

Biorefinery Supply Chain Network Design under Competitive Feedstock Markets: An Agent-Based Simulation and Optimization Approach

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Supporting Information

ABSTRACT: We address the problem of biorefinery supply chain network design under competitive corn markets. Unlike existing methods, the purchase prices of corn are considered to vary not only across time but also across competing biorefineries in a given region for all time periods in the design horizon. As the feedstock cost for purchasing corn is the largest cost component for producing ethanol, it is critical to consider the formation of corn prices in real-world markets involving competition and interactions among biorefineries, among farmers, and between biorefineries and the food market. However, these competitive markets are difficult to formulate in a mathematical program. To simulate the corn markets, an agent-based model is developed. In each market, the dynamic corn prices are determined by a double-auction process participated in by biorefinery agents, farmer agents, and a food market agent. The determined corn prices are then returned to the supply chain design problem, which is a mixed-integer nonlinear program (MINLP) with black-box functions. However, such a problem cannot be solved directly by a MINLP solver. Thus, we use a genetic algorithm to solve the optimization problem and determine the location and capacity of each biorefinery in the network. The proposed method is demonstrated by a case study on a corn-based biorefinery supply chain network design in Illinois in which the optimal net present value of a network of 10 biorefineries increased by 10.7% compared to that of the initial supply chain network.

1. INTRODUCTION

The biofuel industry has continued to grow as society strives to reduce its dependence on imported oils and transportation-related emissions.^{1,2} The Energy Independence and Security Act of 2007 included the Renewable Fuel Standard (RFS) which requires production of 36 billion gallons of biofuels annually, including 15 billion gallons of corn ethanol, by 2015.³

The biorefinery location and capacity design problem is important for evaluating investment decisions in the long run. Liu et al.⁴ provided an overview of typical methodologies of energy systems engineering such as superstructure-based modeling, mixed integer linear and nonlinear programming, multiobjective optimization, optimization under uncertainty, and life cycle assessments. Dunnett et al.⁵ presented a spatially explicit mixed integer linear programming (MILP) model to analyze cost-optimal configurations specific to the European agricultural land and population densities. Zamboni et al.⁶ presented an MILP model for the biofuel supply networks which took into account various factors that affect a biofuel supply chain such as agricultural practice, biomass supplier allocation, and production site locations. Eksioglu et al.⁷ determined the optimal number, size, and location of biorefineries needed to produce biofuel using the available biomass. On the basis of the work of Zamboni et al.,⁶ Mas et al.⁸ developed a dynamic spatially explicit MILP model to optimize the design and planning of biomass-based fuel supply networks according to financial criteria and market uncertainty. Akgul et al.⁹ presented an MILP model which optimized the locations and scales of the bioethanol production plants, biomass, and bioethanol flows. Kim et al.¹⁰ maximized the overall profit by taking into account different types of biomass, conversion

technologies, and several feedstock and plant locations. Bowling et al.¹¹ presented an optimization framework to determine the optimal supply chain, size, operational strategies, and location of the biorefinery and preprocessing hub facilities. Kostin et al.¹² presented a multiscenario MILP model for the strategic design of bioethanol–sugar supply chains under demand uncertainty. Elia et al.¹³ presented an optimization framework for a nationwide energy supply chain network using hybrid coal, biomass, and natural gas to liquid facilities. Mazetto et al.¹⁴ presented an MILP model with corn and ethanol price forecasting models to optimize the bioethanol supply chain in northern Italy. Yue et al.¹⁵ presented a multiobjective mixed-integer linear fractional programming model for the sustainable design and operation of biofuel supply chains which accounted for environmental and economic impacts. Tong et al.^{16–18} presented deterministic and stochastic MILP models and solution methods for the optimal design of an advanced hydrocarbon biofuel supply chain integrated with existing petroleum refineries.

However, the above-mentioned studies do not completely capture competition in real markets between decision makers who continuously adapt to market conditions.¹⁹ For the corn-based ethanol industry, it is crucial that investment decisions can be analyzed with uncertain market prices and supply of corn in the midst of competition among biorefineries, among farmers, and between biorefineries and the food market (represents demand from food, feed, and export sectors).²⁰

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Such competition has been investigated by game-theoretic models.^{21,22} However, these studies formulated bi-level mathematical models (noncooperative Stackelberg game) by assuming the responses of farmers as simple functions of the actions of biorefineries. In practice, the complex interactions among farmers and biorefineries might not be fully captured by simple algebraic models and are better characterized by competitive markets, which are scarcely considered in previous work.

To address this issue, we develop a simulation-based optimization method to optimize the supply chain network of biorefineries by simulating the dynamic interactions between multiple intelligent agents. The outline of the proposed method is presented in Figure 1. A unique feature of this model is that

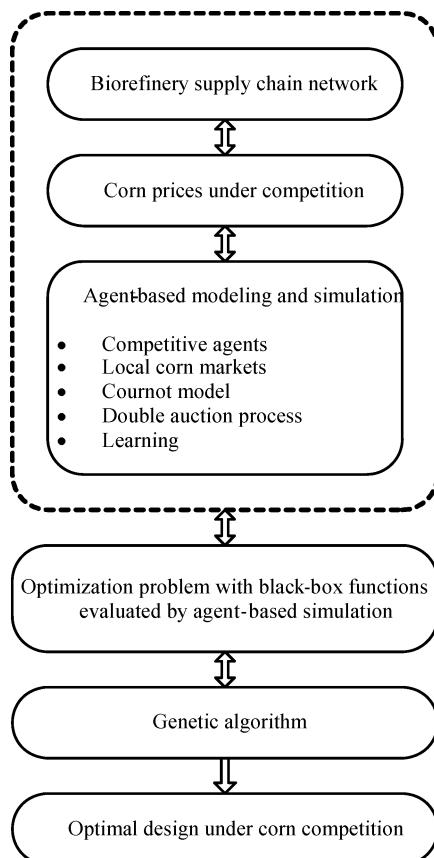


Figure 1. Outline of the simulation-based optimization method.

the prices at which biorefineries purchase corn are considered to be variables which are determined by competition among biorefineries, farmers, and the food market. Additionally, the prices vary over time as the decision makers alter their actions according to their learning in the market. To consider these factors in the price formation process, we developed an agent-based model which incorporates the characteristics of real-world corn markets and strategies of decision makers.

When the biorefinery supply chain network is fixed, the corn purchase prices are determined by the agent-based modeling and simulation. Specifically, the agent-based model comprises the biorefinery agents, farmer agents, and food market agent. These agents participate in the local markets created according to their geographical location. In each market, corn is considered to be a homogeneous good. Thus, the Cournot model is used to determine the quantity that each farmer would supply in a local market.²³ After the supply quantities are determined,

corn prices in local markets are determined by a double-auction process.²⁴ During the double-auction process, the intelligent agents make strategic price offers according to the modified Roth-Erev learning algorithm.²⁴ After each time period, the intelligent agents update their actions for the next period according to previous outcomes.

The determined corn prices are then fed back into the supply chain network design problem which maximizes the total net present value for the design horizon. The problem is solved to determine the location site and capacity level of each biorefinery in the network. These decisions are represented by binary location and capacity selection variables. As the agent-based simulation results in black-box functions, the optimization problem cannot be solved directly by an optimization solver. Therefore, we utilize a genetic algorithm to solve the simulation-based optimization problem.²⁵ The final outcome of the proposed method is the optimal design of the biorefinery supply chain network in the presence of competition among farmers, among biorefineries, and between biorefineries and the food market.

The major novelties of this work can be summarized as follows:

- Innovative method for biorefinery network design with competition for price formation
- Hybrid model formulation including the mathematical model and the agent-based simulation
- Corn price and quantity determination by market simulation via the double-auction process and Cournot model

According to the outline shown in Figure 1, the rest of the paper is organized as follows. Section 2 provides the required background on agent-based modeling, Cournot model, double-auction process, and the learning algorithm. The problem statement and assumptions are given in Section 3. Section 4 describes the agent-based modeling approach for corn competition. On incorporating the results of the agent-based simulation and the mathematical models, the optimization problem including black-box functions is formulated and solved in Section 5. Section 6 presents a case study which illustrates and validates the proposed model using historical data and projections for the state of Illinois. Conclusions are presented in Section 7.

2. BACKGROUND

In this section, we give a brief introduction to the theory which will be used in the following sections. Specifically, the agent-based modeling approach is introduced in Section 2.1. The Cournot model is provided in Section 2.2. The double-auction process is presented in Section 2.3. The learning algorithm is given in Section 2.4.

2.1. Agent-Based Modeling. Agent-based modeling is a new approach to modeling systems comprised of autonomous and interacting agents.²⁶ Agent-based modeling has become widespread as the systems we need to analyze are becoming increasingly complex in terms of their interdependencies.

The fundamental characteristic of an agent is the capability to make independent decisions. Agents should also have the ability to communicate with other agents, react to changes in the environment, and take actions based on prespecified goals.²⁷ Most engineering problems addressed by multiagent systems are the ones in which coordination of multiple entities is required. For example, Chonghun et al. presented an agent-based approach to develop a computer-aided support system for process design.²⁸

Swaminathan et al. presented another agent-based decision support tool for supply chain management.²⁹ Garcia-Flores et al. presented an agent-based model to represent information flow in supply chains of the process industry.³⁰ Katare and Venkatasubramanian presented an agent-based model for studying the behavior of microbes in a binary substrate environment.³¹ Chu et al. presented a novel efficient agent-based model for scheduling network batch processes in the process industry.³² The authors further extended the agent-based modeling framework with a heuristic tree search algorithm to improve the solution quality.³³ A hybrid method was recently proposed for planning and scheduling problems under production uncertainties that iterated between an MILP solver for the planning problem and an agent-based reactive scheduling method.³⁴

2.2. Cournot Model. An oligopoly is a market condition in which there are a few producers and each producer's decision regarding its quantity for sale can affect the profit of other producers. In contrast to a perfectly competitive market, in which the number of producers is large enough to ensure that each producer can safely ignore the reactions of competitors while making output decisions, in an oligopoly, the producers' decisions are interdependent.²³

In this study, a dynamic oligopolistic market model for homogeneous goods is proposed based on the well-known Cournot model.³⁵ Homogeneous goods are goods sold by different sellers which are perfect substitutes of one another. The Cournot model determines the quantities that sellers of a homogeneous good would choose to supply in equilibrium in an oligopolistic market when they try to maximize their profit in the presence of competitors. For example, consider a seller h who must determine the quantity of a homogeneous good that he would offer for sale, q_h , on facing the market demand given by

$$p = A - B \cdot q \quad (1)$$

where p is the price at which $q = \sum_h q_h$ is demanded and A and B are the intercept and absolute value of the slope of the linear market demand function, respectively. The profit Π_h of seller h is given by

$$\Pi_h = (A - B \cdot q) \cdot q_h - c_h \cdot q_h, \quad \forall h \quad (2)$$

where c_h is the marginal cost of seller h . The quantity that each seller would offer for sale is the amount that will maximize the seller's profit. The profit-maximizing quantity of seller h is a function of the quantity sold by other sellers and is given by

$$q_h = \frac{A - c_h}{2 \cdot B} - \frac{q_{-h}}{2}, \quad \forall h \quad (3)$$

where $q_{-h} = \sum_{h' \neq h} q_{h'}$.

Figure 2 presents the Cournot equilibrium condition in a two-seller market in which the profit-maximizing quantity q_1 is given as a function of q_2 , and vice versa.

For a market with n sellers of a homogeneous good, the profit-maximizing conditions of all sellers can be solved simultaneously to determine the quantity that seller h would supply and is given by

$$q_h = \frac{A}{(n+1) \cdot B} + \frac{n \cdot (\bar{c} - c_h) - c_h}{(n+1) \cdot B}, \quad \forall h \quad (4)$$

where \bar{c} is the average marginal cost of all the sellers, calculated by

$$\bar{c} = \frac{1}{n} \sum_h c_h \quad (5)$$

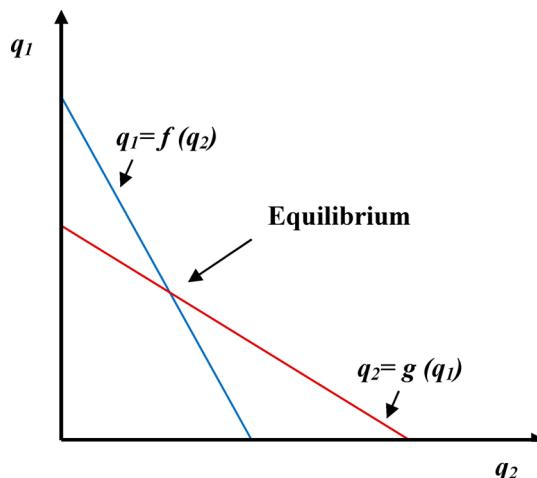


Figure 2. Equilibrium condition in a two seller market.

2.3. Double-Auction Process. Double auction is a simple mechanism that forms a price close to the theoretical equilibrium price and provides an efficient allocation model for a dynamic market.³⁶ Laboratory double auctions with human traders are known to yield results that closely approximate the equilibrium predictions of economic theory in a variety of environments.³⁷ Auction mechanisms provide a useful model for determining resource allocation and transaction price among multiple agents, with the objective of maximizing social welfare by yielding results that closely approximate theoretical equilibrium levels.³⁸ An additional advantage of using an auction mechanism is that it requires little global information and has a decentralized structure.³⁹

The auction consists of four parts: players, object of trade, profit functions, and strategies. Players are defined as rational market participants who are either buyers or sellers, and the number of players is considered constant. The profit function includes the market price which is determined by the auction, the reserve price (marginal revenue for buyer and marginal cost for seller), and transportation cost (in the case of the buyer). The reserve prices of the object vary among players, and players choose strategies to maximize expected gain.⁴⁰ Auctions can be double-sided (when both buyers and sellers submit offers) or single-sided (when either buyers or sellers submit offers). The price and quantity offers made by buyers and sellers are called bids and asks, respectively. Two forms of double auction that have been commonly used to study electricity markets are clearing house double auction and continuous double auction (CDA).^{24,40-43} Under the clearing house double-auction mechanism, bids and asks are collected over a period of time and then cleared by a central agent called the clearing house. Similar to the electricity generators in the electricity market who sell electricity from an existing capacity, farmers sell corn throughout the year from their stocked harvest. In both markets, there are a few producers of homogeneous products, and this situation can be considered to be an oligopoly.²³ Thus, a double-auction mechanism was used to model the short-run trade of corn in local oligopolistic markets.

Gode and Sunder³⁷ found that by merely imposing a budget constraint on the random price offers of artificial agents in a CDA they were able to induce enough regularity in the market to yield allocation efficiency close to 100%. Although there was not any difference between budget-constrained artificial agents and human traders in terms of the total profit extracted in the

CDA markets, there were significant differences in the distribution of profits across agents. Thus, the distributional aspects of market performance were considered to be sensitive to human motivation and learning. They suggested that a profit-maximizing strategy by the agents may reduce the discrepancy in distribution of profits among artificial agents in comparison to the distribution achieved among human traders. Thus, in this study, we consider a clearing house double-auction mechanism with a learning algorithm for strategic price offers as it is crucial for achieving reliable estimates of biorefineries' profits for optimization.

The price set by the clearing house can be either discriminatory (set individually for each matched buyer–seller pair) or uniform (set equally for all matched buyer–seller pair). In our case, a discriminatory midpoint pricing policy was chosen.^{24,43} It is worth noting that price discriminatory double auction has allocation efficiency outcomes similar to those of CDA.^{24,39} Thus, an agent-based model that incorporates the double-auction mechanism can capture the diverse interactions between heterogeneous strategic sellers and buyers. The mechanism of the clearing house double-auction process with discriminatory pricing is illustrated in Figure 5.

2.4. Roth–Erev Learning Algorithm. Learning in strategic environments is a phenomenon that is absent in individual decision-making environments because the environment in which each individual gains experience includes other individuals whose behavior changes as they, too, gain experience.⁴⁴ We model this learning in market transactions with a three-parameter reinforcement learning algorithm.²⁴

The Roth–Erev learning algorithm captures individual learning in strategic environments with multiple decision makers.⁴⁴ It incorporates the widely accepted *law of effect* and *power law of practice* learning principles in psychology. The former principle asserts that the tendency to implement an action should be strengthened if it produces favorable results and weakened if it produces unfavorable results. The latter principle asserts that learning curves tend to be steep initially and flatten out afterward.²⁴

The learning algorithm also incorporates *experimentation* and *recency* effects to account for decision making in response to other decision makers. The *experimentation* principle ensures that not only are choices which were successful in the past more likely to be used in the future but also similar choices are employed often as well. The *recency* effect captures the fact that recent experience plays a larger role than past experience in determining behavior. In this study, we used a modified version of the Roth–Erev learning algorithm proposed by Nicolaisen et al.²⁴

3. PROBLEM STATEMENT

The objective of this study is to optimize the location and capacity of a network of biorefineries with respect to the total net present value in the presence of competition among biorefineries, among farmers, and between biorefineries and the food market. To simulate the competitive markets, each year in the design horizon is divided into a set of time periods, indexed by t .

The key variables for different stakeholders in the supply chain are

- Site-specific corn procurement price
- Location and capacity of biorefineries
- Profit of the biorefineries and farmers in each time period

The known parameters are

- Number of farmers
- Number of biorefineries
- Candidate location sites for biorefineries
- Latitude and longitude values of all locations
- Projected ethanol price for the design horizon
- Projected corn yield for the design horizon
- Variable cost of biorefineries
- Byproduct (distillers grain) selling price for biorefineries
- Storage cost for farmers
- Transportation cost for farmers

The model is formulated based on the following assumptions:

- Farmers are selfish agents that participate in the market to maximize their profit in the presence of competition with other farmers located at a similar distance to the biorefineries.
- Biorefineries are selfish agents that participate in the market to maximize their profit in the presence of competition with other biorefineries and the food market.
- The food market is considered to be an agent that represents the demand from the food, feed, and export sectors.
- Farmers, the food market, and biorefineries adapt their price expectations based on market outcomes in the previous period.
- Transportation distance between locations can be estimated by the distance obtained from longitudinal and latitudinal values of the locations.
- Projected ethanol price for a given year is the same for all biorefineries.
- Corn demand curve is the same for every year in the design horizon.
- Yearly corn yield for farmers is adjusted based on agricultural projections.
- Storage cost is the same for all farmers.
- Transportation cost for farmers to food market is zero.
- Yearly operating cost per planted acre (includes labor, input costs, and utilities) for farmers is adjusted based on agricultural projections and is the same for all farmers.

4. AGENT-BASED MODELING AND SIMULATION OF COMPETITIVE CORN MARKETS

As the price of corn is the largest cost component of ethanol, it is critical to consider the formation of prices in local markets around the biorefineries and to estimate the supply under different market conditions. As the total corn production in the United States that is sold under long-term contracts is barely 10% and the traditional spot-market still governs nearly 60% of the value of agricultural production,^{45,46} a model that can estimate the short-run prices and quantity offered for sale in a dynamic and competitive environment would capture the complex real-world transactions in the corn market.

To simulate the corn price formation procedure, an agent-based model is developed and illustrated in Figure 3. The model includes three types of agents: biorefinery agents, farmer agents, and a food market agent.

Specifically, the main functions of the agents are as follows:

- Biorefinery agents: represent individual biorefineries that participate in the corn market to obtain corn required to operate at full capacity. They also maximize their profit in the presence of competition with other biorefineries and the food market.

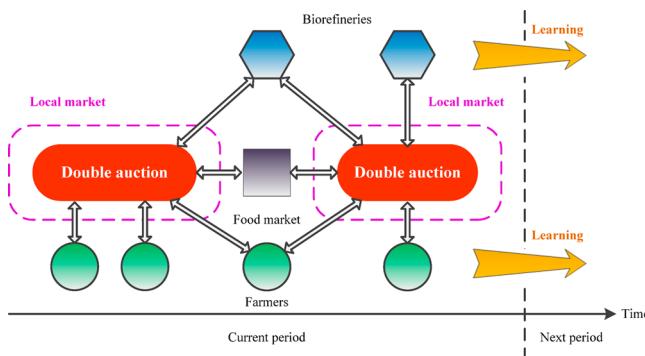


Figure 3. Agent-based model for simulating corn markets.

- Farmer agents: represent groups of farmers (aggregated based on county) that participate in oligopolistic local markets to sell their harvest and maximize their profit in the presence of competition with other farmers located at a similar distance to the biorefineries. This agent incurs a transportation cost in proportion to its distance from a biorefinery.
- Food market agent: represents the demand of the food, feed, and export sectors. As its demand and reserve price cannot be modeled accurately, this agent is considered to have infinite demand and buys corn at only the forecasted price. This agent also participates in all local markets, and the farmers do not incur any transportation cost for delivering corn to this agent.

These agents participate in local markets to sell or buy corn. In each market, the corn price is determined by the double-auction process. The local markets are formed according to the geographic location of the agents. An agent can participate in one or multiple markets according to the quantity and the price at which it would like to sell or buy corn. The double-auction process in a local market is simulated for all time periods. A learning algorithm is used to determine the strategic price offers of the agents during the double-auction process. According to the outcomes of the current period, the biorefinery agents and farmer agents update their strategies for buying and selling corn in the next period. This learning further reflects the intelligence of the biorefineries and farmers in the real world.

The agent-based model simulates the competitive corn markets after the biorefinery network is designed. The simulation determines the price of corn in each time period for all biorefineries. The price is then imported into the mathematical model formulated in Section 5 to calculate the total net present value. According to the calculated value, a new design of the biorefinery can be obtained to improve the objective function value; this procedure is presented in Section 5.

According to the agent-based model shown in Figure 3, this section is structured as follows. The model of farmers is given in section 4.1. Section 4.2 presents the model of the local markets. Section 4.3 illustrates the double-auction process. The learning procedure is given in Section 4.4

4.1. Model of Farmers. As the feedstock price of a biorefinery relies on the actions of farmers, the model for calculating the profit of a farmer is presented in this section. The farmer modeled in this study is an aggregate agent which incorporates all actual farmers in a county.

A farmer is indexed by j . The total profit of farmer j , denoted by tpf_j , is the sum of the yearly profits

$$\text{tpf}_j = \sum_y \text{prf}_{jy}, \quad \forall j \quad (6)$$

where prf_{jy} is the profit of farmer j in year y . It is the difference between the revenue and the production cost

$$\text{prf}_{jy} = \text{rvf}_{jy} - \text{pcf}_{jy}, \quad \forall j, y \quad (7)$$

where rvf_{jy} is the revenue of farmer j in year y and pcf_j is the production cost of farmer j calculated from

$$\text{pcf}_{jy} = \text{CF}_j \cdot \text{YIELD}_{jy}, \quad \forall j, y \quad (8)$$

where CF_j is the unit production cost of farmer j and YIELD_{jy} is the yield of farmer j in year y .

The revenue of farmer j in year y is the sum over periods

$$\text{rvf}_{jy} = \sum_t \text{rft}_{jty}, \quad \forall j, y \quad (9)$$

where rft_{jty} is the revenue of farmer j in period t of year y . It is the product of

$$\text{rft}_{jty} = \text{npr}_{jty} \cdot \text{qtf}_{jty}, \quad \forall j, t, y \quad (10)$$

where npr_{jty} is the average unit selling price of corn and qtf_{jty} is the total quantity sold by farmer j in period t of year y . The total quantity sold is equal to the yearly yield

$$\sum_t \text{qtf}_{jty} = \text{YIELD}_{jy}, \quad \forall j, y \quad (11)$$

The variables qtf_{jty} and npr_{jty} are determined by the corn market simulated by the agent-based model in Section 4.

4.2. Formation of Local Markets. Corn sold by farmers can be considered as a nonhomogeneous good from the standpoint of a biorefinery because the transportation cost is proportional to the distance between farmers and the biorefinery. Thus, corn sold by farmers that are farther away from the biorefinery would cost more and would not be identical to the corn sold by farmers that are closer to the biorefinery. A biorefinery may also prefer farmers that are located closer to it because of shorter lead times and lower backorder costs. In contrast, the food market is considered to be an agent that is locally present for all farmers and the farmers do not incur any transportation cost for delivery. Thus, corn sold by farmers is a homogeneous good from the standpoint of the food market but a nonhomogeneous good from the standpoint of the biorefinery.

The heterogeneity factor between farmers is their distance from the biorefinery. To execute double auction with the Cournot model for a homogeneous good, local markets are formed according to the locations of the biorefineries and the farmers.

The local markets are formed as zones illustrated in Figure 4. Each zone is characterized by a zone radius, ZR , and it is the circular area enclosed by the zone radius. In a given zone, farmers are located within the same range of distance from the biorefinery and this eliminates the heterogeneity in the corn sold by farmers (assuming that the corn sold by farmers is similar in other physical characteristics).

For a given time period, a single double-auction run for every biorefinery is carried out in each of its zones. To illustrate the process, the sequence of events is described for the system of two biorefineries (BR1 and BR2) and a cluster of farmers

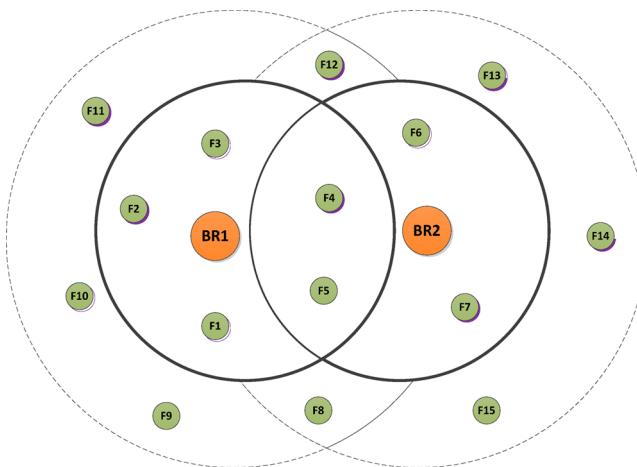


Figure 4. Zones for executing double auction for a homogeneous good.

(F1–F15) in Figure 4. At the beginning of each time period, the zones are identified for the two biorefineries in accordance to the zone radius. As seen in Figure 4, farmers F1–F5 are present in zone 1 of BR1 and farmers F4–F7 are present in zone 1 of BR2. Farmers F4 and F5 are present in zone 1 of BR1 and BR2. The double-auction run is first executed for zone 1 of BR1 in which the buyers are BR1 and the food market and the sellers are F1–F5. The run in zone 1 of BR1 terminates when either the total supply or demand is exhausted. After termination of the run in zone 1 of BR1, a similar double-auction run for zone 1 of BR2 is carried out with buyers (BR2 and food market) and sellers (F4–F7). Farmers F4 and F5 participate in both markets (zone1 of BR1 and zone1 of BR2) and first participate in the double-auction run for the biorefinery which is closer to it. The simulation continues to progress from one zone to the next until either the biorefineries have met their demand or all farmers have finished participating in the double-auction process for all biorefineries.

In the local markets formed as zones, corn is regarded as a homogeneous good. On the basis of the Cournot model in eq 4, the quantity offered for sale by a farmer is determined by

$$qof_{jzty} = \frac{CA_t}{(NF_z + 1) \cdot CB_t} + \frac{NF_z \cdot (\text{avg}_{zty} - \text{ask}_{jty}^{\min}) - \text{ask}_{jty}^{\min}}{(NF_z + 1) \cdot CB_t}, \quad \forall j, z, t, y \quad (12)$$

where qof_{jzty} is the quantity offered for sale by farmer j in zone z in period t of year y and CA_t and CB_t are the intercept and absolute value of the slope of the corn market demand function in period t , respectively. The number of farmers in zone z , NF_z , is given by

$$NF_z = |JF_z|, \quad \forall z \quad (13)$$

where the set JF_z is defined as

$$JF_z = \{j | \text{Farmer } j \text{ is in zone } z\}, \quad \forall z \quad (14)$$

The quantity qof_{jzty} depends on ask_{jty}^{\min} , minimum ask price of farmer j in period t of year y , and avg_{zty} , the average minimum ask price of all farmers in zone z in period t of year y . The minimum ask price is given by

$$\text{ask}_{jty}^{\min} = CF_j + SC_t, \quad \forall j, t \quad (15)$$

where SC_t is the unit storage cost.

4.3. Double-Auction Process. After determining the quantity a farmer offers for sale by the Cournot model, we can determine the market prices in a given period via the clearing house double-auction process. For each run of the double-auction process, buyers (biorefinery and food market) and sellers (farmers) participate repeatedly in auction rounds until either the total demand offered or total supply requested for that run is exhausted.⁴⁷ Each agent is assigned a maximum amount of corn (defined as UD) that it can buy or sell in each auction round.

As illustrated in Figure 5, the farmers submit asks, and buyers, biorefineries, and food market submit bids to the clearing house

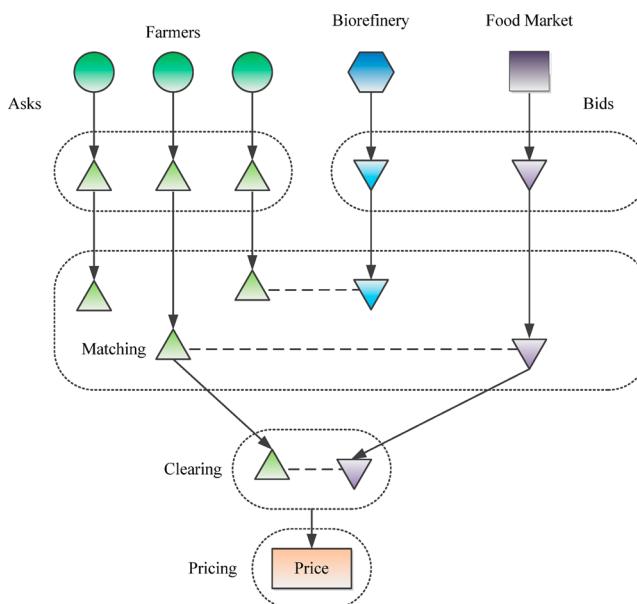


Figure 5. Discriminatory clearing house double-auction process.

in each round. The clearing house then organizes the bids in descending order and asks in ascending order. If the highest bid is greater than or equal to the lowest ask, the clearing house matches the buyer with the highest bid with the seller with the lowest ask. The clearing house then sets the market transaction price and quantity for the matched pair according to eqs 16 and 18, respectively. If the quantity demanded and offered by the first pair are not equal, the clearing house checks if the second highest bid or the second lowest ask could be matched to settle the leftover amount. After settling the leftover amount, the clearing house repeats the process until it cannot find a pair for which the bid is greater than or equal to the ask.

A biorefinery is indexed by i . For the matched buyer and seller, j , the market transaction price is set as the average of the matched bid and ask and is given by²⁴

$$\text{mtp}_{rzty} = \frac{\max\{\text{bof}_{irzty} - \text{tci}_{j,i}, \text{FM}_{ty}\} + \text{fof}_{j,rzty}}{2}, \quad \forall i, j, r, z, t, y \text{ for } \max\{\text{bof}_{irzty} - \text{tci}_{j,i}, \text{FM}_{ty}\} \geq \text{fof}_{j,rzty} \quad (16)$$

where mtp_{rzty} is the market transaction price in round r of zone z in period t of year y , bof_{irzty} the price that biorefinery i offers in round r of zone z in period t of year y , $\text{tci}_{j,i}$ the transportation cost for farmer j if it supplies corn to biorefinery i , $\text{fof}_{j,rzty}$ the price farmer j offers in round r of zone z in period t of year y , and FM_{ty} the food market bidding price in period t of year y .

The difference $\text{bof}_{irzy} - \text{tci}_{\bar{j}i}$ denotes the price offered by the biorefinery after accounting for the transportation cost that will be incurred by the farmer, and $\text{tci}_{\bar{j}i}$ is given by

$$\text{tci}_{\bar{j}i} = \text{dis}_{\bar{j}i} \cdot \text{TC}, \quad \forall \bar{j}, i \quad (17)$$

where $\text{dis}_{\bar{j}i}$ is the distance of farmer \bar{j} from biorefinery i and TC is the unit transportation cost per kilometer. The market transaction quantity, mtq_{rzty} , in round r of zone z in period t of year y is determined according to the buyer which bids a higher price by the following model:

$$\begin{aligned} \text{mtq}_{rzty} = & \begin{cases} \min\{\text{fqt}_{\bar{j}rzty}, \text{bqt}_{irzy}\}, \text{bof}_{irzy} - \text{tci}_{\bar{j}i} \geq \text{FM}_{ty}, \\ \min\{\text{fqt}_{\bar{j}rzty}, \text{UD}\}, \text{bof}_{irzy} - \text{tci}_{\bar{j}i} < \text{FM}_{ty} \end{cases}, \\ & \forall r, z, t, y \end{aligned} \quad (18)$$

where $\text{fqt}_{\bar{j}rzty}$ is the quantity farmer \bar{j} offers in round r of zone z in period t of year y , bqt_{irzy} the quantity that biorefinery i offers in round r of zone z in period t of year y , and UD the quantity that the food market offers. Table 1 provides the algorithm for

Table 1. Assignment of Transaction Price and Quantity Variables

```

If j =  $\bar{j}$ 
  fprjrzty = mtprzty
  qtrjrzty = mtqrzty
Else
  fprjrzty = 0
  qtrjrzty = 0
End if
If biorefinery i was matched with  $\bar{j}$ 
  tprirzty = mtprzty
  tqbirzty = mtqrzty
  ftcirzty = tci $\bar{j}i$ 
Else
  tprirzty = 0
  tqbirzty = 0
End if
If food market was matched with  $\bar{j}$ 
  tpmrzty = mtprzty
  tqfrzty = mtqrzty
  ftcrzty = 0
Else
  tpmrzty = 0
  tqfrzty = 0
End if

```

the assignment of transaction price and quantity variables for all agents in a given round of the auction.

Thus, the double-auction model provides the transaction price and quantity for each agent in every period of the year. The linking variables between the farmer model and the double-auction process are the quantities of corn sold and the corresponding prices. They satisfy

$$\text{qtf}_{jty} = \sum_{r,z} \text{qtr}_{jrzty} = \sum_z \text{qof}_{jzty}, \quad \forall j, t, y \quad (19)$$

$$\text{npr}_{jty} = \frac{\sum_{r,z} (\text{fpr}_{jrzty} - \text{ftc}_{jrzty}) \cdot \text{qtr}_{jrzty}}{\sum_{r,z} \text{qtr}_{jrzty}}, \quad \forall j, t, y \quad (20)$$

where qtf_{jty} is the quantity of corn sold by farmer j in period t of year y and npr_{jty} is the corresponding average selling price. These variables are linked to the farmer model by eqs 10 and 11. The variables on the right-hand sides of eq 19 and 20 are evaluated by the double-auction process.

The price offered by the food market in a given period is set equal to the projected price of corn for that period. The quantity purchased by the food market in period t of year y is

$$\text{qfm}_{ty} = \sum_{r,z} \text{tqf}_{rzty}, \quad \forall t, y \quad (21)$$

The average transaction price for food market in period t of year y is given by,

$$\text{pfm}_{ty} = \frac{\sum_{r,z} \text{tpm}_{rzty} \cdot \text{tqf}_{rzty}}{\sum_{r,z} \text{tqf}_{rzty}}, \quad \forall t, y \quad (22)$$

The model of the biorefineries is linked to the double-auction process via the purchased corn prices. The average price at which corn is purchased by biorefinery i in period t of year y , apc_{ity} , is given by

$$\text{apc}_{ity} = \frac{\sum_{r,z} \text{tpr}_{irzty} \cdot \text{tqb}_{irzty}}{\sum_{r,z} \text{tqb}_{irzty}}, \quad \forall i, t, y \quad (23)$$

where tqb_{irzty} and tpr_{irzty} in each round are determined by double auction.

4.4. Modified Roth–Erev Learning Algorithm. In the real world, farmers and biorefineries are intelligent decision makers who can learn from historical events to modify their strategies for selling or buying corn in competitive markets. In the double-auction process in this study, agents select a price offer in each round in accordance with the probability distribution for their price set. The agents update their probability distribution in each round based on past profit experiences. This update of price offers is governed by a modified version of the Roth–Erev learning algorithm.²⁴

At the beginning of each auction round, biorefineries and farmers submit quantity offers based on eqs 32 and 34, respectively. The price offered by the food market in period t of year y is a parameter, denoted by FM_{ty} . The food market is assumed to have an infinite demand, and the quantity demanded by the food market in each round of the double auction is UD.

Biorefinery. The price bid by biorefinery i in round r of zone z in period t of year y belongs to the range $[\text{bid}_{ity}^{\min}, \text{bid}_{ity}^{\max}]$. This range is discretized into KB_i price choices. The maximum bidding price is

$$\text{bid}_{ity}^{\max} = \frac{\text{PP}_y + \text{DA}_i - \text{pcb}_{ity}}{1 - \text{DB}_i}, \quad \forall i, t, y \quad (24)$$

The minimum bidding price bid_{ity}^{\min} updated from the market price in the previous period is

$$\text{bid}_{ity}^{\min} = \min_{r \in \text{RT}_{z(ty-1)}} \text{mtp}_{rzty}, \quad \forall i, t, y \quad (25)$$

where the set RT_{zty} includes all runs in all zones in period t of year y . The index subtraction $(ty - 1)$ is a shorthand notation to find the previous period, which is defined as

$$(ty - 1) = \begin{cases} (t - 1)y, t \geq 2 \\ (t = \text{NT})(y - 1), t = 1 \end{cases}, \quad \forall t, y \quad (26)$$

The subtraction returns the previous period of the same year if the current period is not the first one. Otherwise, it returns the last period of the previous year. NT denotes the number of periods in a year.

The agent probabilistically selects a choice p' from this set in round r , and this choice is denoted as bof_{irzty} . The propensity for choosing any price option p in round $r+1$ is updated based on the following equations:

$$\begin{aligned} \text{psb}_{ip(r+1)zty} &= (1 - \text{RE}) \cdot \text{psb}_{iprzty} + R(i, p', r) \cdot (1 - \text{EP}), \\ p &= p', \quad \forall i, r, z, t, y \end{aligned} \quad (27)$$

$$\begin{aligned} \text{psb}_{ip(r+1)zty} &= (1 - \text{RE}) \cdot \text{psb}_{iprzty} + \frac{\text{psb}_{iprzty} \cdot \text{EP}}{\text{KB}_i - 1}, \quad p \neq p', \\ \forall i, r, z, t, y \end{aligned} \quad (28)$$

where psb_{iprzty} is the propensity of choosing price p in round r of zone z in period t of year y , RE the *recency* parameter, EP the *experimentation* parameter, and $R(i, p', r)$ the total profit earned by the biorefinery until round r of zone z in period t of year y by choosing p' in round r .

For the first round, the propensity is equal for all price options and is given by

$$\text{psb}_{iprzty} = \frac{\text{SP} \cdot \text{XB}_i}{\text{KB}_i}, \quad \forall i, p, r, z, t, y \quad (29)$$

where SP is the *scaling* parameter in the learning algorithm, KB_i the number of price choices in the discretized range of biorefinery i , and XB_i the expected profit in any given round.

The probability of choosing price p in round $r+1$ is

$$\text{cpb}_{ip(r+1)zty} = \frac{\text{psb}_{ip(r+1)zty}}{\sum_p \text{psb}_{ip(r+1)zty}}, \quad \forall i, p, r, z, t, y \quad (30)$$

For the first round, the probability of choosing price p is equal for all price options and is given by

$$\text{cpb}_{iprzty} = \frac{1}{\text{KB}_i}, \quad \forall i, p, r, z, t, y \quad (31)$$

The quantity demanded by biorefinery i in round r of zone z in period t of year y is

$$\text{bqt}_{irzty} = \min \left\{ \text{UD}, \text{qtb}_{ity} - \sum_{r'=1}^{r-1} \sum_z \text{tqb}_{ir'zty} \right\}, \quad \forall i, r, z, t, y \quad (32)$$

Farmer. The farmer's price range, $[\text{ask}_{jty}^{\min}, \text{ask}_{jty}^{\max}]$, is also discretized into KF_j price choices. The propensity and probability functions are same as those of the biorefinery but are evaluated for KF_j price options and XF_j expected profit in a round. The price offered by farmer j in round r of zone z in period t of year y , fof_{jrzty} is determined in accordance with the probability distribution over its price set. The maximum ask price ask_{jty}^{\max} updated from the market price in the previous period is

$$\text{ask}_{jty}^{\max} = \max_{r \in RT_{z(y-1)}} \text{mtp}_{rzty}, \quad \forall j, z, t, y \quad (33)$$

The quantity offered for sale by farmer j in round r of zone z in period t of year y is

$$\text{fqt}_{jrzty} = \min \left\{ \text{UD}, \text{qof}_{jzt} - \sum_{r'=1}^{r-1} \sum_z \text{qtr}_{jr'zty} \right\}, \quad \forall j, r, z, t, y \quad (34)$$

5. SIMULATION-BASED OPTIMIZATION

The agent-based simulation in Section 4 determines the corn prices for a given biorefinery supply chain network. Using the corn prices, a supply chain design problem is formulated as a mixed-integer nonlinear program (MINLP) in this section. A key difficulty in solving the optimization problem is that the corn prices are determined by the agent-based modeling and simulation rather than explicit mathematical expressions. The simulation procedure results in black-box functions, and such an MINLP with black-box functions cannot be solved directly by an MINLP solver. Thus, a simulation-based optimization method is required. We adopt the genetic algorithm (GA) in MATLAB to solve the optimization problem.⁴⁸ GA is recognized as an effective method for solving complex problems without knowledge of the internal problem structure.^{25,49,50}

The optimization problem is solved to determine the location and capacity of each biorefinery in the network. In this study, the locations and the capacities are represented by binary variables to execute the simulation-based optimization algorithm. The location site of a biorefinery is chosen from a number of candidates. To represent the selection, we introduce the binary variable δ_{is} . If $\delta_{is} = 1$, then biorefinery i is located in candidate site s . The location variables satisfy the constraints

$$\delta_{is} \in \{0, 1\}, \quad \forall i, s \quad (35)$$

$$\sum_s \delta_{is} = 1, \quad \forall i \quad (36)$$

$$\sum_i \delta_{is} \leq 1, \quad \forall s \quad (37)$$

as a biorefinery is located in one candidate site only.

Similarly, the capacity of a biorefinery is also chosen from a set of discrete capacity levels. The discrete capacity levels are indexed by c . The parameter CP_{ic} represents the c th capacity level for biorefinery i . A binary variable γ_{ic} is introduced to select the capacity level from the candidate values. If $\gamma_{ic} = 1$, then the capacity of biorefinery i is equal to CP_{ic}, which is expressed as

$$\gamma_{ic} \in \{0, 1\}, \quad \forall i, c \quad (38)$$

$$\text{cap}_i = \sum_c \gamma_{ic} \cdot \text{CP}_{ic}, \quad \forall i \quad (39)$$

where cap_i is the capacity of the biorefinery i . The capacity selection variables satisfy the equality

$$\sum_c \gamma_{ic} = 1, \quad \forall i \quad (40)$$

as only one capacity level is selected for a biorefinery.

The agent-based modeling and simulation determine the average price of corn for every biorefinery in each time period, according to eq 23. As the outcomes of the double-auction process depend on the binary variables, the average prices of corn for biorefineries are black-box functions represented as

$$\text{apc}_{ity} = \varphi_{ity}(\{\delta_{is}\}, \{\gamma_{ic}\}), \quad \forall i, t, y \quad (41)$$

where $\{\delta_{is}\}$ and $\{\gamma_{ic}\}$ denote the collection of all location and capacity variables, respectively. Clearly, the purchasing price for a biorefinery depends not only on the biorefinery itself but also on other biorefineries present in competitive corn markets.

Thus, the entire biorefinery network should be simultaneously optimized.

The objective of the biorefinery supply chain network design is to maximize the total net present value, which is given by

$$\text{tnp} = \sum_i \text{npv}_i, \quad \forall i \quad (42)$$

where npv_i denotes the net present value of biorefinery i . It is expressed as a sum over the design horizon

$$\text{npv}_i = \sum_y \frac{\text{ypb}_{iy}}{(1 + \text{DR})^y} - \text{KA} \cdot \text{cap}_i^{\text{KC}}, \quad \forall i \quad (43)$$

where ypb_{iy} is the profit for biorefinery i in year y , DR the discount factor, and cap_i the capacity (maximum production rate) of biorefinery i ; KA and KC are parameters. The first term is the discounted total profit, and the second term is the capital investment cost.

The yearly profit is the sum over periods

$$\text{ypb}_{iy} = \sum_t \text{prb}_{ity}, \quad \forall i, y \quad (44)$$

where prb_{ity} is the profit of biorefinery i in period t of year y . It is expressed as

$$\text{prb}_{ity} = (\text{rvb}_{ity} - \text{PC}_i - \text{apc}_{ity}) \cdot \text{qp}_{ity} - \text{boc}_{ity}, \quad \forall i, t, y \quad (45)$$

where rvb_{ity} is the unit revenue for biorefinery i in period t of year y , PC_i the unit production cost, and apc_{ity} the unit corn price. The revenue, production cost, and feedstock cost are proportional to the quantity of corn purchased (qp_{ity}). The variable boc_{ity} represents the backorder cost for biorefinery i in period t of year y .

The unit revenue is expressed by

$$\text{rvb}_{ity} = \text{PP}_y \cdot \text{CR}_i + \text{dgr}_{ity}, \quad \forall i, t, y \quad (46)$$

where PP_y is the predicted unit price of ethanol in year y and CR_i is the conversion rate from corn to ethanol. The unit revenue of distillers grain dgr_{ity} for biorefinery i in period t of year y is a linear function of the unit corn price⁵¹ and is given by

$$\text{dgr}_{ity} = \text{DA} + \text{DB} \cdot \text{apc}_{ity}, \quad \forall i, t, y \quad (47)$$

where DA and DB are parameters.

The quantity purchased is given by

$$\text{qp}_{ity} = \sum_{r,z} \text{tqb}_{irzty}, \quad \forall i, t, y \quad (48)$$

The quantity of corn demanded by a biorefinery is determined by its capacity. Let OD_{ity} be the demand of ethanol for biorefinery i in period t of year y . The quantity of corn required to satisfy the order demand is $\text{OD}_{ity}/\text{CR}_i$. However, the maximum quantity of corn that a biorefinery can process is upper bounded by its capacity. When the order cannot be satisfied, the unfulfilled quantity is produced in the following period by adding a backorder cost in eq 45. The backorder cost is

$$\text{boc}_{ity} = \text{BC}_i \cdot \text{bov}_{ity}, \quad \forall i, t, y \quad (49)$$

where bov_{ity} is the backorder quantity and BC_i is the unit backorder cost.

The quantity of corn required by biorefinery i in period t of year y is the sum of the order demand in the current period and

the backorder in the previous period

$$\text{qtb}_{ity} = \min \left\{ \frac{\text{OD}_{ity}}{\text{CR}_i} + \text{bov}_{i,(ty-1)}, \frac{\text{cap}_i \cdot \text{TP}}{\text{CR}_i} \right\}, \quad \forall i, t, y \quad (50)$$

where TP is the length of a period.

Apart from $\text{bov}_{i,(ty-1)}$, the remaining portion in qtb_{ity} can be used to satisfy the current order demand $\text{OD}_{ity}/\text{CR}_i$. If $\text{qtb}_{ity} - \text{bov}_{i,(ty-1)} < \text{OD}_{ity}/\text{CR}_i$, then the current order demand cannot be completely fulfilled and the difference is the backorder value in the current period, which is expressed by

$$\text{bov}_{ity} = \text{bov}_{i,(ty-1)} + \frac{\text{OD}_{ity}}{\text{CR}_i} - \text{qtb}_{ity}, \quad \forall i, t, y \quad (51)$$

If $\text{qtb}_{ity} - \text{bov}_{i,(ty-1)} = \text{OD}_{ity}/\text{CR}_i$, then the current order demand can be fulfilled and the backorder value is zero.

Specifically, the optimization problem is represented by $\max \text{tnp}$ (eq 42) subject to supply chain model (eqs 35–40 and 43–51) and corn price (eq 41).

The optimization problem involving the black-box functions is solved by the genetic algorithm in the MATLAB global optimization toolbox to determine the biorefinery locations and capacities. After the design problem is solved, the determined biorefinery locations and capacities are then returned to the agent-based simulation to determine the new corn prices, as shown in Figure 6.

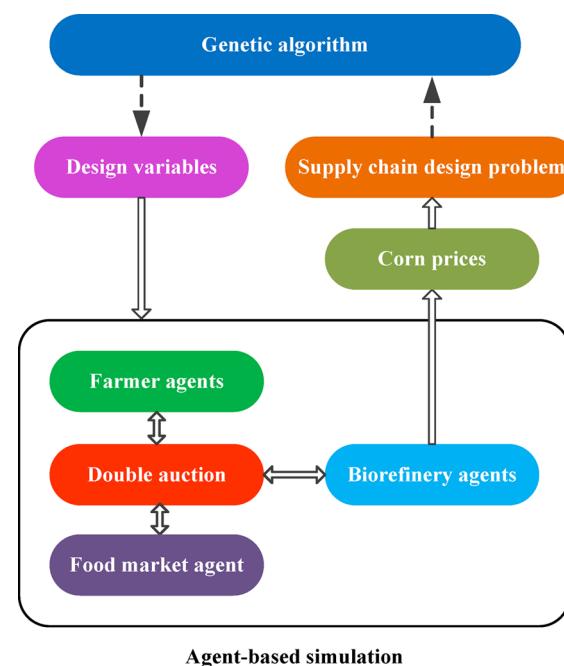


Figure 6. Diagram of the simulation-based optimization method.

6. CASE STUDIES

We demonstrate the proposed method by case studies on the design of a network of biorefineries in Illinois. There are 102 counties in Illinois, and the county-level data on location, distance, and population are taken from the existing literature.^{52–54} The farmers in each county are assumed to make the same decisions for selling their harvest. Thus, all actual farmers in a county are represented by a single farmer agent in the simulation model. The food market and all biorefineries are also modeled as agents. The corn prices are formed by interactions among the farmer agents, biorefinery agents, and food market agent.

The horizon of the design problem is 10 years, and each year is divided into four time periods called quarters. In each quarter, all agents participate in the double-auction markets. At the end of a quarter, the farmer agents and the biorefinery agents update their bidding strategies by learning from historical outcomes. The updated strategies are then utilized in the next quarter. The learning process is not used for the food market agent as it offers a fixed price according to the projected data. The biorefineries' ethanol demand is set equal to one-fourth of its capacity in each quarter of the design horizon.

In the case studies, the agent-based model is implemented in Java and the GA solver in MATLAB is utilized to solve the optimization problem which includes the black-box functions evaluated by the agent-based simulation.

This section is organized as follows. In Section 6.1, the proposed model is validated using historical data for 14 existing biorefineries in the state of Illinois in the marketing year of 2008. In Section 6.2, a new network of 10 biorefineries is optimized for a design period of 10 years. In Section 6.3, the effect of the competition among biorefineries is illustrated.

6.1. Model Validation. The central purpose of the agent-based modeling and simulation is to determine the corn prices in competitive markets. Figure 7 presents the existing biorefineries and the yield of each county in Illinois for 2008. The darker shade of green indicates higher-yield regions, and

the lighter shade of green indicates lower-yield regions. As the unit production cost decreases as the yield increases, farmers in a high-yield region have lower production costs than those in a low-yield region, and this affects the prices at which farmers sell their corn. In Figure 7, the existing biorefineries are marked as red circles.

The existing network of biorefineries is simulated for the 2008 marketing year.²² To validate the model, simulation results are compared to the historical data.^{55,56} The simulation results and historical values for the average fraction of harvest sold and the average price received by the farmers in each quarter of 2008 are presented in Table 2. The fraction of harvest sold in each quarter is defined as the quantity of corn sold in that quarter divided by the total harvest for the year of 2008.

Table 1 provides values of two standard deviations in the average historical values of the fraction of harvest sold in Illinois from the year 1991–2008. It can be seen that despite not precisely accounting for seasonal variations and the food market's demand, the simulation results are within two standard deviations of the historical values.

The average price received by the farmers in the 2008 marketing year was \$3.89 per bushel, and the simulation resulted in an average price of \$3.81 per bushel. The average price paid by the biorefineries in the simulation was \$4.82 per bushel. Table 1 illustrates that the simulation results are in close proximity to the historical values and provides values of one standard deviation in the average historical values of price from the years 2006–2010. The volatility in price, as indicated by the magnitude of the standard deviation, further emphasizes the importance of developing models which can capture price in competitive markets. Thus, this result suggests that the agent-based model has adequately unraveled the market mechanisms and can be used for optimizing the network of biorefineries.

6.2. Optimization Results. To demonstrate the utility of the proposed method in optimizing investment decisions for the strategic design of the biofuel supply chain, a new network of 10 biorefineries is optimized for the state of Illinois. The optimization is carried out for 20 candidate locations with three capacity levels (50, 100, and 150 million gallons per year (MGY)), and the network is simulated for a design period of 10 years (2013–2022). Projected corn prices are used to determine the food market bidding prices in each design year, while projected corn yields and acres harvested are used to determine the farmers' annual production.⁵⁷ The forecasted ethanol prices are used to determine the revenue of the biorefineries.⁵⁸

Figure 8 presents the 20 candidate locations for the optimization problem. As seen in Figure 8, the candidate locations are chosen in order to have a close to equal representation of all regions in the state. The sum of the capacities of the biorefineries is constrained to be equal to 1000 MGY.

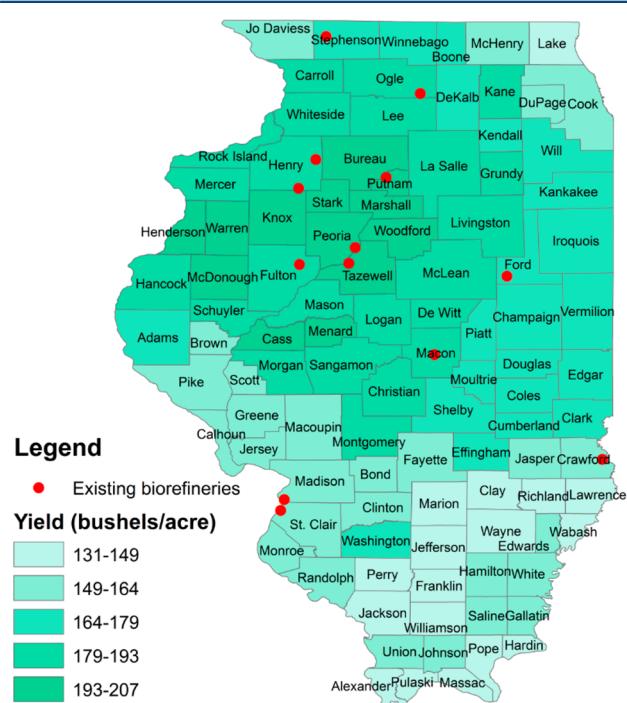


Figure 7. Network of biorefineries and the yield in the counties in Illinois in 2008.

Table 2. Comparison of Simulation Result and Historical Data for Average Fraction of Harvest Sold and Average Corn Price

time period	average fraction of harvest sold by farmers			average corn price received by farmers (\$/bushel)		
	simulation results for 2008	historical values for 2008	historical mean for 1991–2008 (2 STD)	simulation result for 2008	historical values for 2008	historical mean for 2006–2010 (1 STD)
quarter 1	0.272	0.212	0.241 (0.029)	3.76	4.27	3.89 (0.83)
quarter 2	0.236	0.299	0.291 (0.045)	3.78	3.62	4.38 (1.09)
quarter 3	0.208	0.232	0.258 (0.026)	3.81	3.97	4.79 (1.51)
quarter 4	0.284	0.214	0.216 (0.036)	3.87	3.69	4.81 (1.69)

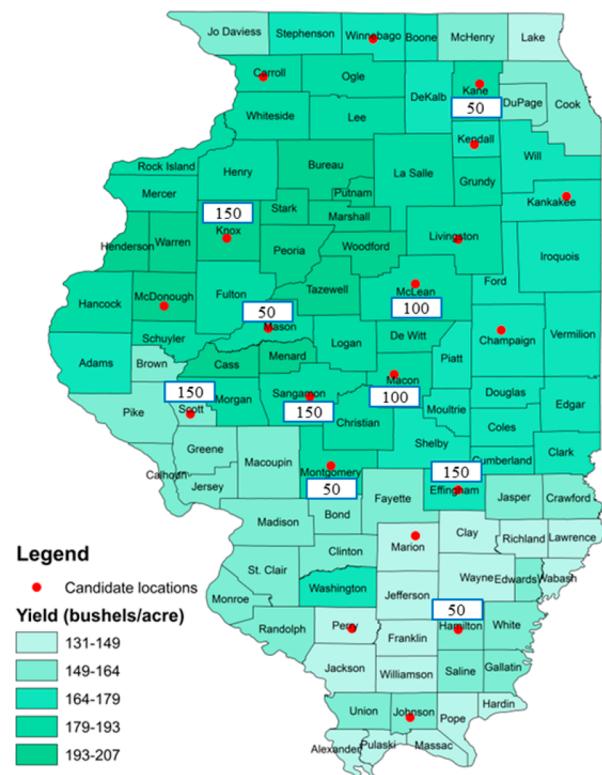


Figure 8. Optimized locations and capacities of biorefineries by the simulation-based optimization method that considers the competitive markets.

GA was run with a stopping criterion of 24 h of computation time for the simulation-optimization method and a population size of 50. Multiple combinations of population size and termination criterion were tested. However, the solution quality did not improve significantly for larger population sizes. The search was initialized with a network of random locations and capacities. This initial network served as a reference supply chain for evaluating the optimization result. The number of generations was 37, and the number of function evaluations was 1900. The objective function value initially increased with respect to the number of generations and then plateaued.

The final optimized network by the simulation-based optimization method, as shown in Figure 8, resulted in a 10.7% increase in the total net present value from \$5.02 B in the initial network (reference supply chain) to \$5.56 B. As seen in the figure, several biorefineries are located in the high-yield region. This makes sense intuitively as farmers in the higher-yield regions would have lower per unit cost of production because the price at which corn is sold in these regions would be lower than the price at which corn is sold in the lower-yield regions. Therefore, biorefineries in the higher-yield regions would earn more profit than those in the lower-yield regions.

It is also evident from Figure 8 that the biorefineries are not located very close to each other. This is due to the effect of competition on market price. Under close geographical proximity, the biorefineries would be competing in the same local markets (several overlapping zones). Thus, to meet their capacity, the biorefineries will have to purchase corn from farmers located farther away, and this will result in higher market prices because of higher transportation costs.

To obtain insights into the competitive corn markets, simulation results for the first design year is provided for the

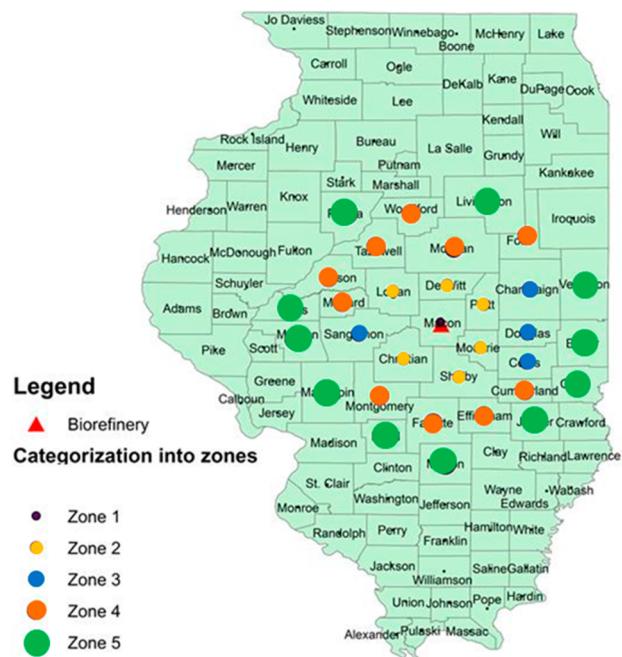


Figure 9. Zones for the biorefinery in Macon County.

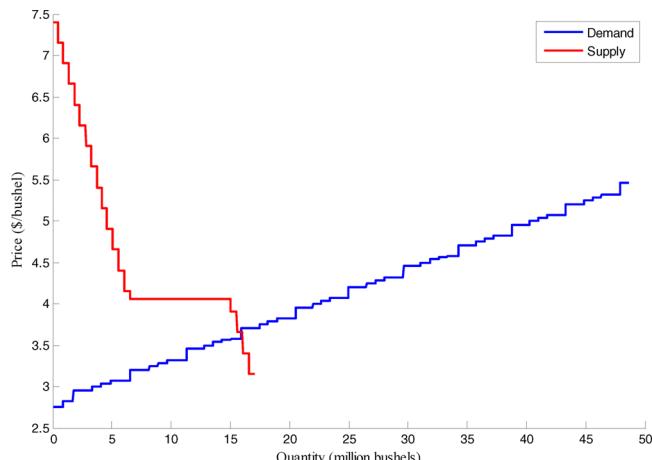


Figure 10. Short run market demand supply in zone 2 of biorefinery in Macon County.

optimized network. Figure 9 presents the selection of zones for the biorefinery located in Macon County. For this biorefinery, Figure 10 captures the short-run market demand and supply in zone 2. The supply curve in Figure 10 is the cumulative quantity offered for sale by all the farmers in zone 2 during the double-auction run. Similarly, the demand curve is the cumulative quantity demanded by the food market and biorefinery in Macon County during the double-auction run in zone 2. As expected, the demand curve is downward sloping and the supply curve is upward sloping. The flat region in the demand curve is due to the constant bidding price of the food market.

The learning parameters of the Roth-Erev learning algorithm were tuned to yield allocation efficiency of around 96% for the double-auction mechanism (see Appendix). A close to 100% allocation efficiency implies that the simulated market is transferring corn from farmers who produced it at the lowest cost to those buyers who value it the most. With 96% allocation efficiency, 96% of the gains from trade under competitive equilibrium are being realized in the simulated market.

It has been reported that laboratory double auctions with human traders yield results that closely approximate the equilibrium predictions of economic theory in a variety of environments.³⁷ Figure 10 thus demonstrates that the discriminatory double-auction mechanism in this study captures the evolution of the local market to the state of equilibrium.

Figure 11 presents the distribution of the average price received by the farmers in the first design year for the optimized network. Figure 12 presents the fraction of harvest sold by

the farmers to the food market in the first design year for the optimized network. As seen in Figure 12, the counties in which biorefineries are located, or in close proximity to, generally sell a smaller fraction of their harvest to the food market. Additionally, the counties which sell a smaller fraction of their harvest to the food market (Figure 12) receive a higher price (Figure 11).

The price received by the farmers is a function of yield, transportation distance, and the number of markets (zones)

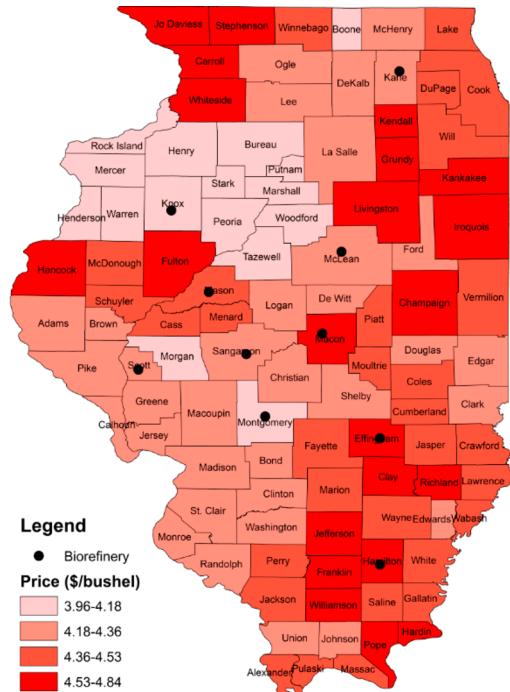


Figure 11. Average price received by farmers.

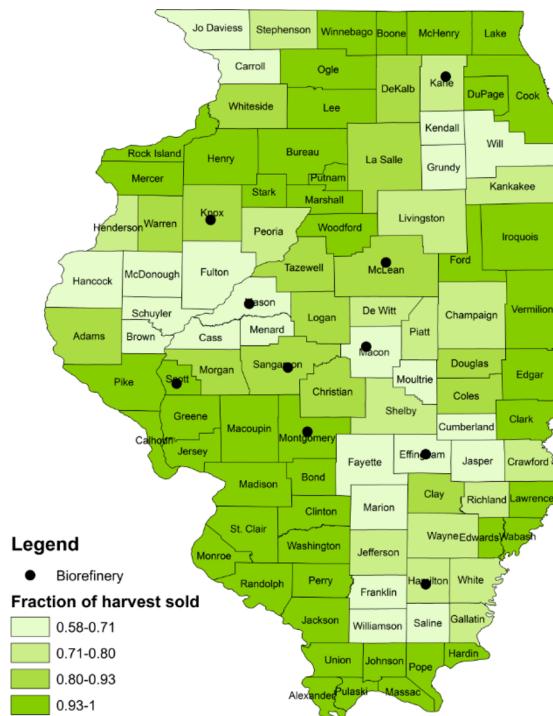
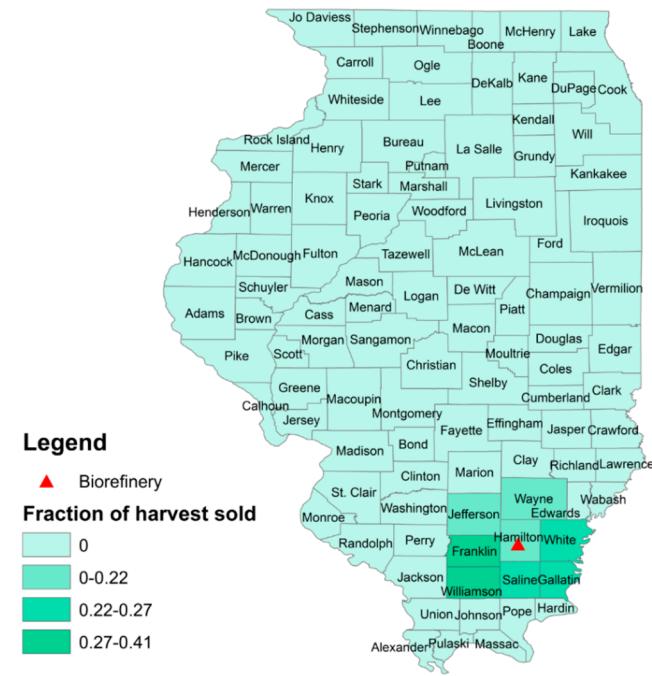
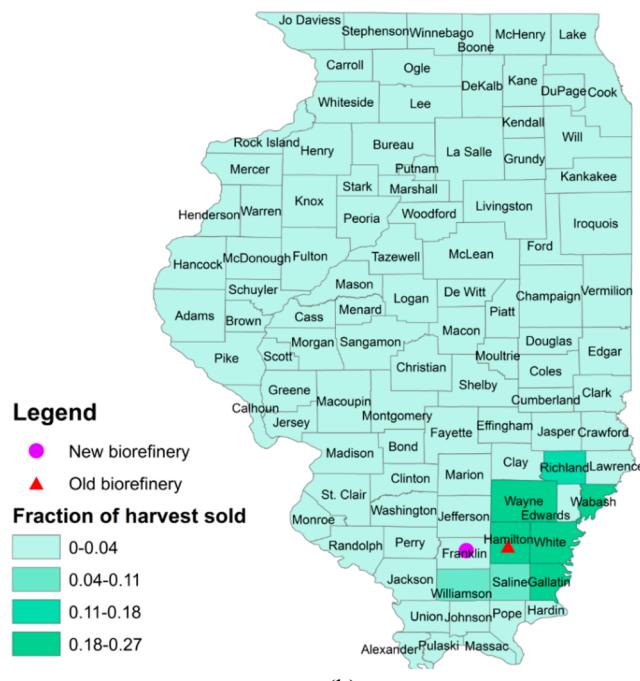


Figure 12. Illustration of the sources of supply for the food market.



(a)



(b)

Figure 13. Illustration of the supply of corn for the biorefinery (50 MGY) in Hamilton County in the (a) absence and (b) presence of a biorefinery (50 MGY) in Franklin County.

in which it participates. According to Figures 11 and 12, Fulton County located in central Illinois has medium yield, sold a small fraction of its harvest to the food market, and received a high price. The high price can be attributed to the presence of several biorefineries in close proximity and to the transportation cost for supplying to the biorefineries. Thus, the farmer agent of Fulton County participated in multiple local markets and received a higher price.

6.3. Illustration of Competition. In the double-auction process, each biorefinery competes directly with the food market in order to meet its supply. The competition with other biorefineries is indirect as counties that have sold a large fraction of their harvest to one biorefinery would have less to sell to another biorefinery. In such a situation, the other biorefinery will have to purchase corn from farmers that are located farther away and thereby pay a higher price to compensate the farmers for the higher transportation cost.

We demonstrate this competition among biorefineries by extending the existing network and placing a biorefinery in Franklin County. As a result, the average raw material cost for the biorefinery in Hamilton County increased and its sources of supply changed significantly. Figure 13 presents the supply sources for the biorefinery in Hamilton County before and after placing a biorefinery in Franklin County.

It is evident from Figure 13b that the new biorefinery competes with the adjacent biorefinery in Hamilton County by absorbing its supply sources and redistributing its supply network. In the absence of the new biorefinery, the biorefinery in Hamilton County obtained a large portion of its supply from Franklin County. However, in the presence of the biorefinery in Franklin County, the biorefinery in Hamilton County obtained an insignificant portion of its supply from Franklin County. The competition from the new biorefinery in Franklin County also increased the average price of corn for the biorefinery in Hamilton County from \$4.62 per bushel to \$4.75 per bushel. As a consequence, the annual profit of the biorefinery in Hamilton County decreases from \$2.57 MM to \$2.38 MM. Thus, the competitive corn markets can have a significant impact on the raw material cost of a biorefinery and in turn its profit. Therefore, such an impact should be taken into account in the biorefinery supply chain network design problem.

7. CONCLUSION

This study presented a novel methodology for the strategic design of an economically sustainable biorefinery supply chain network by incorporating competition between profit-maximizing agents. As real-world interactions between biorefineries, farmers, and the food market take place in a competitive environment, the double-auction mechanism was used to capture the effect of competition on the transaction prices in the local markets around the biorefineries. The case study demonstrated the utility of this method in optimizing investment decisions of establishing biorefineries in a given region. The optimized biorefinery network had a net present value 10.7% greater than that of the initial network. Thus, the simulation-based optimization methodology presented in this study can be used to strategically optimize a biorefinery supply chain network for ensuring the economic sustainability of the industry.

APPENDIX

Tables A1, A2, and A3 provide parameter values for all agents (except food market agent), biorefinery agent, and farmer agent, respectively.

Table A1. Data Used for All Agents

symbol	value	unit	reference
EP	0.97	—	—
RP	0.04	—	—
SP	100	—	—
UD	10^4	bushels	—

Table A2. Data for Biorefinery Agent

symbol	value	unit	reference
BC_i	0.056	\$/bushel	59
CR_i	2.8	gallon/bushel	22
DA_i	0.446	\$/bushel	51
DB_i	0.139	—	51
DR	0.1	—	60
KA	0.72	\$MM/MGY	22
KC	0.7	—	61

Table A3. Data for Farmer Agent

symbol	value	unit	reference
CA_t	4.4	\$(/bushel)	22
CB_t	0.16×10^{-6}	\$(/bushel) ²	22
CF_j	224	\$/acre	62
TC	0.0035	\$(/bushel)(mile)	22
SC_t	0.09	\$/bushel	63
ZR	25	km	—

NOMENCLATURE

Indices

c = capacity level

i = biorefinery

j = farmer

p = price in the price set

r = double-auction round in a given zone

s = location site

t = period

y = year

z = zone

Parameters

BC_i = unit backorder cost for biorefinery i

CA_t = intercept of the corn market demand function in period t

CB_t = absolute value of the slope of the corn market demand function in period t

CR_i = conversion rate of corn to ethanol for biorefinery i

CF_j = unit production cost of farmer j

CP_{ic} = capacity level c for biorefinery i

DA_i = intercept of the distillers grain selling price function of biorefinery i

DB_i = slope of the distillers grain selling price function of biorefinery i

DR = discount rate

EP = experimentation parameter in the modified Roth–Erev learning algorithm

FM_{ty} = food market bidding price in period t of year y

JF_z = set of farmers in zone z

KA = coefficient of the capital cost term

KB_i = number of choices in the price set of biorefinery i

KC = exponent of the capital cost term

KF_j = number of choices in the price set of farmer j

NF_z = total number of farmers in zone z

NT = number of periods in a year
 OD_{ity} = order demand of ethanol for biorefinery i in period t of year y
 PC_i = unit production cost of biorefinery i
 PP_y = ethanol price in year y
 RE = recency parameter in the modified Roth–Erev learning algorithm
 RT_{zty} = set of all runs in all zones in period t of year y
 SC_t = unit storage of farmers in period t
 SP = scaling parameter in the modified Roth–Erev learning algorithm
 TC = unit transportation cost per mile
 TP = length of a period
 UD = maximum amount of corn that an agent can ask or bid in any double-auction round
 XB_i = expected profit of biorefinery i in any given round
 XF_j = expected profit of farmer j in any given round
 $YIELD_{jy}$ = yield of farmer j in year y
 ZR = zone radius

Binary Variables

δ_{is} = biorefinery i is built at site s
 γ_{ic} = capacity of biorefinery i is chosen as level c

Continuous Variables

avg_{zty} = average minimum ask price of farmers in zone z in period t of year y
 apc_{ity} = average price at which corn is purchased by biorefinery i in period t of year y
 ask_{jty}^{\max} = maximum ask price of farmer j in period t of year y
 ask_{jty}^{\min} = minimum ask price of farmer j in period t of year y
 bid_{jty}^{\max} = maximum bid price of biorefinery i in period t of year y
 bid_{jty}^{\min} = minimum bid price of biorefinery i in period t of year y
 bof_{irzty} = price offered by biorefinery i in round r of zone z in period t of year y
 boc_{ity} = backorder cost for biorefinery i in period t of year y
 bov_{ity} = backorder quantity for biorefinery i in period t of year y
 bqt_{irzty} = quantity demanded by biorefinery i round r of zone z in period t of year y
 cap_i = capacity of biorefinery i
 cpb_{iprzy} = probability of choosing p by biorefinery i in round r of zone z in period t of year y
 dgr_{ity} = distillers grain selling price for biorefinery i in period t of year y
 dis_{ji} = distance of farmer j from biorefinery i
 fof_{jrzy} = price offered by farmer j in round r of zone z in period t of year y
 fpr_{jrzy} = transaction price of farmer j in round r of zone z in period t of year y
 fqf_{jrzy} = quantity offered by farmer j in round r of zone z in period t of year y
 ftc_{jrzy} = transportation cost for farmer j in round r of zone z in period t of year y
 mtp_{rzty} = market transaction price in round r of zone z in period t of year y
 mtq_{rzty} = market transaction quantity in round r of zone z in period t of year y
 npr_{jty} = average unit selling price for farmer j in period t of year y
 npv_i = net present value of biorefinery i
 pcb_{iy} = production cost of biorefinery i in period t

pcf_{jy} = production cost of farmer j in year y
 pfm_{ty} = average transaction price for food market in period t of year y
 prb_{ity} = profit of biorefinery i in period t of year y
 prf_{jy} = profit of farmer j in year y
 psb_{iprzy} = propensity for choosing price p for biorefinery i in round r of zone z in period t of year y
 qfm_{ty} = quantity purchased by food market in period t of year y
 qof_{jzy} = quantity offered for sale by farmer j in zone z in period t of year y
 qpb_{ity} = quantity purchased by biorefinery i in period t of year y
 qtb_{ity} = quantity required by biorefinery i in period t of year y
 qtf_{jty} = quantity sold by farmer j in period t of year y
 qtr_{jrzy} = quantity sold by farmer j in round r of zone z in period t
 rft_{jty} = revenue of farmer j in period t of year y
 rvb_{ity} = revenue of biorefinery i in period t of year y
 rvf_{jy} = revenue of farmer j in year y
 tc_{ji} = unit transportation cost for farmer j if it supplies corn to biorefinery i
 tqb_{irzty} = quantity purchased by biorefinery i in round r of zone z in period t of year y
 tqf_{rzty} = quantity purchased by food market in round r of zone z in period t of year y
 tnp = total net present value of the network of biorefineries
 tpr_{irzty} = transaction price of biorefinery i in round r of zone z in period t of year y
 tpm_{rzty} = transaction price of food market in round r of zone z in period t of year y
 tpf_j = total profit of farmer j
 ypb_{iy} = profit of biorefinery i in year y

ASSOCIATED CONTENT

Supporting Information

Mathematical model for biorefinery supply chain with fixed corn purchase cost; designed biorefinery network by MILP model; and data of case studies. This material is available free of charge via the Internet at <http://pubs.acs.org>.

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Notes

The authors declare no competing financial interest.

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