Bioenerg. Res. (2016) 9:1053–1069
DOI 10.1007/s12155-016-9743-1

Financial Risk Assessment and Optimal Planning of Biofuels Supply Chains under Uncertainty

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Published online: 12 May 2016

Abstract Biofuels provide an attractive alternative for satisfying energy demands in a more sustainable way than fossil fuels. To establish a biorefinery, an optimal plan must be implemented for the entire associated supply chain, covering such aspects as selection of feedstocks, location, and capacity of biorefineries, selection of processing technologies, production amounts and transportation flows. In this context, there are several parameters, including the availability of biomass, product demand, and product prices, which are difficult to predict because they might change drastically over the different seasons of the year as well as across years. To address this challenge, this work presents a mathematical programming model for the optimal planning of a distributed system of biorefineries that considers explicitly the uncertainty associated with the supply chain operation as well as the associated risk. The potential of the proposed approach is demonstrated through its application to the production of biofuels in Mexico, considering multiple raw materials and products.

Electronic supplementary material The online version of this article (doi:10.1007/s12155-016-9743-1) contains supplementary material, which is available to authorized users.

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Keywords Biorefineries · Biofuels · Optimization · Supply chains · Financial risk · Uncertainty

Introduction

In the recent past, biomass has gained considerable attention as feedstock for the production of several products, especially for energy production through biorefineries [1]. Biofuels can be produced from selected agricultural biomass, proving a sustainable and eco-friendly energy option [2]. The implementation of biorefineries requires the analysis of several aspects, especially the biomass yield on the farm and the fuel production in the biorefinery because these two factors are the most powerful in determining the efficacy of a biofuel production system [3]. Other important factors include feedstock selection, processing routes, products, harvesting sites, processing facilities, and markets, which can be addressed through the optimization of the corresponding supply chain [4]. According to Georgiadis et al. [5], most of the reported approaches for designing supply chains have addressed decisions about the location of new facilities, selection of technologies, feedstocks, products, and distribution of feedstocks and products. In the context of biorefineries, several works on supply chain design have been developed. This way, Van Dyken et al. [6] presented a mixed-integer linear programming model (MILP) for designing biomass-based supply chains. Natarajan et al. [7] developed a model to determine the optimal locations of processing plants for methanol production. Shabani and Sowlati [8] studied the supply chain configuration of a forest biomass power plant. Lin et al. [9] presented a supply chain optimization model to minimize the annual bioethanol production cost, simultaneously considering strategic and tactical decisions. Additionally, a mathematical approach for the optimization of operational decisions and profits in the supply chain design was proposed by Yue and You [4]. Taking another tactic, Tong et al. [10] presented an approach for the optimal design of an advanced hydrocarbon biofuel supply chain integrated with existing petroleum refineries under uncertainty. Recently, Park et al. [11] studied the effect of the emission carbon cost on the supply chain structure and social welfare. Additionally, a deterministic mathematical programming model for the strategic planning of a supply chain based on biodiesel production from microalgae was developed by Ahn et al. [12]. The efficiency of producing biodiesel from microalgae was studied by Sharma et al. [13]. Additionally, Iglesias and Sesmero [14] evaluated the viability of ethanol production in Brazil, considering the net present value as objective. However, according to Elia and Floudas [15], contributions are lacking regarding the production of multiple products, storage in different facilities and distribution of energy products from processing facilities to distribution centers and consumers. In this context, according to the scheme for biofuel production presented by Zamboni et al. [16], the steps from the harvesting sites to biofuel production are known as upstream, while the steps from the processing facilities to consumers are known as downstream.

Most of the works mentioned above optimize the economic performance of the supply chain as a unique objective. However, several objectives may be considered in the analysis [17]. Multi-objective optimization is well suited for supply chain design problems in which more than one objective must be considered. In a seminal work, Mele et al. [18] integrated environmental aspects in the design of sugar cane supply chains using MILP modeling techniques. Their MILP problem was later used by Kostin et al. [19] to identify redundant environmental objectives in the design of biorefineries. Koltsaklis et al. [20] presented a mixed integer linear programming model for the optimal planning of a national power generation system, showing the trade-off between two objectives: the total cost of the electricity production system and total CO_2 emissions.

A mathematical model including economic, environmental and social aspects was developed by Ng and Lam [21]. Additionally, Čuček et al. [22] proposed a simplified and practical version of an objective dimensionality reduction method within a multi-objective optimization framework. Recently, Zhang et al. [23] proposed a multi-objective optimization framework for the optimization of a sustainable supply chain, considering the total cost and greenhouse gas emissions. In addition, Santibañez-Aguilar et al. [24] and You et al. [25] presented mathematical models capable of considering economic and environmental issues as well as the number of jobs produced, as a social objective. Additionally, Yu and Goh [26] developed a multi-objective approach that includes supply chain visibility and supply chain risk and cost as objective functions.

Most of the models mentioned above assume nominal parameter values and therefore lead to solutions that perform well in the most likely scenario but poorly under other conditions. Hence, uncertainty is an important aspect to take into account in the supply chain design problem, as several uncertainty sources affect biomass conversion. In this context, the use of uncertain models in supply chain management problems is a natural extension of the traditional deterministic approach. There are two main methods for optimization under uncertainty: stochastic programming and robust optimization (see [27] for more details). In the area of supply chain management, substantial research has been conducted on the development of optimization models that can handle several uncertain parameters. Demand has been the most studied uncertainty source [28]. Other models have focused on environmental uncertainties (see [29]). In addition, McCarty and Sesmero [30] considered the importance of price risk for investment in a biofuel plant under an uncertain product price. Unfortunately, the inclusion of uncertainties leads to more complex problems and therefore larger CPU times [31].

Most optimization models under uncertainty optimize the expected value of the objective function distribution. This approach provides no control over the performance of the system in the full uncertain parameter space. One possible means to overcome this limitation is to append a risk metric to the objective function and carry out a multi-objective optimization. In a seminal work, Guillen et al. [28] applied risk management tools to the supply chain design problem. Guillen-Gosalbez et al. [32] proposed a model for designing supply chains that maximizes the expected profit; they also included the probability of not meeting a target profit level, known as financial risk, as an additional criterion to be optimized. Additionally, Kostin et al. [19] developed an approach for the design of supply chains under uncertainty that considers the risk associated with the uncertain demand. Sahling and Kayser [33] proposed a strategy to determine the supply chain configuration for a long planning horizon to meet a given service level, considering uncertainty in demand. In addition, Akbari and Karimi [34] presented a robust optimization approach for the planning of a supply chain taking into account uncertainty in the production capacity requirements. Gholamian et al. [35] proposed a mathematical approach for the production planning of a supply chain under uncertain demand, using as a solution a fuzzy multi-objective optimization model.

None of these previous works considered the uncertainty in raw material prices, which is investigated in this paper. Therefore, this paper proposes a mathematical model to design entire supply chains considering uncertainty in the prices of raw materials and the management of the associated risk.

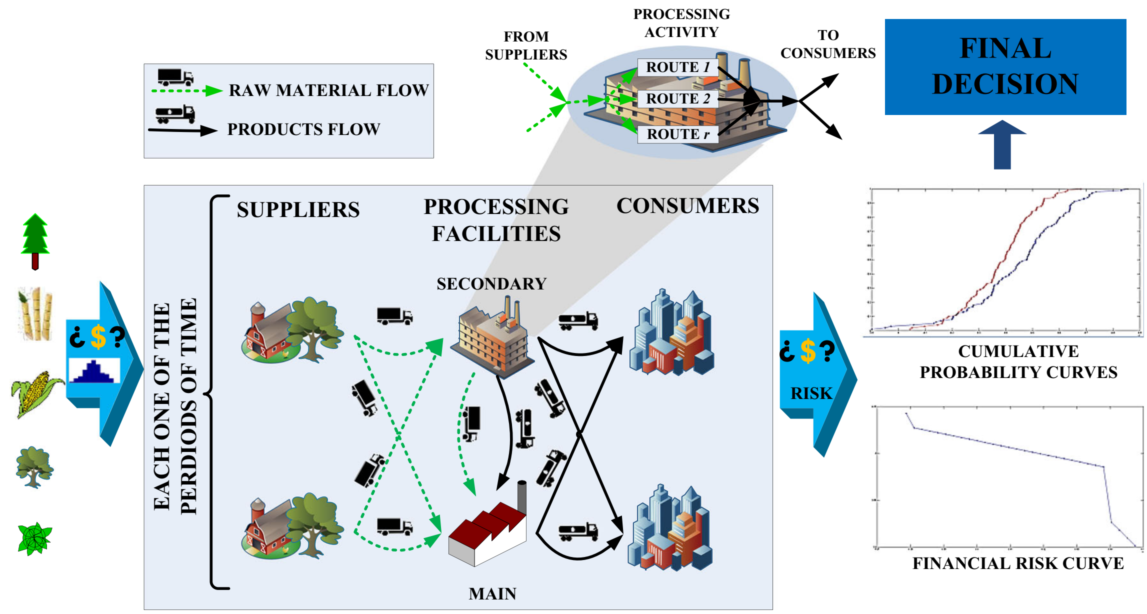


Fig. 1 Superstructure for the proposed methodology

The potential of the presented approach is illustrated through its application to a case study that addresses the design of a supply chain in Mexico. The paper is organized as follows: "Problem Statement" , "Model Formulation", "Results and Discussion", and "Conclusions".

Problem Statement

The problem addressed in this paper is the optimal planning of a distributed supply chain based on biomass conversion considering the dependence over time of the involved variables as well as the uncertainty associated with the price of raw materials. As shown in Fig. 1, the distributed system takes into account a set of suppliers, processing facilities and consumers. The time horizon is divided into time periods of equal length. In every period, decisions on the distribution of raw materials and products, the processing of feedstock, and the selling of final products must be made considering uncertain future prices.

The problem we aim to solve can be formally stated as follows: We are given the availability of the raw material, the upper and lower limits for the capacity of the

Fig. 2 Distribution of raw material prices using the geometric Brownian motion

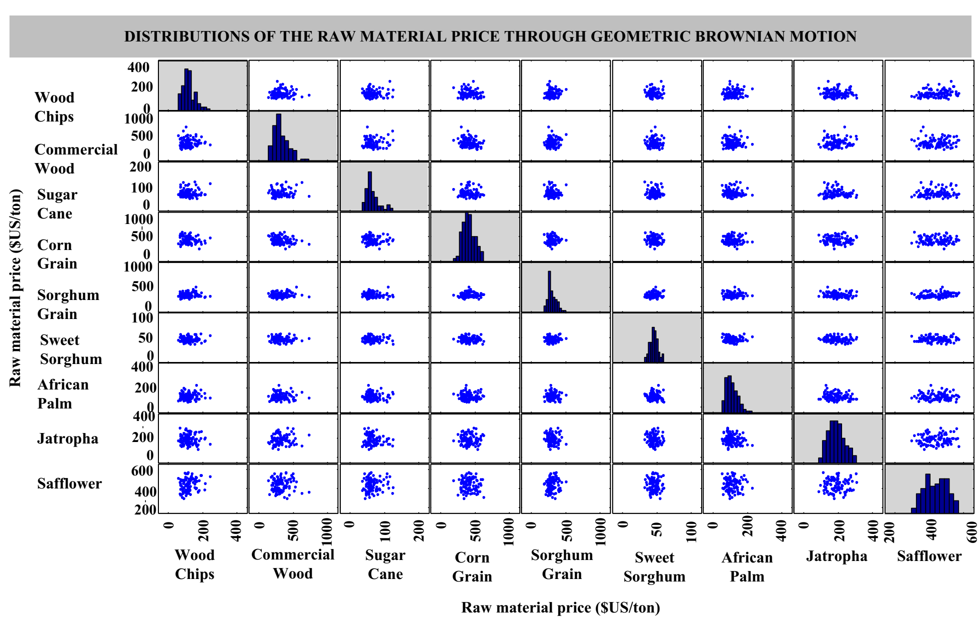


Table 1 Historical information on raw material prices and statistical data for the geometric Brownian distribution (with prices in $US/t)

Year	Wood chips	Wood	Sugar cane	Corn grain	Sorghum grain	Sweet sorghum	African palm	Jatropha	Safflower
2002	28.59	57.19	50.57	240.63	123.52	27.78	21.89	43.43	184.21
2003	44.62	89.24	42.36	197.53	120.18	25.07	34.16	67.76	210.53
2004	36.59	73.19	38.29	190.60	117.74	25.73	28.02	55.58	208.61
2005	32.79	65.57	33.36	237.31	109.83	27.14	25.11	49.80	207.12
2006	38.54	77.09	47.24	199.92	143.55	28.53	29.51	58.54	214.40
2007	70.09	140.18	34.90	242.58	176.09	30.80	53.67	106.45	216.10
2008	53.97	107.93	57.95	261.30	207.36	37.98	41.32	81.96	332.57
2009	53.40	106.79	38.97	211.26	159.96	29.17	40.89	81.10	310.91
2010	80.06	160.13	52.36	245.90	179.73	34.81	61.31	121.60	343.97
2011	88.87	177.74	47.79	295.01	277.60	40.08	68.05	134.97	449.91
2012	86.60	173.20	58.23	357.57	259.12	39.84	66.31	131.52	459.59
Mean log normal	0.192	0.142	0.096	0.066	0.070	0.059	0.242	0.092	0.062
Std log normal	0.290	0.290	0.302	0.177	0.202	0.139	0.290	0.290	0.152
2014	98.95	252.85	50.01	372.83	214.41	31.54	95.32	151.61	315.29

processing plants, the transportation limits, the set of products to be produced, the set of the raw material to be selected as well as several scenarios for the raw material pricing; the goal of the analysis is to find the optimal supply chain configuration, including the associated planning decisions that optimize the expected economic performance and minimize the associated risk.

Model Formulation

The mathematical model is composed of mass balance constraints, capacity limitations, and objective function equations. The notation employed is as follows: Index h represents the harvesting sites involved in the distribution system, index ph denotes the processing facilities where the biomass is processed, and index mk is used for the consumers of products. Furthermore, index m represents the different raw materials, while k is used for the products considered. In addition, index r is defined for the processing routes used in plants, while index q denotes the economies of scale for the different processing facilities. Finally, index t represents the time periods and index s the uncertain scenarios.

The model is a two-stage stochastic programming model in which first-stage variables represent the network topology while second-stage variables denote planning decisions. A set of scenarios with equal probability of occurrence are considered. Without loss of generality, the parameter values in each scenario are generated via sampling on probability functions. The full set of mass balances and constraints of the model are described in detail in the supplementary material. In essence, the model contains continuous and binary variables. The continuous variables model decisions regarding amounts of raw material and products to be transported, processed or produced as well as inventory levels for the materials involved in the supply chain. The binary variables represent the selection of a level of capacity, processing technology, an interval for the processing, and other sets of constraints. The availability of raw materials, maximum product demand, and transportation and processing limits are used to limit

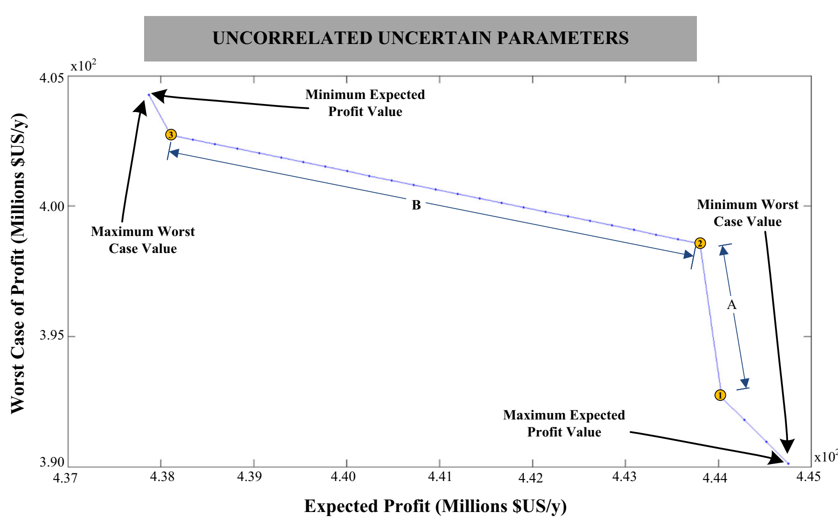
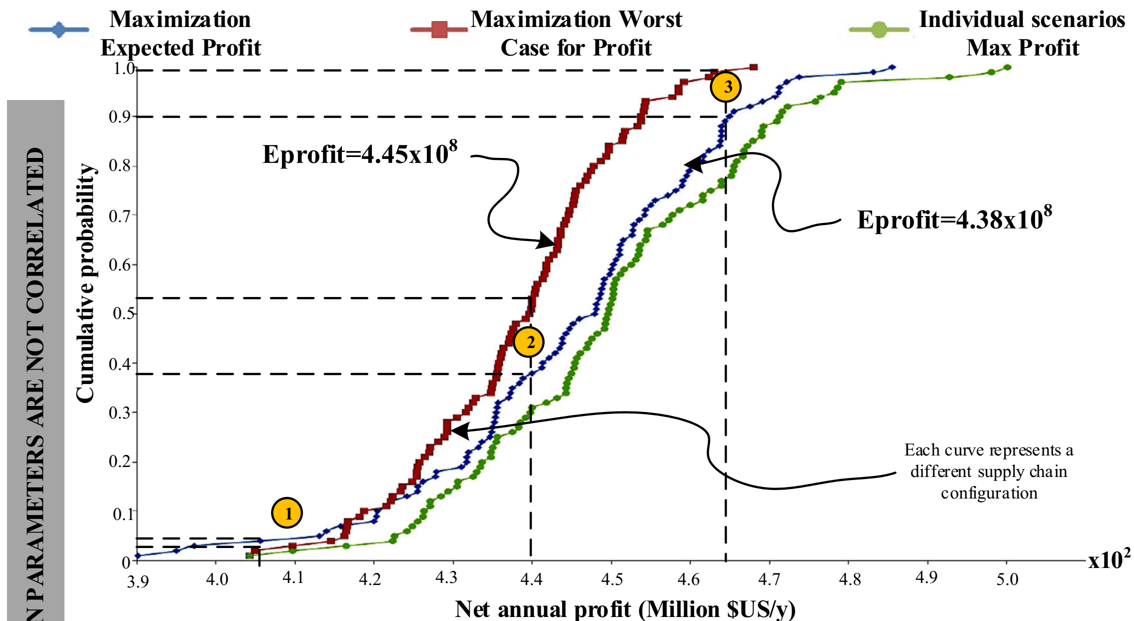


Fig. 3 Pareto curve showing the financial risk for the implementation of a supply chain topology for the uncorrelated data (Expected Profit vs Worst Case for Profit)



Probability of obtaining a value of net profit... (1)	Net Profit: 4.05x10² Millions $US/y — At least	Max	Probability of obtaining a value of net profit... (2)	Net Profit: 4.4x10² Millions $US/y — At least	Max	Probability of obtaining a value of net profit... (3)	Net Profit: 4.65x10² Millions $US/y — At least	Max
Alternative with the highest economic risk	95 %	5 %	Alternative with the highest economic risk	62 %	38 %	Alternative with the highest economic risk	10 %	90 %
Alternative with the lowest economic risk	97 %	3 %	Alternative with the lowest economic risk	46 %	54 %	Alternative with the lowest economic risk	1 %	99 %

Fig. 4 Cumulative probability curves for the uncorrelated distribution

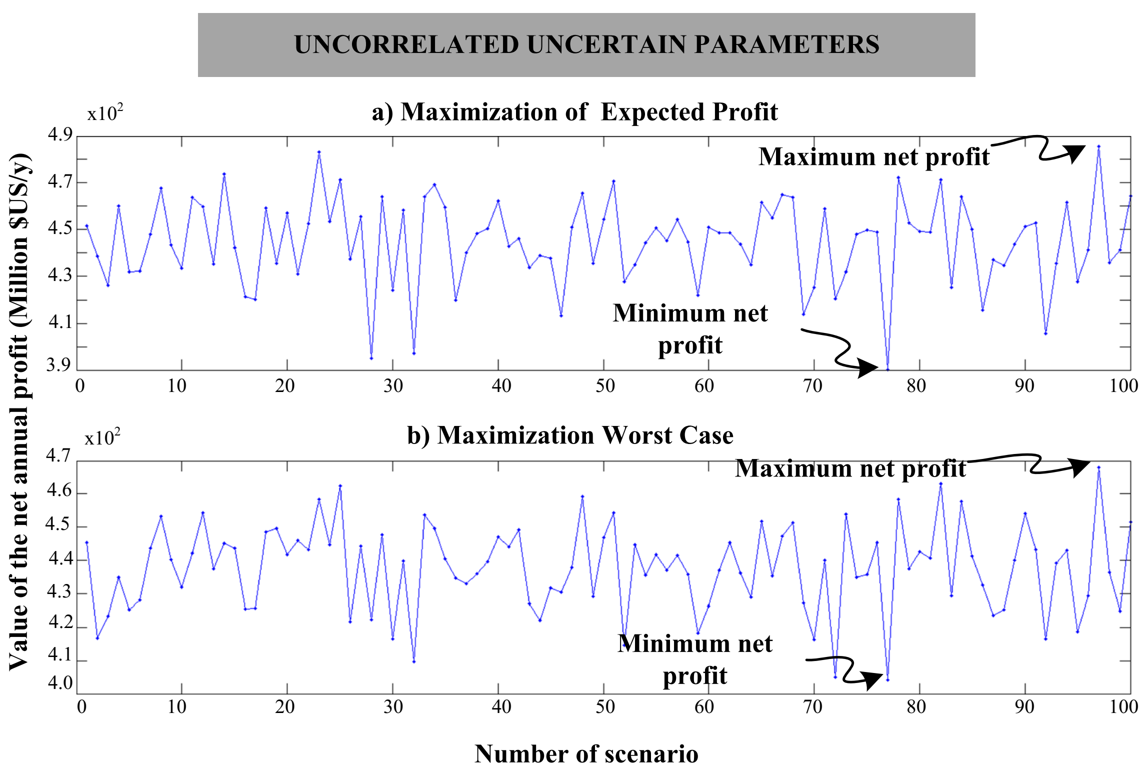


Fig. 5 Net annual profit for each scenario for the highest and lowest risk solutions for the uncorrelated distribution

Table 2 Raw material prices for the scenarios with the highest and lowest profit value in the uncorrelated distribution

	Scenario 77		Scenario 97		Min value $US/t	Mean value $US/t	Max value $US/t
	Value $US/t	% to mean	Value $US/t	% to mean			
Wood chips	189.91	60.01	71.18	−40.03	58.73	118.69	244.09
Wood	307.70	−4.26	430.97	34.10	138.80	321.38	730.49
Sugar cane	52.66	−18.96	97.03	49.33	34.76	64.98	125.28
Grain corn	356.73	−12.16	378.79	−6.73	179.16	406.13	620.77
Sorghum grain	265.75	−10.74	303.12	1.81	184.79	297.73	500.20
Sweet Sorghum	59.10	29.17	50.37	10.10	32.11	45.75	60.04
African Palm	179.74	63.39	71.88	−34.66	50.46	110.01	228.73
Jatropha	199.28	5.05	164.25	−13.42	86.70	189.70	308.06
Safflower	539.31	22.77	497.16	13.18	296.24	439.28	570.67

the values of the continuous variables and define the values of the binary variables. Concerning the objective function, the model must optimize two different objectives: the expected profit and a risk metric that allows for control of the variability of the profit distribution in the scenarios considered in the analysis.

Objective 1: Expected Profit

The expected profit (E[profit]) is the first objective function, calculated as the sum of the individual values of the net annual profit in each scenario (Profit_s) multiplied by the corresponding probability of occurrence (Prob_s):

$$\text{E[profit]} = \sum_s \text{Prob}_s \cdot \text{Profit}_s \quad (1)$$

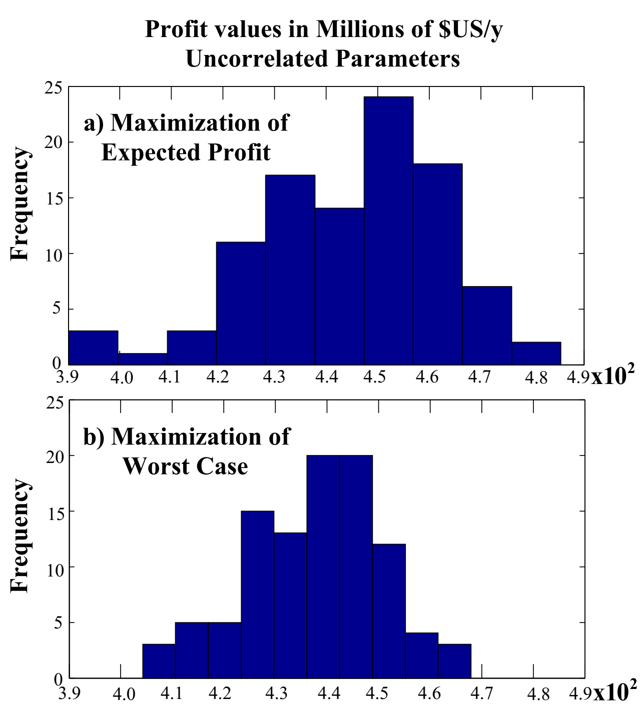


Fig. 6 Frequency histogram for the net annual profit for the highest and lowest risk solutions for the uncorrelated distribution of raw material prices

Objective 2: Worst Case for the Net Annual Profit

To control the variability of the objective function in the uncertain parameters space, we incorporate in the objective function the worst case for the net annual profit (WC), defined as the smallest value of the net annual profit across all scenarios (Profit_s):

$$\text{WC} \leq \text{Profit}_s, \quad \forall s \in \text{SCENARIOS} \quad (2)$$

The model can be expressed in compact form as follows:

$$\begin{aligned} &\max\{\text{E[profit]}, \text{WC}\} \\ &s.t.\, h(x, y) = 0 \\ &g(x, y) \leq 0 \\ &x \in \mathbb{R}, y \in \{0, 1\} \end{aligned}$$

where x represents the continues variables such as the amount of feedstock, the number of products and the inventory levels; and y represents the binary variables for the selection of processing capacity, the interval for the transportation amounts, and the processing technology. The model can be solved using any standard multi-objective optimization algorithm. In this work, without loss of generality, we apply the epsilon-constraint method because it is possible to generate information regarding both of the objectives and their solutions. The method is based on solving the original problem considering only one objective subject to several lower-limit values for the other objective, thus obtaining the complete Pareto curve.

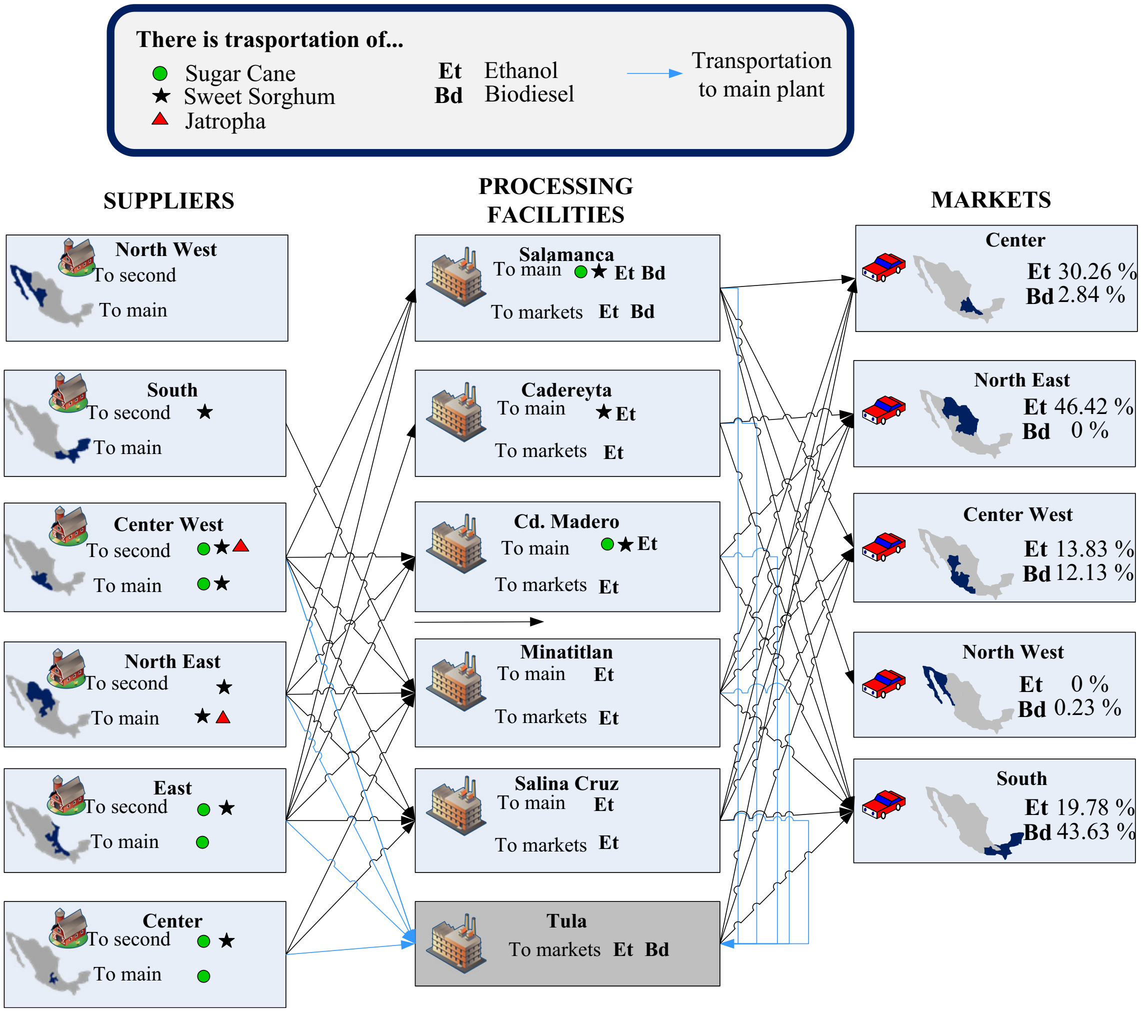


Fig. 7 Configuration of the supply chain for the riskiest solution for the uncorrelated raw material prices

Results and Discussion

The mathematical model is applied to two case studies for biofuel production in Mexico. Both cases consider as uncertain parameters the price of raw materials. However, in the first case, the raw material price is modeled through a geometric Brownian motion that assumes uncorrelated uncertain parameters. Details on how to implement this method are provided in the supplementary materials. In the second case, the uncertain parameters follow correlated multi-variate lognormal distributions. The mean and variance values for both distributions are based on historical information from the Mexican Ministry of Agriculture [36]. The case studies consider 9 raw materials whose production involves 6 different distributed suppliers, 4 processing routes, 5 distributed secondary processing plants, and 1 centralized processing facility. Furthermore, biodiesel and bioethanol are the main products to be distributed in 5 consumption regions. A time horizon of 1 year divided into 12 months is considered.

Distribution of Raw Material Price Without Correlation

Figure 2 shows the distribution of the raw material prices determined through the geometric Brownian motion. In this case, no correlation exists between parameters. Table 1 shows the values for raw material prices based on historical information and the prediction for 2014, which is taken as a reference year. Additionally, the mean and standard deviation for the lognormal distribution are shown.

The model was implemented in the GAMS software as a mixed integer linear programming problem and solved with the solver CPLEX. The model contains 53,194 continuous variables, 18,320 binary variables, and 67,268 equations. Depending on the instance being solved, the solution time

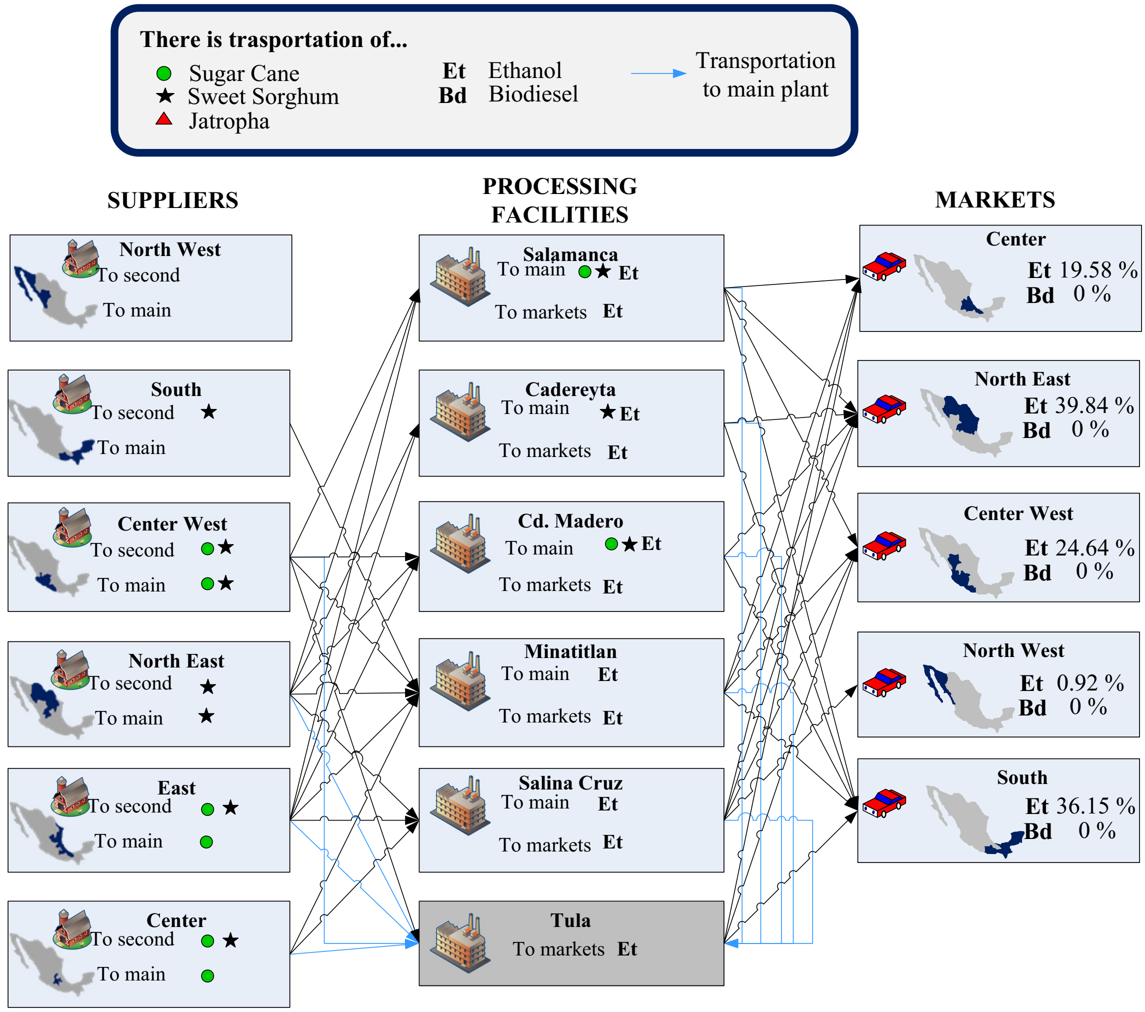


Fig. 8 Configuration of the supply chain for the solution with the lowest risk for the uncorrelated raw material prices

ranges from 17 to 29 s on a computer with processor Intel Core i7-4700 MQ at 2.4 GHz with 24 GB of RAM.

Figure 3 shows the Pareto curve that trades off the expected profit versus the worst case. As is evident, the worst cases (minimum profit over all scenarios) can be improved but at the expense of the expected performance, which can be identified in several sections on the Pareto curve. Each point of Fig. 3 represents a different configuration of the supply chain and may be associated with a risk curve (described later in this section).

Figure 4 shows the cumulative probability curves for the uncorrelated distribution associated with the maximum expected profit solution and the maximum worst case solution (minimum risk solution). The figure also shows an upper bound curve that has been constructed from the optimal profits attained in each scenario. Hence, the upper bound curve does not reflect any realistic solution but rather an ideal case, suggesting a wait-and-see strategy. As is evident, the probability of obtaining at least a given value of profit is different for each solution. For comparison purposes, let us look at three profit targets: 4.05×10^2, 4.4×10^2, and 4.65×10^2 million \$US/year, for which the probabilities of obtaining a lower profit value with the riskiest curve are 5, 38, and 90 %, respectively, and in solutions with a minor risk, 3, 54, and 99 %, respectively. In other words, there is a larger probability of getting a high

Table 3 Percentage of fulfilled demand for products for the highest and lowest risk solutions in the uncorrelated distribution

Product	Consumer	Required demand $\times 10^6$ t	High risk % Fulfilled	Low risk % Fulfilled
Ethanol	Center	1.21	30.26	19.58
	North east	0.54	46.42	39.84
	Center west	0.76	13.83	24.64
	North west	0.64	0.00	0.92
	South	0.47	19.78	36.15
Biodiesel	Center	0.26	2.84	0.00
	North east	0.13	0.00	0.00
	Center west	0.20	12.14	0.00
	North west	0.17	0.23	0.00
	South	0.13	43.63	0.00

Table 4 Amount of biomass used for the highest and lowest risk solutions

	Raw material	Supplier	Amount used ($\times 10^6$ t)	Maximum available ($\times 10^6$ t)	% Used
Highest risk solution	Sugar cane	Center west	0.02	8.39	0.29
	Sugar cane	East	0.40	27.12	1.46
	Sugar cane	Center	0.21	1.87	11.23
	Sweet sorghum	South	0.01	0.01	100.00
	Sweet sorghum	Center west	0.36	1.00	36.33
	Sweet sorghum	North east	0.35	1.65	21.38
	Sweet sorghum	East	0.05	0.05	100.00
	Sweet sorghum	Center	0.02	0.02	100.00
	Jatropha	Center west	0.12	0.53	22.50
	Jatropha	North east	0.15	0.53	28.12
Lowest risk solution	Sugar cane	Center west	0.02	8.39	0.29
	Sugar cane	East	0.40	27.12	1.46
	Sugar cane	Center	0.21	1.87	11.23
	Sweet sorghum	South	0.01	0.01	100.00
	Sweet sorghum	Center west	0.36	1.00	36.33
	Sweet sorghum	North east	0.35	1.65	21.38
	Sweet sorghum	East	0.05	0.05	100.00
	Sweet sorghum	Center	0.02	0.02	100.00

profit value with the maximum risk solution, but there is also a larger probability of getting a low profit value with the minimum risk solution.

Figure 5 presents the net annual profit of each scenario for the maximum expected profit and worst case solutions. As is evident, the maximum profit values are given at the 97th scenario, while the minimum net profit values are given at the 77th scenario for both cases. For the maximum risk solution, the maximum net profit is equal to 4.86×10^2 million $US/year, the worst case is equal to 3.90×10^2 million $US/year, and the expected profit is equal to 4.45×10^2 million $US/year. Meanwhile, for the minimum risk solution, the maximum net profit is equal to 4.68×10^2 million $US/year, the worst case profit is equal to 4.04×10^2 million $US/year, and the expected profit is equal to 4.38×10^2 million $US/year.

Table 2 shows the raw material prices for the two scenarios (the 77th and 97th) as well as information with respect to the minimum, maximum, and mean values. Thus, scenario 97 has a

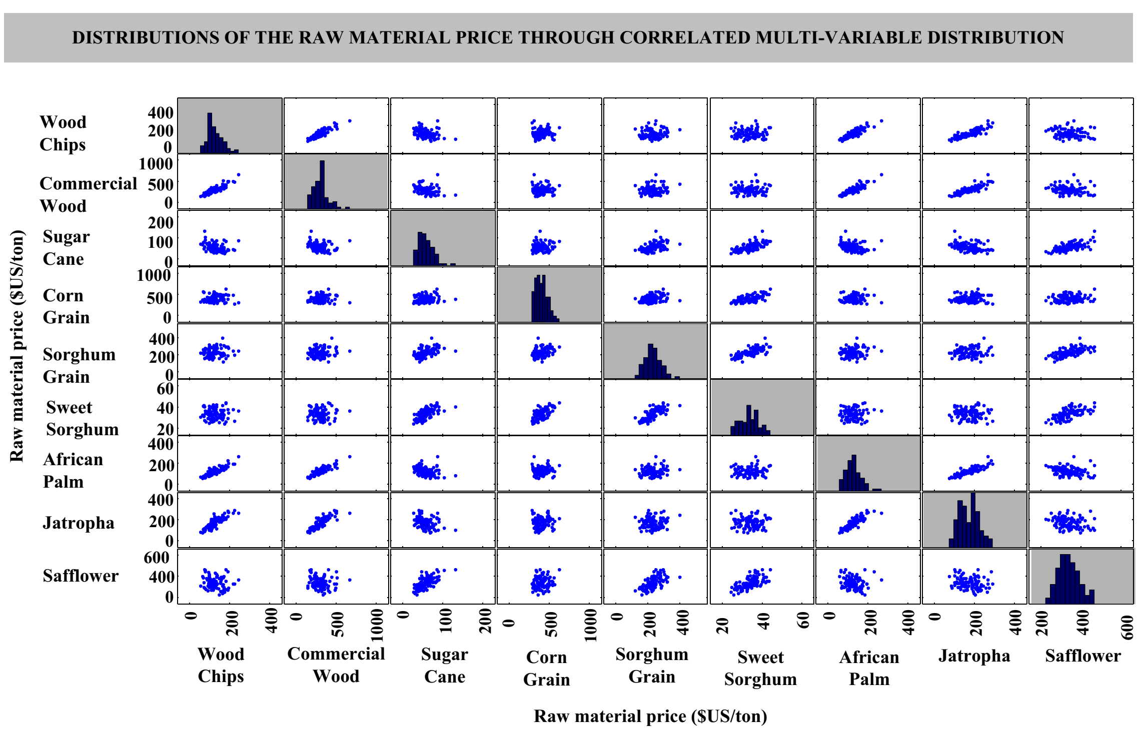


Fig. 9 Distribution of the raw material prices through correlated multi-variable normal random distribution

Table 5 Correlation matrix for the correlated distribution

	Wood chips	Wood	Sugar cane	Corn grain	Sorghum grain	Sweet sorghum	African palm	Jatropha	Safflower
1	1.00	0.90	−0.27	0.04	0.23	−0.01	0.90	0.90	−0.20
2	0.90	1.00	−0.27	0.04	0.23	−0.01	0.90	0.90	−0.20
3	−0.27	−0.27	1.00	0.09	0.30	0.64	−0.27	−0.27	0.59
4	0.04	0.04	0.09	1.00	0.30	0.62	0.04	0.04	0.16
5	0.23	0.23	0.30	0.30	1.00	0.68	0.23	0.23	0.52
6	−0.01	−0.01	0.64	0.62	0.68	1.00	−0.01	−0.01	0.64
7	0.90	0.90	−0.27	0.04	0.23	−0.01	1.00	0.90	−0.20
8	0.90	0.90	−0.27	0.04	0.23	−0.01	0.90	1.00	−0.20
9	−0.20	−0.20	0.59	0.16	0.52	0.64	−0.20	−0.20	1.00

sugar cane price significantly above the mean value, a jatropha price under the mean value and a sweet sorghum price above the mean value. In contrast, scenario 77 presents a sugar cane price significantly under the mean value, a jatropha price near to the mean value, and a sweet sorghum price above the mean value. It is worth noting that the solution produced by the model selects these raw materials (see Figs. 5 and 6), perhaps because the price of jatropha is under the mean value at scenario 97 and the price of jatropha at scenario 77 is only 5.05 % higher with respect to the mean value, while the other prices of raw materials for producing biodiesel range from 22.77 % higher than the mean value (safflower) to 63.39 % higher than the mean value (African palm). The same case works for the price of sugar cane. In addition, the price of sweet sorghum in both cases (the 77th and 97th) is always larger than the mean value, although the price is lower than other raw materials.

Figure 6 shows the frequency histogram for the net annual profit of the different analyzed cases. Figure 5a, b shows that the best profit value in the maximization of the expected profit is larger than the best profit value in the maximization of the worst case; however, the worst profit value in Fig. 5a is lower than the worst profit value in Fig. 5b.

Additionally, Fig. 7 shows the configuration of the supply chain for the maximum expected profit solution. Importantly, the supplier located in the North West region is not selected in any case because that region is too far from the others and the transportation cost increases significantly. In addition, notice that biodiesel is produced only in Salamanca and Tula, mainly because these processing facilities are located in the center of the country and the biodiesel is easily distributed to the different consumers. Notice also that the raw materials for bioethanol production are sugar cane and sweet sorghum and, for biodiesel, mainly jatropha.

The supply chain configuration for the maximum WC solution is presented in Fig. 8. It is worth noting that the North West supplier is not selected in any case; furthermore, no biodiesel production occurs in any processing facility. Additionally, some of the interconnections in the supply chain change. For example, in this configuration,

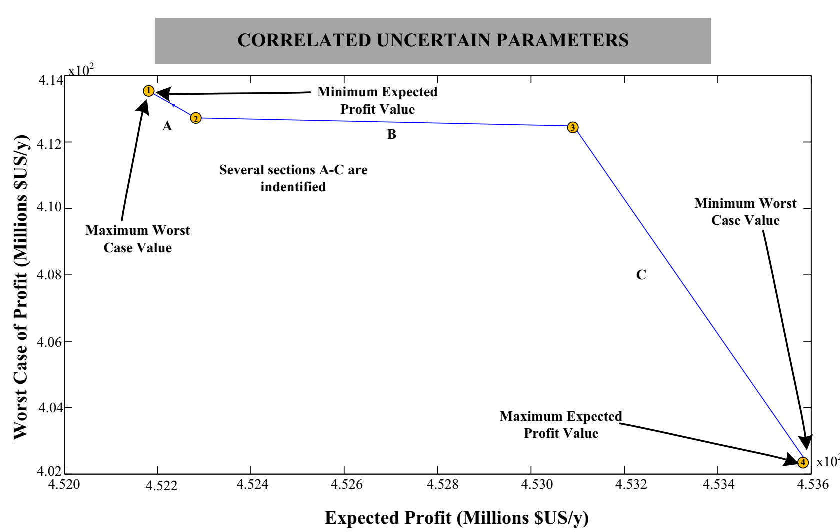
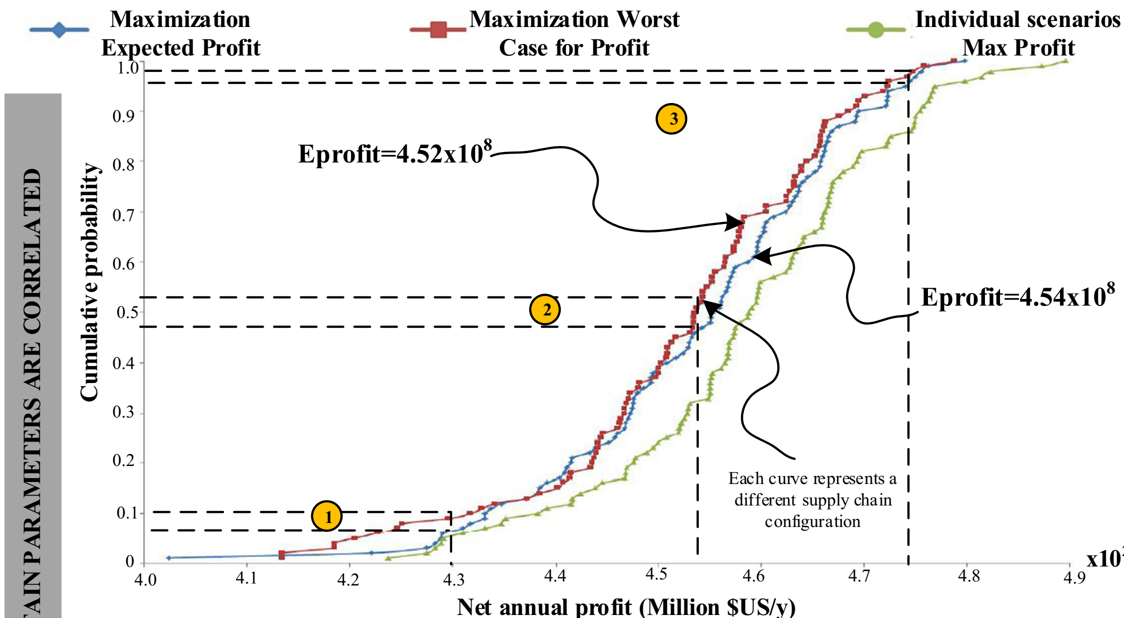


Fig. 10 Pareto curve showing the financial risk of the implementation of a supply chain topology for the correlated data (Expected Profit vs Worst Case for Profit)



Probability of obtaining a value of net profit...	① Net Profit: $4.3x10^2$ Millions $US/y – At least	① Max	② Net Profit: $4.55x10^2$ Millions $US/y – At least	② Max	③ Net Profit: $4.75x10^2$ Millions $US/y – At least	③ Max
Alternative with the highest economic risk	93 %	7 %	53 %	47 %	2 %	98 %
Alternative with the lowest economic risk	90 %	10 %	49 %	51 %	1 %	99 %

Fig. 11 Cumulative probability curves for the correlated distribution

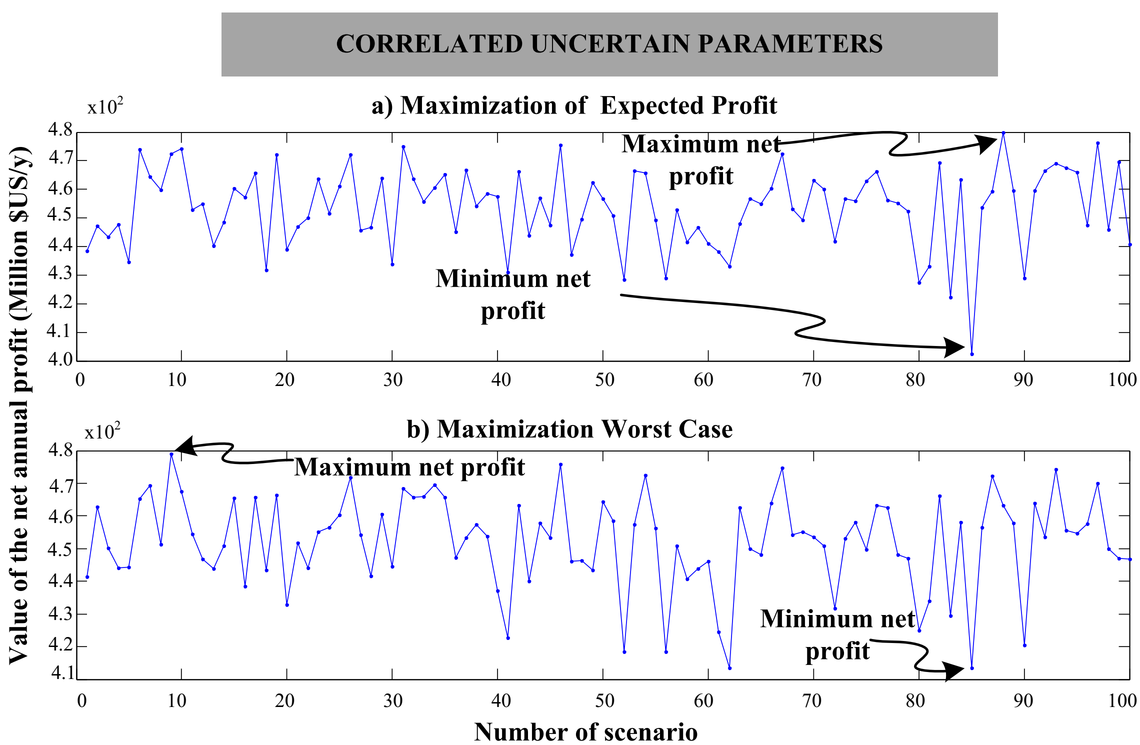


Fig. 12 Net annual profit for each scenario for the highest and lowest risk solutions for the correlated distribution

Table 6 Raw material prices for the scenarios with the highest and lowest profit value in the correlated multi-variable distribution

	Scenario 85		Scenario 9		Scenario 88		Min value $US/t	Mean value $US/t	Max value $US/t
	Value $US/t	% to mean	Value $US/t	% to mean	Value $US/t	% to mean			
Wood chips	74.39	−40.45	80.77	−35.34	174.38	39.59	53.75	124.92	241.74
Wood	181.59	−40.20	243.86	−19.69	416.22	37.07	140.97	303.64	664.94
Sugar cane	130.86	127.31	37.40	−35.04	27.74	−51.82	27.74	57.57	130.86
Grain corn	382.60	−5.41	348.70	−13.79	296.80	−26.62	280.75	404.46	621.05
Sorghum grain	253.34	7.97	172.82	−26.35	202.30	−13.79	121.62	234.64	402.19
Sweet sorghum	40.13	18.73	26.19	−22.52	24.52	−27.46	24.52	33.80	44.18
African palm	87.62	−30.71	96.40	−23.76	167.16	32.20	58.03	126.45	265.37
Jatropha	101.76	−41.17	131.30	−24.10	261.97	51.45	74.93	172.98	289.58
Safflower	466.76	37.61	276.23	−18.56	251.74	−25.78	224.50	339.19	466.76

there is no transportation of sugar cane from the North East supplier, and the processing plant in Salina Cruz city does not distribute any products to the consumers located in the South region.

Table 3 illustrates that the demand satisfied changes drastically between the extreme solutions. Thus, it can be noted that the demand for biodiesel is not fulfilled in the maximum WC solution. Furthermore, the amount of ethanol produced decreases for the Center and North East markets, which have two of the three largest cities in Mexico. On the other hand, the amount of ethanol delivered to the Center West, North West, and South markets is greater in the maximum expected profit solution.

Additionally, Table 4 presents the amount and percentage with respect to the maximum availability of raw materials used in the supply chain for both cases. It is worth noting that the main raw material for producing ethanol is sweet sorghum because its price is almost constant and lower than other raw material prices. In addition, jatropha is used to obtain biodiesel because it is cheaper than the African palm or the safflower, although the price of jatropha shows great variability.

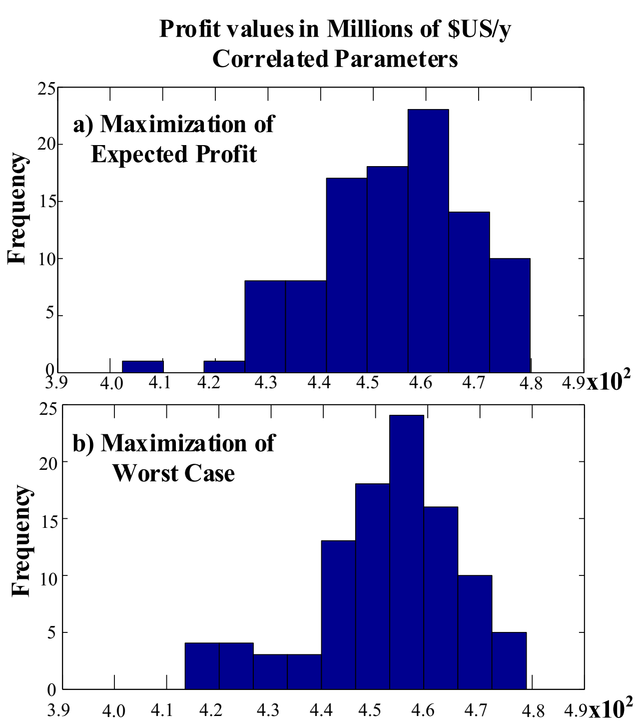


Fig. 13 Frequency histogram for the net annual profit for the highest and lowest risk solutions for the correlated distribution of raw material prices

Case with Correlated Values

Figure 9 illustrates the distribution for the raw material prices through the correlation of a multi-variate lognormal random distribution. The correlation was determined from historical data [36]. Thus, the correlation factors were obtained from the historical information presented previously in Table 1. It is worth noting that the geometric Brownian distribution is a lognormal distribution of the ratio of the raw material price for two different periods, with one period taken as a reference. For that reason, the correlation was done of the ratio of the raw material price for two time periods (for example: price of 2001/price of 2000, price of 2002/price of 2001, etc.) considering a reference price (price of 2015) to make a comparison with the uncorrelated distribution. In this context, Table 5 shows the correlation matrix used to obtain the correlated distribution. Positive and negative correlation factors are evident.

Similarly to the first case study (uncorrelated values), the model was implemented in the GAMS software as a mixed integer linear programming problem and solved with the solver CPLEX. The model contains 53,194 continuous variables, 18,320 binary variables, and 67,268 equations. However, in this case, the solution time ranges from 90 to 150 s on a

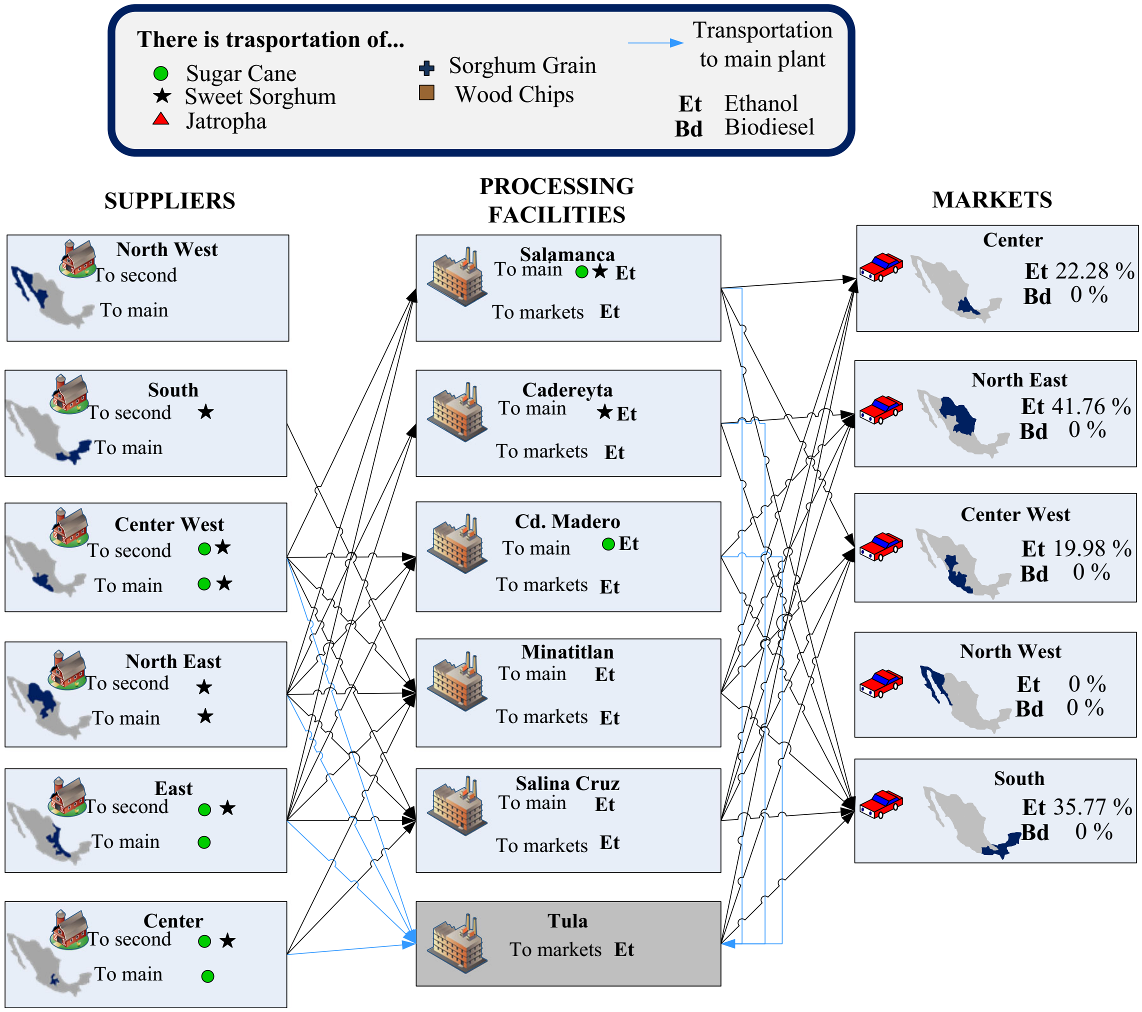


Fig. 14 Configuration of the supply chain for the riskiest solution for the correlated raw material prices

computer with the same characteristics as the previous, depending on the instance being solved.

The Pareto curve associated with the worst profit value and the expected profit value for the case of correlated uncertain data is presented in Fig. 10. Thus, it is possible to identify several sections along this Pareto curve. Section A is located between points 1 and 2, and the main difference between these points is that the interconnections between the processing facilities and markets for bioethanol distribution change drastically from point 1 to point 2; furthermore, biodiesel production decreases in point 2 with respect to point 1. On the other hand, section C is characterized by an increment in bioethanol production in the secondary processing facilities, a decrement in bioethanol production in the main processing facility, and no biodiesel production in the 4th facility, although more raw materials are utilized to obtain ethanol.

Figure 11 presents the graphic for the cumulative probability and the net annual profit when the optimization approach is solved for the maximization of the expected profit and the maximization of the worst case profit. In addition, Fig. 11 shows an upper bound curve constructed from the optimal profits attained in each scenario. Hence, the upper bound curve does not reflect any realistic solution but rather an ideal case, suggesting a wait-and-see strategy.

Similarly to Fig. 4, three values for the net annual profit were selected as follows: 4.3×10^2 million \$US/year, 4.55×10^2 million \$US/year, and 4.75×10^2 million \$US/year. From each one of the profit targets, it is possible to illustrate the probability of obtaining a lower profit, which is 7, 47, and 98 %, respectively, with the riskiest curve and, in solutions with a minor risk, 10, 51, and 99 %, respectively.

The different values for the net profit for the highest risk and the lowest risk alternatives are shown in Fig. 12. As seen, the maximum values for net profit were obtained in the 9th and 88th scenarios for the riskiest and lowest risk curves, while the minimum values for net profit correspond to the 85th scenario in both cases. For the maximum risk solution,

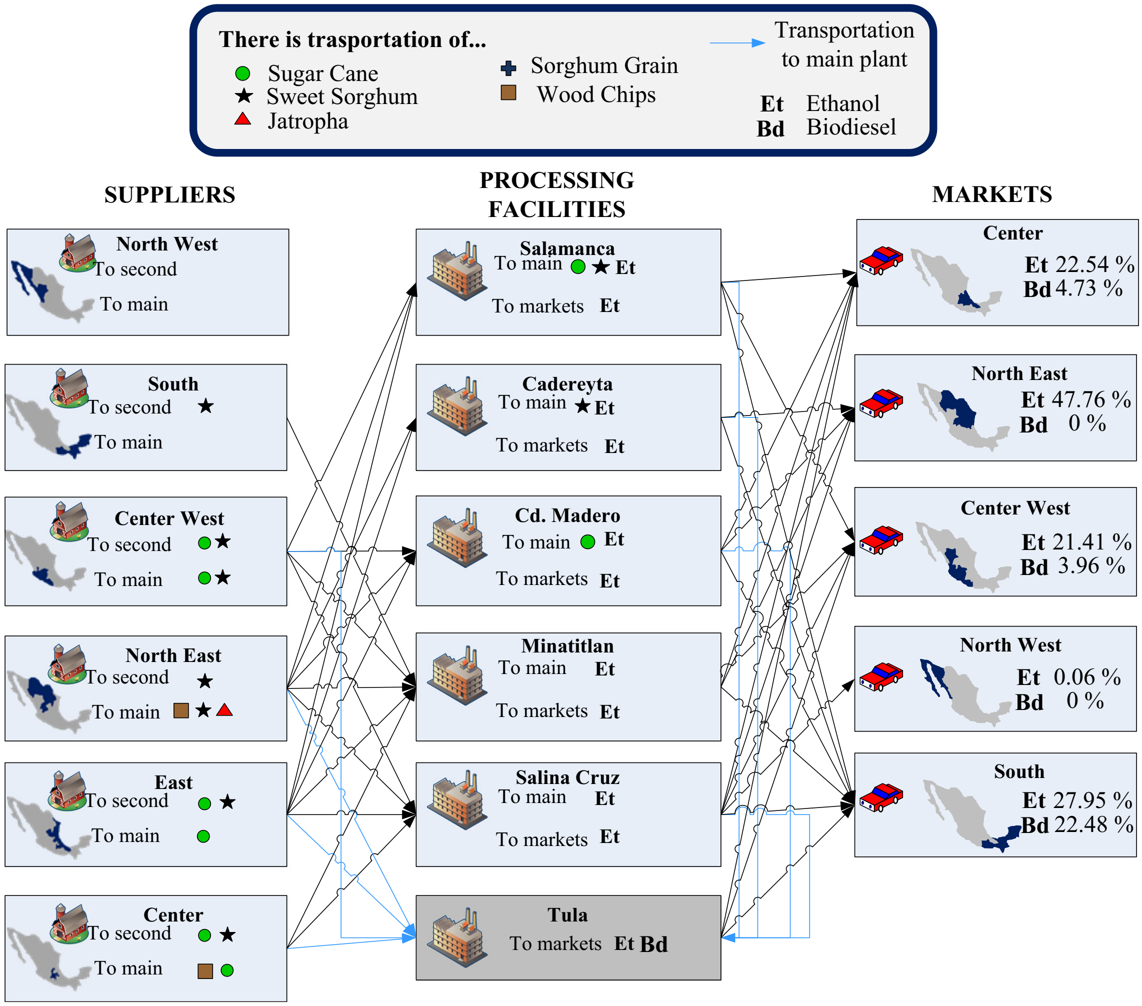


Fig. 15 Configuration of the supply chain for the solution within the lowest risk for the correlated raw material prices

the maximum profit is equal to 4.8×10^2 million \$US/year, the worst case profit is equal to 4.03×10^2 million \$US/year, and the expected profit is equal to 4.54×10^2 million \$US/year. For

Table 7 Percentage of fulfilled demand for products for the highest and lowest risk solutions in the correlated distribution

Product	Consumer	Required demand $\times 10^6$ t	High risk % Fulfilled	Low risk % Fulfilled
Ethanol	Center	1.21	22.28	22.54
	North east	0.54	41.76	47.76
	Center west	0.76	19.98	21.41
	North west	0.64	0.00	0.06
	South	0.47	35.77	27.95
Biodiesel	Center	0.26	0.00	4.73
	North east	0.13	0.00	0.00
	Center west	0.20	0.00	3.96
	North west	0.17	0.00	0.00
	South	0.13	0.00	22.48

the minimum risk solution, the maximum profit is 4.79×10^2 million \$US/year, the worst case profit is equal to 4.13×10^2 million \$US/year, and the expected profit is equal to 4.52×10^2 million \$US/year.

Table 6 illustrates the value for the raw material price for the different aforementioned scenarios (9th, 88th, and 85th) for the correlated distribution as well as a comparison with their maximum, minimum, and mean values. It is worth noting that the selected raw materials in the highest risk solution are sweet sorghum and sugar cane because the price of these raw materials can take values lower than the other raw materials. On the other hand, wood chips are added to the list of raw materials chosen in the solution with the lowest risk because sugar cane presents a high price and wood chips a low price when the data are correlated (see Table 5 and Fig. 9).

Figure 13 shows the histogram for the value of the net annual profit for the solutions from the maximization of the expected profit and the maximization of the worst case when the data are correlated. Notice that the profit values for the correlated data are distributed in a shorter range than the profit

Table 8 Amount of biomass used for the highest and lowest risk solutions in the correlated data

	Raw material	Supplier	Amount used ($\times 10^6$ t)	Maximum available ($\times 10^6$ t)	% Used
Highest risk solution	Sugar cane	Center west	0.02	8.39	0.29
	Sugar cane	East	0.40	27.12	1.46
	Sugar cane	Center	0.21	1.87	11.23
	Sweet sorghum	South	0.01	0.01	100.00
	Sweet sorghum	Center west	0.36	1.00	36.33
	Sweet sorghum	North east	0.35	1.65	21.38
	Sweet sorghum	East	0.05	0.05	100.00
	Sweet sorghum	Center	0.02	0.02	100.00
	Wood chips	North east	0.03	0.06	47.16
	Wood chips	Center	0.01	0.02	45.82
Lowest risk solution	Sugar cane	Center west	0.02	8.39	0.29
	Sugar cane	East	0.40	27.12	1.46
	Sugar cane	Center	0.21	1.87	11.23
	Sweet sorghum	South	0.01	0.01	100.00
	Sweet sorghum	Center west	0.36	1.00	36.33
	Sweet sorghum	North east	0.35	1.65	21.38
	Sweet sorghum	East	0.05	0.05	100.00
	Sweet sorghum	Center	0.02	0.02	100.00
	Jatropha	North east	0.15	0.53	28.12

values for the uncorrelated data. One reason for this behavior is because the selected raw materials in the case of correlated data present negative correlations, and this causes limited behavior for the profit values. Figure 14 represents the supply chain configuration when the expected profit is maximized. It is worth noting that the configuration of the supply chain presents some important differences between the cases of the uncorrelated and correlated data. For example, the fulfilled demands change for all markets. The first important change is in the fulfilled consumer demand for ethanol in the Center, which went from 30.26 % for the uncorrelated case to only 22.28 % for the correlated case. The second main variation occurred in the fulfilled consumer demand in the South because the uncorrelated case has a fulfilled biodiesel demand of 43.63 % and the correlated case has no percentage for the satisfied biodiesel demand. Additionally, the interconnection for the market located in the North West region does not exist in the correlated case.

Finally, Fig. 15 shows the general configuration of the supply chain for the lowest risk solution. Here, it is possible to observe that biodiesel is produced in the main processing facility and more raw materials are selected for ethanol production, namely sweet sorghum, sugar cane, and wood chips. Furthermore, the satisfied demand is almost the same in all markets, although the fulfilled biodiesel demand increases to 22.48 % in the South.

Table 7 illustrates that the demand satisfied changes drastically between the extreme solutions. Thus, it can be noted that the demand for biodiesel is not fulfilled in the maximum WC solution. Furthermore, the amount of ethanol produced decreases for the Center and North East markets, which have two of the three largest cities in Mexico. On the other hand, the amount of ethanol delivered to the Center West, North West, and South markets is greater in the maximum expected profit solution.

Table 8 presents the percentage of satisfied demand for the different products and in the different markets for the extreme solutions when the raw material prices are correlated. The effect of the correlation of the data is evident, with one of the main effects being the selection of more raw materials for the solution with the lowest risk. Another direct effect is a change in biodiesel production because biodiesel production is given in the highest risk solution in the uncorrelated case, but in the correlated case, it is given in the lowest risk solution.

Conclusions

This paper has presented a strategy for optimizing distributed systems of biomass conversion under uncertainty. The problem was modeled in mathematical terms as a two-stage stochastic MILP that seeks to optimize the expected profit and worst case simultaneously.

According to the obtained results, the distribution of the uncertain data can significantly affect the selection of raw materials, products, and interconnections between supply nodes. In the uncorrelated case, the maximum profit solution selects sugar cane, sweet sorghum, and jatropha, while the maximum WC selects only sugar cane and sweet sorghum, with no biodiesel production. In the correlated case, the maximum profit solution chooses sugar cane and sweet sorghum, while the maximum WC selects sugar cane, sweet sorghum, jatropha, and wood chips. In both the correlated and uncorrelated cases, it is possible to reduce the risk associated with the supply chain operation by properly adjusting the design and planning decisions. This is accomplished through adjustments to the inventory levels, amounts of transported materials, types and amounts of raw materials used, as well as the type of product to be produced.

Our tool is intended to facilitate the task of decision-makers concerning the identification of robust alternatives for the production, storage, and delivery of biofuels to the final customers.

Acknowledgments The authors acknowledge the financial support obtained from REMBIO-CONACyT.

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