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Economic and environmental optimization of a large scale sustainable dual feedstock lignocellulosic-based bioethanol supply chain in a stochastic environment

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HIGHLIGHTS

- 2-Stage stochastic MILP model for optimizing the performance of a sustainable lignocellulosic-based biofuel supply chain.
- Multiple uncertainties in biomass supply, purchase price of biomass, bioethanol demand, and sale price of bioethanol.
- Stochastic parameters significantly impact the allocation of biomass processing capacities of biorefineries.
- Location of biorefineries and choice of conversion technology is found to be insensitive to the stochastic environment.
- Use of Sample Average Approximation (SAA) algorithm as a decomposition technique.

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ABSTRACT

This work proposes a two-stage stochastic optimization model to maximize the expected profit and simultaneously minimize carbon emissions of a dual-feedstock lignocellulosic-based bioethanol supply chain (LBSC) under uncertainties in supply, demand and prices. The model decides the optimal first-stage decisions and the expected values of the second-stage decisions. A case study based on a 4-state Midwestern region in the US demonstrates the effectiveness of the proposed stochastic model over a deterministic model under uncertainties. Two regional modes are considered for the geographic scale of the LBSC. Under co-operation mode the 4 states are considered as a combined region while under stand-alone mode each of the 4 states is considered as an individual region. Each state under co-operation mode gives better financial and environmental outcomes when compared to stand-alone mode. Uncertainty has a significant impact on the biomass processing capacity of biorefineries. While the location and the choice of conversion technology for biorefineries i.e. biochemical vs. thermochemical, are insensitive to the stochastic environment. As variability of the stochastic parameters increases, the financial and environmental performance is degraded. Sensitivity analysis shows that levels of tax credit and carbon price have a major impact on the choice of conversion technology for a selected biorefinery. Biochemical pathway is preferred over the thermochemical as carbon price increases. Thermochemical pathway is preferred over the biochemical as the level of tax credit increases. In addition, bioethanol production in the US is shown to be unviable without adequate governmental subsidy in the form of tax credits.

1. Introduction

In order to secure the energy supply and to safeguard the environment, the US federal government in 2007 enacted the Renewable Fuel Standard (RFS) [1,2]. In 2022 the annual gasoline demand for the US is projected to be 120,000 million gallons (MG). The RFS requires by 2022 the use of bioethanol to displace 20% of the annual gasoline demand on an energy equivalent basis. One gallon of gasoline contains the energy equivalent of 1.5 gallons of ethanol [3]. By 2022 the RFS mandates the production of 36,000 million gallons per year (MGPY) of bioethanol, whose energy equivalence is 24,000 MGPY of gasoline. Out of this 36,000 MGPY only 15,000 MGPY can be bioethanol refined from corn starch. Of the remaining 21,000 MGPY, a minimum of 16,000 MGPY is to be bioethanol refined from lignocellulosic feedstocks including crop residue, woody biomass, and dedicated energy crops [3]. In 2012, corn starch was used to produce 13,000 MGPY of bioethanol and is fast approaching its ceiling limit of 16,000 MGPY. Until now

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the production of bioethanol from lignocellulosic feedstock has not been commercialized and is limited to pilot scale projects [3].

The large-scale use of gasoline in the transportation sectors also has an adverse impact on the environment. The combustion of fossil-fuels releases huge quantities of carbon and other pollutants into the atmosphere. Greenhouse gas (GHG) emissions are considered a major contributing cause of global warming [2]. Reduction in GHG emissions due to gasoline being substituted by bioethanol is a major component of the RFS requirements. By 2022, the RFS mandates that bioethanol not only displace 20% of annual gasoline demand on an energy equivalent basis but also achieve a 30% net reduction on 2005 levels in carbon emissions from the transportation sector [2]. In 2005 the total carbon emissions from the transportation sector were 1100 million tons (MT) [1].

In order to encourage investment in cellulosic bioethanol refineries it is imperative that an economically and environmentally viable supply of lignocellulosic biomass is guaranteed [4]. This allows biorefineries to operate at a sufficiently high utilization level needed to exploit the economies of scale inherent in large refineries [5]. Dedicated energy crops like switchgrass [6] show great potential but their cultivation has not yet been commercialized [3]. A strategy for mitigating risk in biomass supply is to use multiple existing sources of lignocellulosic feedstocks for risk pooling [5,7]. Therefore, a portfolio approach to biomass feedstock procurement is needed [8]. Based on current US availability [9], two of the most promising sources of lignocellulosic biomass for the production of bioethanol are: (1) crop residue – including barley straw, corn stover, sorghum stubble, and wheat straw [10]; and (2) woody materials – including urban wood waste, logging and mill residues [11].

Currently the price of fossil-fuel based energy products does not take into account the cost of carbon emissions resulting from their use [12]. National governments can play a role in accomplishing a sustainable shift towards renewable bioenergy products by imposing a tax on carbon emissions [13], thereby increasing the cost of energy produced from fossil fuel. Bioenergy produced from lignocellulosic feedstock is considered as carbon neutral, since the carbon emissions resulting from their use release CO_2 that crops and tress captured during photosynthesis [14]. Emissions trading schemes by way of the Regional GHG Initiative of "carbon tax" adopted by 9 Northeastern states in the US have been effective in reducing annual carbon emissions [15]. Studies show that a national level tax of $40/ton of carbon emissions would raise $2.5 trillion in the US over a 10-year period [16]. Revenue from such a carbon tax could be used to promote and establish renewable-energy projects in general and biofuel plants in particular.

A comprehensive optimization of the various logistical components along the entire lignocellulosic-based bioethanol supply chain (LBSC) is essential to maximize total profit [3] and minimize carbon emissions. The key logistics variables include the biomass processing capacity, optimal location, and choice of conversion technology of biorefineries. The choice of the conversion pathway i.e. biochemical vs. thermochemical is likely to greatly impact on the financial and environmental performance of the LBSC [7].

Recently, a number of authors [17–19] have presented research on deterministic optimization of LBSC that consider the financial objective and also take into account the environmental impact. Work by [20] presents a linear optimization model. The decision variables include biorefinery location, capacity and choice of conversion pathway. Research by [21] presents a mixed integer linear programming (MILP) optimization model that is solved using k-means clustering. The decision variables include biorefinery location and capacity. Work by [12] presents a MILP model along with Pareto optimal curves. The decision variables include biorefinery location, capacity and choice of conversion pathway.

However, there is a great deal of uncertainty relating to prices and supply/demand inherent in a LBSC [3,12]. These uncertainties introduce significant risk in the decision making process, making it imperative that robust decisions are made concerning the key logistics variables in a stochastic environment.

Most work on the stochastic optimization of biomass-to-bioethanol supply chains only consider the financial objective [22,23] and do not take into account the environmental impact. Research by [24] presents a 2-stage MILP optimization model that considers uncertainty in biomass supply and purchase price, biofuel demand and sale price. The first-stage decision variables include biorefinery location, capacity and choice of conversion pathway.

Only a few authors have presented research on stochastic optimization of biomass-to-biofuel supply chains that consider the financial objective and also take into account the environmental impact. Research by [25] presents a MILP model for a methanol supply chain that considers uncertainty over 4 scenarios in biofuel demand. The first-stage decision variables include biorefinery location and capacity. Work by [26] presents a 2-stage MILP model that considers uncertainty over 1000 scenarios in biomass supply and biofuel demand. The first-stage decision variables include biorefinery location, capacity and choice of conversion pathway. The model is solved using Bender's decomposition. Research by [27] presents a MILP model for a bioethanol supply chain that considers uncertainty over 100 scenarios in biomass purchase price. The first-stage decision variables include biorefinery capacity and choice of conversion technology.

To the best of our knowledge, no comprehensive work has been carried out on the stochastic multi-period optimization of dual-feedstock biomass-to-bioethanol supply chains under multiple uncertainties where the financial objective is optimized by also taking into account the environmental impact. The closest work has been done by [25–27]. However, the work by [25] does not deal with bioethanol and the biofuel under study is methanol, and the number of stochastic scenarios is limited to 4. While the work by [26] does not take into account the environmental impact and instead considers downside profit risk as the secondary objective. The work by [27] does not consider uncertainty in biomass supply, bioethanol demand, and sale price of bioethanol. The proposed model considers a single bioethanol refinery and site selection is not a decision variable.

This article proposes a two-stage stochastic MILP formulation to maximize the annualized profit of an integrated dual-feedstock LBSC while simultaneously minimizing carbon emissions. The work is differentiated from other efforts in this field by incorporating the following specific LBSC characteristics: (1) environmental impact is monetized through carbon credits and directly incorporated into the objective function, rather than being traded-off using Pareto optimal curves; (2) uncertainties in lignocellulosic-biomass supply, biomass purchase price, bioethanol demand, and bioethanol selling price are considered; (3) first-stage decision variables include both integer and continuous variables. The integer variable determines the location and conversion technology of biorefineries. While the continuous variables determines the biomass processing capacity of biorefineries; (4) second-stage decision variables include amount of each biomass type to be procured from supply zones, amount of biomass feedstock to be transported from the supply zones to the biorefineries, volume of bioethanol to be directly sold from biorefineries, volume of bioethanol to be transported from the biorefineries to the biofuel demand zones, volume of unmet bioethanol requirement for each demand zone, and the inventory of biomass and bioethanol to be kept by biorefineries; (5) optimal strategies on location of biorefineries, conversion technology selection, and biomass processing capacity of each biorefinery are solved simultaneously within the integrated system by using the Sample