Maximizing Profits in an Ethanol Supply Chain with Hedging Strategies

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In this paper we develop hedging strategies in maximizing profits for an ethanol producer who buys raw materials (corn and cellulosic) and produces end-products (ethanol, corn oil and distillers dried grains soluble). We first develop an optimization model considering maximization of the supply chain profit with hedging. We model the buying (corn and cellulosic feedstock) and selling (ethanol end-product) prices to follow a mean reversion with sample average approximation in order to capture better price volatilities and less usage of sample data to obtain expected results respectively. We use a Multi-cut Benders Decomposition Algorithm to help with efficient computations for the proposed model. We also incorporate the aspect of copula to capture the dependency structures and price relationships between corn and ethanol futures (a hedging strategy that buys or sells a product looking forward into the future). We found that hedging using future prices give additional profit margins for the time period used. We intuitively show that an ethanol price margin between $2.06 and $2.41 per gallon will allow ethanol producers to make profit or at least break-even. A case study using an ethanol plant in North Dakota is used for this study.

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I. INTRODUCTION

Companies face a wide variety of operational and financial risks and as such utilize strategies aimed at systematically managing risk exposures to minimize losses and increase firm value (Boyabatli and Toktay 2004). Some of the popular ways to manage financial risks is to use the variety of trading mechanisms such as options, futures and swaps. The volatility, uncertainties and wide price swings associated with energy prices has made the energy sector an attractive industry for hedging.

While there has been a lot of attention in the hedging of traditional energy products such as crude oil and natural gas, relatively less attention has been given to managing risks of biofuels and other newer renewable energy sources even though those fuel sources are also vulnerable to the risks and uncertainties associated with the more traditional energy sources. Biofuels such as ethanol have been increasingly used as a substitute for fossil fuel energy and its adoption has been accelerated by government mandates across the world. For example, the European Union (EU) requires member states to ensure the substitution of 10% of its transportation fuel with biofuels by 2020 while the US Environmental Protection Agency (EPA) requires that at least 7.5 billion gallons of renewable fuels be blended with conventional gasoline by the year 2012 (McPhail et al. (2011). These mandates have contributed to the widespread use of biofuels as a source of fuel for transportation purposes, hence, making ethanol a very important fuel source.

Similar to the conventional energy sources, the price of ethanol and its inputs are uncertain, volatile and face wide price swings. The process of buying feedstock, processing the ingredients and selling the finished products involves risks that make it important for ethanol producers to utilize strategies to manage risks, minimize losses and improve shareholder value. Ethanol manufacturers are facing extreme price risks from the purchase of feedstock to the sale of end-products (Zhang et al., 2013). These risks are caused by several factors that impact margins, including prices for ethanol, corn, corn oil, Distillers Dried Grains (DDGs), and Renewable Energy Identification Numbers (RINs). In addition, recognizing the period to hedge is challenging and determining how much of the physical commodity is needed adds more complexities to hedging decisions (Wilson et al., 2006). Firms therefore need to strategize and make decisions on how to hedge over short term, medium term, and long term scenarios and to decide which markets or mechanisms to use.

Even though ethanol is a very important energy source, the risks and uncertainties associated with ethanol production and sales are significant making it a prime target for hedging and other forms of risk management. The review of literature demonstrates that very few papers consider hedging strategies for renewable energy fuels, particularly ethanol. Recognizing that gap in the literature, this paper examines hedging strategies available to ethanol manufacturers such as futures, swaps and options. We utilize Platts, a market that is used by most commodity traders as a trusted source of trading and information on the market. We also introduce a number of methodological approaches that have not been traditionally used in the hedging literature. Traditionally, hedgers seek to take equal and opposite positions in related markets and more complex models seek to exploit use of correlations without incorporating dependent relationships. Copula is utilized in this paper since it allows for the incorporation of non-standard dependencies, thus better reflecting conditions faced by ethanol processors. This work also utilizes mean reversion in order to better capture the deterministic and stochastic side of the price volatility. Doing this, enables the capture of upside and downside risks more accurately, thus adding extra flexibility in forecasting returns. The paper also utilizes multi-cut benders decomposition and sample average approximation approaches that are proven to solve the problem at hand more efficiently with fewer data points (Osmani and Zhang 2017.).

There are six main contributions of this study: 1) Explore the different hedging strategies available to ethanol producers, a topic that has been inadequately covered in the literature. 2) Integrate financial and operational hedging risks in the proposed model in order to provide a more complete assessment of the problem as compared to focusing only on financial risks. 3) Utilize copula to capture a better dependency structure which enables us to extend one to one relationship of prices (corn and ethanol) beyond correlation 4) Utilize a Multi-cut Benders Decomposition methodology and also sample average approximation in order to help with efficient computation of the hedged profit margins while using smaller sample data 5) Provide a stylized model for buying (corn and cellulosic feedstock) and selling (ethanol end-product) while these prices follow a mean reversion (MR) in order to more accurately capture price volatilities 6) Provide managers in ethanol manufacturing companies with risk managing strategies through hedging, that can enable them to increase profits and shareholder value.

II. LITERATURE REVIEW

There is a vast literature that focuses on the use of financial hedging instruments to manage risk (example Black and Scholes, 1973; Merton, 1973; Markowitz, 1952). These studies use a variety of methodological approaches to examine risk and uncertainty in multiple industries. They include in the bakery industry (Wilson et al., 2006), soybean crushing industry (Dahlgran, 2005), canola and western barley (Mann, 2010), distillers dried grains (DDGs) (Brinker et al., 2007) and the flour industry (Wagner 2001 and Oberholtzer, 2011). Although financial hedging has been well examined, an increasing numbers of papers have begun to combine financial with operational hedging (e.g. Chod et al., 2010). This is because a large number of papers that examine financial hedging focus on hedging against currency exposure and price variability while ignoring important operational risks such as those associated with capacity constraints and product demand exposure (Chod et al., 2010). Operational hedging strategies, are viewed as real compound options that are exercised in response to the demand, price and exchange rate contingencies faced by firms in a global supply chain and have been examined by a number of studies including (Cohen and Huchzermeier 1996); (Cohen and Mallik, 1997) and (Boyabatli and Toktay, 2004). Some operational strategies include postponing logistics decisions, switching production and sourcing decisions contingent on demand uncertainties and creating production capacity flexibilities (Boyabatli and Toktay, 2004). These operational hedges are utilized to mitigate risk exposure in the long run by reducing the downside risk (Cohen and Huchzermeier, 1999).

In recent years, with the increasing popularity of biofuels and the uncertainty associated with their production and sale, a number of studies have focused more specifically on risk and hedging in the biofuel industry, particularly ethanol. The closest article that draws nearer to this manuscript is (Wiedemann and Geldermann, 2015). The authors modeled a planning problem of a processor of agricultural raw materials and illustrates it with data on the industrial use of linseed oil. A two-stage stochastic optimization model was used in conjunction with a decision support analysis to solve the problem. (Quintino and David, 2013) analyzed proposed ethanol futures for the Brazilian markets to attract sufficient liquidity for market agents. Their paper analyses different cross-hedging scenarios in the ethanol supply chain for sugarcane. The analyses conducted evaluate price volatilities, and correlations with cross hedging viability for ethanol futures.

(Chang et al., 2012) examined the long- and short-run asymmetric adjustments of spot and futures prices, namely corn, soybeans, sugar, and three cross pairs of spot price for each of the products and an ethanol futures price. Their study concludes that the corn spread has the strongest long-run widening adjustment while sugar showed the weakest narrowing adjustment. Their empirical analysis points to the importance of hedging the spot prices of agricultural commodities with ethanol futures contracts.

(Dal-Mas et al., 2011) determined how an ethanol supply chain is optimized according to a comprehensive mathematical framework with multiple decision criteria under uncertain market scenarios. A linear programming framework is used to solve the resulting model. A case study in Italy is used with the results showing that risk mitigating preferences are essential for hedging risk and decision making within the ethanol supply chain with multiple feedstocks.

(Langholtz et al., 2014) developed a risk management framework developed using the Intergovernmental Panel on Climate Change to review current understanding regarding climate-related hazards, exposure, and vulnerability of the bioenergy supply chain. The authors consider a risk management strategy that projects growth of bioenergy feedstocks in regions preferentially exposed to such hazards. The paper discusses implications of climate change on expansion of cellulosic feedstocks. In addition, strategies in advancements of feedstock development, logistics, and extension are provided.

Our paper builds upon the contributions from (Awudu et al., 2016); (Chen et al., 2016). (Awudu et al., 2015); (Langholtz et al., (2014); (Quintino and David, 2013); (Dal-Mas et al., 2011); and (Chang et al., 2010). While these papers have contributed substantially to the risk management literature in the ethanol industry, there are still gaps in the literature that still needs to be addressed. Some of the gaps include: a dearth of robust or stylized models that consider multiple feedstock (raw materials); risk hedging that focuses primarily on financial hedging while not paying adequate attention to operational hedging; and a heavy reliance on correlations to identify relationships between the prices of corn and ethanol, an approach that does not truly capture the full complexity of those relationships. There are also problems that focus on computation since there is an inadequate utilization of state of the art algorithms that reduce computational time and provide faster and better ways of solving stochastic hedging problems.

The gaps identified are bridged in this paper by extending optimization models to include portfolios of ethanol and other products such as DDGs and corn oil. We incorporate a hybrid-generation biofuel supply chain with two types of biomass feedstock; corn and cellulosic to capture the dynamics of operations. By doing so, we can introduce operational risk that is based on capacity manipulations. As part of the uniqueness of our approach to optimize supply chain decisions, and reduce the impact of financial and operational risks, we develop a hedging strategy with a stochastic model, and solve the resulting problem using a Sample Average Approximation (SAA) and Mean Reversion with which gives a more realistic representation of future and spot price movements of ethanol commodities and end-products. This assumption is used because most commodity prices exhibit high and low prices for a temporary period, and then the prices move or shift to the average prices over time (Bessembinder et al., 1995). We also introduce cross hedging strategies involving futures and spot that enable us to manage the risk better. To improve computing time and speed up the process of solving stochastic hedging problems, we develop a Multi-cut decomposition algorithm for better computation and tractability using scenario generations. By introducing new methodological approaches that provide more realistic scenarios, we also help managers to develop more effective risk management strategies.

III. METHODOLOGY

We consider a hybrid-generation biofuel supply chain with two types of biomass feedstock; first and second generation. The first generation consists of corn and the second generation is cellulosic feedstock. The supply chain network consists of pre-determined raw material supply sources, warehouses or pre-treatment facilities, biorefinery plants, and demand zones. Supply sources are responsible for providing the raw materials which are corn and cellulosic feedstock. Warehouse or pre-treatment facilities prepare the raw materials into a suitable form before being transported to the biorefinery plants. The biorefinery plants convert the pre-treated raw materials into end-products, which is biofuel and then ships (via trail or truck) the biofuel produced to the demand.

Considering the hybrid-generation biofuel supply chain described above, the challenges of operational uncertainties (risks) from supply, production and demand are obvious. Uncertainties such as prices of feedstock and end-products are very common in Renewable Energy Supply Chain (RESC). These are usually termed as financial risk. In order to optimize the supply chain decisions, and reduce the impact of financial and operational risk, we develop a hedging strategy with a stochastic model and solve the resulting problem. For computational tractability, we used a Multi-cut Decomposition Algorithm.

As part of capturing the uncertainties in the feedstock and ethanol prices, a Mean Reversion is used to model the prices of the feedstock and end-products. This assumption is used because most commodity prices exhibit high and low prices for a temporary period, and then the prices will move or shift to the average prices over time (Bessembinder et al., 1995). But we further capture the volatility of the prices in a different way by observing the sample price over a limited scenario say 1000 instead of 10,000 and we still get to capture volatilities with minimum impact on the results. This is implemented from the data set obtained from the Iowa University Energy Research Group. The corn biomass purchasing mechanism is based on a heuristic hedging strategy since corn as a commodity has high price volatility. In order to reduce the price variability and hedge against future uncertainties, the corn is procured at a futures price. The cellulosic feedstock is purchased at a spot price since no variability is assumed for its price. The heuristic method uses the mean reversion model to generate sample data for both the corn spot and futures prices. A method of buying corn feedstock using the spot price is used if futures price is greater than say y times the mean of the sample price generated. This characterizes a mean of an additional say $x\%$ increase in each scenario. For example, when futures price of corn is \$30 and the sampled price mean is \$20, then the increase (x is \$10) and the value of y is 1.5). Similarly, the future price is opted if the spot price is greater than the y times the mean of the sample price generated. We further exercise options and swaps in selling the other end products which are distiller's dried grain soluble (DDGS) and corn oil. For the purpose of space, the options and swaps are referred to as cross hedging. In the next section, we develop the modeling framework and discuss the case study.

IV. MODEL DEVELOPMENT

In this section, we develop a model that considers the decision-making process of an ethanol plant which includes the amount of feedstock to purchase, ethanol to produce, feedstock to store, ethanol to store, ethanol sale, DDGs and corn oil. These decision variables are expected to achieve the desired revenue by the ethanol producer. We explore whether the decision to produce and sell ethanol and its by-products based on the hedging strategies are profitable. We impose no restrictions on the ethanol producer in terms of profit realizations if there is capacity to produce and meet the desired demand. The model input variables, including the index, parameters and variables are first listed. The mathematical model is designed to examine hedging strategies of an ethanol producer. The objective function of the model maximizes profit of the ethanol producer. The next sub-sections present the model input variables, objective function and constraints.

4.1. Mathematical model Input variables

Index

j Supplier index j = 1...J
b Buyer index b = 1... B
t Time period t=1...T

Parameters

P_l Cost of corn (cost at hedging); $ per bushel
P_h Cost of cellulosic (cost at hedging); $ per bushel
$1-e$ Quality factor (defined as a factor of the conversion rate of corn to ethanol); gallons per bushel of corn
e Quality factor (defined as a factor of the conversion rate of cellulosic to ethanol); gallons per bushel of cellosic
c Capacity of the ethanol plant; gallons per year
D^l Demand for corn; gallons per year
D^h Demand for cellulosic; gallons per year
S_l Selling price for corn ethanol; dollars per gallon
S_h Selling price for cellulosic ethanol; dollars per gallon

Variables

Q_l Quantity bought for corn; bushels
Q_h Quantity bought for cellulosic; tonnage per year
P_o^l Forced market price for corn (market conditions); dollars
P_o^h Forced market price for cellulosic (market conditions); dollars
y Yield that can be attributed to corn and cellulosic ethanol; bushels for corn and tonnage for cellulosic
y_l The total amount produced from corn; gallons
y_h The total amount produced from cellulosic; gallons

4.2. Objective function

The proposed model seeks to optimize the profit of the ethanol supply chain considering hedging and non-hedging.

4.2.1. Supply chain profit maximization

The supply chain profit maximization being considered here is the ethanol producer. The supply chain maximizes the price of corn and cellulosic ethanol being sold as revenue, against the cost of purchasing corn and cellulosic raw materials at forced market conditions (meaning the best price available for these raw materials during the procurement or purchasing process).

$$Max\left\lfloor S_l Min\left(Q_l(1-e), D^l\right) + S_h Min\left(Q_h(e), D^h\right) - P_0^l Q_l - P_0^{hl} Q_h \right\rfloor - f(e)\ , \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where $e \approx f(e)$ which is a random variable is explained in the objective function.

Equation (1) is defined as the objective function. This objective function is the profit margin made after selling corn and cellulosic ethanol, and then subtracting the cost of buying the corn and cellulosic raw materials. The first two terms, i.e. $S_l Min\left(Q_l(1-e), D^l\right) + S_h Min\left(Q_h(e), D^h\right)$ represent the revenue function. $S_l Min\left(Q_l(1-e), D^l\right)$ means the revenue for the corn ethanol that is sold considers the minimum between the demand and production (since you can always sell what you have produced) times the price of selling corn ethanol. $S_h Min\left(Q_h(e), D^h\right)$ on the other side represents the revenue for the cellulosic ethanol. $P_0^l Q_l$ and $P_0^{hl} Q_h$ represent the cost of purchasing corn and cellulosic raw materials respectively. The random factor expressed as $e \approx f(e)$ represents other costs components (which may include transportation, logistics, tariffs, etc). Also, the objective function considers up-scale and down scale potential and losses respectively in selling the ethanol and buying corn and cellulosic feedstock or raw materials.

4.2.2. Constraints

$$Q_l \leq (1-e)y \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

$$Q_h \leq (e)y \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Note that $1-e$ and e represent the conversion rate (yield quality) of corn and cellulosic ethanol respectively. y_l is the total amount produced from corn and y_h is the amount from cellulosic

$$c \geq (1-e)y_l + ey_h \ \ldots\ldots\ldots\ldots\ldots\ldots(4)$$

$$Min\left(Q_l(1-e), D^l\right) + Min\left(Q_h(e_h), D^h\right) \leq D^l + D^h \ \ldots\ldots\ldots\ldots\ldots\ldots(5)$$

$$P_l \geq P_0^l \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

$$P_h \geq P_0^h \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

Equations (2) and (3) are defined as the constraints that consider the low and high quality of the total conversion of corn and cellulosic to ethanol in relation to the yield that is gotten from that conversion. These equations can be related to the capacity constraints as they provide flexibility in how the total operational time is impacted by the conversion rate. Equation (4) explains the total capacity of ethanol production available being greater than or equal to the sum of the corn and cellulosic ethanol produced. This is what we defined as operational hedging since there is flexibility in the production process. Equation (5) sales made out of selling corn and cellulosic ethanol based on their conversion rates, total quality and upside/downside potential inputs to the function being less than or equal to the demand. In summary, the total amount of ethanol sold (including corn and cellulosic raw materials plus end products) is less than or equal to the total demand. In equations (6) and (7), the constraints explain that the regular prices of corn and cellulosic as well as ethanol commodity prices are always greater than or equal to the forced price of the market conditions. Equations (6) and (7) can only be negated under wild market speculations and an economic meltdown (at least in the commodities markets).

In the next sections we present the sample average approximation (SAA), Multi-Benders Decomposition Algorithm (MBD) and the concept of copula. The SAA and MBD are adopted to address the computational complexity of the problem as part of the methodology used in this paper. The copula concept is drawn to give meaning to the data sets used for hedging in relation to providing more information about the data relationships of ethanol and corn prices beyond correlation.

We assume the revenue for DDGS and corn oil are same since there is no liquidity for their markets and we hedge through swaps and options by adopting a cross hedge. The profit for the hedged equation is always inclusive of the revenue of corn ethanol, revenue of DDGS, revenue of corn oil, corn feedstock purchased cost, cost incurred in taking a futures position, transportation cost of ethanol to demand zones, other supply chain fixed costs, variables costs, and other capital costs.

4.3. Sample Average Approximation (SAA)

In this section, we develop and discuss the sample average approximation (SAA), multi-cut benders decomposition (MBD) algorithm, and the procedure for solving the entire proposed model based on SAA and MBD. In the SAA algorithm, we follow the example developed by (Osmani and Zhang, 2014) with a sample set with B scenarios that is randomly generated from the total number of N scenarios, and then an optimization problem specified by the generated sample set which is solved in (Kleywegt et al., 2002). In the SAA method, the expected value of the objective function $E_{\omega}[Q(x, \xi(\omega))]$ is usually approximated, where $Q(x, \xi(\omega))$ is a realization objective function on scenario ω, and E_{ω} is the expected value.

$$\sum_{b=1}^{B} Q(x, \xi(\omega^b))/B \tag{8a}$$

The optimization problem (given by Eq. 1-7) corresponding to the original two-stage stochastic model is then solved using traditional algorithms. The optimal objective value z_B and an optimal solution $\hat{x}$ provide estimates of their true counterparts in the stochastic model. This process can be simplified by alternatively considering the objective function of the optimization of Eqn (1-7) as equation 8b, where 8a is the stochastic part in 8b. Then for each scenario, a Z_B^i and $\tilde{x}^i$ are obtained.

$$z_B = \max_{x \in X} c^T x + \sum_{b=1}^{B} Q(x, \xi(\omega^b))/B \tag{8b}$$

The SAA method divides N scenarios into A equal size independent sample sets, with each set containing B scenarios. By solving the A stochastic problems using Eq.

1-7 as the objective function, objective values z_B^1, z_B^2, …, z_B^A and candidate solutions $\hat{x}^1$, $\hat{x}^2$, …., $\hat{x}^A$ are obtained. Eq. 9 denotes the average of the A optimal values of the stochastic problems.

$$\bar{z}_B = (1/A)\sum_{a=1}^{A} z_B^a \qquad (9)$$

(Kleywegt et al., 2002) shows that $\bar{z}_B \leq z^U$, where z^U is the global upper bound. Therefore for a maximization problem, $\bar{z}_B$ can be used to estimate the upper bound of the optimal value for the original stochastic problem. For any feasible solution $\hat{x} \in X$, the objective value given by $c^T\hat{x} + E[Q(\hat{x}, \xi(\omega))]$ is a lower bound of the optimal value for the original stochastic problem. This lower bound can be estimated, where $\{\omega^1, \omega^2, …, \omega^N\}$ which are the weights, contain the full set of N scenarios.

$$z_N(\hat{x}) = c^T\hat{x} + \sum_{b=1}^{N} Q(\hat{x}, \xi(\omega^b))/N \qquad (10)$$

The SAA procedure provides A different candidate solution (i.e. one for each sample set). Eq. 11 is used to find $\hat{x}^*$ with the largest estimated objective value (for a maximization problem) over the full set of N scenarios.

$$\hat{x}^* \in \arg\max \{\hat{z}_N(\hat{x}) \mid \hat{x} \in [\hat{x}^1, \hat{x}^2, …., \hat{x}^A]\} \qquad (11)$$

The accuracy of the solution $\hat{x}^*$ is evaluated by computing the optimality gap (as given by Eq. 12) for the full set of N scenarios and comparing it against ε, a pre-set criteria.

$$[\bar{z}_B - \hat{z}_N(\hat{x}^*)]/\bar{z}_B \qquad (12)$$

During the traditional use of the SAA method, the algorithm terminates when the desired optimality gap is achieved. However, for problem with large number of variables and stochastic scenarios, the desired optimality gap for reasonable accuracy (e.g. less than 0.5%) might not be achievable using the traditional SAA method. But the solution results show that unanimity in decisions is achieved within reasonable iterations of the SAA method. Therefore, a modified SAA method is proposed to obtain solutions where each sample set gives the same values for the binary variables.

The use of the "modified" SAA algorithm is explained below.

Step 1: Create A sample sets $\{A = N, N/B_1, N/B_2, ..., 1\}$ with each set populated with B scenarios $\{B = 1, B_1, B_2, ..., N\}$ randomly drawn without replacement from the total N scenarios, such that $A = N/B$.

Step 2: Start with the largest value of A (i.e. N) and create $A = N$ sample sets with each set populated with $B = 1$ scenario randomly drawn without replacement from the total N scenarios.

Step 3: Solve each of the $A = N$ sets, and compute optimality gaps. The SAA algorithm terminates if each sample set gives the same values for the binary variables. Else go to Step 4.

Step 4: If the desired unanimity in the values of the binary decision variables is not achieved, then the next largest value of A sets is used ($A = N/B_1$), with each set populated with B_1 scenarios randomly drawn without replacement from the total N scenarios. The new upper and lower bound including the optimality gap are updated. If the desired unanimity in the values of the binary decision variables is not achieved, then Step 4 is repeated using the next largest value of A until each sample set gives the same values for the binary decision variables.

The algorithm is adopted from (Osmani and Zhang, 2017).

4.4. Multi-cut Benders decomposition (MBD)

Multi-cut Benders decomposition is then used to determine the remaining first-stage continuous decision variables by incorporating the decision variables obtained from the modified SAA method. Eq. 13 is used to describe the general stochastic problem which needs to be minimized (Birge and Louveaux, 1997). For a maximization problem the signs are to be reversed. e.g. loss minimization is equivalent to profit maximization. In Eq. 13, x is a vector that stands for the first-stage continuous decision variables; y_ω are the continuous second-stage decisions for each scenario ω; A and b are parameter matrices independent of the scenarios; and M, h_ω and T_ω are parameter matrices for each scenario ω.

$$\begin{aligned} Min \quad & z = c^T x + E_\omega[q_\omega{}^T y_\omega] \\ s.t. \quad & Ax = b \\ & My_\omega = h_\omega - T_\omega x \\ & x \geq 0, y_\omega \geq 0 \end{aligned} \tag{13}$$

Eq. 13 is decomposed into master problem (Eq. 13a), and sub-problem (Eq. 13b). Advantage is taken of the dual properties of Eq. 13b by introducing a new variable θ to approximate $E_\omega[z_b]$ and iterating between master problem and sub-problem. The inequalities in Eq. 13a are the "cuts" that link the master problem and the sub-problem. d^l and e^l are coefficients for the Benders cut, and π_ω are the optimal dual vectors of constraint in the sub-problem for scenario ω.

$$\begin{aligned} Min \quad & z_a = c^T x + \theta \\ s.t. \quad & \theta \geq d^l x + e^l, l = 1,\ldots,L \\ & d^l = E_\omega[\pi^T_{l,\omega} T_\omega], \\ & e^l = E_\omega[\pi^T_{l,\omega} h_\omega], \\ & Ax = b, \quad x \geq 0 \end{aligned} \tag{13a}$$

$$\begin{aligned} Min \quad & z_b = q_\omega{}^T y_\omega \\ s.t. \quad & Wy_\omega = h_\omega - T_\omega x^* \\ & y_\omega \geq 0 \end{aligned} \tag{13b}$$

The Benders decomposition algorithm is described as follows:

Step 1: Set iteration counter $l = 1$ and $\theta = 0$.
Step 2: Solve master problem Eq. 13a to obtain a lower bound LB_l on the objective value z_a.
Step 3: Fix all the first-stage decisions at their optimum value x^* and solve Eq. 13b for each scenario sub-problem to get an upper bound $UB_l = E_\omega[z_b]$.
Step 4: Proceed to test if $[(UB_l - LB_l)/LB_l] <$ *Tolerance*, return the optimal solution, otherwise, set the iteration counter to
$l = l + 1$. Here tolerance is a pre-determined small value (e.g. < 0.5%) to determine the stopping criterion.
Step 5: Use the duals of the scenario sub-problem to add a Benders cut to Eq. 13a and return to Step 2.

Algorithm adopted from (Awudu and Zhang, 2012).

4.5. Identifying price relationships during hedging

In this section we discuss a novel way of defining corn and ethanol price relationships in our hedging process using a concept called copula. This price relationship between corn and ethanol is crucial as it provides the necessary and dependency for a better hedging position and strategy adaptation. This relationship identification and dependency is referred to as copula. The next section provides a brief overview of copula (Fernandez 2008).

4.5.1. Copula

Copula represents a powerful tool for decomposing the joint distribution into the marginal distribution and dependence structure that can be dealt with separately. One can choose the marginal distribution that best fits each data asset, and afterwards integrate everything using a copula function with some desirable properties. Copulas have been applied to the measurement of credit and market risk, in particular to the assessment of the Value at Risk (VaR) of a portfolio. It allows computation of VaR while avoiding the usual assumption of marginal and joint normality and linear correlation structure.

Implementation of copulas involves three steps including: 1) select and construct a copula, 2) estimate the parameters associated with the copula, and 3) sample from the parameterized copula. Copula parameters are estimated through a maximum likelihood estimation method of the form of

$$\hat{\delta}_2 = argmax_{\hat{\delta}_2} \sum_{t=1}^{T} \ln c\left(\hat{G}_x\left(x_t\right), \hat{H}_y\left(y_t\right), \delta_2\right), \quad (14)$$

where $\hat{\delta}_2$ is the estimated copula parameter, argmax is the mathematical functions that provides the argument associated with the maximum, ln is the natural logarithm, and $\hat{G}_x\left(x_t\right), \hat{H}_y\left(y_t\right)$ are the estimated marginal distributions for x and y. To avoid distributional assumptions, a non-parametric distribution is used for the marginal distributions. Schwarz Information Criteria (SIC) and Akaike Information Criteria (AIC) were utilized for selecting the most appropriate multivariate copula. AIC and SIC are superior goodness of fit statistics to other fit ranking criteria (e.g. chi-squared).

V. CASE STUDY

In this section, we focus on a case study involving an ethanol production plant. The case study will examine a hybrid-generation biofuel supply chain in the U.S. state of North Dakota (ND) which consists of 53 counties. ND has already established corn ethanol biorefinery plants because of the vast availability of corn feedstock (Martin, 1999; Muir et al., 2001). Studies such as (Zhang et al., 2013) show that ND is suitable for the commercial cultivation of both corn and cellulosic feedstock such as switchgrass. Raw materials are purchased from four supply sources. Feedstocks are pre-treated at the warehouse, and the pre-treated raw materials transported to the production facility. Four different biofuel refinery facilities convert the raw materials into end-products; two producing corn-based ethanol, and the other two plants for cellulosic-based ethanol. All the 53 counties in ND are considered as the demand zones.

5.1. Computational analysis

In this section we discuss the resulting solution by using a Multi-cut Benders Decomposition and SAA methods. The proposed optimization models are coded in General Arithmetic Modeling Software (GAMS). The models are solved by the commercial GAMS 26.3.5 version using a CPLEX solver. A Dell Latitude E6440 of processor speed 5.2 GHz is used. We arrived at a solution after 23.45 seconds as compared to an intractable solution without the algorithm using the GAMS 26.3.5 version with a CPLEX solver (generally about 2 hours before NEOS Report via the same computer). This demonstrates the superiority of the algorithm used. The results and subsequent sensitive analyses are presented in the next section. The input parameters used in the case study are provided in Tables 1 and 2. Values of other key input parameters can be referenced from Zhang et al. (2013).

TABLE 1. CORN ETHANOL PLANT DATA

Parameters	Values	Units
Cost of corn feedstock	MR (6.75,0.095)	$ (dollars)/bushel
Price of corn ethanol	MR (2.75,0.095)	$ (dollars)/gal
Corn ethanol demand	Based on county/month	gallons
Capacity of corn biorefinery plant 1	120,000,000	Gallons/yr
Capacity of corn biorefinery plant 2	120,000,000	Gallons/yr
Raw material transportation	0.0718/mile	$ (dollars)
Unit end-products transportation cost	0.0718/mile	$ (dollars)
Inventory holding cost for raw material	0.005	$ (dollars)
Inventory holding cost for end-product	0.005	$ (dollars)
Unit penalty cost for unmet demand	0.000285	$ (dollars)
Unit cost per processing	1.24/bushel	$ (dollars)

TABLE 2. CELLULOSIC ETHANOL PLANT DATA

Parameters	Values	Units
Cost of cellulosic feedstock	MR (3.8,0.095)	$ (dollars)/ton
Price of cellulosic ethanol	MR (2.75,0.095)	$ (dollars)/gal
Cellulosic ethanol demand	Based on county/month	gallons
Capacity of cellulosic biorefinery plant 1	120,000,000	Gallons/yr
Capacity of cellulosic biorefinery plant 2	120,000,000	Gallons/yr
Unit raw material transportation cost to plants	0.158/mile	$ (dollars)
Unit end-products transportation cost	0.158/mile	$ (dollars)
Unit inventory holding cost for feedstock	0.0155	$ (dollars)
Unit inventory holding cost for ethanol	0.15	$ (dollars)
Unit penalty cost for unmet demand	0.005	$ (dollars)
Unit cost per processing	1.24/ton	$ (dollars)

VI. RESULTS AND ANALYSIS

The analysis will be focused on the optimal (best) ethanol price adoptions (meaning prices of ethanol considered as good to sell ethanol and buy corn), logistics analysis (storage space for corn and ethanol) and cluster relationships (copula relationships) between corn and ethanol prices.

In this section, we outline the importance of using copula to develop an optimal level of price to sell ethanol. As discussed earlier, copula distributions allow the ethanol producer to understand price relationships that exist between futures and spot prices of ethanol by understanding the marginal relationships between ethanol spot and futures prices. This price marginal relationships help the ethanol producer to contract for the shipments of ethanol to customer destinations. A motivation for this analysis stems from ethanol sales price which are contracted using the basis price in normal market conditions and deliveries are made on time. Sometimes, deliveries may be late and are delivered at a futures market that is inverted. In this case it is typical that a late delivery is negotiated. To stimulate the impact of the profit margin variations with such delivered contracts, we conduct an analysis that determines the relationships between ethanol price and revenue margins. We assume an agreement between destination markets and ethanol producers that reduces transit time uncertainties by a factor φ , and transportation cost is reduced by $\Im$.

Assume demand for the product is normal, the new profit margin is expressed as: $E(\pi) = f(\varphi, \Im, D_{\xi,n})$. The equation suggests the margin function is dependent on demand, transportation cost, and transit time uncertainties. Analyses are conducted for the derived contract to determine the best price contract to sell ethanol and still maximize profit. For the base case, the ethanol price is reduced by 2 cents and transportation cost \$0.25 per mile. Fig. 1 presents the ethanol price analysis. The best price of ethanol contract ranges between \$2.34 and \$2.44 per gallon and corresponding to approximately five rail 5 cars per day. In summary the base case for the transit time has stochasticity and reducing this uncertainty increases the profit margin. We further simulated different margins and compare to the best contracted price for ethanol sale between the ethanol producer and buyer.

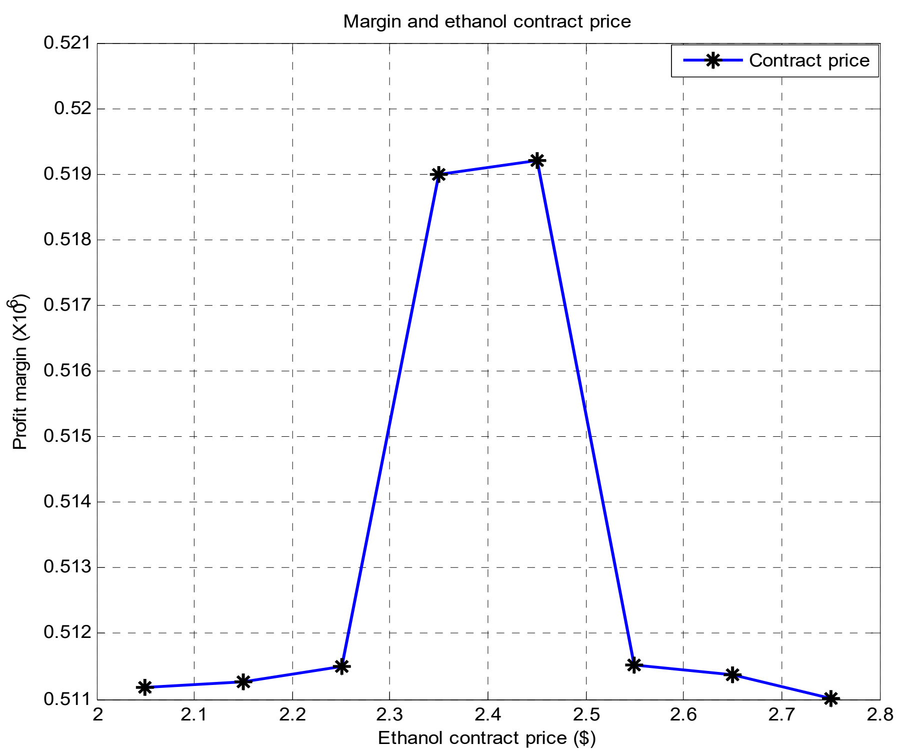

FIGURE 1. ETHANOL PRICE ANALYSIS.

6.1. Logistics analysis

Ethanol hedging process is influenced by logistics strategies including the number of storage space, rail car allocation for automotive, type of transportation routes, etc. It is therefore prudent to conduct a logistic analysis in one of these areas. We conduct a logistics analysis based on storage space available to the ethanol producer which can be termed as a lot size. This lot size calculation can be related to the previous analysis about uncertainties in demand, since demand and transit time impact profit margins. We consider storage cost on profit margins based on the number of days of storage. Number of days and ethanol capacity discounted equation for new facility is used. Fig. 2 illustrates the ethanol and corn storage capacity analyses respectively for variations in demand.

We note that for decreasing demand, ethanol storage shows stable profit of \$0.517M between storage days of 4 and 8 days. A different trend is realized if the demand decreases by 7.5% and 12.5%. Profit margins decrease to \$0.5145M for this period but there is a point of intersection which measures the breakeven that can result in optimal expected margin. This analysis concludes the importance of building new or adding extra storage for a certain profit margin.

Similar analyses are conducted for corn storage capacity (not shown). In addition, 35-38 days of storage for corn means profit margins become stable, with an increasing profit level between 20 and 32 days. This analysis means corn storage capacities lower than 25 to 30 days should consider building extra capacity. When demand is decreased, corn storage shows margins of \$0.515M and \$0.5145M between storage days of 4 and 8 days. Nonetheless, a similar trend is realized if the demand decreases between 9.5% and 12.5%. Profit margins decrease to \$0.513M. Corn storage analysis gives a similar trend as ethanol. It is concluded that extra capacity addition would result in increased profit for a period of demand trend and sales.

6.2. Storage (holding) cost impact on profit

In this section we conduct further sensitivity analysis between storage (holding) cost and ethanol margins. In the base case, the overall storage cost of input and output are incorporated. Inventory issues affect a significant portion of the decision-making process especially in determining safety stock and economic order quantities. Two decisions are made; short- and long-term inventory decisions. The analysis here is motivated by the provision of short-term inventory decision which involves the stochasticity of inventory costs as a result of the uncertainty in demand. This set of analyses is conducted for the overall cost of storage and how it impacts the profit margin.

We introduce a cost factor for the storage which determines how much cost is increased between \$2.2 and 3, where \$2.2 is the least cost increase and \$3 is the highest cost increase. The results show that a decrease in storage cost from a factor of \$2.6 to \$2.4 increases profit from \$0.5152M to \$0.5153M. Subsequent decrease between \$2.3 and \$2.25 factor of the overall cost increases the profit by 0.019%, which is from \$0.5154M to \$0.5155M. Interestingly, an increase in the cost factor \$2.6 to \$2.8 provides a stable profit margin between \$0.5152M and \$0.5151M. Further increase in cost between \$2.8 and \$2.9 does not affect profit margins significantly. This phenomenon is due to the stable cost of storage throughout the entire horizon and therefor the impact of the profit margins might be as a result of the fluctuating demand. The cost of storage varies from the base case to approximately 5%, 10%, 15%, and -5%, -

10%, -15%, to realize the impact of storage price changes and the corresponding demand uncertainties on profit margins. A realization of the profit margin is considered with a small variation or fluctuations in the storage cost. If the storage cost is higher, the impact is significant. Conclusions from this analysis indicate a small change in the storage costs corresponds to an insignificant profit margin. The opposite holds for this change, since there is a greater risk in profit reduction if storage cost changes are high. This analysis is shown in Figure 3 below.

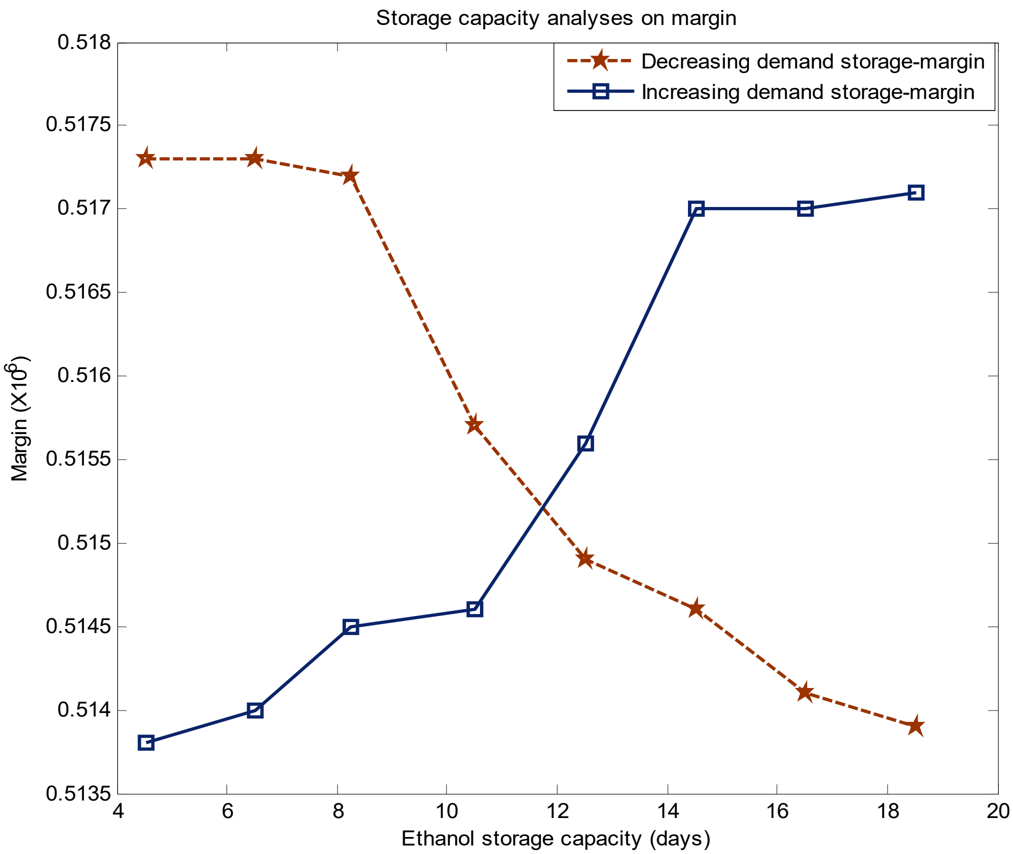

FIGURE 2. ETHANOL LOGISTICS ANALYSIS.

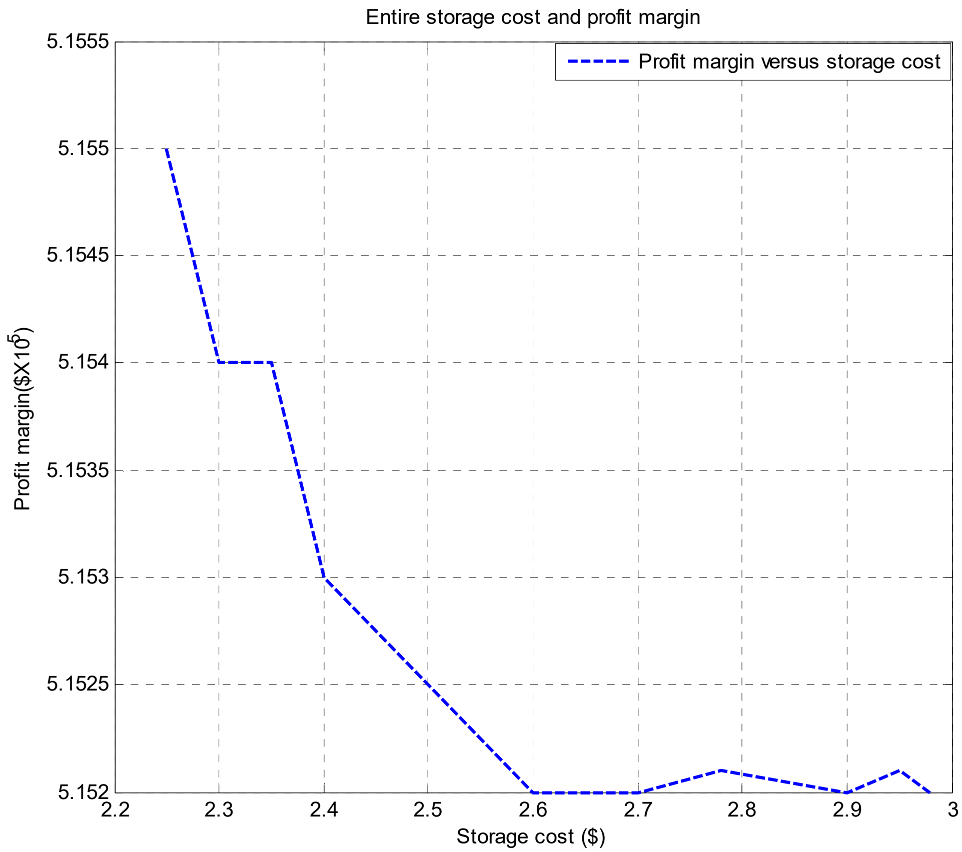

FIGURE 3. ETHANOL LOGISTICS ANALYSIS.

6.3. Price data (ethanol and corn) cluster analysis

In this section we consider insights from an analytical perspective by clustering both corn and cellulosic prices to help with hedge ratios during hedging. Hedge ratios are variable determinants that help an ethanol producer maximize the amount of corn/cellulosic feedstock to ethanol production to enable optimal use of production plant, scheduling, and other internal as well as external operations. Ethanol price data that were clustered over a period of 1000 scenarios indicated similar patterns as cluster of 10,000 data points for our analysis. This confirms that the sample average approximation (SAA) used conform to the theoretical assumption. The cluster diagram for the hedge ratios is shown in the Fig. 4. The SAA method will therefore give ethanol pricing analysts some leverage in identifying fewer trade patterns from a few data sets instead of relying only multiple data points.

In relation to the concept of copula, Figs. 5-6 confirm the analysis we conducted in Fig. 3. We see that based on the definition of copula (dependency and marginal relationships across variables), there is a relationship that follow the different types of dependencies between the corn and ethanol spot and futures prices respectively. In Figs. 4-5, the terms x_4 and x_3 represent the corn and ethanol copula distributions.

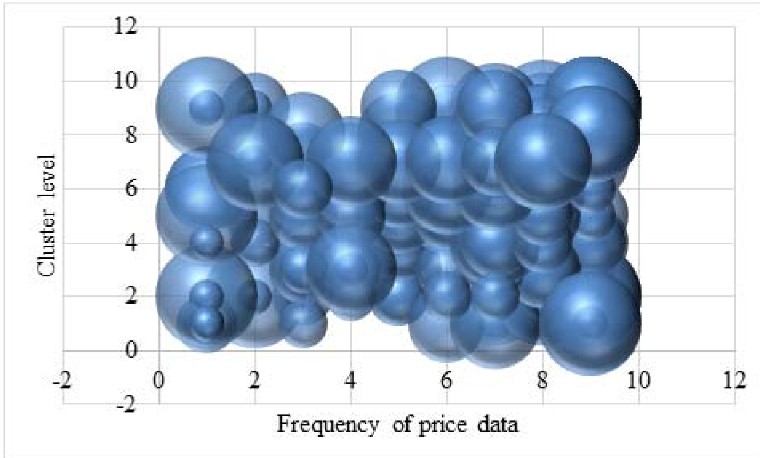

FIGURE 4. CLUSTER ANALYSES OF PRICE DATA POINTS.

In addition, although statistical and regression analysis provide a good indication of relationship between and across variables, we use copula to provides a better understanding of the independencies among prices instead of using correlation which is too simplistic or assumes a linear relationship. For instance, a good ellipse relationship can be demonstrated for the ethanol and corn spot, meaning that the prices of corn and ethanol have some relationship that can be calculated and some level of dependence structure between the two variables. However, a scatter set of relationships from a linear perspective might just give a simple relationship. This makes it clear that copula data analysis provides graphical relationships that are more meaningful for hedging against risk than the copula alone as shown.

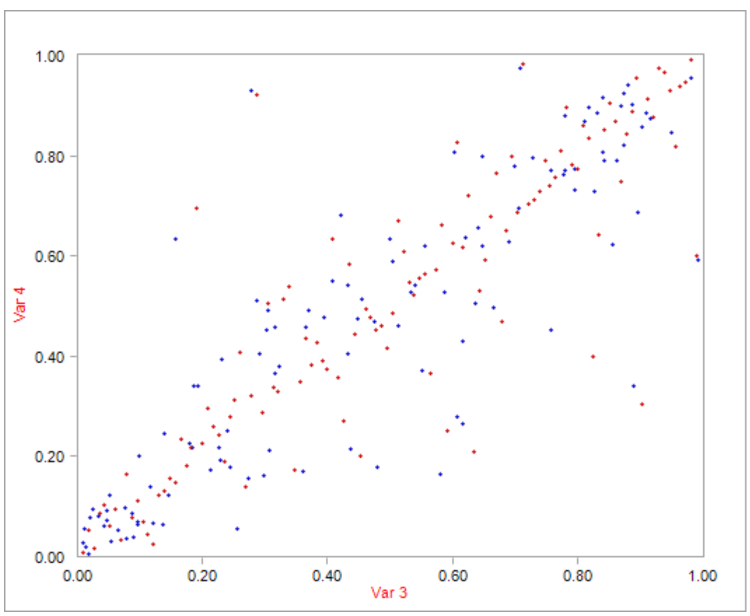

FIGURE 5. COPULA GRAPH BETWEEN ETHANOL FUTURES AND ETHANOL SPOT.

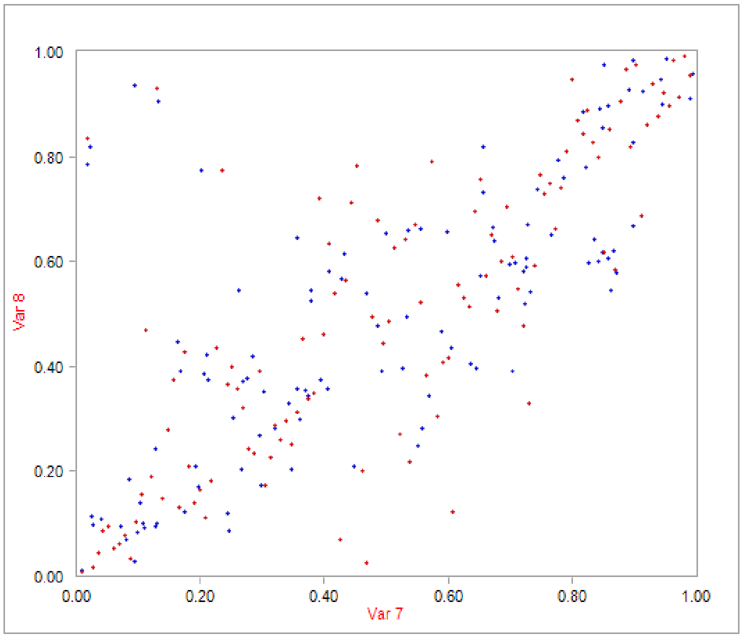

FIGURE 6. COPULA GRAPH BETWEEN CORN FUTURES AND ETHANOL SPOT.

VII. CONCLUSION AND SUMMARY

This paper develops a model that uses hedging strategies in a supplier (farmer) and buyer (ethanol producer) setting. We concentrate on the profit maximization on the side of the ethanol producer. The hedging method considers the futures and spot prices of corn and cellulosic feedstock respectively, while the ethanol end-products are hedged using futures. Non-hedging strategy uses spot prices for the purchase of feedstock and sale of end-products with cross hedging other end products using options and swaps for whichever price is higher.

We concentrate on the computational tractability of the algorithm to achieve better results by capturing the volatilities. A two-stage stochastic linear programming method based on the Multi-cut Benders Decomposition Algorithm is used to solve the resulting model. We analyze differences in profit margins in relation to hedging and non-hedging with the non-hedging being less than the hedging. We show that the profit values for the non-hedging at lower profits are observed to be riskier as compared to the profit values of the hedged decisions. By contracting using hedging positions such as futures and spot based on heuristic price levels, we indicate that the strategy provides a firm a competitive edge by reducing exposure to demand and price uncertainties.

Similarly, we reduce the impact of production costs with the aim of reducing the adverse effects associated with fluctuations in the firm's expected profit or cost. We conclude that by capturing volatility using a weighted sample average approximation for different periods of corn feedstock and ethanol prices, which are assumed to follow a Mean Reversion (MR) process, realistic results are obtained from the case study analysis. Counter intuitively, we determine that an ethanol price margin of \$2.06-\$2.41 per gallon will allow ethanol producers to make profit or at least break-even.

Finally, this model can be used in most if not all energy processing environments, i.e. production or processing environment that convert inputs to outputs, such as converting crude oil to gasoline, kerosene and other co-products. For example, in this case, corn is bought from elevators according to a contractual agreement that spans a period of supply and production is done daily with storage capacity for the ethanol. Also, the production is for a future month being hedged. To some extent, the availability of other commodity materials within ethanol production such as corn oil, DDGs, affect the decision-making process of buying corn and selling ethanol. Similar analyses can also be drawn from the conclusions in this manuscript for other energy sectors such as hydro, wind, etc.

This paper is limited in its scope by not incorporating uncertainties and dynamic hedging scenarios that include transportation challenges. Also, newer transportation models and traveling distances such Riemannian manifolds will be a good a future direction. One other limitation is stochastic inventory models based on periodic and or continuous inventory management. Also, ethanol transportation involves the use of rail cars that can be owned, leased, sub-leased or purchased by an ethanol producer. These rail car strategies affect ethanol transportation costs and therefore do affect ethanol margins. Finally, using other clustering methods to gather data for copula distribution and analyses will be the way to go as algorithms such as CoCluster (combining copula and cluster analysis) from a big data perspective will be a good research direction soon.

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