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Strategic planning of the biodiesel supply chain

Planeación estratégica de la Cadena de Abastecimiento del Biodiesel

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Abstract

Objective: A stochastic bi-objective Mixed Integer Problem - MIP model of biodiesel supply chain networks is presented, ultimately intended to support strategic decisions of stakeholders.

Materials and Methods: The bi-objective MIP model aims to minimize the total cost and environmental impact of five chain echelons, taking into consideration the following constraints: economies of scale, location of facilities, production capacity, raw material supply, product demand, bill of materials and mass balance. The solution procedure resorts to chance constraints, valid constraints and the ε-constraint method.

Results and Discussion: The CPU times for the optimal solution of the problem instances show very good values. Computational experiments allowed assessing the performance of the solution procedure.

Conclusion: The current approach to the modeling of the biodiesel supply chain may serve as the basis of future similar works and associated solution procedures, thus facilitating decision-making at different supply chain stages. The approach fosters the development of new solution approaches such as adequate acceleration; heuristics and meta-heuristics; branch and cut methods; and Lagrangian, Benders and Danzing-Wolfe decompositions. These new approaches are intended to allow comparisons in terms of computational performance level, optimality gap, CPU time and memory usage.

Keywords: Biodiesel, oil palm, logistics, supply chain, mathematical programming, optimization.

Resumen

Objetivo: Este trabajo presenta un modelo MIP estocástico biobjetivo para el diseño de red de la cadena de suministro de biodiesel, con el fin de apoyar las decisiones estratégicas de las partes interesadas.

Materiales y Métodos: El modelo MIP estocástico biobjetivo, minimiza el costo total y el impacto ambiental de los 5 escalones de la cadena, con el fin de apoyar las decisiones estratégicas de las partes interesadas. Las restricciones que se incluyen son: economías de escala, ubicación de las instalaciones, capacidad de producción, oferta de materia prima, demanda de productos, lista de materiales y balance de masa. El procedimiento de solución incluye el planteamiento de restricciones probabilísticas, restricciones válidas y el uso del método de ε-restricciones para resolver el problema biobjetivo.

Resultados y discusión: Se presentaron muy buenos tiempos CPU en las soluciones óptimas de las instancias ejecutadas del problema.

Conclusión: La aproximación del problema de planeación de la cadena de abastecimiento de biodiesel presentado aquí, puede servir de base para nuevos desarrollos tanto en el modelado como en su solución. Futuros desarrollos en la solución puede incluir métodos de aceleración como heurísticas and meta-heurísticas, branch and cut, y métodos de decomposición Lagrangiana, de Benders y de Danzing-Wolfe, que permitan comparaciones en términos de desempeño computacional, gap de optimalidad, tiempo CPU, y uso de la memoria.

Palabras Clave: Biodiesel, Palma de aceite, logística, cadena de abastecimiento, programación matemática, optimización

1. Introduction and Literature Review

As presented in many works recently published on the topic, crude oil supply chain management has been progressively receiving more attention [1]. Furthermore, given the important momentum gained by renewable fuels in substituting fossil based energy, the US Department of Energy (DOE) considers pyrolysis as a promissory mode of obtaining biofuel [2]. However, smart design and favorable conditions are of central importance for bioenergy production in the ambit of renewable energy technologies. In this context, one of the key aspects likely to determine the future competitiveness of this sector is efficient supply chain and logistics management [3].

In reviewing the interface between bio-energy production, logistics and supply chain management, Gold and Seuring [3] found two main challenges, namely, (1) the overall design of supply systems and (2) raw material harvest, storage, transport and pretreatment techniques. The authors discuss these findings in the context of bioenergy as a sustainable and renewable energy option.

Sahebi et al. [1] employed taxonomic approaches and conducted an extensive review of mathematical programming models. Sharma et al. [4] assessed energy needs and targets, biofuel feedstock, conversion processes and biomass supply chain (BSC) design and modeling. The latter work created a classification system based on the following eight aspects: decision level, supply chain structure, modeling approach, quantitative performance measure, shared information, novelty, practical application, assumptions, constraints and future research.

On the strategic level, supply chain networks largely depend on smart design and reengineering processes addressing material flows and the size and location of facilities. In this sense, decision-makers, who include investors, facility managers and government agencies, greatly benefit from insights allowed by quantitative models, especially in terms of the impact of biofuel supply chain design and operational planning [2]. In this sense, some authors consider optimization techniques as key tools for addressing these problems [5].

Sahebi et al. [1] proposed the following five major future research lines: (1) incorporating uncertainty into the model design; (2) focusing on system-wide modeling and optimization; (3) incorporating economic, environmental and social measures into the model; (4) addressing computational complexities and developing large-scale case studies for nationwide analysis; and (5) developing models that can be easily adapted according to the interest of specific stakeholders such as biomass suppliers and refinery owners. Finally, in discussing techniques to address uncertainty, they proposed a simulation technique for BSC optimization.

Known to have considerable impact on supply chain networks [6], sustainable development factors have been the object of many publications since the Bruntland Report [7]. Along these lines, particular aspects of biofuel production and management deserve special attention, as is the case of biomass handling and transportation and biofuel conversion, distribution and consumption. The attention paid to these areas stresses the importance of strategic and operational planning decisions in biorefinery design, particularly for attaining the successful deployment of an advanced biofuel industry. According to Gold and Seuring [3], the most important aspects implied in the logistic management of bioenergy supply chains are harvest, storage, transport, pretreatment, and system design. To address with these aspects, some authors have acknowledged the significance of multi-objective stochastic models, which are sometimes oriented by state-of-the-art solvers [4].

Regarding the upstream phase of the Colombian supply chain, García-Cáceres et al. [8] highlighted the need to balance offer and demand and implement scale economies. Gutiérrez et al. [9] suggested a decision-making methodology for the optimization of the Colombian biodiesel supply network, while Gutiérrez et al. [10] presented additional suggestions in this regard. Finally, García-Cáceres et al. [11] introduced a model intended to aid tactical decisions in the upstream phase of the crude oil palm supply chain (COSC), coupled with its corresponding solution procedure supported on LINGO (© 2017 LINDO Systems, Inc) and a practical application in Colombia.

With regard to agribusiness sustainability, the present work follows the initiative of the Roundtable on Sustainable Palm Oil (RSPO), among other institutions within the sector, which states that the most relevant network design decisions incorporate biorefinery location, flow allocation among echelons, production capacity, scale economies and sustainability bounds in a context of stochastic supply and demand. In this context, the model introduced in the current work seeks to minimize the total cost of material flows through the chain, resorting to a solution procedure that includes chance constraints, valid constraints, and the ε-constraint method. Thus, we intend to address several issues raised in different research areas featured in the literature on biofuel supply chain optimization in strategic contexts. The results presented here constitute a powerful tool to improve the competitiveness of the sector, especially on the national level in Colombia. Notwithstanding, recent works on biodiesel supply chains also address production of raw materials other than from palm oil [12; 13; 14; 15; 16; 17].

2. The model

For the reasons mentioned above, the current work studied crude palm oil (CPO), which is currently an outstanding biodiesel producing commodity. In Colombia the document CONPES 3015 [18] sets the guidelines for the development of the sector, highlighting the elevated logistic and production costs of biofuels in the country as one of the most critical competitiveness challenges of this productive chain. This paper introduces a mathematical programming model for the design of the Colombian biodiesel supply chain, seeking to minimize the following two objective functions: (1) the costs of the three stages of the chain (procurement, production and distribution), which contains five echelons in its three phases (upstream, midstream, downstream) and (2) the environmental impact of the processes that make up the chain using the life cycle analysis (LCA) methodology.

The five echelons of the chain are as follows: 1. supply centers, which, contained in the upstream phase [8], correspond to the crops and plantation conglomerates where the fruit is harvested; 2. extraction plants intended to obtain CPO (which is obtained from the mesocarp of the fruit), palm kernel oil (PKO) and palm kernel cake (PKC) (the latter two being extracted from the seed); 3. biodiesel production plants (CPO biorefineries); 4. mixing plants (wholesalers), where biodiesel is blended with diesel to obtain the final consumer product; and 5. Colombian regions associated with fuel station clusters, which serve the final consumer.

Sets and indexes:
A: set of $(a_1, a_2, \ldots a_{n1})$ oil palm fruit supplying zones
B: set of $(b_1, b_2, \ldots b_{n2})$ extraction plants
B (*): set of extraction plants that can be supplied by offer zone *
D: set of $(d_1, d_2, \ldots d_{n3})$ bio refineries
D (*): set of bio refineries that can be supplied by extraction plant *
E: set of $(e_1, e_2, \ldots e_{n4})$ production scales
E (*): set of production scales associated with facility *
F: set of $(f_1, f_2, \ldots f_{n5})$ mixing plants
F (*): set of mixing plants that can be supplied by refining plant *
G: set of $(g_1, g_2, \ldots g_{n6})$ demand zones
G (*): set of demand zones that can be supplied by mixing plant *
P: set of $(p_1, p_2, \ldots p_{n7})$ products and materials
P (*): set of products and materials associated with plant *

Parameters:
CF_b: fixed cost of operating extraction plant b
CF_d: fixed cost of operating refining plant d
CF_f: fixed cost of operating mixing plant f
CI_{bp}: inventory cost of item p at extraction plant b
CI_{dp}: inventory cost of item p at refining plant d
CI_{fp}: inventory cost of item p at mixing plant f
CP_{bpe}: production cost of item p at extraction plant b and production scale e
CP_{dpe}: production cost of item p at refining plant d and production scale e
CP_{fpe}: production cost of item p at mixing plant f and production scale e

CT_{abp}: cost of transporting item p between offer zone a and extraction plant b

CT_{bdp}: cost of transporting item p between extraction plant b and refining plant d

CT_{dfp}: cost of transporting item p between refining plant d and mixing plant f

CT_{dfp}: cost of transporting item p between mixing plant f and demand zone g

CT_{fgp}: cost of transporting item p between mixing plant f and demand zone g

$D(\xi)_{bp}$: stochastic demand for item p at extraction plant b

$D(\xi)_{dp}$: stochastic demand for item p at refining plant d

$D(\xi)_{fp}$: stochastic demand for item p at mixing plant f

$D(\xi)_{gp}$: stochastic demand for item p at demand zone g

$HMAX_{be}$: maximum bound of production scale e at extraction plant b

$HMIN_{be}$: minimum bound of production scale e at extraction plant b

$HMAX_{de}$: maximum bound of production scale e at refining plant d

$HMIN_{de}$: minimum bound of production scale e at refining plant d

$HMAX_{fe}$: maximum bound of production scale e at mixing plant f

$HMIN_{fe}$: minimum bound of production scale e at mixing plant f

I_{bqp}: amount of item q employed for processing item p at extraction plant b

I_{dqp}: amount of item q employed for processing item p at refining plant d

I_{fqp}: amount of item q employed for processing item p at mixing plant f

M_b: maximum capacity of extraction plant b

M_d: maximum capacity of refining plant d

M_f: maximum capacity of mixing plant f

S_{abp}: environmental impact caused by transporting one unit of item p between offer zone a and extraction plant b

S_{bpe}: environmental impact of producing one unit of item p at extraction plant b and production scale e

S_{dpe}: environmental impact of producing one unit of item p at refining plant d and production scale e

S_{fpe}: environmental impact of producing one unit of item p at mixing plant f and production scale e

$SMAX_{bp}$: maximum admissible contamination bound for item p at extraction plant b
$SMAX_{dp}$: maximum admissible contamination bound for item p at refining plant d
$SMAX_{fp}$: maximum admissible contamination bound for item p at mixing plant f
$SMAX_{gp}$: maximum admissible contamination bound for item p at demand zone g
$O(\xi)_{gp}$: stochastic offer of item p in zone a

Variables:
δ_b: {1, if extraction plant b is of the open type; 0 otherwise
δ_d: {1, if refining plant d is of the open type; 0 otherwise
δ_f: {1, if mixing plant f is of the open type; 0 otherwise
v_{bp}: amount of item p obtained at extraction plant b to satisfy the demand of supply chains different from that of biodiesel
v_{dp}: amount of item p obtained at refining plant d to satisfy the demand of supply chains different from that of biodiesel
v_{fp}: amount of item p obtained at mixing plant f to satisfy the demand of supply chains different from that of biodiesel
w_{bpe}: {1, if item p obtained at extraction plant b is operating at scale e; 0 otherwise
w_{dpe}: {1, if item p obtained at refining plant d is operating at scale e; 0 otherwise
w_{fpe}: {1, if item p obtained at mixing plant f is operating at scale e; 0 otherwise
x_{abp}: amount of item p transported between offer zone a and extraction plant b
x_{bdp}: amount of item p transported between extraction plant b and refining plant d
x_{dfp}: amount of item p transported between refining plant d and mixing plant f
x_{dfp}: amount of item p transported between mixing plant f and demand zone g
y_{bpe}: amount of item p obtained at extraction plant b and production scale e

y_{dpe}: amount of item p obtained at refining plant d and production scale e
y_{fpe}: amount of item p obtained at mixing plant f and production scale e
y_{bp}: amount of item p obtained at extraction plant b
y_{dp}: amount of item p obtained at refining plant d
y_{fp}: amount of item p obtained at mixing plant f

Objective:
Cost minimization:

$$\begin{aligned}
MIN \quad & \sum_{a\in A}\sum_{b\in B(a)}\sum_{p\in P(a)} CT_{abp}x_{abp} \\
&+ \sum_{b\in B}\sum_{d\in D(b)}\sum_{p\in P(b)} CT_{bdp}x_{bdp} \\
&+ \sum_{d\in D}\sum_{f\in F(d)}\sum_{p\in P(d)} CT_{dfp}x_{dfp} \\
&+ \sum_{f\in F}\sum_{g\in G(f)}\sum_{p\in P(f)} CT_{fgp}x_{fgp} \\
&+ \sum_{b\in B}\sum_{p\in P(b)}\sum_{e\in E(b)} CP_{bpe}y_{bpe} + \sum_{d\in D}\sum_{p\in P(d)}\sum_{e\in E(d)} CP_{dpe}y_{dpe} \\
&+ \sum_{f\in F}\sum_{p\in P(f)}\sum_{e\in E(f)} CP_{fpe}y_{fpe} \\
&+ \sum_{b\in B}\sum_{p\in P(b)} CI_{bp}v_{bp} + \sum_{d\in D}\sum_{p\in P(d)} CI_{dp}v_{dp} + \sum_{f\in F}\sum_{p\in P(f)} CI_{fp}v_{fp} \\
&+ \sum_{b\in B} CF_b\delta_b + \sum_{d\in D} CF_d\delta_d \\
&+ \sum_{f\in F} CF_f\delta_f \qquad (1)
\end{aligned}$$

Minimization of environmental contamination:

$$
\begin{aligned}
MIN \quad & \sum_{a\in A}\sum_{b\in B(a)}\sum_{p\in P(a)} S_{abp}x_{abp} \\
& +\sum_{b\in B}\sum_{d\in D(b)}\sum_{p\in P(b)} S_{bdp}x_{bdp} \\
& +\sum_{d\in D}\sum_{f\in F(d)}\sum_{p\in P(d)} S_{dfp}x_{dfp} \\
& +\sum_{b\in B}\sum_{p\in P(b)}\sum_{e\in E(b)} S_{bpe}y_{bpe} \\
& +\sum_{d\in D}\sum_{p\in P(d)}\sum_{e\in E(d)} S_{dpe}y_{dpe} \\
& +\sum_{f\in F}\sum_{p\in P(f)}\sum_{e\in E(f)} S_{fpe}y_{fpe} \qquad (2)
\end{aligned}
$$

Subjected to:

Supply of materials

$$
\sum_{b\in B(a)} x_{abp} \leq O(\xi)_{ap} \qquad b\epsilon B, p\epsilon P(a) \qquad (3)
$$

Extracting plants:

$$
\sum_{p\epsilon P(b)} y_{bp} \leq M_b\delta_b \qquad b\epsilon B \qquad (4)
$$

Refining plants:

$$
\sum_{p\epsilon P(d)} y_{dp} \leq M_d\delta_d \qquad d\epsilon D \qquad (5)
$$

Mixing plants:

$$\sum_{p \epsilon P(f)} y_{fp} \leq M_f \delta_f \qquad f \epsilon F \qquad (6)$$

Mass balance

Extracting plants:

$$\sum_{a \in A(b)} x_{abq} = \sum_{p \in P(b)} I_{bqp} y_{bp} \qquad b \epsilon B, q \epsilon P(a) \qquad (7)$$

Refining plants:

$$\sum_{b \in B(d)} x_{bdq} = \sum_{p \in P(d)} I_{dqp} y_{dp} \qquad d \epsilon D, q \epsilon P(b) \qquad (8)$$

Mixing plants:

$$\sum_{d \in D(f)} x_{dfq} = \sum_{p \in P(f)} I_{fqp} y_{fp} \qquad f \epsilon F, q \epsilon P(d) \qquad (9)$$

Production

Extracting plants:

$$y_{bp} = v_{bp} + \sum_{d \in D(b)} x_{bdp} \qquad b \epsilon B, p \epsilon P(b) \tag{10}$$

Refining plants:

$$y_{dp} = v_{dp} + \sum_{f \epsilon F(d)} x_{dfp} \qquad d \epsilon D, p \epsilon P(d) \tag{11}$$

Mixing plants:

$$y_{fp} = v_{fp} + \sum_{g \in G(f)} x_{fgp} \qquad f \epsilon F, p \epsilon P(f) \tag{12}$$

Scale economies (assignation of a single flow)

Extraction plants:

$$y_{bp} = \sum_{e \epsilon E(b)} y_{bpe} \qquad b \epsilon B, p \epsilon P(b) \tag{13}$$

Refining plants:

$$y_{dp} = \sum_{e \epsilon E(d)} y_{dpe} \qquad d \epsilon D, p \epsilon P(d) \tag{14}$$

Mixing plants:

$$y_{fp} = \sum_{e\epsilon E(f)} y_{fpe} \qquad f\epsilon F, p\epsilon P(f) \tag{15}$$

Bounding of production schedules

Extraction plants:

$$w_{bpe}HMIN_{be} \leq y_{bpe} < HMAX_{be}w_{bpe} \qquad b\epsilon B, p\epsilon P(b), e\epsilon E(b) \tag{16}$$

Refining plants:

$$w_{dpe}HMIN_{de} \leq y_{dpe} < HMAX_{de}w_{dpe} \qquad d\epsilon D, p\epsilon P(d), e\epsilon E(d) \tag{17}$$

Mixing plants:

$$w_{fpe}HMIN_{fe} \leq y_{fpe} < HMAX_{fe}w_{fpe} \qquad f\epsilon F, p\epsilon P(f), e\epsilon E(f) \tag{18}$$

Consistency of the scale

Extraction plants:

$$\sum_{e\epsilon E(b)} w_{bpe} \leq 1 \qquad b\epsilon B, p\epsilon P(b) \tag{19}$$

Refining plants:

$$\sum_{e\epsilon E(d)} w_{de} \leq 1 \qquad d\epsilon D, p\epsilon P(d) \tag{20}$$

Mixing plants:

$$\sum_{e \epsilon E(f)} w_{fe} \leq 1 \qquad f \epsilon F, p \epsilon P(f) \tag{21}$$

Demand

Extraction plants:

$$v_{bp} \geq D(\xi)_{bp} \qquad b \epsilon B, p \epsilon P(b) \tag{22}$$

Refining plants:

$$v_{dp} \geq D(\xi)_{dp} \qquad d \epsilon D, p \epsilon P(d) \tag{23}$$

Mixing plants:

$$v_{fp} \geq D(\xi)_{fp} \qquad f \epsilon F, p \epsilon P(f) \tag{24}$$

Biodiesel demand:

$$\sum_{f \in F} x_{fgp} \geq D(\xi)_{gp} \qquad g \epsilon G(f), p \epsilon P(g) \tag{25}$$

Non-negativity

$$x_{abp} \geq 0, x_{bdp} \geq 0, x_{dfp} \geq 0, x_{fgp} \geq 0, y_{bp} \geq 0, y_{bpe} \geq 0, y_{dp} \geq 0, y_{dpe} \geq 0, y_{fp} \geq 0, y_{fpe} \geq 0, v_{bp} \geq 0, v_{dp} \geq 0, v_{fp} \geq 0 \tag{26}$$

3. Solution procedure

The solution procedure comprises the following steps: 1. treating the offer and demand constraints containing stochastic parameters under parameter normality assumptions [19]; 2. valid constraints configured [20]; 3.

solution of the bi-objective model through the ε-constraint method [21], [22].

3.1. Estimation of stochastic constraints: Constraint deductions are included in Appendix A.

Supply of materials (replaces equation 3)

$$\sum_{b \in B(a)} x_{abp} \leq z_{\propto}\sigma\big(O(\xi)_{ap}\big) + \mathrm{E}\big(O(\xi)_{ap}\big) \quad a\epsilon A, p\epsilon P(a) \tag{27}$$

Where:

$\sigma(O(\xi)_{ap})$: standard deviation of the stochastic offer of item *p* at zone *a*

$\mathrm{E}(O(\xi)_{ap})$: expected value of the stochastic offer of item *p* at zone *a*

Demand

Extraction plants (replaces equation 22):

$$v_{bp} \geq z_{1-\propto}\sigma\big(D(\xi)_{bp}\big) + \mathrm{E}\big(D(\xi)_{bp}\big) \qquad b\epsilon B, p\epsilon P(b) \tag{28}$$

Refining plants (replaces equation 23):

$$v_{dp} \geq z_{1-\propto}\sigma\big(D(\xi)_{dp}\big) + \mathrm{E}\big(D(\xi)_{dp}\big) \qquad d\epsilon D, p\epsilon P(d) \tag{29}$$

Mixing plants (replaces equation 24):

$$v_{fp} \geq z_{1-\propto}\sigma\big(D(\xi)_{fp}\big) + \mathrm{E}\big(D(\xi)_{fp}\big) \qquad f\epsilon F, p\epsilon P(f) \tag{30}$$

Biodiesel demand (replaces equation 25):

$$\sum_{f\in F} x_{fgp} \geq z_{1-\propto}\sigma\left(D(\xi)_{gp}\right) + \mathrm{E}\left(D(\xi)_{gp}\right) \qquad g\epsilon G(f), p\epsilon P(g) \tag{31}$$

Where:

$\sigma(D(\xi)_{bp})$: standard deviation of stochastic demand for item p at extraction plant b

$\sigma(D(\xi)_{dp})$: standard deviation of stochastic demand for item p at refining plant d

$\sigma(D(\xi)_{fp})$: standard deviation of stochastic demand for item p at mixing plant f

$\sigma(D(\xi)_{gp})$: standard deviation of stochastic demand for item p at demand zone f

$\mathrm{E}(D(\xi)_{bp})$: expected value of stochastic demand for item p at extraction plant b

$\mathrm{E}(D(\xi)_{dp})$: expected value of stochastic demand for item p at refining plant d

$\mathrm{E}(D(\xi)_{fp})$: expected value of stochastic demand for item p at mixing plant f

$\mathrm{E}(D(\xi)_{gp})$: expected value of stochastic demand for item p at demand zone f

3.2. Valid constraints configuration

Constraints are intended to improve the statement of the problem through the convolution of its feasible space.

Scale differences in flows associated with extraction plants:

A particular condition imposed by these scales is that $y_{*pe1} \leq y_{*pe2} \cdots y_{*pen1} \quad * \epsilon\{B, D, F\}, p\epsilon P(b), e\epsilon E(b)$. The valid constraints (32 to 37) associated with the scale in which this condition operates are presented below.

$$y_{bpe} \leq y_{bp} \qquad b\epsilon B, p\epsilon P(b), e\epsilon E(b) \tag{32}$$

$$\sum_{e\epsilon E(b)} y_{bpe} \geq y_{bp} \qquad b\epsilon B, p\epsilon P(b) \qquad (33)$$

Scale differences in flows associated with refining plants:

$$y_{dpe} \leq y_{dp} \qquad d\epsilon D, p\epsilon P(d), e\epsilon E(d) \qquad (34)$$

$$\sum_{e\epsilon E(d)} y_{dpe} \geq y_{dp} \qquad d\epsilon D, p\epsilon P(d) \qquad (35)$$

Scale differences in flows associated with mixing plants:

$$y_{fpe} \leq y_{fp} \qquad f\epsilon F, p\epsilon P(f), e\epsilon E(f) \qquad (36)$$

$$\sum_{e\epsilon E(d)} y_{fpe} \geq y_{fp} \qquad f\epsilon F, p\epsilon P(f) \qquad (37)$$

Finally, the set of valid constraints (38 to 40) associating the location status of the facilities to their production possibilities at different scales are presented next.

Extraction plant location and production logic relation:

$$w_{be} \leq \delta_b \qquad b\epsilon B, e\epsilon E(b) \qquad (38)$$

Refining plant location and production logic relation:

$$w_{de} \leq \delta_d \qquad d\epsilon D, e\epsilon E(d) \qquad (39)$$

Mixing plant location and production logic relation:

$$w_{fe} \leq \delta_f \qquad f\epsilon F, e\epsilon E(f) \tag{40}$$

3.3 Solution of the bi-objective-problem

The bi-objective problem is solved by the *a posteriori* method of *ε*-restrictions. In it, one of the objective functions (considered to be more relevant) is optimized, while all other objective functions are considered to be model constraints. By generating a set of optimal solutions that allow a final choice, the method is considered to supply abundant information, thus avoiding weakly efficient solutions. The method is detailed in Appendix B.

4. Results

An analysis was carried out on a LINGO 9 commercial solver operated in a 2.67 GHz Intel Core I5 CPU with 8 GB RAM and a 64-bit operating system (Windows 10). Integer and linear optimality tolerances were fixed at $1*10^{-6}$ (absolute) and $8*10^{-6}$ (relative), respectively. Both the size of the problem and its configuration were inspired on those of the Colombian oil palm supply chain, whose size is smaller than the one considered in the current work. Thus, in a practical context the size of the problem corresponds to that of a world-class producer. The parameters of the problems were analyzed in two different instances (Appendix C and the supplementary material). Instances 1 and 2 address the performance of the solution procedure with and without the valid constraints. The complete solution procedure, which includes the valid constraints (equations 32-40), resulted in a total of 84 model runs (Table 1).

Table 1. Network configuration of the supply chain

Instance 1			
Sets and Indexes	**Quantity**	**Sets and Indexes**	**Quantity**
Supplying Zones	20	Products and materials Associated	6

Extracting Plants	30	Products and materials Associated	6
Bio Refineries	10	Products and materials Associated	6
Mixing Plants	6	Products and materials Associated	6
Demand Zones	33	Products and materials Associated	6
Scales at Extracting	2	Scales at Mixing Plants	2
Scales at Bio	2		
Instance 2			
Sets and Indexes	**Quantity**	**Sets and Indexes**	**Quantity**
Supplying Zones	25	Products and materials Associated	8
Extracting Plants	30	Products and materials Associated	8
Bio Refineries	15	Products and materials Associated	8
Mixing Plants	10	Products and materials Associated	8
Demand Zones	33	Products and materials Associated	8
Scales at Extracting	2	Scales at Mixing Plants	2
Scales at Bio	2		

Prepared by the authors

Table 2 shows steps 1 and 2 of the ε-constraint method (see Appendix B), which allow for the estimation of the optimal and nadir values of the two objective functions. Said values are necessary to proceed to step 3, which is of central importance for the current application.

Table 2. Output parameters of the ε-constraint method

Instance 1 without valid constraints				
Parameters	$\Theta^{Optimal}$	$\Pi^{Optimal}$	Θ^{Nadir}	Π^{Nadir}
Objective function	169,933,722.97	134,296,860.10	192,253,717.98	157,702,754.65
CPU time (Seconds)	108.00	17.00	49.00	205.00
Total variables	7954	7954	7954	7954
Binary variables	598	598	598	598
Number of constraints (Non-negativity constraints not included)	2849	2849	2850	2850
Memory used	2514	2479	2582	2566
Instance 1 with valid constraints				
Parameters	$\Theta^{Optimal}$	$\Pi^{Optimal}$	Θ^{Nadir}	Π^{Nadir}
Objective function	169,933,722.97	134,296,860.10	192,253,717.98	157,702,762.00
CPU time (Seconds)	41,00	25,00	29,00	134,00
Total variables	7954	7954	7954	7954
Binary variables	598	598	598	598
Number of constraints (Non-negativity constraints not included)	4229	4229	4230	4230
Memory used	2657	2623	2726	2709
Instance 2 without valid constraints				
Parameters	$\Theta^{Optimal}$	$\Pi^{Optimal}$	Θ^{Nadir}	Π^{Nadir}
Objective function	328,995,977.48	265,297,761.20	387,320,099.3	342,990,655.11
CPU time (Seconds)	116.00	29.00	613.00	1349.00
Total variables	14527	14527	14527	14527
Binary variables	935	935	935	935
Number of constraints (Non-negativity constraints not included)	4480	4480	4481	4481

Memory used	4506	4438	4630	4596
Instance 2 with valid constraints				
Parameters	$\Theta^{Optimal}$	$\Pi^{Optimal}$	Θ^{Nadir}	Π^{Nadir}
Objective function	328,995,977.48	265,297,761.20	387,320,099.3	342,990,655.11
CPU time (Seconds)	92	61	105	405
Total variables	14527	14527	14527	14527
Binary variables	935	935	935	935
Number of constraints (Non-negativity constraints not included)	6680	6680	6681	6681
Memory used	4737	4668	4861	4826

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To calculate the efficient frontier, the incremental step value of parameter ε was set to 0.05. As a consequence, 20 optimal estimates were solved for the two objective functions. The solution is shown below.

Table 3. Efficient frontier and performance indicators

Instance 1a, without valid constraints						
ϵ	Θ	Π	$\phi 1(x)$	$\phi 2(x)$	CPU time (Sec)	$\Theta+\Pi$
0	169933723	157702754.7	0.999999997	0	39	327636477.68
0.05	170081712.3	156532459.9	0.99336965	0.05	36	326614172.27
0.1	170256994.1	155362165.2	0.985516524	0.1	80	325619159.27
0.15	170452043.2	154191870.5	0.976777762	0.15	48	324643913.67
0.2	170651946.4	153021575.7	0.967821524	0.2	45	323673522.14
0.25	170905288.5	151851281	0.956471068	0.25	47	322756569.51

0.3	171210211.1	150680986.3	0.942809659	0.3	42	321891197.38
0.35	171555339.2	149510691.6	0.927346925	0.35	81	321066030.79
0.4	171895705.4	148340396.8	0.912097543	0.4	69	320236102.20
0.45	172307041.2	147170102.1	0.893668514	0.45	88	319477143.32
0.5	172892188.6	145999807.4	0.867452228	0.5	82	318891995.95
0.55	173542507.3	144829512.6	0.83831608	0.55	55	318372019.90
0.6	174288438.4	143659217.9	0.804896217	0.6	41	317947656.34
0.65	175159585	142488923.2	0.765866345	0.65	81	317648508.18
0.7	176176595.1	141318628.5	0.720301367	0.7	52	317495223.53
0.75	177346889.8	140148333.7	0.667868795	0.75	78	317495223.53
0.8	178777861.6	138978039	0.603757139	0.8	38	317755900.65
0.85	180748914	137807744.3	0.515448321	0.85	80	318556658.30
0.9	182989287.6	136637449.6	0.415073137	0.9	28	319626737.18
0.95	186735420.8	135467154.8	0.247235591	0.95	39	322202575.64
1	192253718	134296860.1	0	1	66	326550578.07
Instance 1b, with valid constraints						
ϵ	Θ	Π	$\phi 1(x)$	$\phi 2(x)$	CPU time (Sec)	$\Theta+\Pi$
0	169933723	157702762	1	0	17.00	327636484.97
0.05	170081711.4	156532466.9	0.993369695	0.05	24.00	326614178.26
0.1	170276244	155362171.8	0.984654074	0.1	44.00	325638415.76
0.15	170452042.2	154191876.7	0.976777809	0.15	32.00	324643918.88
0.2	170651945.2	153021581.6	0.967821576	0.2	41.00	323673526.85
0.25	170905287.1	151851286.5	0.95647113	0.25	73.00	322756573.65
0.3	171210209.4	150680991.4	0.942809736	0.3	29.00	321891200.81
0.35	171581700.5	149510696.3	0.926165864	0.35	50.00	321092396.84
0.4	171895703.9	148340401.2	0.912097609	0.4	20.00	320236105.14
0.45	172307039.2	147170106.1	0.893668604	0.45	38.00	319477145.34
0.5	172892186.7	145999811	0.86745231	0.5	28.00	318891997.79
0.55	173542504.9	144829516	0.838316188	0.55	46.00	318372020.80
0.6	174288436.5	143659220.9	0.804896305	0.6	34.00	317947657.32

0.65	175159582.9	142488925.8	0.765866437	0.65	50.00	317648508.69
0.7	176422299.3	141318630.7	0.709293109	0.7	66.00	317740929.98
0.75	177346888	140148335.6	0.667868878	0.75	60.00	317495223.53
0.8	178777859.3	138978040.5	0.603757245	0.8	37.00	317755899.77
0.85	180748912.3	137807745.4	0.5154484	0.85	34.00	318556657.64
0.9	182989286.2	136637450.3	0.415073203	0.9	37.00	319626736.45
0.95	186735419.7	135467155.2	0.247235643	0.95	40.00	322202574.84
1	192253718	134296860.1	0	1	41.00	326550578.07
Instance 2a, without valid constraints						
ϵ	*Θ*	*Π*	*ϕ1(x)*	*ϕ2(x)*	CPU time (Sec)	*Θ+Π*
0	328995974.4	342990654.5	1.000000053	0	240	671986628.87
0.05	329290068.1	339106010.4	0.99495765	0.05	421	668396078.51
0.1	329505643.5	335221365.7	0.991261489	0.1	483	664727009.20
0.15	329825187.2	331336721	0.985782731	0.15	164	661161908.21
0.2	330166858.5	327452076.3	0.979924583	0.2	134	657618934.86
0.25	330377066.5	323567431.6	0.976320449	0.25	114	653944498.14
0.3	330904879.8	319682786.9	0.967270792	0.3	79	650587666.74
0.35	331511451	315798142.2	0.956870786	0.35	148	647309593.25
0.4	332239672.2	311913497.5	0.944385022	0.4	88	644153169.79
0.45	333016423.6	308028852.9	0.931067181	0.45	133	641045276.44
0.5	334031911.7	304144208.2	0.913656065	0.5	92	638176119.82
0.55	335322769.4	300259563.5	0.891523581	0.55	71	635582332.81
0.6	336702301.5	296374918.8	0.867870724	0.6	73	633077220.24
0.65	338493315.9	292490274.1	0.83716277	0.65	79	630983589.99
0.7	340623012.8	288605629.4	0.800647914	0.7	110	629228642.20
0.75	343417865.3	284720984.7	0.75272859	0.75	71	628138850.00
0.8	347154670.4	280836340	0.688658957	0.8	222	627991010.39
0.85	351126133.3	276951695.3	0.620565983	0.85	71	628077828.63
0.9	357301788.8	273067050.6	0.514680883	0.9	67	630368839.41

0.95	367049921	269182405.9	0.347543653	0.95	90	636232326.87
1	387320073	265297761.2	4.51677E-07	1	584	652617834.20
Instance 2b, with valid constraints						
E	*Θ*	*Π*	*ϕ1(x)*	*ϕ2(x)*	CPU time	*Θ+Π*
0	328995977.5	342990655.1	1	0	324	671986632.59
0.05	329295850.1	339106010.4	0.994858514	0.05	189	668401860.55
0.1	329609858.8	335221365.7	0.989474658	0.1	139	664831224.52
0.15	329825190.3	331336721	0.985782678	0.15	231	661161911.35
0.2	330166861.7	327452076.3	0.979924529	0.2	139	657618938.04
0.25	330377066.5	323567431.6	0.976320449	0.25	89	653944498.14
0.3	338933637.6	319682786.9	0.829613206	0.3	38	658616424.53
0.35	331511451	315798142.2	0.956870786	0.35	80	647309593.25
0.4	332239672.2	311913497.5	0.944385022	0.4	85	644153169.79
0.45	333016426.8	308028852.9	0.931067126	0.45	145	641045279.68
0.5	334032191.4	304144208.2	0.913651268	0.5	87	638176399.57
0.55	335322769.4	300259563.5	0.891523581	0.55	51	635582332.81
0.6	336702301.5	296374918.8	0.867870724	0.6	71	633077220.24
0.65	338493315.9	292490274.1	0.83716277	0.65	42	630983589.99
0.7	340623016.3	288605629.4	0.800647854	0.7	42	629228645.72
0.75	343417865.3	284720984.7	0.75272859	0.75	50	628138850.00
0.8	347154670.4	280836340	0.688658957	0.8	277	627991010.39
0.85	351129480.4	276951695.3	0.620508596	0.85	98	628081175.65
0.9	357301788.8	273067050.6	0.514680883	0.9	34	630368839.41
0.95	367049918.7	269182405.9	0.347543691	0.95	81	636232324.64
1	387320099.3	265297761.2	0	1	317	652617860.54

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The minimization of the two objective functions lay between 0.7 and 0.75 of ε in the case of instance *1a* and 0.75 in the case of instance *1b*. For their part, instances *2a* and *2b* reached said minimization at $\varepsilon = 0.8$. The CPU times for the solution of the instances of the problem show very good values. In a general sense, the instance *b* of the problem, that is, those including the valid constraints, showed a better average performance. Specifically, observing the number of cases, a 24.55% improvement in the average CPU time was attained by instance 1, and 18 out of the 21 cases exhibited better performance for instance *b* over instance *a*. Regarding instance 2, an 18% average CPU time improvement was reached, and 17 of the 21 cases showed better counts for instance *2b*.

5. Conclusions

The current approach to the modeling of decision-making in the biodiesel supply chain may facilitate said process at different stages of the chain and provide a basis for future similar works and associated solution procedures.

The computational analysis performed in this work aims to determine the efficient frontier of the stated problem under the paradigm of minimization of its two objective functions. The size of the problem was defined according to that of the Colombian case. The CPU times for the optimal solution of the instances of the problem show very good values.

Although the stochastic bi-objective MIP model and the proposed solution procedure proved adequate to solve the practical instances of the current problem, they might not be enough to solve larger instances in the context of global supply chains. However, the current approach can be improved by further modeling efforts and/or the development of solution procedures that allow its practical application to larger instances. These research areas may include the development of adequate acceleration, heuristics and meta-heuristics, or branch and cut methods, as well as Lagrangian, Benders and Danzing-Wolfe decompositions.

As a pioneering work, the current approach actually fosters the development of new solution approaches allowing comparisons in terms of computational performance level, optimality gap, CPU time and memory usage.

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Check Appendixes in the following link:
http://revistas.javeriana.edu.co/index.php/iyu/article/view/19030
* Ver anexo A
* Ver anexo B
* Ver anexo C

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