Optimization of Bio-fuel Logistics in the Southwestern United States

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***Abstract*—Bio-fuels have gained much attention over the last decade. However, most of the research efforts have been focused on improving the quality and increasing the productivity of bio-fuels, and there have been minimal attempts to develop research on the supply and delivery issues of these sources. We believe that the viability of bio-fuels is strongly related to the efficiency of the distribution networks. This paper presents an optimization model and its application to an infrastructure for bio-fuels distribution network. Unlike other studies on the topic acknowledging the fact that traditional sources of fuel (i.e. petroleum) will not readily disappear from the competitive landscape, we focus on the dynamic nature of how the "new" and "old" energy sources may ultimately co-exist by adjusting their geographic product offerings based on production and transportation costs. To handle the uncertain demands of bio-fuels, we adopt the concept of stochastic programming. The presented model also considers two different modes of transportation with heterogeneous fleet size. The applicability of the optimization model is demonstrated in the case study of Bio-fuels distribution network in the Southwestern United States. The results demonstrate that the model is a practical and flexible tool in solving realistic distribution planning problem of bio-fuels.**

Keywords*— *Bio-fuel; Distribution network; Mixed-Integer Linear Program; Stochastic Program

I. INTRODUCTION

Over the last decade, a noticeable increase of interest in the area of renewable energy has been observed. In general, renewable energies are considered clean and limitless alternatives to fossil and nuclear fuels [1]. As of 2013, renewable energies are the least consumed forms of energies in the US, and among these energy sources, biomass and hydropower are the main sources utilized [2]. In contrast to hydropower, biomass has growth potential since much of the waste material that we produce in our daily activities can be effectively converted into a usable form of energy by utilizing the right conversion technology.

The United States have embraced the use of biofuels as a reliable form of transportation fuel and have been continuously working toward increasing and accelerating the commercialization of this industry [3]-[4]. Although biofuels have gained much attention over the past decade, much of the research efforts have been focused on improving the quality and increasing the productivity of biomass in more efficient ways. Aside from a handful of government reports and one practitioner conference, formal investigation of supply chain and distribution issues of bio-fuels is essentially absent.

Recently, there have been some attempts at optimizing the biofuel supply chains by private companies and research institutions (see [5]-[10]). However, in order to assure the economic viability of biofuels in a commercialized large scale, a lot more research needs to be done on the distribution infrastructure of the biofuels supply chain. In this short paper, we present an optimization model for biomass and biofuels supply chain network in the southwestern United States. The proposed model closely follow the work by [5] and [10]. Unlike their studies, however, two different modes of transportation are considered in the proposed model, and traditional sources of fuel does not readily disappear from the competitive landscape, and thus, we focus on the dynamic nature of how the "new" and "old" energy sources may ultimately co-exist by adjusting their geographic product offerings based on production and transportation costs.

II. PROBLEM DESCRIPTION

The generalized but well accepted structure of the biofuels supply chain model consists of three main layers namely, upstream, midstream, and downstream. Figure 1 shows a depiction of the biofuels supply chain structure.

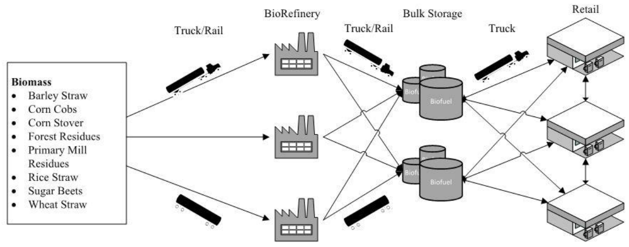

Figure. 1. BIOFUELS SUPPLY CHAIN

The upstream layer begins by having a selection of biomass fields of different types and production capacities. If driven by demand, biomass should be moved by truck or rail tankers to the most appropriate bio-refinery. At this point, biomass gets converted into a liquid fuel. Each type of biomass has different biomass-to-biofuel conversion factor, which means that the liquid fuel produced will vary depending upon the type of biomass that is being input. After the refining process, the biomass gets delivered to a bulk storage or blending location via truck or rail tanker, which represents the midstream layer of the supply chain. After that, the fuels are delivered to the end-customers. Since this final stage occurs within city limits, only a single transportation mode, i.e., truck, is considered in our model.

III. MATHEMATICAL MODELING

The entire supply chain is broken down into two major parts, i.e., one for the upstream and midstream layers of the supply chain and another for the downstream layer. To handle the uncertainty issue of biofuels demand, we adopt the concept of the stochastic programming. In the model, the first-stage decision variable represents the amount of biomass delivered, whereas the second-stage decisions are the amount of biofuels transported to end-customers. The random events are the amounts of biofuels demand. A pre-determined number of scenarios were used with a relative probability of occurring.

A. *MILP for upstream and midstream*

The first part considers the upstream and midstream layers of the supply chain. We include various types of biomass for biofuel production in the region, as well as a limited number of bio-refineries with specific production capacities. The model also includes the bulk blending/storage locations that are readily available for biofuels. We consider the existing fuel stations that report to actually sell ethanol in the region. The presented model also considers two different modes of transportation with heterogeneous fleet size. For convenience, all notations used in the model formulation are summarized as below:

Sets:

L	Set of biomass types indexed by l
I_l	Set of biomass fields of type l indexed by i
J	Set of refinery locations indexed by j
K	Set of storage locations indexed by k
M	Set of transportation modes indexed by m. (i.e. 1-truck, 2-rail tanker)
Ω	Set of Scenarios indexed by ω

Input Parameters:

P_l	Cost of harvesting biomass of type l
v_m	Average speed (MPH) for transportation mode m
cap_m^b	Capacity of vehicle m for bulk solids
cap_m^l	Capacity of vehicle m for liquids
$tran_m^{db}$	Distance dependent transportation cost of bulk solids by transportation mode m
$tran_m^{tb}$	Time dependent transportation cost of bulk solids by transportation mode m
$tran_m^{dlq}$	Distance dependent transportation cost of liquids by transportation mode m
$tran_m^{tlq}$	Time dependent transportation cost of liquids by transportation mode m
d_{ij}^{up}	Distance from biomass location i to refinery j for upstream operations
d_{jk}^{mid}	Distance from refinery j to blending/storage location k for midstream operations
d_{kg}^{down}	Distance from blending/storage location k to fuel station g for downstream operations
u_m^b	Loading and unloading costs for bulk solids by mode m
u_m^{lq}	Loading and unloading costs for liquids by mode m
MC_l	Moisture content of biomass of type l
b_l	Conversion factor of biomass type l into liquid fuel
$dem(\omega)$	Biofuel demand in scenario ω
TC_1	Transportation costs for upstream operations
$TC_2(w)$	Transportation costs for midstream operations in scenario ω
S_k	Blending/Storage cost at location k

R_j	Fuel production cost at refinery *j*
λ	Penalty cost for fuel shortage
$Cap_{il}^{Biomass}$	Produced biomass of type *l* in field *i*
Cap_j^{ref}	Capacity at refinery *j*
Cap_k^{Bulk}	Storage capacity at location *k*
$\Delta(\omega)$	Fuel shortage in scenario *ω*
E_ω	Probability of scenario *ω*

Decision Variables:

Y_{il}	Amount of biomass harvested of type *l* in field *i* during time period
x_{ilj}^m	Amount of biomass of type *l* collected in field *i* and transported to refinery *j* by mode m
$z_{jk}^m(\omega)$	Amount of biofuel transported from refinery *j* to storage location *k* in time scenario *ω*
Up_{ij}^m	1 if vehicle *m* is selected to transport biomass from field *i* to refinery *j*, 0 otherwise
$Mid_{jk}^m(\omega)$	1 if vehicle *m* is selected to transport biofuel from refinery *j* to blending/storage location *k* in scenario *ω*, 0 otherwise

The objective function (1) minimizes the costs of harvesting the biomass, delivering biomass to bio-refineries, fuel production at refineries, biofuel to bulk blending/storage locations, and penalties for fuel shortages taking into consideration several different scenarios with different probabilities. While considering both feedstock delivery and fuel distribution, the transportation costs are calculated based on [10], i.e., travel distance and time are divided by vehicle capacity in order to convert the delivery quantity to number of vehicle loads (see (2) and (4)). The model also considers the loading / unloading costs and allows for the option of selecting either trucks or rail tankers as the mode of transportation. Equations (3) and (5) keep track of the biomass distributed from each field and biofuels transported from each bio-refinery, respectively.

$$\text{Min } \sum_{l\in L}\sum_{i\in I_l} P_l X_i^{tot} + TC_1 + \sum_{\omega\in\Omega} E_\omega \left\{ \sum_{j\in J} R_j Z_j^{tot}(\omega) + TC_2(\omega) + \sum_{k\in K} S_k Z_k^{tot}(\omega) + \lambda\,\Delta(\omega) \right\} \quad (1)$$

where

$$TC_1 = \sum_{\substack{l\in L,\, i\in I_l,\\ j\in J,\, m\in M}} \left\{ \left(tran_m^{db} + \frac{tran_m^{tb}}{v_m} \right) \frac{d_{ij}^{up}}{cap_m^b} + u_m^b \left\{ \frac{x_{ilj}^m}{1-MC_l} \right\} \right\} Up_{ij}^m \quad (2)$$

$$X_{il}^{tot} = \sum_{l\in L}\sum_{m\in M} x_{ilj}^m \quad \forall i\in I_l \quad (3)$$

$$TC_2(\omega) = \sum_{\substack{j\in J,\, k\in K,\\ m\in M}} \left\{ \left(tran_m^{dlq} + \frac{tran_m^{tlq}}{v_m} \right) \frac{d_{jk}^{mid}}{cap_m^{lq}} + u_m^{lq} \right\} \left(z_{jk}^m \right) \left\{ Mid_{jk}^m(\omega) \right\} \quad \forall \omega\in\Omega \quad (4)$$

$$Z_j^{tot}(\omega) = \sum_{k\in K}\sum_{m\in M} z_{jk}^m \quad \forall j\in J,\ \omega\in\Omega \quad (5)$$

This objective function is subject to various constraints as follows:

$$Cap_i^{Biomass} \geq \sum_{l\in L}\sum_{m\in M} x_{ilj}^m \quad \forall i\in I_l \quad (6)$$

$$Cap_j^{ref} \geq \sum_{i\in I}\sum_{l\in L}\sum_{m\in M} x_{ilj}^m \quad \forall j\in J \quad (7)$$

$$Cap_k^{Blend} \geq \sum_{j\in J}\sum_{m\in M} z_{jk}^m(\omega) \quad \forall k\in K,\ \omega\in\Omega \quad (8)$$

Constraint (6) ensures that the amount of biomass transported for biofuel conversion does not exceed the available capacity from each location. Likewise, constraints (7) – (8) impose capacity restrictions for the bio-refineries as well as the blending/storage locations for each scenario.

$$\sum_{k\in K}\sum_{m\in M} Mid_{jk}^m(\omega) = 1, \quad \forall \omega\in\Omega,\ j\in J \quad (9)$$

$$\sum_{j\in J}\sum_{m\in M} Mid_{jk}^m(\omega) = 1, \quad \forall \omega\in\Omega,\ k\in K \quad (10)$$

$$\sum_{i\in I}\sum_{m\in M} Up_{ij}^m = 1, \quad \forall j\in J \quad (11)$$

$$\sum_{j\in J}\sum_{m\in M} Up_{ij}^m = 1, \quad \forall i\in I \quad (12)$$

Constraints (9) – (12) ensures that, for each distribution route in upstream and midstream operations, only one mode of transportation can be selected.

$$\sum_{i\in I_l}\sum_{l\in L} X_{il}^{tot}(\omega) b_l \geq \sum_{j\in J} Z_j^{tot}(\omega) \quad (13)$$

Constraint (13) ensures that the output of the refinery should not exceed the amount of biomass that was transported times the conversion factor for each biomass type.

$$\sum_{j\in J} Z_j^{tot}(\omega) - dem(\omega) = \Delta(\omega), \quad \forall \omega\in\Omega \quad (14)$$

Constrain (14) ensures that if there is a shortage on the demand amount of biofuels, then the objective function will be penalized.

A. MILP for downstream

The second part of the model covers the downstream of the supply chain. While building up the model, it is assumed that the capacity of the vehicle is large enough to supply the fuels to multiple locations, which enables us to adopt the concepts of the multi-depot vehicle routing problem (MDVRP).

Sets:

Ω	Set of scenarios indexed by *ω*
I	Set of Blending/Storage stations indexed by *i*
J	Set of fuel stations indexed by *j*
K	Set of vehicles indexed by *k*

Input Parameters:

E_ω	Probability of scenario *ω*
α	Variable transportation cost
β	Fixed Transportation cost
D_{ij}	Distance between node *i* and *j*
λ	Penalty cost for bio-fuel shortage
$dem_j(\omega)$	Fuel demand at station *j* in scenario *ω*
Q_k	Maximum capacity for vehicle *k*

Decision Variables:

$X_{ijk}(\omega)$	1 if customer *j* is visited right after customer *i* by vehicle *k* in scenario *ω*, 0 otherwise.
$\Delta(\omega)$	Bio-fuel shortage in scenario ω
$fossil(\omega)$	Fossil fuel for replacing biofuel shortage

The downstream operations of the biofuel supply chain can be formulated as a mixed integer linear programming model whose objective function (15) is to minimize the total downstream logistics cost subject to various constraints:

$$\text{Min} \sum_{\omega\in\Omega} E_\omega \left\{ \sum_{i\in I\cup J}\sum_{j\in I\cup J}\sum_{k\in K} \alpha D_{ij} X_{ijk}(\omega) + \sum_{k\in K} \beta X_{ijk}(\omega) + \lambda \Delta(\omega) \right\} \quad (15)$$

Subject to

$$\sum_{i\in I\cup J}\sum_{k\in K} X_{ijk}(\omega) = 1, \quad \forall j\in I\cup J,\ \omega\in\Omega \quad (16)$$

$$\sum_{j\in I\cup J}\sum_{k\in K} X_{ijk}(\omega) = 1, \quad \forall i\in I\cup J,\ \omega\in\Omega \quad (17)$$

$$\sum_{j\in J} dem_j(\omega) \sum_{i\in I\cup J} X_{ijk}(\omega) \le Q_k, \quad \forall k\in K,\ \omega\in\Omega \quad (18)$$

$$\sum_{i\in I\cup J} X_{ihk}(\omega) - \sum_{j\in I\cup J} X_{hjk}(\omega) = 0, \quad \forall k\in K, h\in I\cup J, \omega\in\Omega \quad (19)$$

$$\sum_{i\in J}\sum_{j\in J} X_{ijk}(\omega) \le |J| - 1, \quad \forall k\in K,\ \omega\in\Omega \quad (20)$$

$$\sum_{i\in I\cup J}\sum_{j\in I\cup J} X_{ijk}(\omega) \le 1, \quad \forall k\in K,\ \omega\in\Omega \quad (21)$$

$$\sum_{j\in J} dem_j(\omega) \sum_{i\in I} X_{ijk}(\omega) \le V_i, \quad \forall i\in I,\ \omega\in\Omega \quad (22)$$

$$\sum_{j\in J} dem_j(\omega) = \sum_{j\in J} dem_j(\omega) \sum_{i\in I} X_{ijk}(\omega) + fossil(\omega), \quad \forall \omega\in\Omega \quad (23)$$

$$\Delta(\omega) = fossil(\omega) - \sum_{j\in J} dem_j(\omega) \sum_{i\in I} X_{ijk}(\omega), \quad \forall k\in K, \omega\in\Omega \quad (24)$$

Constraint (16) and (17) ensure that each customer is served by only one vehicle. Our model allows for heterogeneous fleet and constraint (18) sets the capacity of each vehicle. Constraint (19) is the flow balance constraint. Constraint (20) ensures the elimination of the sub-tours. Constraint (21) ensures that each arc in the network is covered by at most once by any delivery route. Constraint (22) is the capacity constraint for each blending/storage location. Constraint (23) ensures that the demand has to be met either by biofuels or conventional fuels. Finally, constraint (24) ensures that if the fuel demand is not completely met by biofuels, then the conventional fuels have to fill in the shortage amount.

IV. Results and Discussion

The proposed optimization model was applied to a real-world case study of biofuel supply chain in New Mexico. Our study includes a total of 33 locations as the sources of biomass. The amount of biomass and type of biomass that is available at each location varies from one to another. In the New Mexico state area, the five major sources of biomass are Corn Stover, Forest Residues, Primary Mill Residues, Urban Wood and Secondary Mill Residues, and Wheat Straw, from which it is expected to have a total biomass potential of 356,560 dry tonnes per year. There is only one biofuel refinery in New Mexico, which can process biomass for ethanol conversion with a yearly production capacity of 25,000,000. There are 14 fuel stations that are readily equipped to sell biofuel such as E85. Our study also considers six blending/storage stations, which are capable to handle biofuels. They can store several types of petroleum products such as gasoline and oil. Their total combined capacities are 21,733,688,844 gallons (i.e., 24,811,982 barrels). We assume that there exists a total demand of 6,678,000 gallons of biofuel for each fuel stations.

By applying the proposed mathematical method, we are able to identify the best routing decisions for the delivery of biofuels. It determines the optimal assignments of biomass locations to the bio-refinery and allocates the bio-refinery to the bulk blending/storage locations, and routes the vehicles for the delivery of fuels from the bulk bending/storage locations to the fuel stations. Figures 2 and 3 show the original and proposed distribution plans of this case study, respectively. If we were to simply account for a single batch of biomass to be transported from each optimal location to the bio-refinery, and then, transporting a single batch of fuel to each one of the three blending stations, the estimated cost is about \$5,895. However, if we consider every source location and blending station, the estimated cost become \$17,395. As a result, total annual savings of \$115,000 are achieved. Based on this scenario, it is clearly seen that the proposed plan can achieve the total savings of \$115,000 (i.e., approximately 66% of cost savings).

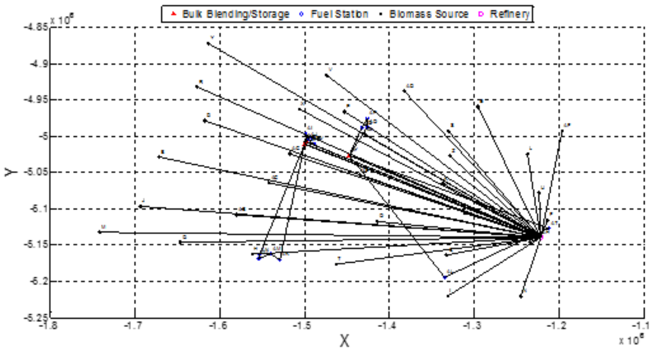

Figure. 2. SCHEMATIC MAP OF ORIGINAL DISTRIBUTION PLAN

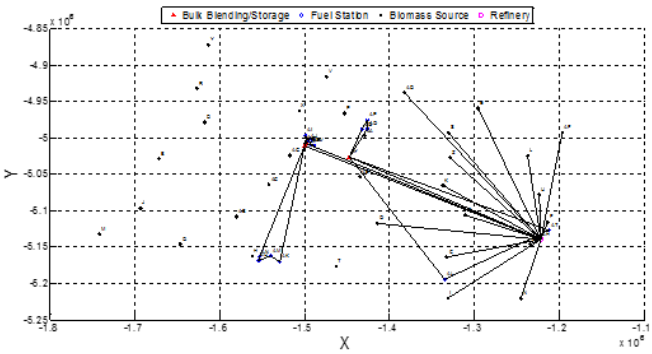

Figure. 3. SCHEMATIC MAP OF PROPOSED DISTRIBUTION PLAN

According to the result (see Figure 3), some biomass sources were never been used. This is because their locations are too far away from the processing plant, which makes difficult for these sources to be processed for fuel conversion. This indicates that the future planning of bio-refineries should be carefully planned since they will need to be placed at strategic locations in order to maximize the amount of biomass which can be utilized, and still make the fuel price competitive.

V. CONCLUSION

In this research, we presented an optimization model for the biofuel supply chain network in the southwestern US. The entire supply chain was broken down into two major parts, and, to handle the uncertainty issue of biofuels demand, we adopted the concept of the stochastic programming. Our model optimally chooses which biomass sources need to be selected for fuel production and it also decides which refineries are the most profitable in the biofuels supply chain. As a result, it helps reduce transportation cost of the biofuels significantly, which makes the biofuels more competitive.

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