Renewable Energy xxx (2016) 1–13

Contents lists available at ScienceDirect

Renewable Energy

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

# Design of biofuel supply chains with variable regional depot and biorefinery locations

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ARTICLE INFO

*Article history:*
Received 4 February 2016
Received in revised form
2 May 2016
Accepted 3 May 2016
Available online xxx

*Keywords:*
Cellulosic ethanol
Biorefinery
Mathematical programming
Optimization
Reformulation

ABSTRACT

We propose a multi-period mixed-integer linear programming (MILP) model for the design and operational planning of cellulosic biofuel supply chains. Specifically, the proposed MILP model accounts for biomass selection and allocation, technology selection and capacity planning at regional depots and biorefineries. Importantly, it considers the location of regional depots and biorefineries as continuous optimization decisions. We introduce approximation and reformulation methods for the calculation of the shipments and transportation distance in order to obtain a linear model. We illustrate the applicability of the proposed methods using two medium-scale examples with realistic data.


## 1. Introduction

Renewable energy can play an important role in reducing our dependence on fossil fuels, mitigating climate impacts and increasing energy security. In 2014, electricity generation from biomass accounts for 12% of all renewable energy generated in the United States [1]. In addition to heat and power generation, cellulosic biomass can be converted into biofuels (e.g., ethanol, biodiesel, “drop-in” fuels, etc.) via various technologies. Based on the REmap 2030 analysis report published by the International Renewable Energy Agency [2], the total biofuel production in the United States is expected to be 39 billion gallons.

Process systems engineering (PSE) methods have been widely applied for the design and operation planning of biofuel supply chains (SCs) [3–7], as well as the design of integrated biorefineries [8–11]. Most of the proposed SC optimization models employ economic criteria and consider a single period [12,13]. The introduction of multi-period models allows the modeling of seasonal biomass availability and biomass deterioration [14–16]. Furthermore, environmental [17,18] and social considerations [19,20] have been studied. Finally, several approaches have been proposed for the optimization of biofuel SCs under uncertainty; for example, stochastic programming [21,22], chance constraint programming [23], and robust optimization [24] methods.

Two aspects that have received limited attention are (1) the consideration of local depots for biomass densification and/or pretreatment, and (2) the selection of the location of depots and biorefineries. Specifically, most previous approaches either neglect the installation of depots or consider depots that are co-located with harvesting sites and, furthermore, are based on the assumption that biorefineries can only be installed at predefined locations that meet certain criteria (e.g., population census, transportation network, etc.) [25,26]. However, the efficiency of the biofuel SC, in terms of both cost and $CO_2$ emissions, can be improved by the installation of depots and the *optimization* of depot and biorefinery location [27–29] (e.g., the optimal depot location can be between two harvesting sites). Recently, Ng and Maravelias proposed the first optimization model to account for depot installation and variable depot location [30]. However, the proposed mixed-integer non-linear programming (MINLP) model is computationally expensive and may not be used to address medium- and large-scale problems.

Accordingly, the goal of this paper is to propose a computationally tractable multi-period mixed-integer linear programming (MILP) model that accounts for biomass selection and allocation, technology selection and capacity planning at depots and

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http://dx.doi.org/10.1016/j.renene.2016.05.009
0960-1481/

Please cite this article in press as: R.T.L. Ng, C.T. Maravelias, Design of biofuel supply chains with variable regional depot and biorefinery locations, Renewable Energy (2016), http://dx.doi.org/10.1016/j.renene.2016.05.009

biorefineries, inventory and shipment planning, and, importantly, variable depot and biorefinery locations. The reduction of the computational requirements is achieved through a series of approximations and reformulations.

The rest of this article is structured as follows: In Section 2, we present background on biofuel SC, a formal problem statement, and the assumptions used for the formulation of the model. In Section 3, we present a basic optimization model, while in Section 4 we describe several model enhancements. In Section 5, we present two examples to illustrate the applicability of our methods. We close in Section 6 with concluding remarks. We use lowercase Greek letters for parameters; Latin letters for variable; lowercase Latin italic letters for indices; and uppercase U/L in superscript for upper/lower bounds.

## 2. Background

### 2.1. Cellulosic biofuel supply chain

Biomass feedstocks are harvested and potentially stored at harvesting sites. Biomass can be either shipped to a biorefinery or a regional depot where it is pretreated and/or densified into a stable and dense intermediate. The primary function of the regional depot is to allow the densified biomass to be transported economically over long distances, thus improving the overall SC economics and reducing $CO_2$ emissions [31]. Regional depots can be categorized as *standard* and *quality* depots [32]. The primary function of the former is to dry and densify biomass via mechanical and thermal processing technologies such as grinding, drying and pelleting. In the latter, in addition to drying and densification, biomass is converted into intermediates that meet specific biorefinery needs. Pretreatment technologies that have low operating and capital costs, simple catalyst recovery and produce an intermediate that reduces processing intensity at the biorefinery can be considered [31]; e.g., ammonia fiber explosion (AFEX) [33], dilute acid [34], alkaline peroxide [35]. Pretreated and/or densified biomass can be stored at a depot before it is sent to the biorefinery. At the biorefinery, biomass and intermediate can be converted into biofuel via biochemical [36], thermochemical [37,38] and catalytic [39,40] platforms.

### 2.2. Problem statement

In this work, we consider a one-year horizon divided into time periods $t \in \mathbf{T}$, though a multi-year horizons can also be considered. We are given biomass feedstocks (e.g., corn stover and switchgrass) at the harvesting site, intermediates produced at depots (e.g., AFEX-treated pellets), intermediates at the biorefinery, and a product (ethanol). Biomass can be converted to intermediates and ethanol through different technologies, including drying and densification with or without AFEX pretreatment at the depot. The unit production cost and conversion yield of all technologies are known. The locations of harvesting sites and biomass availability at each site and time period are given, while the locations of depots and biorefineries are optimization decisions. The unit costs associated with feedstock acquisition, inventory, and transportations are known. We are also given the regions within which potential biorefineries can be installed and the upper and lower bounds on ethanol demand.

Formally, the problem we consider is stated in terms of the following sets, subsets and parameters:

a) Compounds $i \in \mathbf{I}$ with unit price $\lambda_i$, unit inventory cost $\iota_i$ and fixed/variable transportation unit cost $\kappa_i^F/\kappa_i^V$.
   i. Biomass feedstocks $\mathbf{I}^F \subset \mathbf{I}$ at harvesting sites.
   ii. Intermediates $\mathbf{I}^{ID} \subset \mathbf{I}$ produced at depots.
   iii. Intermediates $\mathbf{I}^{IB} \subset \mathbf{I}$ produced at biorefineries.
   iv. Products $\mathbf{I}^P \subset \mathbf{I}$ with minimum $\beta_{i,t}^L$ and maximum $\beta_{i,t}^U$ product demand.
   v. By-products $\mathbf{I}^B \subset \mathbf{I}$.
b) Harvesting sites $j \in \mathbf{J}$ with $x$-Cartesian coordinate $x_j$ , $y$-Cartesian coordinate $y_j$, and biomass availability $\alpha_{i,j,t}$.
c) Potential depots $k \in \mathbf{K}$ with variable locations.
d) Potential biorefineries $l \in \mathbf{L}$ with variable locations within certain region.
e) Technologies $m \in \mathbf{M}$ with unit production cost $\mu_m$ and conversion coefficient $\eta_{i,i',m}$.
   i. Pretreatment/densification technologies at depots $\mathbf{M}^{PD} \subset \mathbf{M}$.
   ii. Pretreatment technologies at biorefineries $\mathbf{M}^{PB} \subset \mathbf{M}$.
   iii. Conversion technologies $\mathbf{M}^{CB} \subset \mathbf{M}$.

Our goal is to determine the optimal number, capacity, and location of depots and biorefineries, as well as the production, inventory, and shipment profiles of all SC nodes such that the total annual cost is minimized.

### 2.3. Assumptions

It is assumed that all biomass at the harvesting site will be shipped to the depots/biorefineries if the harvesting site is selected in the SC optimization model. This assumption can be easily relaxed by dividing a site into multiple *sub-sites* and thereby allowing the selection of a fraction of the availability of the site. For example, a county (a unit for which biomass availability data are typically available) can be divided into rectangular or square cells (sub-sites).

Furthermore, we assume that the biomass from a harvesting site is sent to only one downstream node, either a depot or a biorefinery; and, similarly, the intermediates from a depot are shipped to a single biorefinery. While better solutions can be obtained, in theory, by shipping to multiple nodes and/or continuously changing the destination of shipments coming from the same SC node, it is difficult to implement such "dynamic" operation in practice [30]. Thus, the second assumption is realistic.

It is further assumed that no biomass feedstock is stored at depots and biorefineries, and no intermediates are stored at biorefineries. Rather, biomass is stored at harvesting sites only and intermediates at depots only. This assumption has minimal effect because inventory unit costs and material deterioration coefficients are practically independent of location, which means that the solutions we obtain equivalent and representative of a family of solutions. Furthermore, in general, material storage at the origin is preferred because material losses occur before transportation and thus result in lower transportation cost.

## 3. Basic model

In this section, we present a basic model for the design of biofuel SC with regional depots. We introduce the following binary variables:

- $W_j/W_k/W_l = 1$ if harvesting site $j$/depot $k$/biorefinery $l$ is selected.
- $U_{k,m}/U_{l,m} = 1$ if technology $m$ at depot $k$/biorefinery $l$ is selected.
- $Z_{j,k}/Z_{j,l}/Z_{k,l} = 1$ if transportation along arc $j \to k/j \to l/k \to l$ is selected.

and the following nonnegative continuous variables:

- $S_{i,j,t}/S_{i,k,t}/S_{i,l,t}$: inventory level of compound $i$ at SC node $j/k/l$ at the end of period $t$.