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Long term planning and hedging for a lignocellulosic biorefinery in a carbon constrained world

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ABSTRACT

While bioethanol has become a promising candidate for replacing fossil based transportation fuels, its economic feasibility still eludes industry investors. In particular, uncertainties exist in both production processes and associated markets. Hence, it is critical to develop process technology and strategize the operation and hedging decisions that improve financial viability. This paper considers long-term production scheduling under the impact of carbon tax constraints and ethanol spot price uncertainty, as well as risk management via ethanol swap contracts. More specifically, a framework consisting of a two-stage stochastic program and a two-factor time series model is presented to determine the weekly production rate and swap portfolios to maximize the process profit under spot price uncertainty.

1. Introduction

Fuel production from biomass feedstock is hindered by uncertainties in process technology, logistics and market development. Non-food feedstocks such as corn stover and perennial grasses have the most potential to be adopted in future generation biofuel facilities. A recent report from Larsen et al. [1] suggests although the process is developed, and the products are on the market, further policy and market research are still imperative to ensure the construction of commercial plants. Therefore, both optimal conversion process design and financial risk management are essential to develop a commercially viable industry.

A typical biochemical conversion lignocellulosic biorefinery includes feedstock storage and handling, pretreatment, saccharification and fermentation, ethanol, water and solid recovery as well as waste water treatment. Several alternative technologies are available for each step. Therefore, an optimal design of the process is achieved by choosing an effective technology for each step based on a specific objective. To date, researchers have proposed different optimal process configurations under diverse objectives.

For example, Martín and Grossmann [2,3] have proposed energy-optimized biorefinery conceptual models via hydrolysis and gasification of switchgrass. They postulate a superstructure that contains multiple candidate technologies in each conversion step, and formulate a mixed integer nonlinear program to solve for the optimal configuration after considering both heat and water integration. El-Halwagi et al. [4] have established a biorefinery optimization model based on economic and safety constraints. In addition to the economic factors, risk metrics are used in the decision-making problem of selection, location, and sizing of a biorefinery. Santibañez-Aguilar et al. [5] have proposed a biorefinery optimization model based on economic and environmental constraints. The economic objective considers the availability of bioresources, processing limits, and the demand of the product, while the environmental objective uses eco-indicator-99 to measure the total environmental impact. In their later study, Santibañez-Aguilar et al. [6] have formulated an optimization model for design and plan sustainable biorefinery supply chains that considers economic, environmental and social objectives. The social objective is measured as the jobs generated by the supply chains' implementation. Huang et al. [7] have analyzed five biomass species and tested different plant sizes to determine the optimal process efficiency and economical performance. Results show that aspen wood has the largest ethanol production rate, and switchgrass can generate the most amount of excess electricity. Furthermore, the optimal plant production size locates between 2000 and 4000 dry Mg per day. Grisi et al. [8] have considered the optimal short-term scheduling strategy of a biorefinery, which aims to maximizing the hourly plant economic profit.

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The formulated mixed integer linear programming model takes into account production costs, products price, and energy demand. Lythcke-Jørgensen and Haglind [9] have integrated lignocellulosic ethanol production into a heat and power plant with the goal of minimizing ethanol production cost. The results suggest that the ethanol production cost rises continuously as the processing capacity increases, and the average yearly exergy efficiency decreases with increasing ethanol production capacity.

As a result of developing markets for energy products, biorefineries are exposed to exogenous price risk. Thus, effective management of the financial risk arising from price fluctuations is a major concern in the industry. To date, several researchers have investigated this topic [10–17].

In the pioneering work by Barbaro and Bagajewicz [10], a two-stage programming methodology has been proposed and different risk measures such as downside risk, value-at-risk (VaR) and conditional value-at-risk (cVaR) are suggested. In some later studies, financial tools such as forward contracts and futures are incorporated to hedge the risk. For example, the work by Park et al. [11] considers the financial risk management of a refinery via diversifying suppliers and futures contracts. In the work of Yun et al. [12], the authors implement futures contracts to hedge against the fluctuating price pattern for raw materials and create a model for multi-product biorefinery to enhance the process profitability. Recently, researchers also develop other methodologies to address the challenge in price risk. For example, Calfa and Grossmann [13] develop an optimization framework to address both contract selection and price optimization with different price models. A deterministic optimization is implemented first, and then followed by a stochastic counterpart that considers demand and raw material price uncertainty. In their later study of the optimal procurement process in an oil refinery [14], financial derivatives and production flexibility strategies have been introduced in their one stage stochastic program framework. The work of Cheng and Anderson [17] creates a sequential stochastic program model to determine the short-term production commitment and hedging decisions for a lignocellulosic biorefinery. The environmental constraints are considered by imposing tiered carbon tax constraints. Cheali et al. [16] explore the effect of market price uncertainty on the design of optimal biorefinery configuration through developing a computer-aided decision support tool. Geraili and Romagnoli [15] add downside risk measure to their previous decision framework (Geraili et al. [18]) to control the price uncertainty. Such choice leads to a multiobjective optimization.

Several earlier researchers have focused on finding the ethanol threshold prices of entering and exiting the business for a corn biorefinery under policy and supply-side price uncertainty [19–24]. Schmit et al. [19] have determined the ethanol gross margin for different scales of corn ethanol plants under increasing price volatility. They further concluded that the ethanol margin variability delays the new plant investment and exiting of operating plants. In their later study [20], the recent US renewable energy policy change is investigated and their impact on the development of corn biorefinery is quantitatively measured. This line of inquiry concluded that the existence of these policies has ensured the survival of the plants, and narrowed the distance between optimal entry and exit curves. The work of Kirby and Davison [21] uses Monte Carlo methods to assess the value of a corn ethanol facilty under a real options framework, showing that even a modest increase in correlation between gasoline and corn prices would singificantly devalue the plant. Based on the Kirby and Davison [21] work, Maxwell and Davison [22] determine the managerial decision for a corn biorefinery to switch between operating and suspending the plant. They also demonstrate that increasing correlation between corn and ethanol prices is detrimental to the biorefineries, and without government subsidy, the plant is still profitable but embraces larger risk. Maxwell and Davison [23] generalize to develop a quantitative framework to model and interpret regulatory changes during the life of a corn biorefinery, and arrive at the conclusions that the policy uncertainty may impact the plant's profitability either way depending on the subsidy level. And since the operator is risk averse, it is always optimal to switch off the plant before policy changes. Finally, Li et al. [24] evaluate whether it is a good time to invest in cellulosic biorefinery in Iowa, and find out that it is profitable yet non-optimal to invest in pyrolysis-based biorefinery and the gain from waiting exceeds the costs of delaying the investment project.

The findings of these papers suggest that the financial feasibility of biofuel production is subject to financial and policy risk, thus management of the risk becomes essential for the industry sustainability. However, each of these studies uses financial derivatives to *value* the project, not as an operational strategy for risk management. This approach fails to reflect the current practice of fuel trading industries. Interviews with biorefinery operators have shown long-term production and risk management strategies are more favorable compared to the short-term ones. As for the financial instruments used in risk management, swaps have gained substantial popularity in the last decade for long term risk management [25]. Therefore, it is essential to quantitatively model the use of swap contracts in long term risk management for biorefinery industry.

Moreover, in most of the biorefinery process models, the environmental concerns, such as greenhouse gas (GHG) emission, are overlooked. According to Boldrin and Astrup [26], although a biorefinery is generally recognized as a tax credit earning facility thanks to its greenhouse gas emission reduction, this is not universally true due to the choice of calculation criteria in implementing life cycle analysis. As a result, it is necessary to consider the production strategy under a stringent carbon tax policy. Finally, unlike an ordinary oil refinery where the price uncertainty mainly arises from the supply side, the fair price of the feedstock of the second generation biorefinery is still in the exploration stage, therefore, no solid market has been formed to effectively manage the potential price uncertainty (Larson et al. [27]). However, the price volatility for the final product can be a major concern.

The only existing literature that explicitly considers the effect of environmental policy on the production and risk management strategy is the work in Cheng and Anderson [17]. However, the framework of Cheng and Anderson [17] considers a short-term decision horizon, allowing simpler time series models and risk management tools. Therefore the current study contributes to the state of the art in the following directions:

- Related previous work such as Cheng and Anderson [17] or Ji et al. [14] assumes that the spot price follows Geometric Brownian Motion (GBM), which is appropriate for short time horizons. Under a long-term horizon, the use of GBM to represent the underlying product price is no longer acceptable. The inherent drift in this type of model would result in more conservative production and hedging decisions for the biorefinery operator, thus leading to a suboptimal profit level. Therefore, for the longer term model developed here, a more realistic model is required. Specifically, a sophisticated two-factor model is applied based on Schwartz and Smith [28] to simulate the ethanol spot price and the fixed rate (formally introduced in Section 3.3) pricing of the swap contract.
- Previous research on the use of financial derivatives for risk management in this industry has focused on simple forward contracts. However, forward contracts are not frequently used in the commodity derivative industry, so this work extends the existing literature by considering the use of swap contracts for hedging.

- Compared with the previous studies invoking a real option approach to determine the projects' profitability and entry/exit threshold margin [19–24], this study extends the richness and flexibility of operation and hedging decisions. Unlike the aforementioned works that address binary planning decision of switching on or off, this study also investigates the weekly optimal production level while adding hedging decisions as an extra layer of profit protection.
- Finally, in order to implement the improvements proposed above, and to account for influences between production, risk management, and storage decisions, the problem is solved in a two-stage stochastic optimization approach. This method, though more sophisticated than a sequential or single-stage optimization model, incorporates the appropriate time-sequence of production, storage, and sales decisions that will be made in practice.

It is our hope that the results obtained from this work can provide concrete and feasible long-term production and hedging recommendations to practitioners with customized risk preferences.

The remainder of the paper is organized as follows. Section 2 describes the problem in detail. In Section 3, the optimization model is formulated and time series model described. Results are provided and discussed in Section 4. Finally, conclusions are delineated in Section 5.

2. Problem statement and assumptions

Given a lignocellulosic biorefinery facility exposed to two major external constraints; a specific carbon tax structure, and fluctuating ethanol spot price dynamics, the goal is to determine the long-term production and hedging strategies to maximize the facility's total profit and control the financial risk. The target biorefinery drawn from Humbird et al. [29] has the process flow diagram in Fig. 1. The carbon tax structure described in Benjaafar et al. [30]; Cheng and Anderson [17] which increases marginal carbon tax with emissions level, is implemented. It is further assumed that there exist four swap contracts that mature quarterly. In this case, it is assumed maturity dates are in March, June, September and December, though these can be customized as necessary. The choice of four quarterly swap contracts matches with the long term hedging framework while ensuring the strategy flexibility. Although it is also possible to use swap contracts with longer tenor, such as one-year, this will result in a suboptimal profit level as the operator loses the flexibility to adjust the hedging decisions.

Such a strategic planning problem can be further decomposed into two sets of decisions, first the quarterly hedging level, the weekly production schedule over a year, and second, the weekly storage and selling decisions. The choice of hedging and production plan in an annual time frame corresponds with the goal of long-term planning, whereas weekly selling and storage decisions ensures the flexibility to adjust to different product price scenarios.

In the world of mathematical programming, such a problem can be formulated as a two-stage stochastic program. Under the commonly acknowledged no-arbitrage financial assumption, long-term hedging (H_q) and production decisions ($prod_i$) need to be determined in the first stage before observing any spot price information ($spot_{i,j}$), whereas quick responses, such as selling ($Sa_{i,j}$) and storage policy ($St_{i,j}$) can be strategized in real time as recourse in the second stage once the product spot price scenarios are revealed. A complete nomenclature table is presented in Table 1 and a detailed formulation is introduced in Section 3.

3. Model development

As described in Section 2, the problem can be modeled by a framework consisting of a two-stage stochastic program and a supporting time series model (described in 3.2).

More specifically, first an ethanol spot price time series based on Schwartz and Smith [28] is created to provide long-term ethanol spot price simulations and forecast. Second, the fixed rates of four swap contracts are calculated from the spot price forecast. Subsequently, spot price simulations are input to the two-stage stochastic program as the source of uncertainty. Finally, the two-stage stochastic program is solved to provide hedging, production, selling and storage decisions. The above framework is illustrated in the following algorithm:

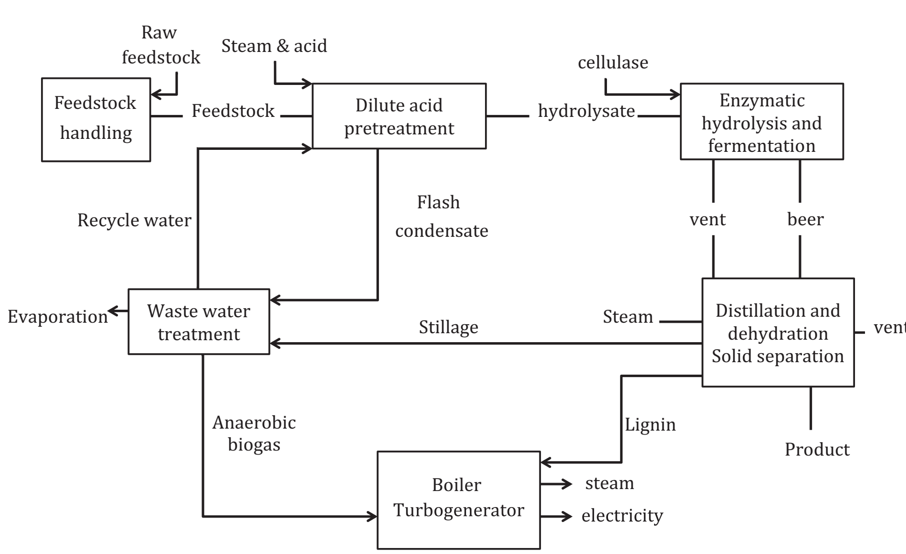

Fig. 1. Process flow for biochemical conversion to ethanol.

Table 1
Nomenclature.

Sets	
i	week
j	scenario
q	quarter
Parameters	
T	total weekly operating hours
S	total number of scenarios
Q	conversion factor
FOC	fixed operating cost
FCC	annualized fixed capital
$spot_{i,j}$	simulated ethanol spot prices
$Icap$	inventory capacity
$Pcap$	production capacity
$\bar{C}_q$	fixed rate of ethanol swap
k_1	unit carbon tax for region 1
k_2	unit carbon tax for region 2
b	threshold hourly emission level between two regions
Cf_1	coefficients for greenhouse gas emission level
Cf_2	coefficients for variable operating cost
I	unit inventory cost
Variables	
First stage variables	
$prod_i$	hourly production level of week i
GHG_i	Green house gas emission rate
CT_i	carbon tax
H_q	weekly hedging level of quarter q
Sh_q	weekly contract shares of quarter q
VOC_i	variable operating cost
Pr_{1_q}	first stage profit
Second stage variables	
$Sa_{i,j}$	weekly spot market sales for scenario j
$St_{i,j}$	weekly storage level for scenario j
$Pr_{2_{i,j}}$	second stage profit
$cost_i$	total cost
TP_j	total profit for each scenario

Algorithm 1. Solution Framework

1. Estimate the Schwartz-Smith two-factor model with Iowa State ethanol weekly spot price data from 2006 to 2014.
2. Simulate 1000 one-year ahead spot price scenarios ($spot_{i,j}$) and estimate one-year ahead spot price forecast ($\bar{S}_i$) from the model trained in 1.
3. Input $\bar{S}_i$ to the fixed rate formula (Eq. (18)) to calculate specific fixed rates ($\bar{C}_q$) corresponding to quarterly swap contracts.
4. Input $spot_{i,j}$ from 2, and $\bar{C}_q$ from 3 to the two-stage stochastic program.
5. Solve the optimization model with the probability-weighted scenarios to determine the following decision variables:
   - First stage-quarterly swap contract shares (Sh_q), weekly production level ($prod_i$).
   - Second stage-weekly spot market sales ($Sa_{i,j}$), weekly storage level ($St_{i,j}$).

3.1. A two-stage stochastic program

The two-stage stochastic program aims to maximize the total expected profit and is formulated as a mixed integer linear program (MILP). In the first stage, key decision variables are production levels $prod_i$ (continuous) and shares of swap contracts Sh_q (integer). In the second stage, continuous recourse variables are weekly spot market sales $Sa_{i,j}$ and storage level $St_{i,j}$.

To facilitate description of the model, nomenclature is delineated in Table 1.

The two-stage stochastic program is formulated as follows, where the process is not modeled in detail here. Instead, the relation between greenhouse gas emission and product (Cf_1), as well as the relation between variable operating cost and product (Cf_2), are extracted from the process model described in Cheng and Anderson [17] (also attached in the Supplementary Material). This relieves the computation complexity.

The objective is to maximize the total expected profit:

$$\max \sum_j \pi_j TP_j \tag{1}$$

where π_j is the probability of spot price scenario j, and TP_j is the total profit in each spot price scenario. subject to the following constraints:

$$prod_i \times T + St_{i-1,j} = Sa_{i,j} + H_q + St_{i,j} \quad \forall i \in 1,\ldots,N \quad \forall j \in 1,\ldots,S \tag{2}$$

$$H_q = Sh_q \times Q \tag{3}$$

where $St_{0,j}$ is defined as zero as storage is assumed to be empty at the start of the planning horizon, and (2) refers to the weekly production level ($prod_i$), storage ($St_{i,j}$), spot market sale ($Sa_{i,j}$), and hedging (H_q) balance. The relation between the swap contract shares (Sh_q) and the underlying hedging amount (H_q) is given in (3), where there are Q tons ethanol per share of swap contract. The quarter index q is defined as: $q = \frac{i_q}{13}$ for all weeks $i_q - 12 \leqslant i \leqslant i_q$, where $i_q \in \{13, 26, 39, 52\}$. In other words, the weeks of a year are grouped into four quarters with Week 13, 26, 39, and 52 representing the end of each quarter.

The model assumes limited storage and production capacity as detailed below, where $Icap$ and $Pcap$ are the upper bound of the inventory and production level respectively. The last capacity constraint regulates the quarterly hedging quantity should not exceed the quarterly production commitment.

$$St_{i,j} \leqslant Icap \tag{4}$$

$$prod_i \leqslant Pcap \tag{5}$$

$$H_q \leqslant \sum_{i=1}^{q_t} prod_i \tag{6}$$

A piecewise linear carbon tax is implemented in (7) and (8) in accordance with Benjaafar et al. [30] and maintains the linearity of the program.

$$CT_i \geqslant k_1 GHG_i \tag{7}$$

$$CT_i \geqslant k_2 GHG_i + b \tag{8}$$

where k_1 and k_2 ($k_1 \leqslant k_2$) corresponds to the unit carbon tax rate for distinct emission regions while b is the intercept which keeps the continuity of the piecewise linear function.

The relation between Greenhouse gas emission level in each week (GHG_i) and production level is approximated as:

$$GHG_i = Cf_1 \cdot prod_i \tag{9}$$

where Cf_1 is the correlation factor between greenhouse gas emission level and production rate.

Finally, cost and profit related constraints are as follows:

$$cost_i = T \cdot CT_i + VOC_i \tag{10}$$

$$VOC_i = Cf_2 \cdot prod_i \tag{11}$$

$$Pr_{1_q} = \bar{C}_q \cdot H_q \tag{12}$$

$$Pr_{2_{i,j}} = spot_{i,j} \cdot Sa_{i,j} - I \cdot St_{i,j} \tag{13}$$

$$TP_j = \sum_{q=1}^{4} Pr_{1_q} - \sum_{i=1}^{52} cost_i + \sum_{i=1}^{52} Pr_{2_{i,j}} \tag{14}$$

where cost in each week ($cost_i$) is comprised of carbon tax (CT_i) and variable operating cost (VOC_i), and variable operating cost is proportional to the production level. Furthermore, the first-stage ancillary profit (Pr_{1_q}) contains the revenue from selling the product by swap contract and the second-stage ancillary profit ($Pr_{2_{i,j}}$) contains spot market revenue net the storage cost. Finally, the total profit in each scenario, TP_j, is defined as the annual sum of the first-stage profit, the second-stage profit minus the cost.

The other primary element of this model framework is the stochastic process of ethanol spot price, described in Section 3.2.

3.2. A long-term time series model for ethanol spot price

Early studies in commodity price modeling typically assumed the commodity price followed Geometric Brownian Motion (GBM) since this distribution is used to model stock price in the famous Black-Scholes option pricing formula. Later, research showed a mean-reverting price model would be more appropriate for commodity price series due to the underlying supply-demand equilibrium [31]. Schwartz and Smith [28] discovered that although the commodity price appeared to be mean-reverting, the equilibrium price remained uncertain. As a response, a two-factor model was developed and has been adopted ever since for long-term commodity price modeling [32,33].

The two-factor model represents the spot price at time t, denoted as S_t as a function of two stochastic factors:

$$\ln(S_t) = \chi_t + \xi_t \tag{15}$$

where χ_t depicts the short term deviation and follows a mean reverting process:

$$d\chi_t = -\kappa\chi_t dt + \sigma_\chi dz_\chi \tag{16}$$

the equilibrium level ξ_t is modeled as a Brownian motion process:

$$d\xi_t = \mu_\xi dt + \sigma_\xi dz_\xi \tag{17}$$

The terms dz_χ and dz_ξ are correlated increments of a standard Brownian motion process, such that $dz_\chi dz_\xi = \rho_{\chi\xi} dt$. In order to simulate the spot price process, it is essential to have an accurate estimation of the process parameters, namely $\kappa, \sigma_\chi, \mu_\xi, \sigma_\xi$, and $\rho_{\chi\xi}$. However, these parameters are associated with two "hidden processes", χ_t, and ξ_t, whose values are not directly observable. Therefore, the Kalman filter is used to estimate their values [34]. For detailed steps of applying Kalman filter in a two-factor model parameter estimation, spot price forecast and simulation, interested readers are referred to Goodwin [33]. Once the time series for the ethanol spot prices is established, the fixed rates of the four ethanol swap contracts can be determined from the spot price forecast. This process is described in Section 3.3.

3.3. A simple pricing formula for ethanol swap contracts

A commodity swap contract is an agreement between two parties to exchange a series of cash payments generated by the underlying assets over a specified period for the purpose of securing the selling price of the underlying asset [35]. No physical commodity is transferred between the two parties. Specifically in energy swap contracts, the energy producer is willing to pay a floating rate to the counter-party in exchange for a fixed rate so, in effect, the underlying energy product is sold at a fixed price (see Fig. 2). While the floating rate is mainly based on the spot price of the commodity, the fixed rate is determined in the contract.

As stated in Section 2, four quarterly-matured swap contracts are considered, each of which has weekly payments within the quarter. The initiation and maturity sequence of the four swap contracts is illustrated in Fig. 3. Under the no-arbitrage pricing scheme, the fixed rate of an ethanol swap contract, $\overline{C}$ is priced by the following formula [36]:

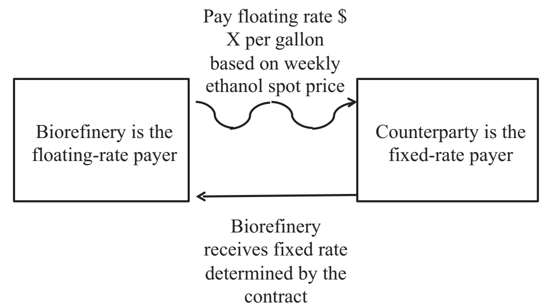

Fig. 2. Bioethanol hedging using swap contracts.

$$\sum_{t=T_1}^{T_N} \frac{\overline{C}}{(1+r_t)^t} = \sum_{t=T_1}^{T_N} \frac{C_t}{(1+r_t)^t} \tag{18}$$

where C_t is the time-varying ethanol spot price forecast at time t, r_t is the risk-free rate at time t, T_1 and T_N are the initial date and the maturity date of the swap contracts respectively.

4. Results

In this section, the parameterization of the Schwartz-Smith two-factor time series model is discussed first. The second stage ethanol spot price process is then represented with a sample of (1000) price trajectories from the Schwartz-Smith model. The stochastic program determines a portfolio of long-term strategies to maximize the total expected profit and has 161,225 variables and 161,274 constraints. A risk neutral case is first considered, as formulated by constraints Eqs. (5)–(19). A risk averse case is considered next, in which operator is able to define their own risk level by incorporating additional risk constraints (defined in Section 4.4). And finally, a discussion of sensitivity is performed, in which the impact of alternative spot price trajectories and storage capacities have been explored (Section 4.5). All the optimization models are solved with CPLEX 12.5.0.1.

4.1. Results for Schwartz-Smith (SS) two-factor models

The SS two-factor ethanol spot price model was built on training data corresponding to weekly New York Ethanol (Platts) Futures one month, three months, five months, nine months, and eleven months to maturity, as well as the Iowa state spot prices from November 2006 to September 2014. All historical spot price data was obtained from Bloomberg L.P. [37]. The parameter estimates for the ethanol spot price SS two-factor model are summarized in Table 2.

A table (Table 3) comparing the goodness of fit of the two-factor model and Geometric Brownian Motion in terms of Akaike information criterion (AIC) and Bayesian information criterion (BIC) is also presented. Since the two-factor model demonstrates lower AIC and BIC values than Geometric Brownian Motion, it is safe to assume the two-factor model outperforms GBM in modeling the ethanol spot time series.

The spot price simulations, which represent possible annual price trajectories in the future, are shown in Figs. 4 and 5. These figures illustrate year 2014 spot price and one-year ahead conditional expectation forecast with the associated range of uncertainty. Rather than reflecting a specific price pattern in the future one year, the forecast price demonstrates a scenario mean trend, which is the requirement to determine the fair price of the swap

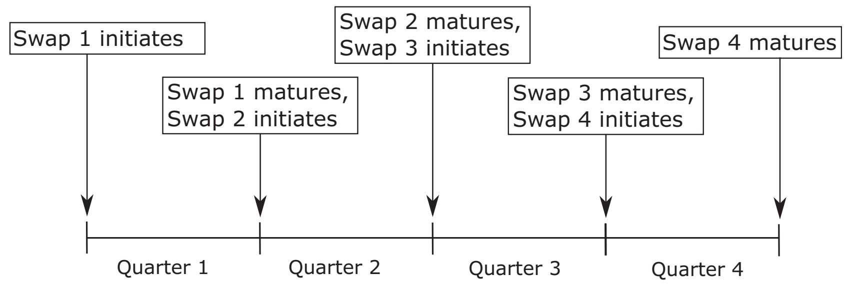

Fig. 3. The sequence of the four swap contracts used in the model.

Table 2
Parameter values for the SS two-factor model.

Parameter	κ	σ_χ	μ_ξ	σ_ξ	$\rho_{\chi\xi}$	s_1	s_2	s_3	s_4	s_5
Value	0.32	0.76	−0.056	0.64	−0.92	0.0015	0	0	0	0.088

Table 3
Model selection criteria for two reference models.

Model	AIC	BIC
Two-factor model	15.32	56.28
GBM	16.07	57.76

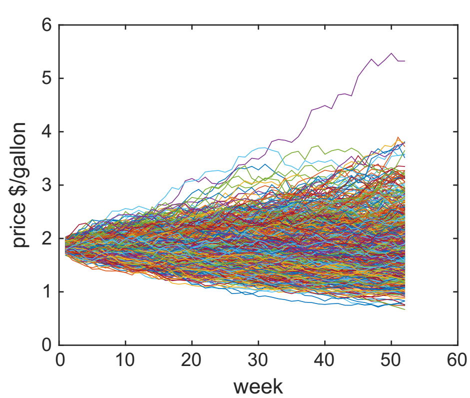

Fig. 4. A sample set of weekly ethanol spot price scenarios

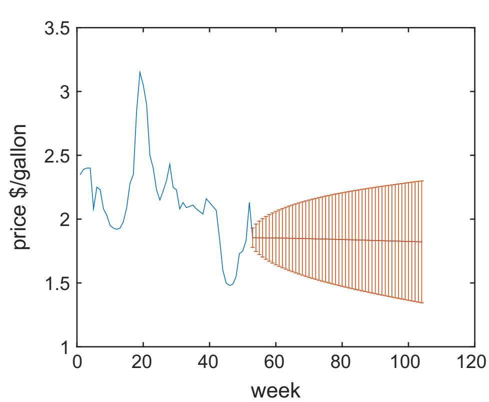

Fig. 5. Blue line is 2014 weekly spot price and red area represents one-year ahead price forecast with error bars.

contracts. The decreasing trend of the forecast price observed in Fig. 5 corresponds to the recent ethanol spot price pattern.

In the following sections, the SS two-factor model is used as input to represent ethanol price uncertainty.

4.2. Production schedule and hedging decisions

In this section, the results of the stochastic optimization model are presented. For this purpose, the key parameter values for the case-study are listed in Table 4.

The optimization model is solved using the price scenarios and fixed rates determined in the previous sections. The key decision variables in the first-stage are weekly production levels and quarterly hedging levels. Fig. 6 shows that the weekly production level follows a decreasing trend and is influenced by both scenario mean spot prices and second region unit carbon tax rates. As the scenario mean spot prices decrease over time, the optimal production level experiences a decline from full capacity, approximately 20 ton/h, to partial capacity, approximately 10 ton/h. The second region carbon tax rate (k_2 in the model) also plays an important role. From the lower bound, 620 $/ton GHG to the upper bound, 640 $/ton GHG, a higher second region unit carbon tax always leads to a decrease of the production level. In the extreme case of carbon tax 640 $/ton GHG, the production level stays at approximately half capacity (10 ton/h) throughout the planning period. This result is counter-intuitive, since typically a positive marginal

Table 4
Case-Study Parameters for two-stage stochastic program.

Parameter	Value
Scenario probability (π_j)	0.001[a]
Conversion factor (Q)	125 ton/share
Storage capacity ($Icap$)	14,816 ton
Production capacity ($Pcap$)	20 ton/h
Unit carbon tax for region 1 (k_1)	50 ton/h
Unit carbon tax for region 2 (k_2)	Varies
Threshold hourly emission level (b)	Varies with k_2
GHG coefficient (Cf_1)	0.98
Variable operating cost coefficient (Cf_2)	451.8 $/ton
1st fixed rate ($\bar{C}_1$)	1.85 $/gallon
2nd quarter fixed rate ($\bar{C}_2$)	1.84 $/gallon
3rd quarter fixed rate ($\bar{C}_3$)	1.83 $/gallon
4th quarter fixed rate ($\bar{C}_4$)	1.82 $/gallon
Storage cost (I)	10 $/ton

[a] Since every scenario is generated with equal weights, the probability for each scenario is $\frac{1}{N}$, where N is 1000 here.

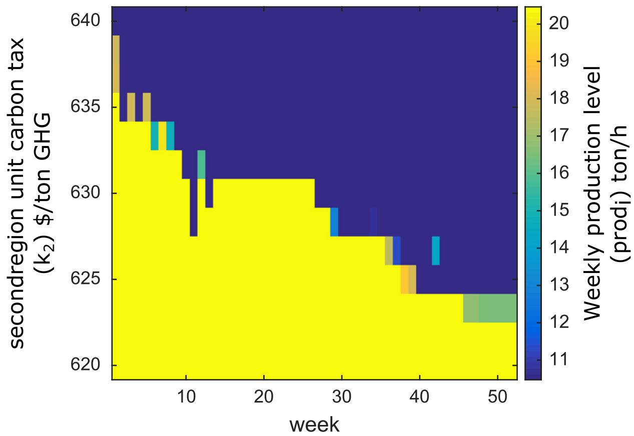

Fig. 6. Weekly production levels corresponding to second region unit carbon taxes (k_2), with decreasing spot price trend, shows that increasing carbon tax leads to declining production.

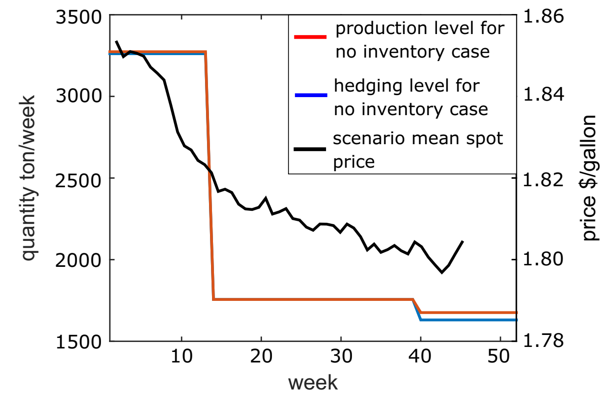

Fig. 8. Production and hedging level with no storage capacity.

profit leads to maximum production, though in this case carbon tax can become prohibitive. The sporadic production decrease at intermediate-high carbon tax cases, i.e. k_2 equals to 632–636 $/ton GHG, shows that the profit margins are small enough that the producers' optimal production strategy is influenced by storage capability. In this case, producing at a higher capacity requires higher marginal profit to overcome carbon tax expenses. The operator can achieve this higher profit through inter-temporal arbitrage with storage. When storage reaches full capacity, the production level decreases. As stored product is sold, and storage capacity once again becomes available, the production level returns to a higher value to rebuild inventory in anticipation of higher future prices. At lower carbon tax rates, it is profitable to produce ethanol at full capacity, regardless of the available storage capacity. It is worth noting that the choice of the second region unit carbon tax rate, ranging from 620 $/ton GHG to 640 $/ton GHG, is higher than any current practice in existence. However, this choice is used as an indication of the impact of stringent carbon tax policy on the optimal operation decisions.

In the first stage, the ratio of ethanol to be hedged via swap contracts are also determined. In this case, the second region unit carbon rate is fixed to be 630 $/ton GHG and weekly scenario mean spot price is drawn as a proxy to represent the forecasted price trend. Fig. 7 displays the optimal hedging level (blue line), the production level (red line), the spot price forecast (black line) and is compared with Fig. 8, where the same set of decision variables are illustrated for a synthetic case with no storage.

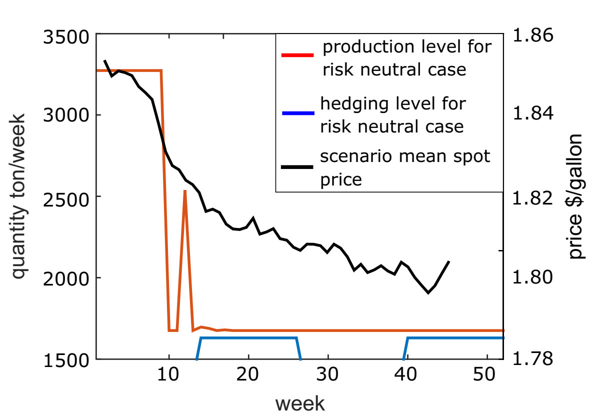

Fig. 7. Production and hedging level for risk neutral case, with storage.

Comparison of Figs. 7 and 8 shows the influence of inventory on production and sales strategy. Specifically, the optimal hedging level is not only impacted by spot price forecast, but also by storage capacity. Specifically, in the absence of storage, production decisions are well behaved and consistent with the price trajectory; what is produced is hedged and production declines with lower product prices. Conversely, with the ability to store product, although the production level declines in general, a spike in production occurs when storage becomes available (approximately week 12 in Fig. 7), to allow for potentially favorable future prices. This shows that while financial risk can be managed with hedging contracts, the capability to store product provides additional benefits to the producer.

4.3. Storage and selling decisions

In the second stage, recourse decisions, such as weekly sales on spot market and storage level, are made based on updated spot price information. Among the total one thousand spot price realizations, decisions for three scenarios, which represent a high spot price, a medium spot price and a low spot price are plotted in Fig. 9.

Regardless of the spot price realizations, sales on the spot market declines dramatically in the later quarters, which tallies with the full hedging strategy decided in the first stage. However, the relation between the spot price and selling on the spot market is indistinctive due to the fact that larger part of the product is hedged with a fixed rate rather than exposed to the spot price, so ethanol sales are less sensitive to spot price fluctuations in the second stage.

The storage level, on the other hand, exhibits distinct behavior for different spot price scenarios. In the high spot price scenario, the storage level features on an escalation trend, which allows the decision maker to maximize their profit by postponing the sales on the spot market. In both medium and low spot price scenarios, an oscillation and reduction pattern persists due to the decision maker's dichotomous choice of either "hedging for now" or "waiting, and seeking a higher price in the future". It is obvious that the lower spot price scenario always favors the choice of hedging over storing.

4.4. Risk management with cVaR constraints

In addition to hedging with swap contracts, the model can be further tuned to include the operator's preference for more stable revenues. In this section, these risk preference levels are considered by adding the following cVaR constraints [38]:

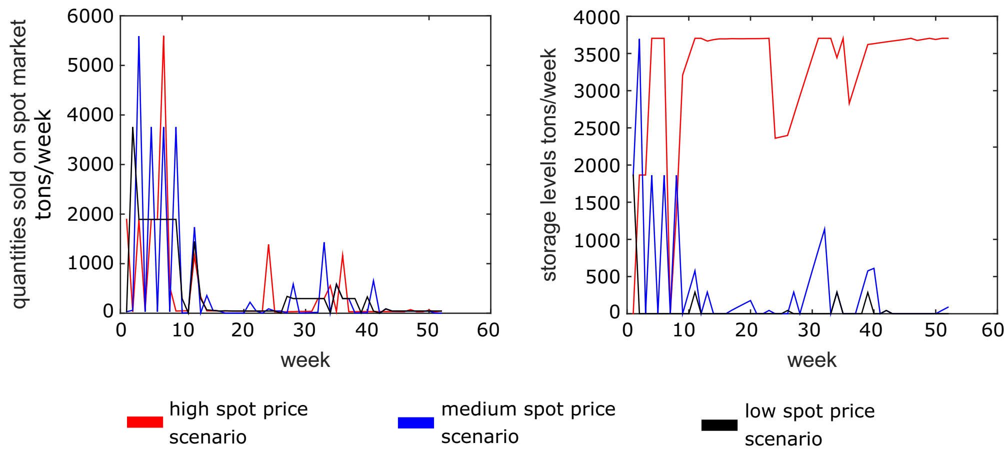

Fig. 9. Sales and storage behavior for high, medium, and low spot price trends: ethanol spot market sales (left panel) and storage level (right panel).

$$z_j = [TP_j - VaR]^- \tag{19}$$

$$cVaR = VaR + \frac{1}{1-\alpha}\sum_j \pi_j z_j \tag{20}$$

$$cVaR \geqslant K \tag{21}$$

where z_j is a nonpositive auxiliary variable, *VaR* and *cVaR* are value-at-risk, and conditional value-at-risk at probability level α, and K is a user-defined risk level. In the practical setting, the model with cVaR constraints informs the operator of the precise shares of swap contracts in hedging, thus leading to customized risk management.

Table 5 compares the profit distribution for the risk neutral case (without risk management) to two risk averse cases with different risk-level constraints. And the tradeoff between a reduced total expected profit and increased profit certainty is shown for different cases.

An increased cVaR level corresponds to a higher risk aversion level and less sale on spot market, thus leading to higher certainty in profit distribution and less expected total profit. In the extreme case of $cVaR \geqslant 6.43 \times 10^6$, the cVaR achieves maximal achievable value, above which the optimization program becomes infeasible. The resulting profit becomes significantly lower but more deterministic. This implies the model not only selects the optimal number of contract under various risk aversion levels, but also informs the maximum achievable risk aversion level given the spot price and the availability of swap contracts.

Fig. 10 provides the optimal hedging strategy for producers at different risk levels. The number of swap contracts at higher risk aversion levels is consistently more than the lower risk aversion levels. At the extreme, full hedging throughout the entire production period leads to a constant selling price.

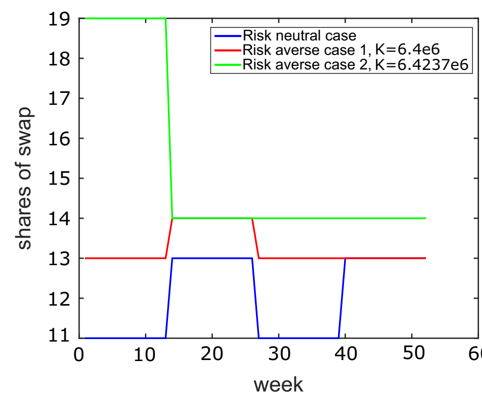

Fig. 10. Shares of swap entered for decreasing risk levels.

Throughout this section, the risk averse case is used as with cVaR lower bound (K) setting to 0.

4.5. Sensitivity analysis

The results presented thus far have been based on specific spot price forecast patterns and storage capacity. It is worthwhile to consider alternative spot price patterns and storage capacities to test the sensitivity of the optimal strategy to these factors.

4.5.1. Spot price patterns

In order to investigate the impact of spot price patterns on production decisions, three other sets of spot price scenarios are simulated. As the price scenario of the risk averse case is generated from a two-factor model, it is necessary to use the same time series model to generate other spot price patterns. Therefore, different lengths of the original dataset are applied as the training datasets. The characteristics of the spot price patterns and the specific periods are listed in Table 6. These patterns are input to the two-stage stochastic program to determine the resultant strategies for each case. Fig. 11 represents the optimal production levels for each of the alternative patterns. Here the red line is the scenario mean spot price forecast, which represents different spot price forecast patterns. Results show that production level encounters a switch once the spot price reaches a threshold. For example, in the case of rapid increase, gradual decrease, and rapid decrease pattern, the price

Table 5
Expected profit and normalized standard deviation for decreasing risk levels.

Example	E[profit]/million $	Normalized std
Risk neutral case	6.50	0.212
$cVaR \geqslant 6.4 \times 10^6$	6.49	0.123
$cVaR \geqslant 6.43 \times 10^6$	6.46	0.0466

Table 6
Alternative spot price patterns, generated from historical data (weeks indicated).

Spot price patterns	Range of weeks
Gradual increase	1–200
Rapid increase	1–250
Gradual decrease (risk averse case)	1–426
Rapid decrease	1–400

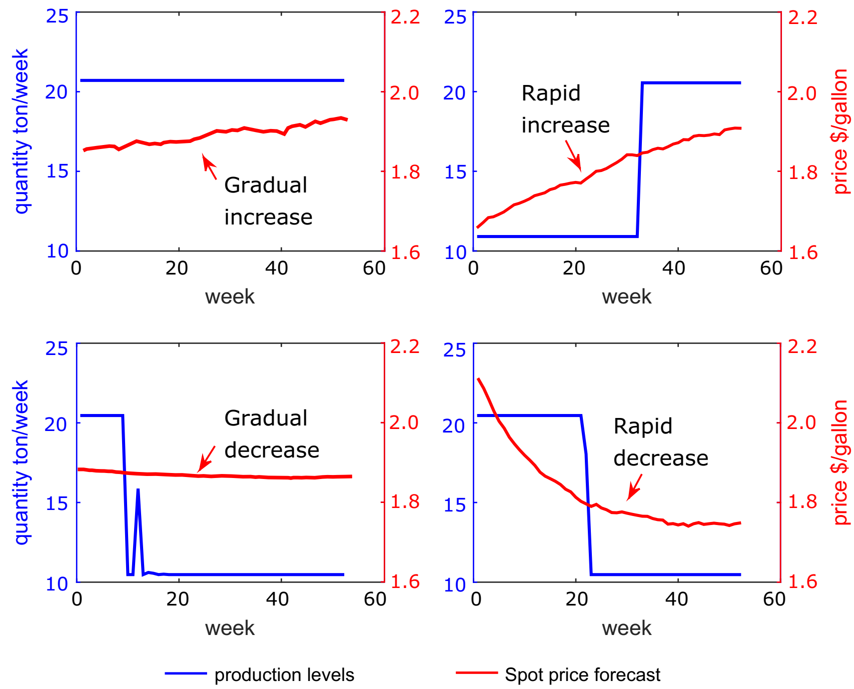

Fig. 11. Production levels for alternative spot price trends.

threshold that triggers the production switching occurs around 1.8 $/gallon. In the gradual increase case, the production remains at full capacity throughout the planning period because the minimum forecast price is well above 1.8 $/gallon.

As previously discussed, the storage capacity influences the hedging level within the planning horizon. Therefore, the next section examines the effect of a range of storage capacities on the hedging levels and profit distributions,

4.5.2. Storage capacity

Four capacity values, i.e. 25%, 50%, 200%, and 400% of risk averse case capacity are explicitly selected to compare with the risk averse case. The risk level is set to be $cVaR \geqslant 6.4 \times 10^6$ for all storage capacities. The expected total profit and the normalized standard deviation for these cases are compared in Table 7. Shares of contract entered are plotted in Fig. 12.

At the same risk level, cases with higher storage capacity seek to maximize the expected profit by using fewer swap contracts in Q1 when the spot price is relatively high. Higher storage capacity provides the flexibility of storing more and selling at higher spot price periods. When the spot price declines to unfavorable region, as is seen in Q2, Q3 and Q4, the product is fully hedged across all the cases, leading to both an identical number of swap contracts throughout different storage capacity and an equal value of risk aversion level. In conclusion, cases with higher storage capacity

Table 7
Expected profit and normalized standard deviation for cases with different storage capacity, showing that higher storage capacity leads to higher expectation and standard deviation of profit, at the same risk level.

Examples	E[profit]/million $	Normalized std
25%*Icap*	6.44	0.0557
50%*Icap*	6.46	0.0802
Risk averse case	6.49	0.123
200%*Icap*	6.55	0.189
400%*Icap*	6.63	0.291

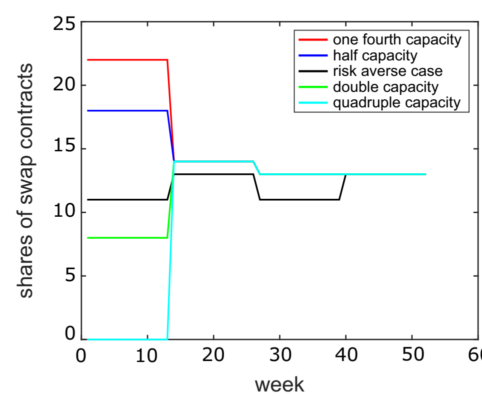

Fig. 12. Hedging level for risk averve case and different storage capacities, note higher storage capacity leads to more storage in Q1, thus decreasing the shares of swap contracts used.

increase total profit by exploiting the storage capacity and spot sales in Q1.

5. Conclusion

This study has presented a framework to determine the optimal production, hedging, selling and storage decision for a dilute-acid pretreatment based lignocellulosic biorefinery. A two-stage stochastic program is formulated in light of the decision sequence, while the underlying spot price is characterized by a Schwartz-Smith two factor model. In the first stage, weekly production is jointly determined by carbon tax rate and scenario mean spot price trend. Under the parameter setting presented, it is observed that the production level switches from full capacity to half capacity once the scenario mean spot price falls below 1.8 $/gallon. Moreover, customized risk management decisions can be obtained by adjusting the conditional value-at-risk constraint (21) in the model. The corresponding optimization results represent a tradeoff between the shares of swap contract to enter and the inventory level. In other words, a dynamic balance between ‘‘hedge for now" and ‘‘store, and seek a higher price in the future" is achieved.

In the second stage, strategies for spot market sales, and storage levels are scenario-specific, and are recourse to facilitate further increase of the total profit. In the three representative spot price scenarios, it has been shown that while sales on the spot market are largely governed by hedging level, the storage level positively correlates to spot price patterns.

Finally, it has been demonstrated that higher storage capacity also boosts the facility's profit. At the same risk preference level, a higher storage capacity leads to increasing storage level and fewer shares of swap contracts to enter. In other words, the storage capability enables the possibility of postponing the sale of the product to high price periods.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.enconman.2016.08.017.

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