(r)f} = w_f + (W_f - w_f)/4 \tag{17}$$

The other one is a left-skewed distribution. Its mode, $O_{(l)f}$, is located at

$$O_{(r)f} = W_f - (W_f - w_f)/4 \tag{18}$$

For Equations (17) and (18), we assume that a mode is located at $(W_f, - w_f)/4$ to the right side of the minimum amount (w_f) for the right-skewed distribution and to the left side of the maximum amount (W_f) for the left-skewed distribution, respectively.

5. Numerical Results and Observations

We assume shortage costs to be equal to zero, since the occurrence of biofuel shortage would not affect the optimal locations of BRs and CFs. We solve the developed model for forty (40) different sets of simulated biomass yields for each probability distribution and present the frequencies of BR and CF to be included in the optimal solutions in Tables 2a through 2d. ‘1’ for BR location columns in these tables denotes that this location is selected in the optimal solution and ‘0’ otherwise. For the case of normal distribution (see Table 2a), the frequencies for selected BR location set 1 {Branchville, Cayce} and BR location set 2 {Prosperity, Cayce} are 23 and 17, respectively, whereas for the case of uniform distribution, the frequencies for BR location set 1 {Branchville, Cayce} and BR location set 2 {Prosperity, Cayce} are exactly same (see Table 2b). However, for the skewed triangle distribution case, one BR location set is dominant over the other. For the right-skewed triangle distribution, the simulated biomass yields are more likely to be less than the middle value of w_f and W_f. Due to this, the BR location set 2 {Prosperity, Cayce} is selected more frequently (33 times out of 40) as shown in Table 2c, whereas the BR location set 1 {Branchville, Cayce} is selected more frequently (36 times out of 40) for the left-skewed distribution as shown in Table 2d.

The selected locations of CFs depend upon the locations of BRs. As the results in Tables 2a through 2d and Table 3 suggest, when the BR location set 1 {Branchville, Cayce} is chosen, the CF location set {Colleton, Dorchester, Newberry, Orangeburg, Richland} is selected 83 times out of 86 (see Table 3). Given that the BR location set 2 {Prosperity, Cayce} is selected, the CF location set {Chester, Newberry, Orangeburg, Richland} is selected 39 times out of 73. The total capacity of these four (4) CF locations is sometimes insufficient. Therefore, the second most frequent CF location set, {Chester, Newberry, Orangeburg, Richland, Darlington} selected 16 times out of 17, is considered. From Table 3, we observe that two CF candidates, {Orangeburg, Richland}, are always selected regardless of the types of distribution or the selected BR locations. Another candidate CF location, {Newberry}, is selected 158 times out of 160. From now on, we refer to the location {(Branchville, Cayce), (Colleton, Dorchester, Newberry, Orangeburg, Richland)} as ‘Robust Location 1’ and {(Prosperity, Cayce), (Chester, Newberry, Orangeburg, Richland, Darlington)} as ‘Robust Location 2,’ respectively.

To evaluate the efficiency of Robust Locations 1 and 2, we consider the following extreme scenarios:

Scenario I: Each HS yields the minimum amount of biomass, w_f, $\forall f \in F$.

Scenario II: Each HS yields the middle amount of biomass, $(w_f, + W_f)/2$, $\forall f \in F$.

Scenario III: Each HS yields the maximum amount of biomass, W_f, $\forall f \in F$.

	Biorefinery					Frequency
Combination of location selected	Branchville	Cayce	Lake City	Prosperity	Ridgeland	
1	1	1	0	0	0	23
2	0	1	0	1	0	17
Average capacity (in 1000 gallons)	1670	1860	0	1836	0	

	Collection Facility							
Location selected	Allendale	Chester	Colleton	Darlington	Dorchester	Newberry	Orangeburg	Richland
Frequency	3	16	23	5	23	40	40	40
Average capacity (in 1000 Metric Tons)	500	631	526	760	947	885	995	1000

Selected location for biorefinery		Selected location for collection facility	Frequency
Branchville	Cayce	Colleton, Dorchester, Newberry, Orangeburg, Richland	23
Prosperity	Cayce	Chester, Newberry, Orangeburg, Richland	9
Prosperity	Cayce	Chester, Darlington, Newberry, Orangeburg, Richland	4
Prosperity	Cayce	Allendale, Chester, Newberry, Orangeburg, Richland	3
Prosperity	Cayce	Darlington, Newberry, Orangeburg, Richland	1
		Total	40

Table 2a. Simulation Results of Locations of Biorefinery and Collection Facility for Case 1 (Normal Distribution)

	Biorefinery					Frequency
Combination of location selected	Branchville	Cayce	Lake City	Prosperity	Ridgeland	
1	1	1	0	0	0	20
2	0	1	0	1	0	20
Average capacity (in 1000 gallons)	1760	1830	0	1780	0	

	Collection Facility							
Location selected	Allendale	Chester	Colleton	Darlington	Dorchester	Newberry	Orangeburg	Richland
Frequency	5	20	19	6	20	39	40	40
Average capacity (in 1000 Metric Tons)	500	590	579	500	920	895	995	1000

Selected location for biorefinery		Selected location for collection facility	Frequency
Branchville	Cayce	Colleton, Dorchester, Newberry, Orangeburg, Richland	18
Prosperity	Cayce	Chester, Newberry, Orangeburg, Richland	7
Prosperity	Cayce	Chester, Darlington, Newberry, Orangeburg, Richland	6
Prosperity	Cayce	Allendale, Chester, Newberry, Orangeburg, Richland	5
Branchville	Cayce	Colleton, Dorchester, Orangeburg, Richland	2
Prosperity	Cayce	Etc.	2
		Total	40

Table 2b. Simulation Results of Locations of Biorefinery and Collection Facility for Case 2 (Uniform Distribution)

	Biorefinery					Frequency
Combination of location selected	Branchville	Cayce	Lake City	Prosperity	Ridgeland	
1	1	1	0	0	0	7
2	0	1	0	1	0	33
Average capacity (in 1000 gallons)	1828	1770	0	1830	0	

	Collection Facility							
Location selected	Allendale	Chester	Colleton	Darlington	Dorchester	Newberry	Orangeburg	Richland
Frequency	3	32	7	4	7	39	40	40
Average capacity (in 1000 Metric Tons)	500	632	543	625	914	969	990	1000

Selected location for biorefinery	Selected location for collection facility	Frequency
Prosperity Cayce	Chester, Newberry, Orangeburg, Richland	23
Branchville Cayce	Colleton, Dorchester, Newberry, Orangeburg, Richland	6
Prosperity Cayce	Chester, Darlington, Newberry, Orangeburg, Richland	4
Prosperity Cayce	Allendale, Chester, Newberry, Orangeburg, Richland	3
Branchville Cayce Prosperity Cayce	Etc.	4
	Total	40

Table 2c. Simulation Results of Locations of Biorefinery and Collection Facility for Case 3 (Right-Skewed Triangle Distribution)

	Biorefinery					Frequency
Combination of location selected	Branchville	Cayce	Lake City	Prosperity	Ridgeland	
1	1	1	0	0	0	36
2	0	1	0	1	0	3
3	1	0	0	1	0	1
Average capacity (in 1000 gallons)	1870	1734	0	1800	0	

	Collection Facility							
Location selected	Allendale	Chester	Colleton	Darlington	Dorchester	Newberry	Orangeburg	Richland
Frequency	1	3	37	2	37	40	40	40
Average capacity (in 1000 Metric Tons)	500	600	616	500	978	820	995	995

Selected location for biorefinery	Selected location for collection facility	Frequency
Branchville Cayce	Colleton, Dorchester, Newberry, Orangeburg, Richland	36
Prosperity Cayce	Chester, Darlington, Newberry, Orangeburg, Richland	2
Prosperity Cayce	Allendale, Chester, Newberry, Orangeburg, Richland	1
Branchville Prosperity	Colleton, Dorchester, Newberry, Orangeburg, Richland	1
	Total	40

Table 2d. Simulation Results of Locations of Biorefinery and Collection Facility for Case 3 (Left-Skewed Triangle Distribution)

	Biorefinery					Frequency
Combination of location selected	Branchville	Cayce	Lake City	Prosperity	Ridgeland	
1	1	1	0	0	0	86
2	0	1	0	1	0	73
3	1	0	0	1	0	1
Average capacity (in 1000 gallons)	1787	1799	0	1816	0	

	Collection Facility							
Location selected	Allendale	Chester	Colleton	Darlington	Dorchester	Newberry	Orangeburg	Richland
Frequency	12	71	86	17	87	158	160	160
Average capacity (in 1000 Metric Tons)	500	619	578	556	961	861	995	997

Selected location for biorefinery	Selected location for collection facility	Frequency
Branchville Cayce	Colleton, Dorchester, Newberry, Orangeburg, Richland	83
Prosperity Cayce	Chester, Newberry, Orangeburg, Richland	39
Prosperity Cayce	Chester, Darlington, Newberry, Orangeburg, Richland	16
Prosperity Cayce	Allendale, Chester, Newberry, Orangeburg, Richland	12
Prosperity Cayce Branchville Cayce	Etc.	10
	Total	160

Table 3. Summary of Simulation Results of Locations of Biorefinery and Collection Facility

In Table 4, we compare the optimal solutions of each simulated biomass yield scenario with Robust Location 1 and Robust Location 2. We also report the percentage deviation (PD) of Robust 1 and Robust 2 from the optimal solution for each scenario. As expected from Tables 2 and 3 and seen in Table 4, for Scenario I, which is an extreme case of the right skewed distribution, Robust 2 performs better than Robust 1. For Scenario III, an extreme case of the left skewed distribution, Robust 1 outperforms Robust 2. For Scenario II, both Robust 1 and Robust 2 perform well compared to the optimal solution, since the PDs yielded by Robust 1 and Robust 2 are 0% and 0.04%. In terms of the maximum PD (MXPD) for all scenarios, Robust 1 with 11.4% performs better than Robust 2 with 18.3%. On the average of PD (AVPD), Robust 1 with 6.3% performs slightly better than Robust 2 with 7.3%, which is consistent with the results shown in Table 3.

6. Summary and Conclusions

In this paper, we develop an IBFL (Integrated Biofuel Facility Location) model to simultaneously find the optimal locations of collection facilities (CFs) and biorefineries (BRs) for a biomass and bio-energy logistics network. We formulate the proposed model as a mixed integer quadratic program (MIQP), construct an Excel spreadsheet model, and solve it using Excel Analytic

Solver Platform with VBA (Visual Basic for Applications). For the biomass and bio-energy logistics network, the uncertainty in biomass yield has been a critical factor for determining the optimal locations of BRs and CFs, since it significantly affects the logistics network operational costs. To demonstrate the developed model's capability and to evaluate the effects of the uncertainty in biomass yield, a case study is conducted using the data from United States EPA as shown in Figure 2. We simulate the biomass yield uncertainty by randomly generating biomass yield for each HS using normal, uniform, and triangular probability distributions. We then find the optimal locations of BRs and CFs for each generated set of biomass yield data.

Scenario		**Optimal**	**Robust 1**	**Robust 2**
I **(Each HS yields the minimum amount of biomass)**	BR Location	1. Prosperity 2. Cayce	1. Branchville 2. Cayce	1. Prosperity 2. Cayce
	CF Location	1. Newberry 2. Orangeburg 3. Richland	1. Colleton 2. Dorchester 3. Newberry 4. Orangeburg 5. Richland	1. Chester 2. Newberry 3. Orangeburg 4. Richland 5. Darlington
	TLC (PD)	$7,834.54	$8,726.16 (11.4%)	$8,018.08 (2.3%)
II **(Each HS yields the middle amount of biomass)**	BR Location	1. Branchville 2. Cayce	1. Branchville 2. Cayce	1. Prosperity 2. Cayce
	CF Location	1. Colleton 2. Dorchester 3. Newberry 4. Orangeburg 5. Richland	1. Colleton 2. Dorchester 3. Newberry 4. Orangeburg 5. Richland	1. Chester 2. Newberry 3. Orangeburg 4. Richland 5. Darlington
	TLC (PD)	$8,130.64	$8,130.64 (0%)	$8,134.30 (0.04%)
III **(Each HS yields the maximum amount of biomass)**	BR Location	1. Branchville 2. Prosperity	1. Branchville 2. Cayce	1. Prosperity 2. Cayce
	CF Location	1. Chester 2. Colleton 3. Dorchester 4. Orangeburg 5. Richland	1. Colleton 2. Dorchester 3. Newberry 4. Orangeburg 5. Richland	1. Chester 2. Newberry 3. Orangeburg 4. Richland 5. Darlington
	TLC (PD)	$9,075.30	$9,757.85 (7.5%)	$10,737.18 (18.3%)
	Average (PD)	$8,346.83	$8,871.55 (6.3%)	$8,963.18 (7.3%)

*PD stands for percentage deviation, (TLC yielded by Robust location – Optimal TLC)/Optimal TLC

Table 4. Comparison between Results of Optimal and Robust Locations

Based on the simulation results, we identify some most frequently chosen locations of BRs and CFs, which are referred to as 'Robust Locations,' for the randomly generated biomass yields. To evaluate the capability of 'Robust Locations' to deal with the uncertainties in biomass yield, we select two sets of robust locations, 'Robust Location 1' and Robust Location 2'. They are applied to three extreme scenarios and their solutions are compared against the corresponding optimal solutions. We find that the two robust locations work well in terms of the total logistics costs.

Thus, the model developed in this paper would help decision-makers find the robust locations of biorefinery and collection facility, which require huge investments, and would assist the potential investors in identifying the most profitable or important facilities to invest in the biomass and bio-energy industry. This model could be a very useful tool that helps them minimize the investment risk.

For future research, it would be necessary to consider truck routing for collecting less-than-truckload biomass from farms, as this very likely could lead to improved transportation efficiency in the biomass collection process.

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