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AGENT-BASED METHOD FOR SOLVING COMPETITIVE BIOREFINERY NETWORK DESIGN PROBLEM

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ABSTRACT

We propose a novel simulation-based optimization method to solve the biorefinery location problem in competitive corn markets. As the feedstock cost is the largest cost component for producing ethanol, it is critical to consider the formation of corn prices in the local markets around biorefineries. The corn prices are determined by competition among biorefineries, among farmers, between biorefineries and the food market. However, the competition is often ignored in previous studies. In this work, we formulate the competition in the biorefinery location problem by agent-based modelling and simulation of the local corn markets. The corn prices are determined by double auction mechanism in which the biorefineries and the food market are buyers and the farmers are the sellers. The determined prices are then imported to the optimization problem, which is solved by a genetic algorithm. The proposed method is demonstrated by a case study on biorefinery locations in Illinois.

1 INTRODUCTION

The biofuel industry has continued to grow as society strives to reduce its dependence on imported oils and transportation related emissions (Yue et al 2014; You et al. 2012).The Energy Independence and Security Act of 2007 included the Renewable Fuel Standard (RFS) which requires production of 36 billion gallons of biofuels annually by 2015. Of this, 15 billion gallons of corn ethanol is required to count towards the RFS (Bai et al. 2012).

The biorefinery location and capacity design problem is important for evaluating investment decisions in the long run. Kim et al. (2011) have reported that feedstock price, demand and supply are key uncertainties in the biofuel industry. This motivates the need to develop tools which can help assess investment decisions and thereby reduce risk. The common approaches are mathematical programming methods. Kevin et al. (2014) presented a single level and bilevel programming representations for the timberland supply chain with a new biorefinery. Yue and You (2014) presented a mixed-integer linear programming model to simultaneously optimize operational decisions and profit allocation mechanisms, namely material transfer prices and revenue share policies among the supply chain participants. However, the above mentioned studies do not completely capture competition in real markets between decision makers who continuously adapt to market conditions.

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For the corn based ethanol industry, it is crucial that investment decisions required to meet the RFS mandate can be analysed with uncertain market prices and supply of corn in the midst of competition among biorefineries, among farmers, and between biorefineries and the food industry (You and Wang 2011; Gebreslassie et al. 2012; Yue et al. 2013; Tong et al. 2014). Each participant makes its decisions by maximizing its own profit. To address this issue, we build an agent-based model to optimize the location of a network of biorefineries by simulating the dynamic interactions between multiple intelligent agents. In order to develop estimates of the market price, the evolution of the local markets to the state of equilibrium is modelled using a discriminatory clearing house double auction mechanism. The double auction is a mechanism that forms a price close to the theoretical equilibrium price and provides an efficient allocation model for a dynamic market (Shubik 2005).

The agent-based model and simulation determine the transaction prices and quantities for each biorefinery in the network. These variables then determine the profit of the biorefinery in competitive local markets. The location of a biorefinery has a significant effect on its profit because the price at which the farmers sell corn is geographically heterogeneous depending on the yield distribution. Furthermore, the location determines the transportation distance and cost, affecting the corn price for the biorefinery. Therefore, determining biorefinery locations is critical for the industry's economic sustainability. The biorefinery location problem is formulated into an optimization problem which maximizes the total profit of all biorefineries according to the corn prices determined by the agent-based simulation. The simulation-based optimization problem is solved by a genetic algorithm. The proposed method is demonstrated by a case study of optimizing the investment decisions of establishing new biorefineries in Illinois. We use the 2008 data of 14 biorefineries present in the state and then solve the competitive location problem to determine the location of 5 new biorefineries that will be required to meet the RFS target.

2 PROBLEM STATEMENT

The objective of this study is to determine the optimum location and capacity of a network of biorefineries with respect to the total net present value of the system. The model is based on the following key assumptions.

- Food Market is a combination of the food, feed and export industry.
- All farmers in a county are regarded as a single entity.
- Transportation distance between locations is calculated by the distance obtained from longitudinal and latitudinal values.
- Ethanol price is the same for all biorefineries.
- Farmers bear transportation cost for biorefineries but no transportation cost for the Food Market.
- Each design year is divided into four time periods.

Based on the assumptions, the competitive biorefinery problem is stated as follows

Given

- Number of farmers and biorefineries
- Candidate location sites for optimization
- Discrete capacity choices for optimization
- Corn planting costs, unit storage and transportation costs for farmers
- Ethanol selling price, capacities and unit production costs of biorefineries.
- Base price for the food market

Determine

- Biorefinery locations and capacities
- Prices and quantities of corn sold to biorefineries

- Prices and quantities of corn sold to the food market
- Profits of biorefineries

Objective

- To maximize the total net present value of biorefineries

3 AGENT-BASED SIMULATION AND OPTIMIZATION

3.1 Biorefinery design problem

The biorefinery design problem is solved to determine the biorefinery locations that maximize the total profit as

$$\max \sum_i prof_i, \tag{1}$$

where a biorefinery is indexed by i, $prof_i$ is the profit for biorefinery i. The profit is expressed as

$$prof_i = f_i\left(cc_i, x_{i1}, \cdots, x_{iN}\right), \forall i \tag{2}$$

where cc_i is the cost for biorefinery i to buy the unit amount of corn. The biorefinery location from N candidate sites is defined as

$$x_{ij} = 1 \tag{3}$$

if biorefinery i is located in site j ,where j is the index of the candidate site for building a biorefinery. In (2), the function f_i describes the dependence of the profit on the unit corn cost and the biorefinery locations.

3.2 Agent-based double auction

In this study, the discriminatory clearing house double auction mechanism is used to determine the prices and supplies of corn in the local markets around the biorefineries. To describe corn competition in a market, we model farmers, biorefineries, and the food market by intelligent agents (Macal and North 2005). Each agent is an autonomous entity that aims to maximize its own profit and interactions among agents determine the corn prices. Specifically, the biorefinery agents and the food market agent are buyers while the farmer agents are sellers. The price of corn sold from the sellers to the buyers is determined by an auction.

The auction consists of four parts – players, object of trade, profit functions and strategies. The profit function includes the market price which is determined by the auction, the reservation price and transportation cost (in case of sellers). The double auction process takes place in rounds and the rounds terminate once either the total demand or the total supply for the run is exhausted.

Figure 1 illustrates the double auction process for a round. Each agent is assigned a maximum amount of corn that it can buy or sell in each round. Farmers submit asks (price and quantity offered for sale) and buyers (biorefinery and Food Market) submit bids (price and quantity demanded) to the clearing house. 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. If the quantity demanded and offered by the first pair was 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 till it cannot find a pair for which the bid is greater than or equal to the ask. The clearing house then informs the agents about the trade (clearing stage) and sets the market transaction price and quantity for the matched pair. The market transaction price is set to be the average of the ask price and bid price. The clearing house factors the transportation cost for the farmers while matching bids from the biorefinery.

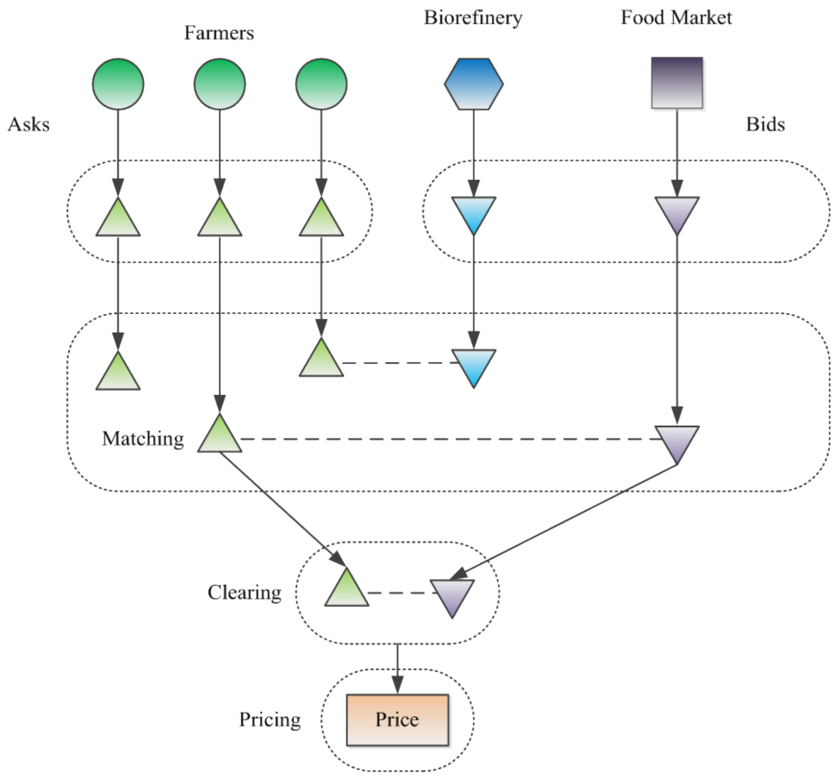

Figure 1: Discriminatory clearing house double auction process

The Food Market bids at a constant price which is equal to the projected corn price. The farmers and biorefineries are given a price range. The lower bound of the biorefineries' range and upper bound of the farmers' range is updated to the average market price after each round. The upper bound of the biorefineries' range and lower bound of the farmers' range is equal to the price at which that agent will earn a zero profit. The price ranges are discretized and 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 in the previous round. This update of price offers is governed by a modified version of the Roth-Erev learning algorithm as proposed by Nicolaisen, et al. (2001).

3.3 Cournot Oligpoly model

The double auction mechanism determines the average price that a farmer would receive for his output in a given time period. Farmers make decisions regarding their quantity offered for sale in an oligopolistic market. An oligopoly is a market structure in which a producer's decisions regarding its quantity for sale can affect the profit of other producers.

In this study, a dynamic oligopolistic market model is formulated based on the well-known Cournot model (Ledvina and Sircar 2012). The Cournot model determines the quantities that producers of a homogeneous good would chose to supply in equilibrium when they try to maximize their profit in the presence of competitors. Goods that are homogeneous are perfect substitutes for one another and only one price prevails in such a market. In our case, the corn sold by farmers can be considered as a non-homogeneous good from the standpoint of a biorefinery as the distance between farmers and the biorefinery can lead to higher transportation costs for the farmers that are farther away and thus, corn sold by such farmers would cost more and wouldn't be identical to the corn sold by farmers that are closer to the biorefinery.

A biorefinery may want to reduce its overall environmental impact by preferring farmers that are closer to the plant due to lower fuel consumption during transportation. A biorefinery may also prefer farmers that are located closer to the plant due to shorter lead time durations and lower backorder costs. In contrast, the Food Market is considered to 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 non-homogeneous good from the standpoint of the biorefinery. The heterogeneity factor between farmers is their distance from the biorefinery. In order to utilize the Cournot model, the region around each biorefinery was partitioned into circular zones (Figure 2).

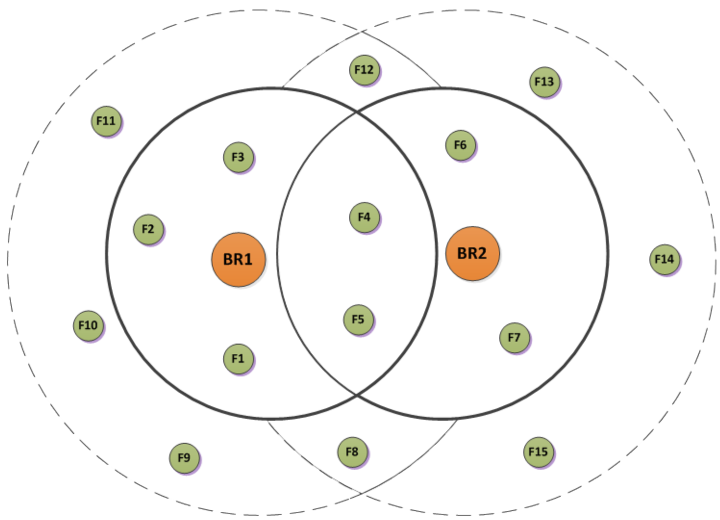

Figure 2: Zones for executing double auction for a homogeneous good

In a given zone, farmers are located at nearly the same distance from the biorefinery and this eliminates the heterogeneity factor between the outputs sold by the farmers in a zone (assuming that the corn sold by farmers is similar in other physical characteristics).

The producers then receive profits based on the price determined by a linear inverse demand function of the total market supply. The first order derivative condition of the profit function of all farmers selling homogeneous goods can be simultaneously solved. The solution in (4) gives the quantity, qof_{jzty}, which a given farmer *j* in zone *z* in time period *t* of design year *y* would offer for sale:

$$qof_{jzty} = \frac{CA}{(NF_z+1)CB} + \frac{NF_z\left(avg_{zty} - ask_{jty}^{Min}\right) - ask_{jty}^{Min}}{(NF_z+1)CB} \tag{4}$$

where NFz is the number of farmers in z, CA and CB are coefficients in linear demand curve, avg_{zty} is the average ask price in zone z and ask_{jty}^{Min} is the lower bound of the price range of farmer j . From (4) it is evident that a farmer would sell more corn in a zone in which it has more competitive advantage (higher positive difference between avg_{zty} and ask_{jty}^{Min}), and less corn in a zone in which it has less competitive advantage.

In order to execute the double auction rounds for corn as a homogeneous good, for a given time period a single double auction run for every biorefinery is carried out in 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 (F1-F15) in Figure 2. 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 2, 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 zone1 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 (run for BR1 and run for BR2). The simulation continues to progress to the next zone until either the biorefineries have met their demand or the territory limit is reached (all farmers have finished participating in the market).

3.4 Simulation-based optimization

The optimization problem involving the black-box functions is solved by a simulation-based optimization approach (Andradóttir, 1998; Asmussen & Glynn, 2007; Azadivar, 1999; Carson & Maria, 1997; Fu, 2002; Fu et al., 2005; Swisher et al., 2000). We use the genetic algorithm (GA) in the MATLAB global optimization toolbox to determine the biorefinery locations and capacities. GA is an exploratory procedure which has obtained optimal and near optimal solutions to a wide variety of complex problems (Frenzel 1993).

After the design problem is solved, the determined biorefinery locations and capacities are then returned to the agent-based simulation to determine the new values of the corn prices. The diagram of the simulation-based optimization approach is shown in Figure 3. The iteration between the agent-based simulation and the search algorithm terminates when a stopping criterion of the GA search is met.

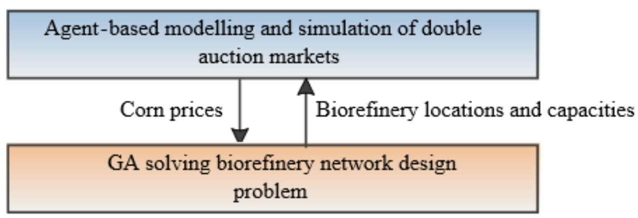

Figure 3: Diagram of simulation-based optimization

4 CASE STUDY

To demonstrate the utility of this model in optimizing investment decisions for the strategic design of the biofuel supply chain, a network of 19 biorefineries is optimized for Illinois in which 14 biorefineries are considered fixed as they currently exist in Illinois. The total capacity for the network is set to be 17% of the 15 billion gallons target set by RFS (corn harvest in Illinois was 17% of the total U.S harvest in year 2008). The year 2008 is chosen for the case study as estimates of the demand curve for the Cournot Oligopoly model are available for the year 2008 (Bai et al. 2012). Thus, yield and operating costs are set to the values in 2008.

The total capacity of the 5 new biorefineries is set equal to the difference between 17% of 15 billion gallons and current ethanol production in Illinois. The capacity of each new biorefinery is set to $1/5^{th}$ of the total capacity. The limit of the total computational time is set as 1 hour. The total profit of the designed biorefinery network is 0.68 billion dollars. Figure 4 presents the optimized location for the 5 new biorefineries in Illinois. The darker shade of green represents higher corn yield counties and the lighter shade of green represents lower corn yield counties. The higher yield regions demand a lower corn price compared to the lower corn yield regions due to lower marginal cost of production.

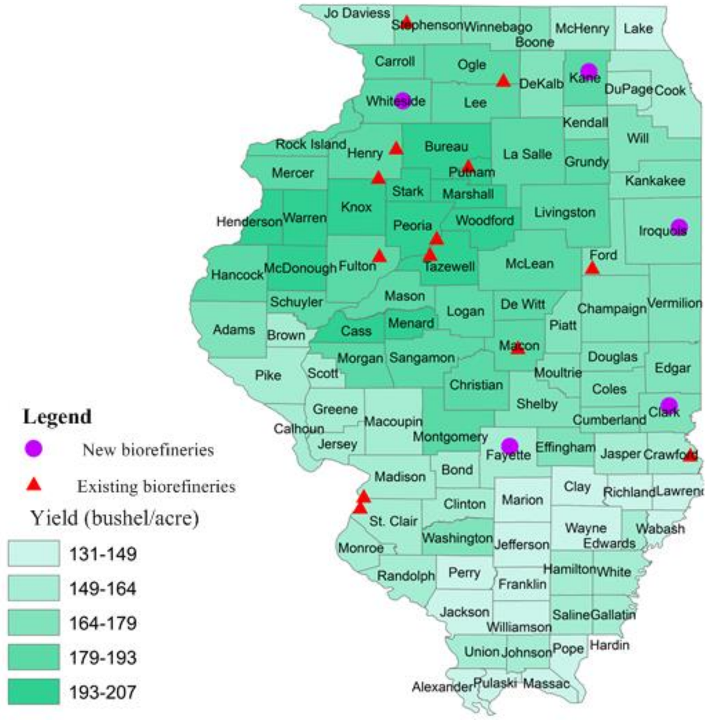

Figure 4: The biorefinery network designed in the case study

It is evident from Figure 4 that the optimal locations for the new biorefineries are in the higher yield region due to lower corn prices and thus, larger profits for the biorefineries. The new biorefineries are also spread out from each other and are not located in the cluster of existing biorefineries in the high yield region. If the new biorefineries were located close to each other or within the cluster of existing biorefineries, the total system profit would have lower as greater competition in such a scenario would compel biorefineries to purchase corn from farmers that are located farther away. Thus, the optimized biorefineries achieve the target ethanol production while facing competition from multiple agents.

5 CONCLUSION AND FUTURE WORK

This study presented a novel methodology for the strategic design of an economically sustainable biorefinery network by incorporating competition between profit maximizing agents. As real world interactions between biorefineries, farmers and the food industry take place in a competitive environment, the double auction mechanism was used to capture the effect of competition between biorefineries and the food industry on the transaction prices in the local markets around the biorefineries. The case study demonstrated the utility of this model in optimizing investment decisions of establishing new biorefineries in a given region. The details of the agent-based model and discussion of the optimization approaches which have not taken competition into account will be addressed in a future work. Thus, the simulation based optimization methodology presented in this study can be extended to strategically optimize the design of a biorefinery network in the long-run with uncertain market prices and supply of corn and ensure the economic sustainability of the industry.

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