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A Switchgrass-based Bioethanol Supply Chain Network Design Model under Auto-Regressive Moving Average Demand

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A B S T R A C T

Switchgrass is known as one of the best second-generation lignocellulosic biomasses for bioethanol production. Designing efficient switchgrass-based bioethanol supply chain (SBSC) is an essential requirement for commercializing the bioethanol production from switchgrass. This paper presents a mixed integer linear programming (MILP) model to design SBSC in which bioethanol demand is under auto-regressive moving average (ARMA) time series models. In this paper, how a SBSC design is affected by ARMA time series structure of bioethanol demand is studied. A case study based on North Dakota state in the United States demonstrates application of the proposed approach in designing the optimal SBSC. Moreover, SBSC optimal design is forecasted for the time horizon of 2013 to 2020 with the bioethanol demand acquired from the ARMA models to provide insights for designing and minimizing total cost of SBSC in the future efficiently. Finally, in order to validate the proposed approach, a reproduction behavior test is done. Also, a comparative analysis based on a SBSCND model from the recent literature is elaborated to show the performance of the proposed approach.

1. INTRODUCTION

Energy consumption in the world, specifically, in the industrial countries has been increased by changes in the life style and population growth. Moreover, fossil fuels consumption which is associated with various environmental and social problems in addition to being non-renewable [4] has increased concerns related to energy consumption. In recent years, biofuel production as a promising solution to this problem has attracted many researchers to develop biofuel supply chains. Biomass as a feedstock includes agricultural residues (consisting of vegetal and animal substances), forests products, urban and industrial waste, which are used for producing biofuels and generating heat and power in the bioenergy supply chain.
The biomass types and biofuels are divided into three generations. The first generation biofuels are produced from sugars and vegetable oils which are turned into biofuel through ordinary technologies. Most of first generation feedstock can be used as food so it may endanger the safety of human food supply; therefore, non-food feedstock usage for producing biofuels has been increased. Nevertheless, the use of this type of feedstock is associated with many challenges [5]. Biomass feedstock for producing second generation biofuels includes lignocellulosic biomass, and agricultural residues or waste and woody crops. Recently, Algae was introduced as the third generation biomass used for producing biodiesel. Bioethanol is the most applicable biofuel in transportation section that is widely produced from first generation biomass. Nowadays, decisions to use land for cultivation food products or first generation feedstock is debatable; therefore, researchers are studying lignocellulosic biomass feedstock intensively to solve this problem. Switchgrass as a second generation biomass is a type of lignocellulosic feedstock cultivated in marginal lands [6]. It is a perennial grass native to North America. Some features of switchgrass such as high net energy yield per used land, low cost production, low fertilization requirement, soil erosion prevention, easy to grow, developing rural area and reduction of GHG emissions have made it one of the best second generation feedstock for bioethanol production [2, 7].
In a switchgrass-based bioethanol supply chain (SBSC), switchgrass flows from the harvesting sites to the bioethanol demand centers. Along this route, the switchgrass passes through some facilities such as

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switchgrass harvesting site, collection sites and biorefineries. Fig. 1 shows the main processes involved in a SBSC. There are a number of decision alternatives and sequential activities such as land selection, seeding and fertilization, harvesting, transportation, and bioethanol production in this supply chain. Trade-offs between these decisions arise through the supply chain. Cropland has a high biomass yield; however, its rental cost is also high. Seeding time and seeding method are dependent; therefore, it needs to consider various scenarios. Complex decision making processes and trade-offs between the decisions in a biofuel production system need optimization models or compact decision support systems to be developed.

Mixed Integer Linear Programming (MILP) is one of the most popular modeling approaches in biomass supply chain network design (BSCND) problems. Facility location is an important objective for using MILP models. Facility location decision variables can consider both the technology as well as the capacity used in a facility in a binary form. Decision makers optimize BSCND and material flow between facilities, simultaneously; because BSCND affects biomass logistics [8].

In this regard, they develop MILP models and simultaneously optimize the BSCND and find the optimum material flow between facilities [8-10]. For the first time, Mol et al. [11] developed an MILP model wherein locations of the processing sites are optimized by minimizing biomass logistic costs. Biomass supply chain strategic planning and optimal allocation of biomass under uncertain location decisions (Chen and Fan [12]) and optimal design of bioethanol supply chain together with determining the optimum harvesting and bioethanol production (Akgul et al. [13]) are some examples of MILP models in BSCND.

The main barrier to the commercialization of biofuels is their complicated production process [14]. This complexity is made by different form of variability in the parameters. Uncertainty is one of the common forms of variability in biofuel supply chain parameters [15]. Biomass feedstock supply, biofuel demand, price, and logistics are common parameters which can be with uncertainty [16]. By reviewing MILP models, we can observe many studies related to the BSCND optimization models under uncertainty.

For example, Dal-Mas et al. [17] developed a stochastic dynamic MILP model to design a biofuel supply chain under market condition uncertainties. Giarola et al. [18] proposed a multi-echelon, multi-period MILP model to optimize the BSCND considering biomass and carbon markets uncertainties. Li and Hu [19] proposed a two-stage stochastic MILP based on bio-oil gasification wherein they assumed such factors as biomass availability, technology advancement, and biofuel price as uncertain. Tong et al. [20] proposed a multi-period, stochastic MILP model under varying and uncertain conditions of biomass availability, fuel price, crude oil demand, and production technology wherein the existing uncertainties are considered under several scenarios. Babazadeh et al. [21] and Bairamzadeh et al. [22] used different form of robust possibilistic programming approach for sustainable BSCND in which, economic, environmental and social parameters are under uncertainty. Reviewing the studies shows that different stochastic and possibilistic programming approaches have been used for considering uncertainty in BSCND models; nevertheless, none of the them have used times series data as the other form of variability in biofuel supply chain parameters. The need for using time series models to design supply chains becomes more crucial when we need to determine optimal design of supply chains based on future or forecasted values of key parameters.

Times series data is a form of variability defined as a sequence of numerical data points in a successive order, usually occurring in uniform intervals [23]. Auto-regressive moving average (ARMA) models as one of the time series models have provided some managerial insights about supply chain dynamics [24]. Gilbert [24] proposed a multistage supply chain model based on auto-regressive integrated moving average (ARIMA) time series models.

He first used the general class of ARIMA time-series models for modeling the consumer demand in a supply chain and then proposed ARIMA models of orders and inventory. By this model, bullwhip effect phenomenon was also discussed. Bullwhip effect in supply chains also was analyzed by Lee et al. [25].

They analyzed demand signal processing, rationing game, order batching, and price variations as four sources of the bullwhip effect. The review of supply chain-based papers shows that up to this time, the application of time series models for designing supply chain has not been considered in the literature. In a bioethanol supply chain, the demand of bioethanol is a key parameter that affects the optimal design of this supply chain. Variability of bioethanol demand through time increases the complexity of decision-making.

Thus, in this study, we propose a switchgrass-based bioethanol supply chain network design (SBSCND) model in which bioethanol demand is under variation through time. In order to model the variability of bioethanol demand, ARMA time series models are used, and then the results of these models are used in the SBSCND model. Finally, the optimal design of this supply chain is determined based on forecasted values of bioethanol demand.

The rest of paper is organized as follows. The next section provides the methodology of the study. Section 3 describes mathematical modeling of the proposed approach step by step. Finally, conclusion of this paper is explained in section 4.

2. METHODOLOGY

2.1. Problem description

In this paper, designing a bioethanol supply chain in which bioethanol production is based on switchgrass feedstock is studied. As shown in Fig. 1 switchgrass is cultivated in available marginal lands located in i supply zones, then, switchgrass is collected into square bales. The harvested switchgrass is transported to the j collection sites and stored. Storage of square bales in the collection facilities will result in deterioration of switchgrass during each time period. When it is required, the stored square bales are shipped from the j collection facilities to the r biorefineries. The switchgrass is converted into bioethanol in biorefineries. Finally, bioethanol is transported from r biorefineries to k demand zones. Bioethanol demand is in terms of ARMA models. A MILP model is proposed for minimizing total cost of supply chain by determining the optimal values of decision variables.

Harvesting site [2] Collection facility [3] Biorefinery [1] Demand zone [3]

Figure 1. A switchgrass-based bioethanol supply chain structure

According to the researches, timing and frequency of switchgrass are the most affective factors on the crop yield and harvest cost. McLaughlin and Kszos [27] and lee and owes [28] indicated that the most economic and environmental switchgrass harvest frequency in North America is once a year after the first killing frost. Therefore, in our study, frequency of switchgrass is considered once a year after the first killing frost.

Transportation mode is an important factor that affects total logistics cost. Moreover, logistics cost increases linearly as distance increases and decreases when capacity of transportation mode increases [2]. Comparing different transportation modes (e.g. truck, rail, barge etc.) used for transporting biomass from farms to the biorefineries indicates that truck is the most economic transportation mode when the travel distance is less than 400 km [2]. Also, for delivering bioethanol from biorefineries to demand centers, road transportation mode using tanker is the best transportation mode among other transportation modes such as pipeline, rail and etc. while the travel distance is less than 800 km [2].

Since the road transportation is available everywhere in North Dakota, this paper only considers the road transportation (using truck and tankers) for the transportation of biomass and bioethanol.

2.2. Mathematical modeling

In this paper a mixed integer linear programming (MILP) model is developed for minimizing total SBSC cost. The optimal values of decision variables with regard to time periods and cultivation areas are determined by solving the MILP model. The objective funtion and the constraints of the proposed model are explained in detail in the following sections.

2.2.1. Objective function

The objective function of the proposed model is minimizing the total cost of SBSC in the time horizon. This objective function includes 11 components as follows: the first component refers to the rental cost of marginal lands in all i supply zones in all time periods. The second one refers to the cultivation cost of switchgrass in all i supply zones in all time periods; harvesting cost of switchgrass from all i supply zones in all time periods is calculated in the third one. Forth part refers to the storage cost of switchgrass in all j collection facilities in all time periods. Fifth and sixth one refer to the switchgrass transportation cost between all i supply zones and all j collection facilities and the switchgrass transportation cost between all j collection facilities and all r biorefineries in all time periods, respectively. Seventh one refers to the bioethanol transportation cost between all r biorefineries and all k demand centers in all time periods. Eighth one refers to the fixed cost of all r biorefineries in all production capacity levels in all time periods. Finally, ninth part is production cost of bioethanol at all r biorefineries in all time periods.

$$\begin{aligned}\text{Min } Z = &\sum_{i=1}^{I}\sum_{t=1}^{T} C_i^t Y_i^t + \sum_{i=1}^{I}\sum_{t=1}^{T} Cu_i^t Y_i^t + \sum_{i=1}^{I}\sum_{t=1}^{T} \delta_i^t Y_i^t + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} S_j S_{ij}^t \\ &+ \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} \varphi_{ij} D_{ij} S_{ij}^t + \sum_{j=1}^{j}\sum_{r=1}^{R}\sum_{t=1}^{T} \alpha_{jr} D_{jr} V_{jr}^t + \sum_{r=1}^{R}\sum_{k=1}^{K}\sum_{t=1}^{T} \beta_{rk} D_{rk} N_{rk}^t \\ &+ \sum_{r=1}^{R}\sum_{q'=1}^{Q'}\sum_{t=1}^{T} F_{rq'}^t X_{rq'} + \sum_{r=1}^{R}\sum_{t=1}^{T} W_r N_r^t \end{aligned} \tag{1}$$

2.2.2. Constraints

Eq. (2) ensures that the used marginal land in each supply zone i cannot be more than the available marginal lands. Eq. (3) ensures that a maximum of one biorefinery of all production capacity levels can be situated at each biorefinery location r. Eq. (4) is related to maximum storage capacity of a collection facility and it ensures that the stored switchgrass in each collection facility cannot exceed its storage capacity during time period t. Eq. (5) ensures that the bioethanol production of a biorefinery with capacity level at location r does not exceed its production capacity during each time period t. Eq. (6) ensures that the annual bioethanol production rate of each biorefinery is greater than its minimum capacity utilization rate. Eq. (7) ensures that during each time period t, the production capacity of all biorefineries is greater than or equal to the bioethanol demand in all k demand zones. Eq. (8) ensures that the amount of switchgrass from each collection facility j sent to all r biorefineries during each time period t is less than the amount of stored switchgrass in the collection facility j discounting dry-matter loss during storage. Eq. (9) ensures that in each time period t, the amount of harvested switchgrass in each supply zone i is equal to the amount of switchgrass sent to the all j collection facilities. Eq. (10) ensures that all amount of switchgrass received by all biorefineries is converted into bioethanol during the time horizon. Eq. (11) ensures that the volume of produced bioethanol assigned to each demand zone k is not less than its demand. Eq. (12) ensures that for each biorefinery r, the produced bioethanol sent to the all demand zones k does not exceed its production capacity during each time period t. Eq. (13) is a binary constraint, and Eqs. (14)–(18) are non-negativity constraints.

$$Y_i^t \le M_i \qquad \forall i,t \qquad (2)$$

$$\sum_{q'=1}^{Q'} X_{rq'} \le 1 \qquad \forall r \qquad (3)$$

$$\sum_{i=1}^{I} S_{ij}^t \le Q_j^t \qquad \forall j,t \qquad (4)$$

$$N_r^t \le \sum_{q'=1}^{Q'} P_{rq'}^t X_{rq'} \qquad \forall r,t \qquad (5)$$

$$\sum_{r=1}^{R} N_r^t \ge \sum_{r=1}^{R}\sum_{q'=1}^{Q'} O_{rq'} P_{rq'}^t X_{rq'} \qquad \forall t \qquad (6)$$

$$\sum_{r=1}^{R}\sum_{q'=1}^{Q'} P_{rq'}^t X_{rq'} \ge \sum_{k=1}^{K} Z_k^t \qquad \forall t \qquad (7)$$

$$\sum_{r=1}^{R} V_{jr}^t \le \sum_{i=1}^{I} S_{ij}^t (1-L) \qquad \forall j,t \qquad (8)$$

$$A_i^t Y_i^t = \sum_{j=1}^{J} S_{ij}^t \qquad \forall i,t \qquad (9)$$

$$N_r^t = \sum_{j=1}^{J} \theta_r V_{jr}^t \qquad \forall r,t \qquad (10)$$

$$\sum_{r=1}^{R} N_{rk}^t \ge Z_k^t \qquad \forall t, \mathrm{k} \qquad (11)$$

$$\sum_{k=1}^{K} N_{rk}^t \le N_r^t \qquad \forall r,t \qquad (12)$$

$$X_{rq'} \in \{0,1\}, \qquad \forall r,q' \qquad (13)$$

$$S_{ij}^t \ge 0 \qquad i,j,t \qquad (14)$$

$$V_{ir}^t \ge 0 \qquad \forall i,\mathrm{r},t \qquad (15)$$

$$Y_i \ge 0 \qquad \forall i \qquad (16)$$

$$N_{rk}^t \ge 0 \qquad \forall r,k,t \qquad (17)$$

$$N_r^t \ge 0 \qquad \forall r,t \qquad (18)$$

2.3. Mathematical modeling

In the statistical analysis of time series, ARMA models present a short description of a stationary stochastic process in terms of two polynomials, the first one for the auto-regression (AR) and the second one for the moving average (MA) (see Equation (19)).

$$Z_t = C + \varepsilon_t + \sum_{i=1}^{p} \varphi_i Z_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \qquad (19)$$

ARMA model is usually shown as the ARMA (p,q) where, p is the order of AR part and q is the order of MA part. When the time series data is not stationary, ARIMA (p,d,q) model is used instead of ARMA (p,q) in which, d is the degree of differencing. ARIMA models form an important part of the Box-Jenkins approach in time-series analysis. In time series analysis, the Box–Jenkins method applies ARMA or ARIMA models to find the best fit of a time-series model to past values of a time series. For estimating ARIMA or ARMA models, Box-Jenkins method is usually used as follows [29]:

A. Identification: selecting several models from the group of ARIMA models, in other words, sample values for p and q, with considering the self–integrated functions are determined.

B. Estimation: estimating the model (or models) based on the data and the parameters obtained from the first stage.

C. Diagnostic checking: evaluating the satisfactory condition of the model (or models) chosen in the first stage and estimated in the second stage. The assessment criteria are intended for the same purpose.

Researchers have presented some criteria for selecting the best ARIMA model. In this study, Schwarz Bayesian Criterion has been considered for selecting the best one. Based on this criterion, the model with the least Schwarz Bayesian Criterion will be selected as the best model. It is also assumed that the bioethanol demand has the ARMA (p,q) pattern. In this regard, the bioethanol demand is forecasted by formulating the bioethanol demand as ARMA models. Then optimal flows in the SBSC, marginal land used, location, and production of biorefineries are determined by the proposed model and based on ARMA bioethanol demand.

3. CASE STUDY

The proposed method is used to design a SBSC in North Dakota state of the United States in order to illustrate its application in a real situation. Switchgrass, as one of the best second generation bioethanol resources in North Dakota state [2] is under consideration in this paper. In this case study, a SBSC in North Dakota state will be studied. The MILP model aims to demonstrate whether or not all the gasoline demand in North Dakota state can be met by a switchgrass-based bioethanol supply chain.

3.1. Input parameters The following input assumptions relevant to the case study are also made:

(1) Modeling horizon is 32 years. Each year will be considered as a time period (t = 1, . . . , 32).

(2) 10 counties of all 53 counties of North Dakota state having the most marginal lands are selected as the potential locations of supply zones (i = 1, . . ., 10), collection facilities (j=1,2,. . .,10), biorefineries (r=1,2,. . .,10), and bioethanol demand zones (k = 1,. . ., 10). Switchgrass production and bioethanol demand to be centered at the county ‘‘seat’’ (e.g. Fargo is the seat of Cass County).

(3) Biorefineries with capacity levels of 760 MLPY and 1520 MLPY will be considered.

(4) There is no seasonality effect in the demand of bioethanol.

(5) Demand of bioethanol in each county is assumed to be a proportion of population. Population of each county in North Dakota state is assumed to be constant during time horizon. Parameters and data sources are listed in Table 1 and 2.

The proposed model is coded in the GAMS 24.1.2 optimization software which uses the CPLEX solver, and all the empirical experiments were run on an Intel core i7 with 2 GHz processor and 8 GB RAM.

3.2. Results The total cost of SBSC is 4.36×104 M USD for a 32-year time horizon (1981-2012). As it is shown in Fig. 2, 4 counties from 10 counties are selected for installation of the biorefineries (i.e., Rolette, Ramsey, and Richland are selected as the locations for installing biorefineries with maximum capacity 760 MLPY and Grand Forks as the location for installing a biorefinery with maximum capacity 1520 MLPY).

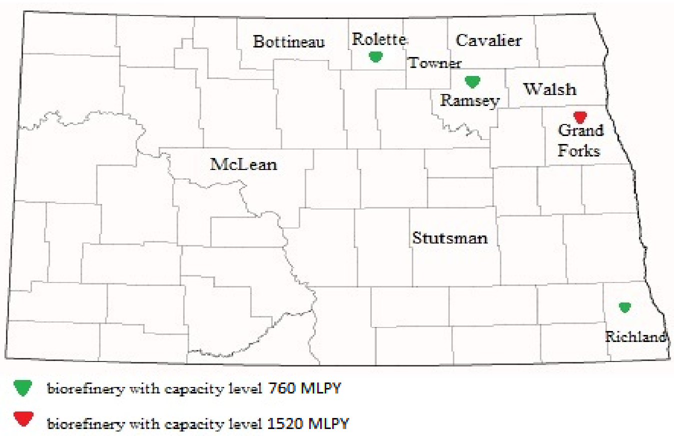

Figure 2. Optimal locations of the biorefineries in North Dakota state

TABLE 1. Values of input parameters [2]

i	County	Population	$C_i(\$/ha)$	$A_i(tonne/ha)$	$M_i(ha)$
1	Rolette	13937	28.4	17.2	33508
2	Walsh	11119	29.6	17	33116
3	Richland	16321	53.1	20.2	29425
4	Grand Forks	66861	25.9	18.1	29021
5	McLean	8962	28.4	16.4	24821
6	Cavalier	3993	27.2	16.7	24725
7	Stutsman	21100	39.5	17.1	24066
8	Ramsey	11451	29.6	17.5	23556
9	Towner	2246	28.4	15.3	23023
10	Bottineau	6429	32.1	17.1	21623

TABLE 2. Values of other key input parameters

Reference	Parameter	Unit	Value
[30]	Cu_i	($/ha)	395 (for all i)
[31]	δ_i	($/ha)	27.9 (for all i)
[31]	S_j	($/tonne)	21.7 (for all j)
[31]	φ_{ij}	($/tonne $\times$km)	0.18 (for all i and j)
[31]	α_{jr}	($/tonne $\times$km)	0.18 (for all r and j)
[30]	β_{re}	($/l $\times$km)	2.8×10^{-5} (for all r and e)
[32]	$F_{rq'}$	($)	3.9×10^{7} for a biorefinery with capacity of 760 MLPY
[32]	$F_{rq'}$	($)	7.2×10^{7} for a biorefinery with capacity of 1520 MLPY
[32]	W_r	($/l)	0.2 (for all r)
assumed	Q_j^t	(tonne)	1511975(for all j, t)
assumed	$P_{rq'}^t$	(l)	7.6×10^{8} (for all t,r and $q'=1$)
assumed	$P_{rq'}^t$	(l)	1.52×10^{9} (for all t,r and $q'=2$)
[30]	$O_{rq'}$	-	0.88 (for all r and q')
[33]	θ_r	(l/tonne)	(for all r) 313
[2]	L	-	0.0028

TABLE 3. ARMA model of the bioethanol demand for each county

	County	ARMA equation
1	Rolette	$Z_t = 1.05\times10^{8} + 2.08Z_{t-1} - 1.09Z_{t-2} + \varepsilon_t - 1.55\varepsilon_{t-1}$
2	Walsh	$Z_t = 8.37\times10^{7} + + 2.08Z_{t-1} - 1.09Z_{t-2} + \varepsilon_t - 1.55\varepsilon_{t-1}$
3	Richland	$Z_t = 1.23\times10^{8} + 2.08Z_{t-1} - 1.09Z_{t-2} + \varepsilon_t - 1.55\varepsilon_{t-1}$
4	Grand Forks	$Z_t = 5.04\times10^{8} + 2.08Z_{t-1} - 1.09Z_{t-2} + \varepsilon_t - 1.55\varepsilon_{t-1}$
5	McLean	$Z_t = 6.75\times10^{7} + 2.08Z_{t-1} - 1.09Z_{t-2} + \varepsilon_t - 1.55\varepsilon_{t-1}$
6	Cavalier	$Z_t = 3\times10^{7} + 2.08Z_{t-1} - 1.09Z_{t-2} + \varepsilon_t - 1.55\varepsilon_{t-1}$
7	Stutsman	$Z_t = 1.5\times10^{8} + 2.08Z_{t-1} - 1.09Z_{t-2} + \varepsilon_t - 1.55\varepsilon_{t-1}$
8	Ramsey	$Z_t = 8.63\times10^{7} + 2.08Z_{t-1} - 1.09Z_{t-2} + \varepsilon_t - 1.55\varepsilon_{t-1}$
9	Towner	$Z_t = 1.69\times10^{7} + 2.08Z_{t-1} - 1.09Z_{t-2} + \varepsilon_t - 1.55\varepsilon_{t-1}$
10	Bottineau	$Z_t = 4.84\times10^{7} + 2.08Z_{t-1} - 1.09Z_{t-2} + \varepsilon_t - 1.55\varepsilon_{t-1}$

3.2.1. SBSC optimal design under ARMA demand

Here, $\dot{Q}$, $\dot{W}$ and h are heat transfer, work and specific enthalpy of the streams crossing the device boundary.

In the Kalina cycle, ammonia-water mixture is used as the working fluid and ammonia concentration is one of the important parameters in the cycle especially in separator and mixer modeling. Therefore the concentration balance presented for each component is as shown [24]:

$$Z_t = c + \varepsilon_t + \varphi_1 Z_{t-1} + \varphi_2 Z_{t-2} + \theta_1 \varepsilon_{t-1} \qquad (20)$$

Bioethanol demand is predicted by ARMA models for the next eight periods (2013-2020). The predicted data is used in MILP model for a new run in GAMS 24.1.2. Based on the forecasted bioethanol demand for the periods of 2013 to 2020, the total cost of SBSC is equal to 1.85×104 M USD. In comparison with previous state, the results show the same selection for the locations of biorefineries (Fig. 3). However, in this case, the maximum capacity of biorefinery located in Rolette will be changed from 760 MLPY to 1520 MLPY.

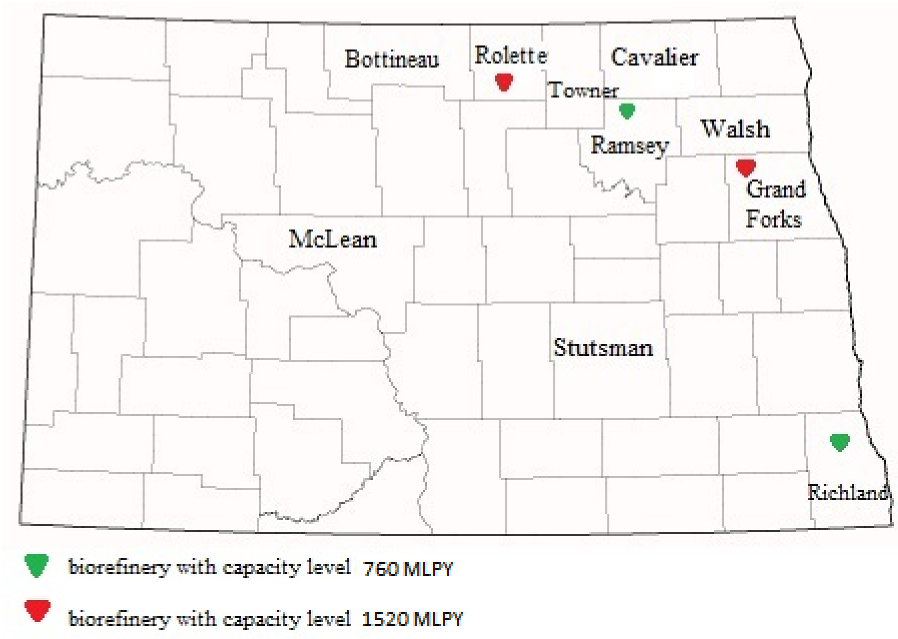

Figure 3. Optimal locations of the biorefineries in North Dakota state based on ARMA demand models

3.3. Validation

In this section, validation of the proposed method under ARMA demand will be done by behavior reproduction test in two steps [34]. In this regard, bioethanol demand of Ramsey is chosen for the validation process. At the first step, the parameters of the ARMA models are estimated based on the existing data of all time periods (1981-2012) [35]. At the second step, the trend of real bioethanol demand and the estimated one by ARMA models are compared from periods t=4 to t=32 (1984-2012). Fig. 4 shows the comparison results of real demand trend and ARMA demand trend. Similarity of these two trends approves the validity of the ARMA models.

3.4. Comparative analysis

Since we have used a conventional data set, making a comparison between our model and other models using the same data set would be useful. In this regard, we have selected the model proposed by Zhang et al. [2] for comparing with our model. Zhang et al. [2] have used the conventional data set similar to which we have used; however, some assumptions related to the input parameters in our case study such as time horizon and time period duration, biorefinery capacity levels, number of supply zones, demand zones, and biorefinery potential locations are different from those in Zhang et al. study [2]. Although these differences between these two studies have led to different results, regarding the vicinity of optimality level of our model (1362.5 M USD average per year) to the Zhang et al. model [2] (1300 M USD), we can conclude that our model has resulted a great performance like Zhang et al. model [2]. As for SBSCND, our model selects four counties including Ramsey, Richland, Rolette, and Grand Forks as the optimal locations for installing biorefineries, while Zhang et al. model [2] selects six counties including Ramsey, Richland, Rolette, Stutsman, Walsh, and Williams. As it is indicated, three out of four optimal locations of the biorefineries determined by our proposed model (Ramsey, Richland, and Rolette) are determined as the optimal locations of biorefineries by Zhang et al. model [2] as well, which indicates that our model and Zhang et al. model [2] have approximately similar performance in SBSCND.

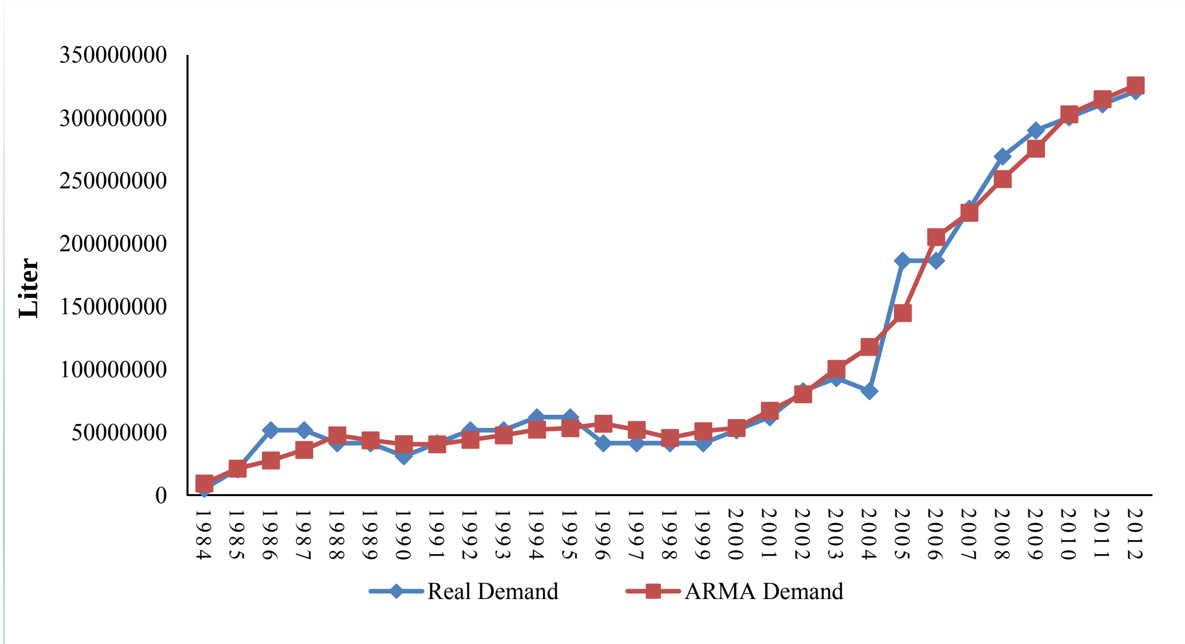

Figure 4. ARMA demand and real demand trends

4. CONCLUSIONS AND FUTURE RESEARCHES

In this paper, a Mixed Integer Linear Programming (MILP) model is proposed for designing a switchgrass-based bioethanol supply chain (SBSC) in which, the bioethanol demand is under Auto-Regressive Moving Average (ARMA) time series models. The developed model integrates upstream and downstream sections of the SBSC and determines the related strategic and tactical level decisions such as location and allocation decisions, capacity levels of established biorefineries, production and flow amount of switchgrass and bioethanol, thereby minimizing the total cost of this supply chain during the time horizon. This paper studies how ARMA time series structure of the bioethanol demand affects the supply chain design. In this regard, a case study based on North Dakota state in the United States demonstrated application of the proposed model in order to design the most optimal SBSC. Furthermore, SBSC optimal design is forecasted for the time horizon from 2013 to 2020 with the bioethanol demand obtained from ARMA models to provide insights for efficient designing and minimizing the total cost of SBSC in the future. The acquired results illustrated the usefulness and efficiency of the proposed approach in helping policymakers to take suitable strategic and tactical level decisions related to the design of SBSC in the future. In addition, a two-step reproduction behavior test is done to validate the proposed approach; then, a comparison with another technique using the same data set showed the great performance of the proposed approach. It is worthy to mention that the proposed approach could be used in a multi-feedstock bioethanol as well as a biodiesel supply chain network design optimization by applying some modifications. Furthermore, considering other uncertain parameters with other time series models could be another future direction for researchers.

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Nomenclature

Indices

i Switchgrass supply zones $(i=1,\ldots,I)$

J Switchgrass collection facility locations $(j=1,\ldots,\mathrm{J})$

r Biorefinery locations $(r=1,\ldots,R)$

k Bioethanol demand zones $(k=1,\ldots,K)$

q' Capacity levels of biorefineries $(q'=1,\ldots,Q')$

t Time periods $(t=1,\ldots,T)$

Binary decision variables

$X_{rq'}$ {1, if biorefinery with capacity level q' setup in location r ; Else 0}

Continuous decision variables

Y_i^t Marginal land area in supply zone *i* (ha)

S_{ij}^t Amount of switchgrass from supply zone *i* sent to collection facility *j* during time period *t* (tonne)

V_{jr}^t Amount of switchgrass from collection facility *j* sent to biorefinery *r* during time period *t* (tonne)

N_{rk}^t Volume of bioethanol from biorefinery *r* sent to demand zone *k* during time period *t* (l)

N_r^t Volume of bioethanol produced by biorefinery *r* during time period *t* (l)

Parameters

C_i^t Annual rental cost of marginal land in supply zone *i* ($/ha)

Cu_i^t Cultivation cost of switchgrass in supply zone *i* ($/ha)

δ_i^t Harvesting cost of switchgrass in supply zone *i* ($/ha)

S_j^t Storage cost of switchgrass in collection facility *j* ($/tonne)

φ_{ij}^t Transportation cost of switchgrass from supply zone *i* to collection facility *j* ($/tonne ×km)

D_{ij} Distance between supply zone *i* and collection facility *j* (km)

α_{jr}^t Transportation cost of switchgrass from collection facility *j* to biorefinery *r* ($/tonne ×km)

D_{jr} Distance between collection facility *j* and biorefinery *r* (km)

β_{rk}^t Transportation cost of bioethanol from biorefinery *r* to demand zone *k* ($/l ×km)

D_{rk} Distance between biorefinery *r* and demand zone *k* (km)

$F_{rq'}^t$ Annualized fixed cost of biorefinery *r* with capacity level q' ($)

W_r^t Bioethanol production cost at biorefinery *r* ($/l)

M_i Maximum marginal land area available for switchgrass cultivation in supply zone *i* (ha)

Q_j^t Maximum capacity of collection facility *j* in time period *t* (tonne)

$P_{rq'}^t$ Maximum bioethanol production volume of biorefinery *r* with capacity level q' during time period *t* (l)

$O_{rq'}$ Minimum capacity utilization rate of biorefinery *r* with capacity level q'

Z_k^t Bioethanol demand in demand zone *k* during time period *t* (l)

A_i^t Amount of switchgrass yield from marginal land in supply zone *i* (tonne/ha)

θ_r Bioethanol production rate from switchgrass in biorefinery *r* (l/tonne)

L Deterioration rate of switchgrass in the collection facilities

T Time horizon (year)

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