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A mathematical model to design a lignocellulosic biofuel supply chain system with a case study based on a region in Central Texas

Heungjo An [a], Wilbert E. Wilhelm [a,*], Stephen W. Searcy [b]

[a] Department of Industrial and Systems Engineering, Texas A&M University, TAMUS 3131, College Station, TX 77843-3131, United States
[b] Department of Biological and Agricultural Engineering, Texas A&M University, TAMUS 2117, College Station, TX 77843-3131, United States

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ABSTRACT

This study formulates a model to maximize the profit of a lignocellulosic biofuel supply chain ranging from feedstock suppliers to biofuel customers. The model deals with a time-staged, multi-commodity, production/distribution system, prescribing facility locations and capacities, technologies, and material flows. A case study based on a region in Central Texas demonstrates application of the proposed model to design the most profitable biofuel supply chain under each of several scenarios. A sensitivity analysis identifies that ethanol (ETOH) price is the most significant factor in the economic viability of a lignocellulosic biofuel supply chain.

1. Introduction

As petroleum reserves are being depleted and the demand for a sustainable source of environmentally friendly fuel is increasing, a number of countries are relying upon biofuels generated from edible crops. However, these first-generation biofuels can lead to higher crop prices because they bid resources (e.g., land) as well as edible crops away from the food industry. In addition, in terms of life-cycle energy use and greenhouse gas (GHG) emissions, several studies have assessed the advantage of the second generation biofuels by using life cycle assessment methodology (Singh et al., 2010) and herbaceous lignocellulosic crops show higher advantage than the first-generation biomass (Rettenmaier et al., 2010). Thus, interest in second-generation biofuels, which are produced from energy crops as well as non-edible parts of food crops, has increased dramatically, and several pilot plants are currently studying ways to enhance conversion technologies to improve efficiency.

The biofuel industry faces unique challenges. First, biomass has low energy density and high moisture content, is geographically dispersed, and degrades during storage. Second, major feedstocks (e.g., dedicated energy crops and crop residues) can be harvested only in specific seasons but must satisfy year around demand. Third, biomass moisture content as well as the price of fuel change over time. Furthermore, alternative technologies to convert lignocellulosic biomass to biofuel, such as biochemical (e.g., enzymatic hydrolysis), thermochemical (e.g., steam explosion and pyrolysis), and bio-thermochemical (e.g., carboxylate pathway) processes, are still under development to improve conversion efficiency in the most economical way (Munasinghe and Khanal, 2010). Finally, since the biofuel industry must ultimately compete with petroleum-based fuels, determining the most profitable biofuel supply chain design is crucial to attracting the investment needed to build this emerging industry into an economically viable enterprise.

Most studies of the biofuel supply-chain have focused on upstream processes with the goal of acquiring a stable and sustainable feedstock supply. The term upstream is commonly used to refer to supply chain echelons that deal with biomass from feedstock production and biomass storage to conversion plants; and downstream, to echelons from conversion plants, which are included in both upstream and downstream, to customers, including storage and transportation of biofuel.

A major thrust of prior research has focused on estimating the cost of each process in the biofuel supply chain. Several studies (Hamelinck et al., 2005b; Tatsiopoulos and Tolis, 2003) used economic analyses to estimate logistics costs for several types of biomass (e.g., crop and forest residues). Computer simulations of biomass logistics have been used successfully to estimate relevant measures such as costs, energy consumption, and carbon emissions (De Mol et al., 1997; Sokhansanj et al., 2006). Several related studies (Constantino et al., 2008; Murray, 1999) have optimized forest harvesting schedules, maximizing profit while contributing to sustainability and observing environmental regulations. Recently,

* Corresponding author. Tel.: +1 979 845 5493; fax: +1 979 847 9005.
E-mail address: wilhelm@tamu.edu (W.E. Wilhelm).

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Gnansounou and Dauriat (2010) reviewed the economic evaluation of lignocellulosic ETOH conversion processes.

A few studies have focused on improving conversion processes. Koch et al. (2010) proposed a simulation model to study the process of generating biogas from grass silage based on the International Water Association Anaerobic Digestion Model No. 1, which can deal with highly complex chemical process.

Some prior research has addressed strategic and tactical supply chain issues simultaneously. De Mol et al. (1997) formulated a single-period Mixed Integer Program (MIP) to prescribe facility openings (for collection, transshipment, pre-processing, and conversion); and logistics for a mix of biomass types (e.g., forest prunings, waste wood, and waste paper).

Several multi-period models have been proposed to deal with the changes that parameter values may undergo over time. Gunnarsson et al. (2004) formulated a multi-period MIP with a one-year planning horizon and monthly time periods to prescribe biomass supply alternatives (self-owned forests, contracted sawmills, and foreign sources), while limiting the use of low quality biomass. Another multi-period supply chain design model (Acharya et al., 2008) prescribed facility locations and material flows, considering dry mass loss in producing ETOH from corn and corn stover. Huang et al. (2010) developed a strategic planning model to determine the locations and sizes of new refineries, additional capacities added onto existing refineries, and material flows by year, providing a case study for waste biomass resources in California with a 10-year horizon.

Several studies deal with a one-year horizon. In 2009, Ekşioğlu et al. formulated a MIP that determines the number, size and location of collection facilities, biorefineries and blending facilities, and the amount of materials (i.e., biomass and biofuel) flows during multiple time periods with a case study in the State of Mississippi. Ekşioğlu et al. (2010) considered the transportation mode additionally. Zhu et al. (2010) proposed a MIP to prescribe locations of biomass storage and conversion facilities, modes of transportation from farms to refineries, and flows of biomass over a one-year planning horizon.

The biofuel industry is subject to uncertainty; for example, biomass yield and moisture content change as functions of weather conditions, and biofuel demand and price depend on the market environment. Cundiff et al. (1997) formulated a two-stage stochastic program to prescribe logistics for herbaceous biomass, considering the uncertainty of biomass yield due to weather conditions during growing and harvesting seasons. The first stage prescribes storage capacity; and the second, biomass transportation quantities. However, they dealt with neither the moisture content of biomass nor strategic-level decisions other than storage capacity.

To date, only Cundiff et al. (1997) have formulated a stochastic model to prescribe biofuel logistics; other researchers have focused on deterministic models. Even though a stochastic model is required to address the uncertainties that the biofuel industry faces, a comprehensive and accurate, multi-period deterministic model is a necessary first step and can lead to important insights about system operation and interactions among its components.

Each previous model has assumed that the technologies are predetermined, rather than incorporating decision variables to prescribe an optimal combination and did not consider the moisture content of biomass even though it comprises a large portion of biomass (e.g., 20–60% on a wet basis) and is a significant factor in planning transportation and preprocessing. In addition, while all previous models have held the objective of minimizing total cost while meeting all demands, in practice, unmet demands could be satisfied using compatible (i.e., petroleum-based) fuels.

This study enhances prior models by incorporating decision variables to select facility technology from among alternatives, practical features (e.g., effects of moisture content and dry matter loss), and intra facility structure (i.e., storage facility before and after process and processing facility) in preprocessing and conversion facilities. To our knowledge, only a few studies, even in generic supply chain studies, have considered such intra facility issues (Goetschalckx et al., 2002). Moreover, rather than using the assumption that any unmet demand must assessed a penalty cost, this paper proposes an objective of maximizing profit because petroleum-based fuels could fill biofuel shortfalls in the coming several decades while biofuel supply is being ramped up. A solution that maximizes profit can be much different from one that minimizes cost.

We formulate a deterministic, time-staged model to maximize total system profit by prescribing strategic-level decisions (e.g., facility locations, capacities, and technology types) as well as a strategic plan for material flows, including production, transportation, and storage levels. This study deals with biomass in the upstream and biofuels in the downstream as different (i.e., multiple) commodities, integrating feedstock suppliers, preprocessors, refineries, distributors, and customers. Our model can also be used at the tactical level for which the supply chain design has been fixed and short-term and, thus, more accurate-forecasts of demands, weather conditions, and other features are available to plan specific processing, transporting, and storage quantities, for example, in each month over a year-long planning horizon.

This study holds two primary research objectives. The first is to formulate a mathematical model to prescribe an optimal biofuel supply chain that allows use of various types of lignocellulosic biomass and deals with upstream and downstream material flows. The second is to apply the model in a case study to demonstrate its use in providing decision support for industry managers and government officials.

The body of this paper comprises three sections. Section 2 describes our mathematical model and discusses a case study based on a region in Central Texas. Section 3 analyzes impacts of several economic factors based on computational results and gives recommendation of future research. Finally, Section 4 gives conclusions.

2. Methods

2.1. System description

The biofuel supply chain system considered comprises five echelons: feedstock production, preprocessing, production in conversion plants, distribution, and consumption by customers, and including possible storage locations. Each facility can use one of several technology alternatives. For example, biomass can be stored using outdoor-uncovered, outdoor-covered, indoor-aerobic, or indoor-anaerobic technologies. Preprocessing technology could include size reduction, drying moisture content, or both. Moreover, conversion technology may involve a biochemical, a thermochemical, or a bio-thermochemical process. Even though improving technologies and efficiencies in each echelon is important, integrating technologies and coordinating echelons is necessary for the system to be most successful economically.

Materials flowing in the supply chain must be stored before being processed either at preprocessing or conversion facilities, and again stored as they wait to be transported after processing. While it is being stored at upstream locations, biomass degrades over time, losing some portion of its mass due to chemical reactions (e.g., fermentation and breakdown of carbohydrates) (Sokhansanj et al., 2006). The rate of dry matter loss in storage depends on the type of biomass, moisture content, and storage conditions.

Some feedstocks contain high moisture content and must be dried on the field immediately after harvesting and/or in a preprocessing facility to reduce the cost of transporting it and to meet requirements of the conversion technology selected. Since lignocellulosic biomass typically has low energy density, it is important to reduce moisture content so that energy is not expended in transporting it. In particular, transportation routes must be carefully prescribed so that the system is able to achieve a net production of energy while managing green house gas emissions. Preprocessing facilities may also involve a size reduction operation to reduce the transportation cost by increasing density and to facilitate the conversion process.

fuel it can store; that of a preprocessing (conversion) facility is the maximum amount of biomass (biofuel) that it can process in a year.

Our model prescribes two types of decisions variables: binary variables select facilities to open and arcs representing routes; and continuous variables prescribe the capacities of open facilities and the quantity of material flow on each arc.

We now describe our formulation verbally; the appendix presents the actual mathematical model.

Maximize profit
Subject to

Select at most a single facility type to open at each potential location	(1)
Impose a capacity limit for each open facility	(2)
Establish a link from a field storage to a unique preprocessing facility or from a preprocessing facility to a unique refinery	(3)
Impose a capacity limit for each selected arc	(4)
Balance the flow of materials into and out of each open facility	(5)
0 – 1 *restriction on binary variables and non – negativity, on continuous variables*	(6)

In the upstream, the various types of feedstocks must share the capacities of transportation vehicles and processing facilities. In the downstream, some biofuels (e.g., ETOH) must be transported and/or stored separately from petroleum-based fuels, while other biofuels (i.e., the so-called drop-in fuels) are compatible with petroleum-based fuels and can be handled easily within the existing infrastructure.

The variability of several important factors over time (e.g., the seasonality of biomass availability, biomass moisture content, and the demand and price of fuel) could significantly affect the supply chain design so that a time-staged model is required. A strategic model, which deals with a long-range forecast of demand can capture such dynamics using a time period of one quarter (i.e., 3 months) duration.

We invoke several assumptions to structure the system: available feedstock supplies are known; the demand for biofuel in each customer zone in each period is known; preprocessors, refineries, and distributors collaborate perfectly in all operations from field storage to customer zones to maximize total profit; preprocessing includes drying and size-reduction operations. We model the types of preprocessing technologies that appear to be the most attractive among the ones currently under development. Since the energy density of biomass is relatively meager, it cannot be transported over long distances if the supply chain is to result in a net production of energy. Further, transport over longer distances increases green house gas emissions. We invoke the single destination assumption to reflect the needs to result in net energy production and manage green house gas emissions as well as to promote management efficiency.

2.2. Mathematical model

We use a multi-commodity flow model to represent several kinds of biomass feedstocks in the upstream and of biofuels in the downstream. In the upstream, each commodity represents a combination of a feedstock type and a range of moisture content. Commodities must be processed, stored and transported, based on prescribed capacities of processing plants and storage facilities, and on the available capacities of transportation routes. The capacity of a storage facility is the maximum amount of biomass or bio-

The objective is to maximize the present worth of total system profit, defined as the discounted revenue earned from selling biofuels in the customer echelon minus all discounted costs, including the fixed cost of capital for each facility opened and variable costs associated with operating facilities, purchasing feedstocks, carrying inventory, and transporting biomass and biofuel.

Constraint (1) requires that a single technology type be selected for each facility that is opened. Constraint (2) limits material flow in accordance with the capacity prescribed at each opened facility and with the given capacity on each transportation route. To facilitate management and promote energy efficiency and reduced GHG emissions, constraint (3) invokes single-destination flows (i.e., each field storage (preprocessing) facility selected can ship to a single opened preprocessing (refining) facility). However, in the downstream, we assume that biofuel can be supplied to a customer zone from multiple facilities, i.e., directly from conversion facilities or through distribution centers. Constraint (4) restricts material flow, invoking the capacity of each transportation route, each storage and processing (i.e., preprocessing and refining) facility. Constraint (5) balances the incoming and outgoing flow of each commodity at each facility, considering moisture content reduction at each preprocessing facility, the ratio of biofuel output per unit of feedstock input at each refinery, chemical dry matter loss rate specific to the type of technology used at a storage facility, and biofuel flow balance at a biofuel storage facility. Constraint (6) restricts binary variables to be 0 or 1 and continuous variables to be non-negative.

2.3. Case study

We now present a case study to demonstrate the types of analysis our model will support. We select nine counties in Central Texas as a test bed because this region has relatively high biomass availability (Milbrandt, 2005) and it is representative of regions that cannot provide a sufficient amount of crop residues to meet its own biofuel needs, so they must be supplemented with energy crops to meet demand. Even though this region has relatively high biomass availability, our analysis found that most crop residues must be left in the fields after harvest to maintain soil fertility (see Section 2.3.3). Thus, instead of crop residues, we employ switchgrass as a feedstock to meet demand under the assumption that it will be grown on some of the land currently used to grow food crops as well as some of the land set aside by the Conservation Reserve Program (CRP), which is a voluntary conservation program administrated by United States Department of Agriculture (USDA) to assist agricultural producers in enhancing environmentally sensitive lands.

We assume that a single biofuel (i.e., ETOH) is produced from several types of lignocellulosic feedstocks (i.e., switchgrass, mill residues, and urban wood wastes). We use a one-year planning horizon in which each period represents a quarter (i.e., 3 months).

We study the effect of four factors on supply chain design (switchgrass cost, ETOH price, switchgrass yield, and ETOH demand) under 18 scenarios that evaluate switchgrass cost vs. ETOH price and three other scenarios that assess supply vs. demand (see Table 1). We analyze several measures of the prescribed supply chain performance (e.g., profit, revenue, cost, material flow pattern, ratio of supply to demand, and land area used) for each scenario. We base ETOH price on the trend forecasted by the US Energy Information Administration for the price of regular-grade gasoline, including taxes. Even though counties are in the same region, each may offer different soil, terrain, and weather conditions, affecting the price of biomass. Furthermore, contracts with growers may differ. While our model can accommodate county-dependant parameter values, our case study assumes the same values for all counties due to the lack of more specific data.

The following subsections describe the data we gathered to formulate our case study. Most data are available from papers, reports and data services provided by the US government.

2.3.1. Cost estimates and technical factors

Table 2 presents a list of cost estimates and technical factors used in the case study. We have consulted a number of publically available sources to gather data with the goal of making the case study as realistic as possible. We employ a one-year planning horizon and amortize the cost of capital for opening a facility over a 20-year lifetime at a 10% discount rate. However, since the biofuel industry is in an early stage of development, not much recent data is available. Therefore, a case study solution might over- or underestimate the actual value a bit because data that describe the change of cost parameters over time is not yet available.

It was not possible to find sources for some parameters, so we estimate them based on values associated with similar processes. We assume that cost for an outdoor-uncovered storage facility is 10% of the cost of an indoor anaerobic storage facility, and that of transporting ethanol involves a fixed cost of $1.00/Mg plus a variable cost of $0.08/Mg km. We estimate the cost of biofuel storage based on the cost of oil storage tanks posted on some commercial online shopping malls (eBay.com, NorthernTool.com), augmented with the fixed cost of capital for land ($1000) and the variable operating cost ($0.01/l). We assume that the cost for the single-destination limitation relates to administration and is about $100/month. A wide range of efficiencies of characterizing the technologies that convert cellulosic biomass to ETOH has been reported (e.g., 35–68% (Hamelinck et al., 2005a)). We assume a 70% of conversion efficiency for each type of biomass, based on their theoretical estimates. The theoretical ETOH yield of biomass estimated based on Theoretical Ethanol Yield Calculator by US Department of Energy are 397.6 l/Mg for switchgras, 381.6 l/Mg for secondary mill residues, and 439.1 l/Mg for urban wood waste.

2.3.2. Demand

This sub-section describes how we estimate biofuel demand in the Central Texas region. We assume that the demand for ETOH is 10% of the demand for gasoline, because E10 (a mixture of 10% ETOH and 90% gasoline) can be distributed easily in the current infrastructure for petroleum-based fuel.

Table 3 gives the population of each county in the region, the average annual consumption of gasoline from 1998 to 2007 in Texas and an estimate of the demand for ETOH (10% of gasoline consumption based on the population of each county). The overall average demand for ETOH is 1425 l/year/person (National Priorities Project Database).

2.3.3. Biomass supply

We now describe our analysis procedure and estimate biomass availability in the selected region. We estimate the amount of available crop residue based on farmed land area and crop yield in each county as provided by USDA-National Agricultural Statistics Service. Wilhelm et al. (2004) reported that some residue associated with certain crops should be left in the field to maintain soil quality: more than 6.0 Mg/ha/year for corn residue; and more than

Table 1
Scenarios of sensitivity analysis for a region in Central Texas.

Group scenario	Scenario No.	Switchgrass cost ($/Mg)	ETOH price ($/gal)	Switchgrass yield (Mg/acre)	ETOH demand (Mg/ha)		
A. Cost vs. price	1	50	2.50	0.66	10.00	24.71	E10 for local area
	2	50	2.60	0.69	10.00	24.71	E10 for local area
	3	50	2.70	0.71	10.00	24.71	E10 for local area
	4	50	2.80	0.74	10.00	24.71	E10 for local area
	5	50	2.90	0.77	10.00	24.71	E10 for local area
	6	50	3.00	0.79	10.00	24.71	E10 for local area
	7	60	2.50	0.66	10.00	24.71	E10 for local area
	8	60	2.60	0.69	10.00	24.71	E10 for local area
	9	60	2.70	0.71	10.00	24.71	E10 for local area
	10	60	2.80	0.74	10.00	24.71	E10 for local area
	11	60	2.90	0.77	10.00	24.71	E10 for local area
	12	60	3.00	0.79	10.00	24.71	E10 for local area
	13	70	2.50	0.66	10.00	24.71	E10 for local area
	14	70	2.60	0.69	10.00	24.71	E10 for local area
	15	70	2.70	0.71	10.00	24.71	E10 for local area
	16	70	2.80	0.74	10.00	24.71	E10 for local area
	17	70	2.90	0.77	10.00	24.71	E10 for local area
	18	70	3.00	0.79	10.00	24.71	E10 for local area
B. Supply vs. demand	19	60	2.90	0.77	7.00	17.30	E10 for local area
	20	60	2.90	0.77	13.00	32.12	E10 for local area
	21	60	2.90	0.77	10.00	24.71	E20 for local area

Table 2
Cost estimates and technical factors.

Parameters	Value	Reference	Remark
Refinery			
Fixed opening cost	$4,511,168	Nguyen and Prince (1996)	
Variable opening cost	$0.0071/l	Nguyen and Prince (1996)	
Variable operating cost	$0.032/l	Aden et al. (2002)	
Preprocessing facility			
Fixed opening cost	$60,000	Sokhansanj et al. (2006)	Using a Tub Grinder and a biomass dryer
Variable opening cost	$1.00/Mg	Sokhansanj et al. (2006)	
Variable operating cost	$18.14/Mg	Sokhansanj et al. (2006)	
Biomass storage facility			
Indoor anaerobic			
Fixed cost	$15,153	Anderson and Noyes (2010)	
Variable cost	$151.46/m^2	Anderson and Noyes (2010)	
Outdoor uncovered			
Fixed cost	$1515	Assumption	10% of uncovered
Variable cost	$15.15/m^2	Assumption	
Biofuel storage facility			
Fixed cost	$1000	Assumption	
Variable cost	$0.063/l	Assumption	Referred to eBay and Northern Tool
Transportation cost			
Biomass	$6.81/Mg + $0.08/Mg km	Glassner et al. (1998)	Based on bale system. Same for all biomass
ETOH	$1.00/Mg + $0.08/Mg km	Assumption	
Single destination			
Management cost	$100/month	Assumption	
Biomass purchase cost			
Switchgrass	$50, $60 and $70/Mg	Perrin et al. (2008)	
Mill residues	$4/Mg	Fehrs (1999)	
Urban wastes	$12/Mg	Fehrs (1999)	
Conversion factor			
From biomass to ETOH	70% of the theoretical estimate	Assumption	Hamelinck et al. (2005a)
Dry matter loss			
Outdoor uncovered			
Switchgrass	2%/month	Shinners and Binversie (2004)	
Wood wastes	2%/month	Kofman (2006)	
Indoor anaerobic			
Switchgrass	0.3%/month	Shinners and Binversie (2004)	
Wood wastes	0.5%/month	Kofman (2006)	
Moisture content			
Switchgrass	Uniform (20%, 50%)	Kumar and Sokhansanj (2007)	
Wood wastes	Uniform (10%, 20%)	Fehrs (1999)	

Table 3
Estimated biofuel demand and switchgrass availability.

County	Hill	McLennan	Falls	Bell	Williamson	Travis	Hays	Comal	Bexar
Demand									
Population (2008)[a]	35,637	230,213	16,900	285,084	394,193	998,543	149,476	109,635	1,622,899
Gas consumption[b]	50,769	327,962	24,076	406,131	561,568	1,422,526	212,944	156,186	2,311,985
Demand for ETOH (KL/year)	5077	32,796	2408	40,613	56,157	142,253	21,294	15,619	231,198
Supply									
Farm land area (2009) (ha)	72,843	60,662	56,535	53,580	57,749	9105	1012	6111	11,250
CRP land area (2009) (ha)	1,912	69	140	349	379	0	0	0	0
Total area (ha)	74,755	60,732	56,675	53,929	58,128	9105	1012	6111	11,250
Switchgrass production amount (Mg/year)									
Yield: 7 Mg/ha/year	523,285	425,121	396,725	377,503	406,893	63,738	7082	42,775	78,752
Yield: 10 Mg/ha/year	747,550	607,316	566,750	539,289	581,276	91,054	10,117	61,108	112,503
Yield: 13 Mg/ha/year	971,815	789,511	736,775	701,076	755,659	118,371	13,152	79,440	146,253

[a] The US Census Bureau (2008).
[b] 1425 l/year/person (National Priorities Project Database) (KL/year).

3.0 Mg/ha/year for wheat residue. Based on their estimates, most crop residues available in the Central Texas region should be left in the field. Thus, we have not considered crop residues as possible feedstocks.

To supply an amount of biomass sufficient to meet demand, we assume that switchgrass will be grown on some farm lands instead of the current food crops and on some CRP land areas as well. Table 3 gives an estimated amount of switchgrass that could be made available in each county. In addition to using switchgrass as a feedstock, we include other lignocellulosic biomass (i.e., mill residues and urban wood wastes) as feedstocks based on the data provided by Milbrandt (2005) so that we consider three types of biomass as a feedstock. We assume that switchgrass is harvested only in Summer and Fall and other biomass (i.e., mill residues and wood wastes) is supplied uniformly in all seasons.

2.3.4. Transportation cost

We estimate transportation distance based on the length of the straight line between the center points of each pair of counties. We invoke two assumptions to estimate transportation distances within each county: preprocessing, biorefinery, and distribution center facilities are at the same location so that the cost of transportation between each relevant pair of echelons is very small; farms and customer zones are uniformly distributed within a county so that the transportation distance between each pair of field storage and preprocessing facilities, and between each pair comprising a distribution center and a customer zone is about 19 km, because the size of most counties is approximately 50 by 50 km and the average distance from any location in a county to the center point is about 19 km. The transportation mode considered in this case study is a truck. We assume that the bale system is used to transport biomass.

3. Results and discussion

This section analyzes the results of our computational experiments for 21 scenarios (see Table 1). The number of binary and continuous variables are 2034 and 96,030, respectively. IBM ILOG CPLEX 12 solved each instance within 1 h in a personal computer with Core (TM)2 Duo CPU 3.16 GHz and 4G RAM, prescribing an optimal solution for each scenario.

3.1. Basic results

This section describes results prescribed by the optimization model for scenario 11, which we consider to be a basic (i.e., bench marking) scenario because it has the smallest ETOH price (i.e., $0.77/l) while meeting all customer-zone demands for biofuel using the median cost of switchgrass (i.e., $60/Mg).

3.1.1. Facility location, technology, and capacity

Table 4 describes results about the strategic level decisions. While preprocessing facilities are opened at three counties (i.e., 2, 5, and 9), refineries are only opened at counties 2 and 5. Note that we consider only single technology for preprocessing facility and refinery in this case study. Alternative technology is considered for the selection of storage types in preprocessing facility (i.e., outdoor-uncovered and indoor-anaerobic). However, only field storage facilities, the type of which is an outdoor-uncovered, are opened mainly due to high fixed cost of other storages in echelons of preprocessing facility and refinery. Relatively large field storages are prescribed at counties 1, 3, 5, and 6.

3.1.2. Material flow pattern

We analyze the material flow pattern in each time period under the scenario 11. Fig. 1 depicts the material flow pattern in each season. Each straight arc represents the aggregated flow of all types of biomass in the upstream and ethanol in the downstream. Rectangular icons in the field storage echelon represent inventory carryovers from one period to the next. Using facilities opened (see Table 4), materials flow through three preprocessing facilities (in counties 2, 5, and 9), and two refineries (in counties 2 and 5).

Since we assumed that switchgrass is harvested only in Summer and Fall, significant amounts of biomass inventory are carried over in field storage to meet year-round demand. Even though some portion of biomass is degraded in field storage due to chemical dry matter loss, our model prescribes inventory carryover only in the field storage echelon, because the capital cost of storage in other echelons (i.e., preprocessing facility and refinery) is relatively high compared to the potential cost of dry matter loss. The amounts of dry matter loss in storages are 198,256 Mg of switchgrass, 821 Mg of mill residues, and 7,803 Mg of wood wastes, respectively.

A quarter-by-quarter plan for material flow is essential to support strategic decisions and can give useful information to Energy companies in support for tactical-level decisions (e.g., in planning manpower and equipment needs in each period). However, to support tactical-level plans most effectively, the duration of a time period should be defined as a month, if not an even shorter time. In fact, time periods need not be of the same duration. Shorter time periods could be used to model the dynamics of harvesting and longer ones could be used to plan inventories and material flows at other times of the year.

3.2. Sensitivity analysis

This section discusses results from several scenarios and analyzes factors that are significant to the biofuel supply chain.

Table 4
Facility location, capacity, and technology type for scenario 11.

Echelon	Location		Capacity	Technology type
	No.	County name		
Field storage	1	Hill	575,722 Mg	Outdoor-uncovered
	2	McLennan	4950 Mg	Outdoor-uncovered
	3	Falls	403,626 Mg	Outdoor-uncovered
	4	Bell	9950 Mg	Outdoor-uncovered
	5	Williamson	583,141 Mg	Outdoor-uncovered
	6	Travis	114,813 Mg	Outdoor-uncovered
	7	Hays	8759 Mg	Outdoor-uncovered
	8	Comal	63,341 Mg	Outdoor-uncovered
	9	Bexar	16,001 Mg	Outdoor-uncovered
Preprocessing	2	McLennan	1,299,048 Mg/year	Grinding and drying
	5	Williamson	938,998 Mg/year	Grinding and drying
	9	Bexar	64,192 Mg/year	Grinding and drying
Biorefinery	2	Bell	205,920 KL/year	70% conversion efficiency
	5	Williamson	222,569 KL/year	70% conversion efficiency
DC layer	–	–	–	–

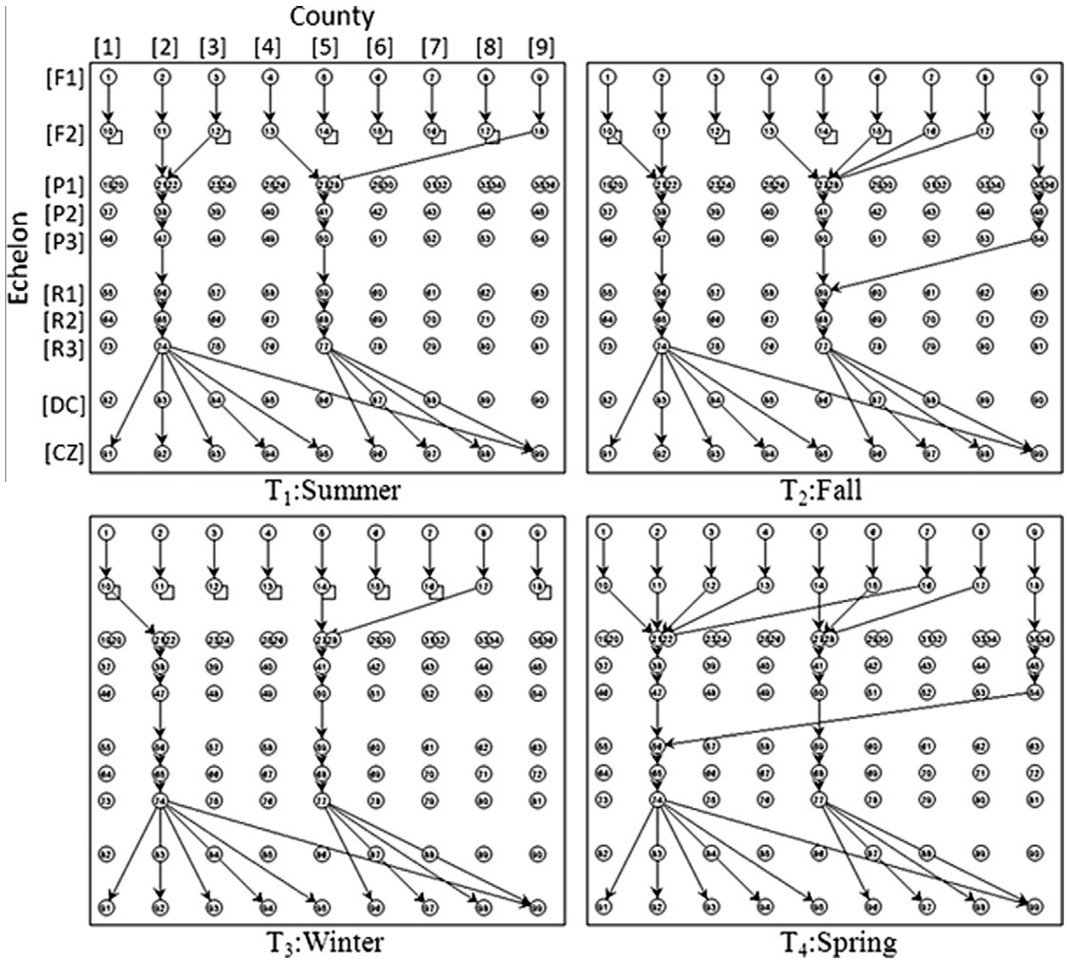

Fig. 1. Material flow pattern for scenario 11 in each time period.

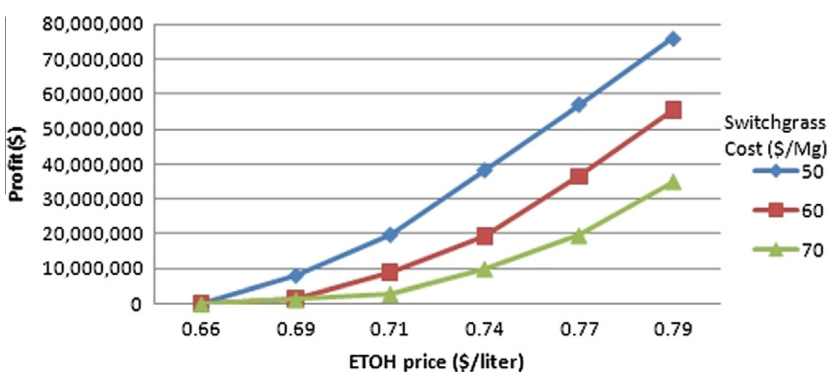

Fig. 2. Relationship of profit to combinations of feedstock cost and ETOH price.

3.2.1. Impact of the combination of feedstock cost and ETOH price

We compare performance measures (i.e., profit, revenue, and cost) that result in scenarios 1–18 to identify the impact of the combination of feedstock cost and ETOH price. Fig. 2 shows that profit increases faster as feedstock cost reduces than as ETOH price increases. This reinforces the expectation that feedstock cost is a significant factor in determining profit. When the price of ETOH at the pump is less than $0.66/l (i.e., scenarios 7 and 13), the biofuel supply chain is not economically viable; our model opens no facilities and prescribes no material flow.

Table 5 details results for scenarios 1–21 (ETOH production; profit; revenue; total cost; cost breakdown on detail processes; the percentage of land area used to grow switchgrass; and the ratio of supply to demand). The refinery represents the most significant cost component in the supply chain. The cost to both purchase and collect feedstocks, is also a significant component. These results suggest that the components of the biofuel supply chain that offer the most leverage to improve the economic viability of the biofuel industry are the costs of refining and of feedstocks.

Table 5
Comparison of scenarios to analyze combinations of feedstock cost and ETOH price.

Scenario No.	ETOH production (KL)	Profit ($)	Revenue ($)	Total cost ($)	Cost breakdown					Used/given area (%)	Supply/demand (%)
					FS[c]	FT[d]	PR[e]	RF[f]	ET[g]		
1	129,116	57,829	115,710,527	115,652,698	16.45	7.96	8.93	66.25	0.39	34.6	24.5
2	253,460	7,764,851	236,229,115	228,464,264	18.56	8.07	8.96	63.93	0.48	63.2	48.1
3	427,976	19,542,153	414,222,801	394,680,649	20.60	7.77	8.79	61.70	1.13	96.6	81.2
4	527,157	38,188,889	529,117,456	490,928,558	21.41	6.68	8.76	61.81	1.34	98.6	100.0
5	527,157	57,085,950	548,014,508	490,928,558	21.41	6.68	8.76	61.81	1.34	98.6	100.0
6	527,157	75,983,002	566,911,560	490,928,558	21.41	6.68	8.76	61.81	1.34	98.6	100.0
7[b]	–	–	–	–	–	–	–	–	–	–	–
8	57,433	1,431,448	53,528,573	52,097,125	12.50	8.40	8.61	70.23	0.24	7.8	10.9
9	248,363	8,862,751	240,381,774	231,519,024	21.29	7.73	8.66	61.86	0.45	61.3	47.1
10	362,200	19,290,223	363,544,743	344,254,519	22.99	7.48	8.52	60.07	0.94	78.3	68.7
11[a]	527,157	36,558,390	548,014,508	511,456,118	24.56	6.41	8.41	59.33	1.29	98.6	100.0
12	527,157	55,455,442	566,911,560	511,456,118	24.56	6.41	8.41	59.33	1.29	98.6	100.0
13b	–	–	–	–	–	–	–	–	–	–	–
14	41,369	1,221,476	38,556,930	37,335,453	8.18	9.09	8.49	73.97	0.24	1.0	7.8
15	54,609	2,816,185	52,854,063	50,037,878	12.90	8.38	8.50	69.97	0.24	6.6	10.4
16	246,584	9,973,884	247,499,534	237,525,650	23.80	7.51	8.38	59.88	0.44	60.4	46.8
17	362,200	19,495,985	376,528,484	357,032,498	25.74	7.21	8.22	57.92	0.90	78.3	68.7
18	527,157	34,952,361	565,901,332	530,948,971	27.22	7.34	8.05	56.20	1.19	98.6	100.0
19	380,859	28,144,334	395,926,768	367,782,433	23.85	7.72	8.39	59.06	0.97	96.6	72.2
20	527,157	41,958,476	548,014,508	506,056,032	23.99	6.40	8.47	59.96	1.18	94.8	100.0
21	529,493	39,925,524	550,439,343	510,513,818	24.72	6.48	8.46	59.69	0.65	98.8	50.2

[a] A basic scenario to compare other scenarios about supply/demand changes.
[b] Non-profitable.
[c] FS: feedstock.
[d] FT: feedstock transportation.
[e] PR: preprocessing.
[f] RF: refinery.
[g] ET: ETOH transportation.

In terms of material flows, as ETOH price increases and feedstock cost reduces, the total amount of ETOH supplied increases so that the revenue increases. Our model prescribes the same amount of material flows for a set of scenarios (i.e., for those with a cost of switchgrass that is either $50/Mg ($60/Mg) with a price of ETOH that is above $0.74/l ($0.77/l)) because all demands are met in these instances and the amounts of processing materials are same. In addition, this also describes the reason why the total costs of scenarios 4, 5, and 6 are same and those of scenarios 11 and 12 are same.

Energy companies would be able to use a sensitivity analysis to evaluate the economic feasibility of generating biofuels in a selected region. Moreover, applying our model and method of analysis to a region or the entire country would provide useful information for government policy makers, for example, in estimating the subsidy levels required to induce investment in the bioenergy industry.

3.2.2. Impact of the combination of feedstock supply and ETOH demand

We now analyze the significance of combinations of feedstock supply and ETOH demand, studying scenarios based on scenario 11, which meets all customer-zone demands for biofuel. Scenarios 19, 20 and 21 are the same as scenario 11, except 19 tests a switchgrass yield of 17.30 Mg/ha (7.00 Mg/acre); 20 tests a switchgrass yield of 32.12 Mg/ha (13.00 Mg/acre); and 21 assumes that E20 can be used, doubling ETOH demand in comparison to scenario 11, which assumes that E10 is used.

Table 5 compares results for scenarios 19, 20 and 21 with those of scenario 11. As switchgrass yield decreases (i.e., scenario 19), the amount of ETOH produced, profit and land-area used decrease. Even though the amount of biomass is not sufficient to meet demand, some portion of land area is not used, because using it is not profitable. On the other hand, as switchgrass yield increases (i.e., scenario 20), the amount of ETOH produced and profit increase and the land area used decreases. As demand increases (i.e., scenario 21), the land area used increases slightly so that profit and the amount of ETOH produced also increase.

Energy companies can analyze land areas requirements to determine which farms they should contract to supply feedstocks in the most profitable way. For example, even though feedstock supply is not sufficient to meet demand under scenarios 19 and 21, some portion of land area in county 9 is not used because of prohibitive transportation cost.

3.3. Discussions and recommendations for future research

Our mathematical model, which deals with a multiple commodity flows, represents specific characteristics of several types of lignocellulosic biomass as well as the changes biomass undergoes in storage and processing in the various echelons of the supply chain. To our knowledge, this is the first model to deal with all echelons of the biofuel supply chain, including both upstream and downstream; the selection of technology and location for each opened facility; biomass moisture content; dry matter loss in storage; and single destination in the upstream of the biofuel supply chain.

Our case study demonstrates the use of our model as a decision support tool based on a set of data we have been able to gather from public sources to represent the biofuel industry in Central Texas. Our case study indicates that this region would be able to meet all local demand for ethanol only under certain scenarios that utilize E10. In particular, case studies provide informative results, identifying relationships that have not been investigated previously. Even though other factors (i.e., feedstock cost, feedstock yield, and ETOH demand) affect the economic viability of the supply chain, ETOH price appears to be the most significant factor to economic viability; moreover, based on profits, the overall supply chain structure prescribed could be much different from one based on minimizing cost.

Biofuel manufacturers can use our mathematical model to plan the most profitable supply chain design and estimate the profit that a particular region might generate. In addition, government policy makers can employ our model to identify policies most likely to support a viable biofuel industry, for example, through a combination of providing subsidies and attracting private investment.

Future research can extend this study in several ways. First, specialized solution algorithms must be developed to solve large-scale instances, which could cover a larger geographical area and prescribe detailed, tactical-level decisions that must deal with more time periods in the planning horizon. Second, the relationship between storage capacity and replenishment policy in the multi-echelon system must be determined so that both can be prescribed more accurately. Third, considering several alternative transportation modes (e.g., rail and truck) may allow costs to be reduced since large quantities of biomass must be transported. Fourth, dealing explicitly with uncertainty by using stochastic programming models can be expected to lead to robust supply chain designs. Lastly, models could be formulated to represent the interests of specific stake holders (e.g., biomass suppliers, refineries, and distribution centers) so that ways in which they could co-operate to improve efficiency and profitability can be identified.

4. Conclusions

The model we formulate to design a lignocellulosic biomass/biofuel supply chain design considers strategic- and tactical-level decisions in both upstream and downstream echelons over multiple periods. In addition, our model deals with the unique features of the biofuel industry. Through a case study that represents the Central Texas region, we identify several important applications of our model and provide insights into the significance of system components and interactions among them.

Appendix A. Notation

A.1. Sets

T	Time Periods (monthly)
L	Echelons, $\{F1, F2, P1, P2, P3, R1, R2, R3, DC, CZ\}$ ($F1$: farm, $F2$: field storage, $P1$–3: preprocessing facilities, $R1$–3: conversion facilities, DC: distribution center, and CZ: customer zone) F_1: Candidate locations for facilities in echelon l or feedstock supply site (F_{F1}, F_{F2}) or customer zone $(F_{CZ}), l \in L$
F_{UP}	Upstream facilities $:= F_{F1} \cup F_{F2} \cup F_{P1} \cup F_{P2} \cup F_{P3} \cup F_{R1}$
F_{DOWN}	Downstream facilities $:= F_{R2} \cup F_{R3} \cup F_{DC} \cup F_{CZ}$
F	All facilities $:= F_{UP} \cup F_{DOWN}$
F_{WHO}	Warehouses where biomass is held before preprocessing $:= F_{F2} \cup F_{P1}$
F_{WH1}	Warehouses where biomass is held $:= F_{WHO} \cup F_{P3} \cup F_{R1}$
F_{WH2}	Warehouses where biofuel is held $:= F_{R3} \cup F_{DC}$
F_{WH}	Warehouses $:= F_{WH1} \cup F_{WH2}$
F_{PR}	Process facilities (preprocessing, refinery) $:= (F_{P2} \cup F_{R2})$
F_{OP}	Operating facilities $:= F \setminus (F_{F1} \cup F_{CZ})$
R_f	Types of technologies at facility $f, f \in F_l$
P_f	Feedstock (biomass) types raised or gathered at $f \in F_{F1}$
K_1	Feedstock commodities $:= \{(f, t, p)\}, f \in F, t, \in T, p \in P_f$
K_2	Biofuel commodities $:= \{e\}, e \in E$
K	Commodities $:= K_1 \cup K_2$
$A^+_{frt}(A^-_{frt})$	Directed arcs in period t that start or end at node frt
A^{inv}_{frt}	Arc that represents inventory held at facility f of type r from period t to period $t+I$
A	Directed arcs: $A^+_{frt} \cup A^{inv}_{frt}$

A.2. Indices

f	facility, $f \in F$
r	technology type, $r \in R$
t	time, $t \in T$
p	biomass type, $p \in P$
e	biofuel type, $e \in E$
k	commodity type, $k \in K$
a	arc, $a \in A$
l	layer, $l \in L$

A.3. Parameters

P_{kft}	Price of biofuel type k in customer zone f in period t (dollar)
D_{kft}	Demand of end product k in customer zone f in period t, $k := e$ (l)
δ_k	Moisture content of commodity k (decimal fraction)
C_k	Cost of commodity k, $k \Rightarrow$ feedstock p from farm f in period t (dollar)
$\alpha_{K_1 k_2} fr$	Amount of biofuel k_2 produced from one unit of preprocessed feedstock k_l at conversion plant f using technology r (decimal fraction)
γ_{kfr}	Chemical dry mass loss rate (fraction) of feedstock k held at warehouse f of storage type r
C^o_{fr}	Fixed cost of opening facility f of type r (dollar)
V_{fr}	Variable cost per unit of capacity of opening facility f of type r (dollar)
C^a_T	Fixed cost associated with arc a (fixed transportation cost on a transportation arc, fixed holding cost on an inventory arc) (dollar)
V^a_T	Variable cost for a unit of flow on arc a (variable transportation cost on transportation arc, variable holding cost on inventory arc) (dollar)
Q^T_a	Flow capacity of arc a (Mg/single period)
Q^F_f	Capacity of facility f (biomass storage (Mg), preprocessing (Mg), refinery (l), or biofuel storage (l))
Q^F_k	Supply capacity of commodity k at farm f during period t for feedstock type p (Mg)

Appendix B. Model

Decision variables

x_{fr} 1 if facility f of type r is open, 0 otherwise	$f \in F_{OP},\ r \in R_f$
y_a 1 if arc a is used, 0 otherwise	$a \in A$
q_{fr} Capacity of facility f of type r	$f \in F_{OP},\ r \in R_f$
z_{ka} Flow amount of commodity k on arc a	$k \in K,\ a \in A$

Objective function
Maximize profit

$$\text{profit} = \sum_{k \in K_z} \sum_{f \in F_{CZ}} \sum_{t \in T} \sum_{a \in A^-_{frt}, r=0} P_{kft} z_{ka} - \sum_{f \in F_{op}} \sum_{r \in R_f} \left(C^O_{fr} x_{fr} + V_{fr} q_{fr} \right) - \sum_{a \in A} C^T_a y_a - \sum_{k \in K} \sum_{a \in A} V^T_a z_{ka} - \sum_{k \in K} \sum_{f \in F_{f1}} \sum_{t \in T} \sum_{a \in A^+_{frt}, r=0} C_k z_{ka}$$

Constraints

$$\sum_{r\in R_f} x_{fr} \leqslant 1, \qquad f\in F_{OP} \tag{1}$$

$$q_{fr} - Q_f^F x_{fr} \leqslant 0, \qquad f\in F_{OP},\ r\in R_f \tag{2}$$

$$\sum_{a\in A_{frt}^+} y_a \leqslant 1, \qquad f\in F_{P1}\cup F_{R1},\ r\in R_f,\ t\in T \tag{3}$$

$$\sum_{k\in K} z_{ka} - Q_a^T y_a \leqslant 0, \qquad f\in F,\ r\in R_f,\ t\in T,\ a\in A_{frt}^+ \tag{4a}$$

$$\sum_{k\in K} z_{ka,a\in A_{frt}^{inv}} - q_{fr} \leqslant 0, \qquad f\in F_{WH},\ r\in R_f,\ t\in T \tag{4b}$$

$$\sum_{k\in K}\sum_{a\in A_{frt}^+} z_{ka} - q_{fr} \leqslant 0, \qquad f\in F_{PR},\ r\in R_f,\ t\in T \tag{4c}$$

$$\sum_{a\in A_{frt}^+} z_{ka} \leqslant Q_k^F, \qquad k\in K,\ f\in F_{F_1},\ r\in R_f,\ t\in T \tag{5a}$$

$$\sum_{a\in A_{frt}^+} z_{ka} - \sum_{a\in A_{frt}^-} (1-\delta_k) z_{ka} = 0, \qquad k\in K_1,\ f\in F_{P2},\ r\in R_f,\ t\in T \tag{5b}$$

$$\sum_{a\in A_{frt}^+} z_{ka} + z_{ka,a\in A_{frt}^{Inv}} - \sum_{a\in A_{frt}^-} z_{ka} - (1-\gamma_{p1fr}) z_{ka,a\in A_{frt-1}^{Inv}} = 0, \qquad k\in K_1,\ f\in F_{WH1},\ r\in R_f,\ t\in T \tag{5c}$$

$$\sum_{a\in A_{frt}^+} z_{k_2a} - \sum_{k\in k_1}\sum_{a\in A_{frt}^-} \alpha_{k_1k_2fr} Z_{k_1a} = 0, \qquad k_2\in k_2,\ f\in F_{R2},\ r\in R_f,\ t\in T \tag{5d}$$

$$\sum_{a\in A_{frt}^+} z_{ka} + z_{ka,a\in A_{frt}^{Inv}} - \sum_{a\in A_{frt}^-} z_{ka} - z_{ka,a\in A_{frt-1}^{Inv}} = 0, \qquad k\in K_2,\ f\in F_{WH2},\ r\in R_f,\ t\in T \tag{5e}$$

$$\sum_{a\in A_{frt}^-} z_{ka} \leqslant D_{kft}, \qquad k\in K_2,\ f\in F_{CZ},\ r\in R_f,\ t\in T \tag{5f}$$

$$x_{fr}\in\{0,1\}, \qquad f\in F_{op},\ r\in R_f \tag{6a}$$

$$y_a\in\{0,1\}, \qquad a\in A \tag{6b}$$

$$q_{fr}\geqslant 0, \qquad f\in F_{op}, r\in R_f \tag{6c}$$

$$z_{ka}\geqslant 0, \qquad k\in K, a\in A \tag{6d}$$

Constraint (1) At most, one technology type can be selected for each facility
Constraint (2) If facility f is opened, the amount of flow out of it is restricted by its capacity; otherwise, the facility can sustain no flow
Constraint (3) Each field storage (preprocessing) facility must use a transport link to a single destination preprocessing (refinery) facility
Constraint (4-a) If arc a is selected, the flow amount is restricted by the arc capacity; otherwise, the flow amount on the arc must be zero
Constraint (4-b) The capacity of storage facility $f\in F_{WH}$ restricts the amount of inventory that it can hold
Constraint (4-c) The capacity of processing facility $f\in F_{PR}$ restricts the amount that it produces
Constraint (5-a) The capacity at farm $f\in F_{F1}$ (i.e., supply limit) restricts the amount of biomass it can supply
Constraint (5-b) Flow balance at preprocessing facility $f\in F_{P2}$
Constraint (5-c) Flow balance at biomass storage facility $f\in F_{WH1}$, including dry mass loss
Constraint (5-d) Flow balance at conversion facility $f\in F_{R2}$
Constraint (5-e) Flow balance at biofuel storage facility $f\in F_{WH2}$
Constraint (5-f) Flow balance at customer zone $f\in F_{CZ}$ (the inflow of biofuel must be less than or equal to demand)
Constraint (6-a) Binary restrictions on decision variables x_{fr}
Constraint (6-b) Binary on decision variables y_a
Constraint (6-c) Non-negativity restrictions on decision variables q_{fr}
Constraint (6-d) Non-negativity restrictions on decision variables z_{ka}

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