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# Design a Sustainable Supply Chain under Uncertainty using Life Cycle Optimisation and Stochastic Programming

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This work addresses the life cycle economic and environmental optimisation of a supply chain network considering both design and operational decisions under uncertainty. A general modelling framework is proposed that integrates the functional-unit-based life cycle optimisation methodology and the two-stage stochastic programming approach for sustainable supply chain optimisation under uncertainty. a stochastic mixed-integer linear fractional programming (SMILFP) model is developed to tackle multiple uncertainties regarding feedstock supply uncertainty and product demand uncertainty. To address the computational challenge of solving large-scale SMILFP problems, an efficient solution algorithm that takes advantage of the efficiency of parametric algorithm and the decomposition-based multi-cut L-shaped method is used. A case study based on a spatially explicit model for the county-level hydrocarbon biofuel supply chain is presented in Illinois to demonstrate the applicability of the proposed modelling and algorithmic framework.

## 1. Introduction

Recently, a functional-unit-based life cycle optimization approach has been proposed (Yue et al., 2016), which systematically optimizes the economic and environmental performance of a biofuel supply chain based on a functional unit associated with the production system. The product-centric perspective embedded in this approach not only captures the major features of a process-based life cycle analysis (LCA), but potentially leads to more cost-effective and sustainable supply chains (Gao and You, 2015a).

Despite the wide application of LCA-based approaches, criticisms are raised for their vulnerability to uncertainty. Uncertainties are ubiquitous in the biofuel supply chain and inherent in quantitative measurements of environmental impacts (Yue and You, 2016). Simply doing sustainable optimisation of a biofuel supply chain without considering uncertainty would be reckless (Emara et al., 2016), since both the optimality and feasibility of a supply chain design can be easily impaired (Garcia and You, 2015). Therefore, it is imperative to develop a general modelling framework that enables us to effectively handle multiple uncertainties in sustainable design and operations of supply chains.

In this paper, a novel integrated modelling framework for a sustainable biofuel supply chain design under uncertainty is proposed. It simultaneously addresses economic and environmental concerns based on the functional-unit-based life cycle optimization framework. Major decisions including supply chain network design, conversion technology selection, capital investment regarding biorefineries, production planning, transportation and storage, etc. are fully addressed. Meanwhile, a two-stage stochastic programming structure is used to quantitatively account for uncertainty in this design and planning problem. In this way, all possible future outcomes are taken into account. Consequently, the economic objective is minimizing the expected unit cost per functional unit associated with biofuel product. The environmental objective is defined as minimizing the life cycle GHG emission (in terms of $CO_2$ equivalent based on 100-y time horizon) per functional unit (Yue et al., 2013). Because the quantity of functional units generated in the system is an important decision variable to optimize along with the production decisions, the resulting problem is a bi-criterion stochastic mixed-integer linear fractional programming (SMILFP) problem, which is extremely challenging to solve, featuring both a two-stage stochastic structure and fractional objective functions. Thus, a tailored solution algorithm that integrates both a parametric algorithm (Zhong and You, 2014) and the multi-cut L-shaped method (You et al., 2009) is used efficient solution of the resulting bi-criterion SMILFP.

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## 2. Problem statement

To illustrate the application of the proposed modelling framework and tailored solution algorithm, a county-level case study on hydrocarbon biofuel supply chains in Illinois is considered. It focuses on the sustainable design under uncertainty of county-level hydrocarbon biofuel supply chains in the state of Illinois. The functional unit is defined as unit gasoline-equivalent gallon (GEG) liquid biofuels characterized in terms of energy content (Yue et al., 2014). Correspondingly, the economic objective is to minimize the expected unit cost per GEG of biofuels. The environmental objective is to minimize the life cycle GHG emission (in terms of $CO_2$ equivalent based on 100 y time horizon) per GEG of biofuels. The goal is to determine the optimal supply chain configuration (including locations, capacities, and technologies of biorefineries), and corresponding operational decisions (including the amount of material flows, inventory levels, and product sales) under different scenarios. A supply chain superstructure is presented in the following Figure 1.

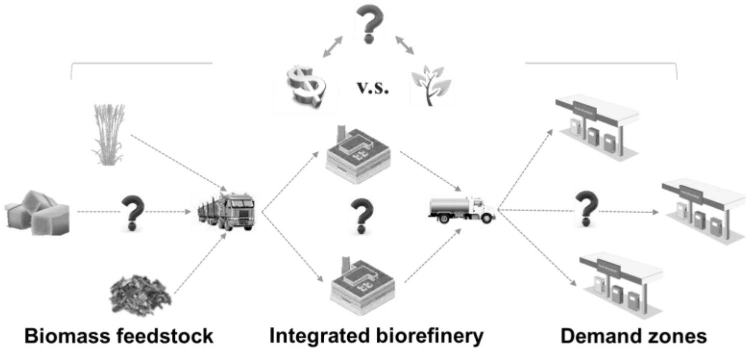


*Figure 1. Supply chain network for hydrocarbon biofuels*

In this problem, it is given a set of biomass feedstocks, including agricultural residues (e.g., corn stover), wood residues (e.g., forest residues and urban wood residues), and energy crops (e.g., switchgrass). The biomass feedstocks can be converted to a set of hydrocarbon biofuels (e.g., gasoline and diesel) through a set of conversion technologies (Ng et al., 2015). This work focuses on integrated biorefineries, and the specific technologies considered include gasification followed by Fischer-Tropsch (FT) synthesis (Wang et al., 2013) and fast pyrolysis followed by hydroprocessing (Zhang et al., 2014). On the basis of the annual production amount, two ranges of capacities are considered for both conversion technologies. The total investment costs of biorefineries in each capacity level are modelled using piecewise linear cost curve to account for the economy of scale. In addition to direct conversion, the biomass feedstock can also be stored at biorefineries temporarily as inventory. However, degradation and extra charges for inventory will occur at this storage phase. Similarly, biofuels can either be distributed directly to demand zones for sale or be held as inventory at biorefineries. Two major biofuel products are considered in this work, namely gasoline and diesel. In addition, demand zones can also purchase gasoline and diesel through external sources. Accordingly, a penalty cost will be charged. Uncertainties are in biomass feedstock availability and biofuels demand simultaneously, both of which follow normal distribution with a 10 % deviation (Gebreslassie et al., 2012). In order to reduce the number of scenarios required, this approach further incorporates the sample average approximation (SAA) approach for this two-stage stochastic programming problem (Kleywegt et al., 2002). By setting an initial sample size of 25 scenarios and consider a 98 % confidence interval. The number of scenarios is finalized as 80.

## 3. Model formulation and global optimisation algorithm

### 3.1 Model formulation

Following the proposed modelling framework, the resulting problem is a multi-objective SMILFP problem. The economic objective is to minimize the expected unit cost per GEG of biofuels. Here $tc_1$ stands for the sum of first-stage cost corresponding to design decisions and $tc_{2,s}$ stands for the second stage cost corresponding to operational decisions in scenario $s$. $qt_s$ is the variable quantity of functional unit generated in scenario s, and scenario probability is denoted by $p_s$. The environmental objective is to minimize the life cycle GHG emission per GEG of biofuels. $te_s$ stands for the second stage GHG emissions in scenario $s$. For the compactness of this paper, we do not provide the detailed model formulation for all the constraints.

$$\text{Economic Objective: } \min \frac{tc_1 + \sum_{s\in S} p_s \cdot tc_{2,s}}{\sum_{s\in S} p_s \cdot qt_s} \qquad \text{Environmental Objective: } \min \frac{\sum_{s\in S} p_s \cdot te_s}{\sum_{s\in S} p_s \cdot qt_s} \tag{1}$$

s.t. Mass balance constraints
Capacity constraints
Logic constraints

The components of the first-stage cost $tc_1$ include the capital investment, fixed O&M cost, and incentive received for biorefineries; the second-stage cost $tc_{2,s}$ equals the summation of costs regarding: biomass acquisition, biofuels production, transportation, storage, backorder, and incentives; the total GHG emissions $te_s$ include similar components for biomass acquisition, biofuels production, transportation, and storage.

### 3.2 Tailored global optimisation algorithm

The SMILFP problem, as a combination of stochastic programming and MILFP problem, requires special solution techniques to be solved efficiently (Gao and You, 2015b). After exploiting the problem structure, a tailored global optimization algorithm that integrates the parametric algorithm (Chu and You, 2013) for handling the fractional term, as well as the multi-cut L-shaped method (You et al., 2013) is used for dealing with the scenario planning structure of SMILP problem. Figure 2 summarizes this solution algorithm in a pseudo code, and note that this is by far the most computationally efficient algorithm for globally optimizing general SMILFP problems to 0% optimality gap.

***Global Optimisation Algorithm***

Transform $F(qw) = min\ \left(N(x,y) - qw \cdot D(y)\right) \leftarrow min\ N(x,y)/D(y)$
Initialization: $qw \leftarrow 0$ , $Iter^{out} \leftarrow 1$
**while** (objective function $F(qw) \geq Tol^{out}$ ) **do**
  $Iter^{out} \leftarrow Iter^{out} + 1$
  $LB \leftarrow -\infty$ , $UB \leftarrow +\infty$ , $Iter^{in} \leftarrow 1$ , $Gap \leftarrow +\infty$
  Solve Master Problem (**MP**) to obtain $x^*$
  **while** ( $Gap \geq Tol^{in}$ ) **do**
    $Iter^{in} \leftarrow Iter^{in} + 1$
    **while** (*Terminate* **=false**) **do**
      Scenario $s \leftarrow s+1$,
      Solve Subproblem (**SP**) with fixed $x^*$
      Generate optimality cut: $\theta_s \geq e_s y + d_s$
      **if** $count(s) \geq |S|$ **then**
        $Terminate \leftarrow$ **true**
      **end if**
    **end while**
    Add $\theta_s \geq e_s y + d_s$ to **MP**, update *UB*
    Solve **MP** with updated cuts
    Update *LB,* $Gap = (UB - LB)/(1 + |LB|)$
  **end while**
  Update parameter $qw = N(x^*, y^*)/D(y^*)$
**end while**
Output $qw^*$

*Figure 2. Pseudo-code of the tailored solution algorithm*

## 4. Case study

In this county-level hydrocarbon biofuel supply chain network, a total of 102 regions are considered, each of which corresponds to a single county in Illinois (Gebreslassie et al., 2012). The resulting biofuel supply chain network consists of 20 biomass harvesting sites, 8 potential integrated biorefinery facilities, and 35 demand regions (Tong et al., 2014). A 10 y planning horizon is considered, and each year is further divided into 12 time periods, corresponding to 12 months/y, to account for the seasonality of biomass supply (You et al., 2012). A

10 % discount rate is adopted for each year (You and Wang, 2011). The resulting problem has 52,094,579 continuous variables (Stage I: 170; Stage II: 52,094,409), 32 discrete variables (Stage I: 32; Stage II: 0), and 3,412,636 constraints (Stage I: 222; Stage II: 3,412,414). All of the models and solution procedures are coded in GAMS 24.4.1. The MILP problems are solved using CPLEX 12.6. The solution of Point C was obtained after 5 outer iterations within a total of 2,311 CPU seconds. The resulting multi-objective SMILFP problem is solved by the algorithm proposed above. By solving 10 instances with uniform intervals of GHG emissions per GEG biofuels, an approximated Pareto-curve is obtained in Figure 3. The *x*-axis represents the GHG emission corresponding to unit GEG of biofuels. The *y*-axis represents the total cost per GEG of biofuels. On the Pareto-curve, three points are chosen for further demonstration. Point A and C are two extreme solutions with the lowest GHG emission per GEG biofuels and lowest cost per GEG biofuels, respectively. Point B is a compromised solution that features with good economic performance and decent emission performance. In addition to the curve itself, we add pie charts above the curve to show the cost breakdowns for different solutions. Similarly, the donut charts below the curve are emission breakdowns. The size of these charts are proportional to the absolute value of total cost and emission, and the percentage corresponds to different activities/processes in the hydrocarbon biofuel supply chain.

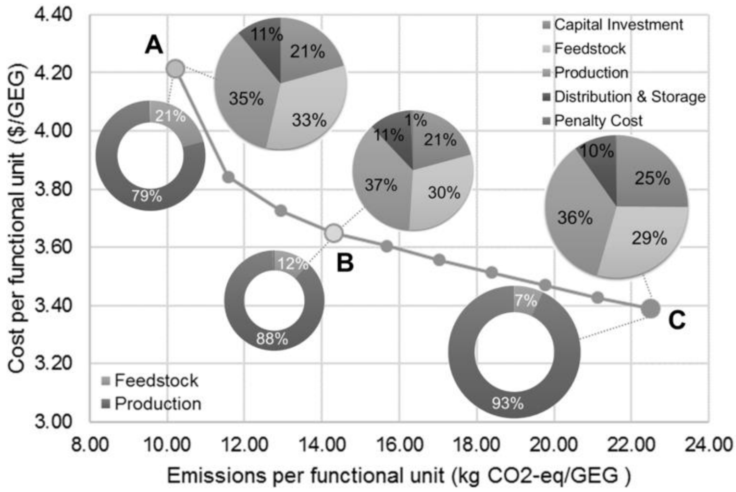


*Figure 3. Pareto-optimal curve of the case study with breakdowns*

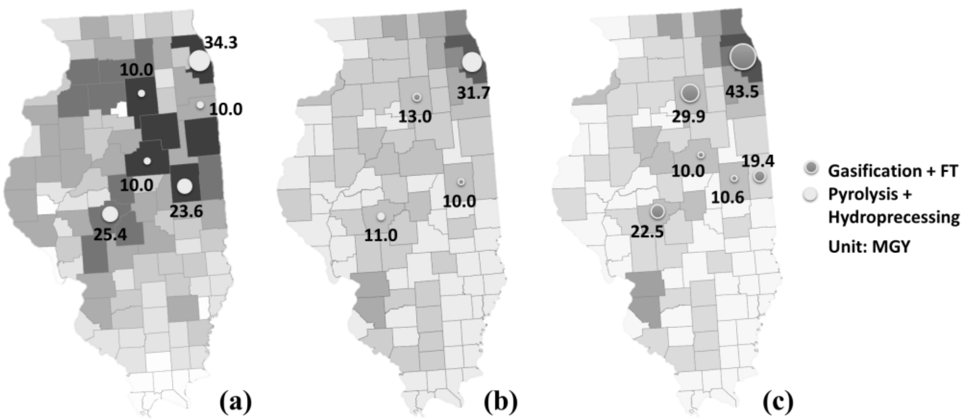


*Figure 4. Optimal biofuel supply chain design in different solutions: (a) Point A, (b) Point B, (c) Point C*

The Pareto-curve shows that the most sustainable solution point A has the lowest GHG emission per GEG biofuels of 10.22 kg $CO_2$-eq/GEG, and it has the highest cost per GEG biofuels of 4.21 $/GEG. By contrast, point C has the lowest cost per GEG biofuels of 3.39 $/GEG and the highest GHG emission per GEG biofuels of 22.50 kg $CO_2$-eq /GEG. The cost per GEG biofuels for point B is 3.65 $/GEG, and the GHG emission per GEG biofuels is 14.31 kg $CO_2$-eq /GEG. Next, we present the supply chain profiles of all the solutions, given in Figure 4. The number and locations of integrated biorefineries are depicted on a county-based map of Illinois.

The capacity for each biorefinery in terms of million gallon per y (MGY) is provided as well. As can be seen, for point A, a total of 6 biorefineries are built, all of which adopt pyrolysis and hydroprocessing technology. For point C, there are also 6 biorefineries to be built with gasification and FT technology. The optimal supply chain design for point B is a combination of point A and B, where both technologies are adopted. In order to review and compare the results related to operational decisions. One specific scenario out of the 80 scenarios is considered to demonstrate the different operational decisions. The biomass feedstock composition is provided in Figure 5. Additionally, due to the seasonality of biomass availability, and taking the uncertainties of biomass supply and product demand into account, the inventory planning becomes one important section in the operation of biofuel supply chains (Yue and You, 2016). The inventory profile is summarized in Figure 6.

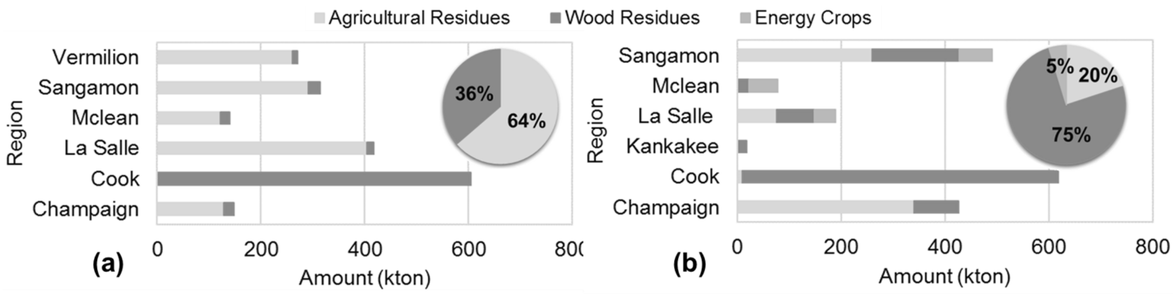


*Figure 5. Biomass feedstock compositions for (a) point A, (b) point C*

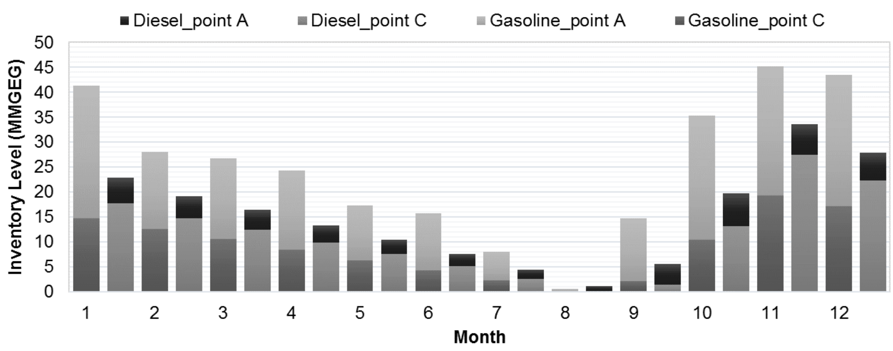


*Figure 6. Biofuels inventory levels for point A and point C*

Obviously, due to the competitive acquisition cost for agricultural residues and wood residues, they are chosen as major biomass feedstocks in the cost-minimization case. Meanwhile wood residues become a popular choice in the emission-minimization case thanks to its much lower carbon footprint generated in the biomass acquisition process. Energy crops accounts for 5 % of the feedstock supply in point A because of its relatively lower carbon footprint compared with agricultural residues. Additionally, in regions such as Cook County where wood resource is abundant, it easily becomes the dominant biomass feedstock. For the inventory strategy, an obvious ditch of inventory level can be observed near August, which is the month before the harvesting period of agricultural residues. In point A, more gasoline is stored; while in that of point C, diesel is major stored product. This difference is mainly driven by the underlying conversion technology choices. For gasification and FT technology, with unit amount of biomass input, more diesel is produced; in contrast, fast pyrolysis and hydroprocessing will yield more gasoline than diesel with unit biomass input.

## 5. Conclusions

In this work, a general modelling framework was proposed that integrates the functional-unit-based life cycle optimisation methodology with stochastic programming framework. The resulting problem is a bi-criterion SMILFP problem and can be solved efficiently by a tailored global solution algorithm. Furthermore, a county-level hydrocarbon biofuel supply chain model in Illinois was presented to demonstrate the proposed modelling framework and corresponding solution algorithm. The most environmentally sustainable design achieves a point with 10.22 kg $CO_2$-eq/GEG emission per GEG biofuels and 4.21 \$/GEG cost per GEG biofuels. The most economical design corresponds to a point with 22.50 kg $CO_2$-eq/GEG emission per GEG biofuels and 3.39

\$/GEG cost per GEG biofuels. The results showed that the proposed approach is by far the most efficient algorithm for dealing with uncertainty in functional unit based life cycle optimization.

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