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Designing and planning the downstream oil supply chain under uncertainty using a fuzzy programming approach

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ABSTRACT

This paper addresses the strategic and tactical planning of a downstream oil supply chain (DOSC) subject to different sources of uncertainty. This problem is formulated as a mixed-integer linear programming (MILP) model, whereas uncertainty is tackled using chance constrained programming with fuzzy parameters. The MILP model aims at determining the network design and the products distribution plan in a cost-effective way. A real case study on the Brazilian oil industry is used to validate the model. The proposed model shows to be a valuable decision-support tool in order to aid the decision-making process in the strategic and tactical planning of real-life problems.

1. Introduction

All over the globe, the energy industry is undergoing through a major transformation driven by disruptive forces such as decarbonization of energy systems, electrification, technological digitalization and energy efficiency (EY, 2019). In turn, the oil and gas industry has been under much pressure from all sides (Deloitte, 2020), coping with substantial disruption on multiple fronts, e.g., oil price volatility, digital technologies, greener energy, regulation changes and newer consumer behaviors (Accenture, 2019). These driving forces have oriented the industry stakeholders in the direction of cost reduction, integration, efficiency improvement and process optimization across the supply chain (KPMG, 2018). To thrive in this emerging energy landscape, oil and gas companies must develop more agile and flexible business models in order to better exploit their assets, respond promptly to changing market dynamics, match the consumer expectations and meet the stakeholder demands (Accenture, 2019).

This uncertain environment around the energy market has affected too much the downstream sector of the oil supply chain (Deloitte, 2019), where companies should revise supplies, capacities, and cost-to-serve different markets. By doing so, many companies might focus less on differentiated carbon-based fuels supplies, besides changing contracts and logistics to satisfy future demand for new greener fuels (Accenture, 2011). These companies should also plan strategically how to source the infrastructure and assets needed to match the future demand, and how much capacity will be necessary to store both conventional and non-conventional fuels (Accenture, 2013). However, this strategic problem under market uncertainty can be tackled by mathematical programming, so that decision-support tools can be built to enable the data-driven decision making to determine the optimal design and planning of the downstream sector of the oil supply chain (Lima et al., 2016).

Along the transformation in the energy sector, some works in the academic literature have employed optimization techniques to optimally design and plan the downstream oil network under uncertainty from different perspectives, for instance, facility location and capacity expansion (Ghatee and Hashemi, 2009); facility location, capacity determination and route expansion (i.e., Carneiro et al., 2010; Ribas et al., 2010); storage capacity expansion (MirHassani and Noori, 2011); storage capacity expansion, technology selection and route design (Oliveira and Hamacher, 2012); storage capacity and route expansion (Oliveira et al., 2013, 2014); facility location-allocation and technology selection (Tong et al., 2014a, b, c), route design (Wang et al., 2019); and facility location and route design (Zhang et al., 2019). Although these optimization tools have planned strategically the downstream sector of the oil supply chain, none of them has analyzed and set the optimal network structure from scratch under uncertain conditions, what is critical in order to design a network that is thoroughly integrated into all strategic and tactical decisions associated with its structure and material flow (Sahebi et al., 2014).

In fact, such complex activity becomes even more challenging and difficult due to the presence of uncertainty, which is reflected

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as price volatility, inaccurate costs, demand fluctuation, bulky inventories, and so on (Lima et al., 2019). In this business, despite of the imprecise and limited information about prices, costs, demand, etc., the decision-making process needs to be effective and efficient, as well as agile and fast (Barbosa-Póvoa and Pinto, 2020). Hence, specific methods have been embedded into optimization-based decision support tools in order to cope with uncertainty when defining the downstream oil network and determining its logistics operations. Put differently, uncertainty has been tackled in this optimization problems by approaches based on stochastic programming, robust optimization and fuzzy programming (Lima et al., 2016). In this set, stochastic programming has been the method mostly used (i.e., Carneiro et al., 2010; Ribas et al., 2010; MirHassani and Noori, 2011; Oliveira and Hamacher, 2012; Oliveira et al., 2013, 2014; Tong et al., 2014b; Wang et al., 2019; Zhang et al., 2019); while fuzzy mathematical programming (i.e., Ghatee and Hashemi, 2009; Tong et al., 2014a); and robust optimization (i.e., Tong et al., 2014c) have been much less applied. Therefore, uncertainty has been treated by few works to manage the strategic and tactical planning of the DOSC network, and thus it has not been sufficiently studied in the scientific literature, although its critical relevance in the core of this kind of problem (Lima et al., 2018). This topic has been a research challenge (Lima et al., 2016; Barbosa-Póvoa and Pinto, 2020), and modeling approaches and solution techniques have still been under development (Sahebi et al., 2014).

At the same time, the DOSC models incorporate few sources of uncertainty, such as product demand (MirHassani and Noori, 2011; Oliveira and Hamacher, 2012; Oliveira et al., 2013, 2014; Wang et al., 2019), product demand, market prices and oil supply (Carneiro et al., 2010; Ribas et al., 2010), biomass supply, product demand, oil prices and technology evolution (Tong et al., 2014a, b, c), and also in product demand and depot failure probability (Zhang et al., 2019). As the most approaches are based on stochastic programming, which models uncertainty using statistical data that are difficult to obtain in case of design problem (Pham and Yenradee, 2017), few sources of uncertainty are incorporated by them. In contrast, robust optimization needs less information to model uncertainty through its uncertainty sets, and thus can enlarge the sources of uncertainty (Lorca and Sun, 2015). Similarly, fuzzy programming also needs less data to model uncertainty by means of fuzzy numbers and fuzzy sets (Sahinidis, 2004), in which random parameters are assumed as fuzzy numbers and constraints as fuzzy sets (Liu and Sahinidis, 1996). In this direction, robust optimization and fuzzy programming emerge as promising research methods, through which uncertainty specification should be more explored, as well as more sources of uncertainty might be incorporated (Sahebi et al., 2014; Lima et al., 2016). In summary, few works have applied other optimization techniques than stochastic programming to design and plan the downstream sector of the oil supply chain under uncertain conditions, and product demand is often considered as the unique source of uncertainty. Furthermore, authors often recognize that the major difficulty in dealing with uncertainty is the access to information on it (Barbosa-Póvoa et al., 2018).

Against this background, the question on how to design, plan and operate DOSC network in an uncertain environment, e.g., under multiple sources of uncertainty, is still a research question to be answered. Moving towards this research direction, this paper is motivated to contribute to the academic community to overcome such research challenge, and thus it aims at evaluating the impact of diverse sources of uncertainty on the DOSC structure and its logistics operation. The strategic and tactical problem is tackled by a MILP model, whose strategic decisions comprise facility location, storage capacity and facility operation, while tactical decisions include distribution activity and storage management. Uncertainty is incorporated into the optimization model by using fuzzy mathematical programming techniques, so that uncertain costs, as well as uncertain demand, are considered. For the sake of simplicity and considering the complexity of the model, symmetric triangular fuzzy numbers are employed to deal with uncertain parameters in the constraints and objective functions of the proposed models. The MILP model aims at cost optimization direction. A real-world case study based on Brazilian oil industry is developed in order to test the adequacy of the proposed model.

The fuzzy possibilistic programming approach presents some particularities and properties that make it adequate and suited to aid the decision-making processes under uncertainty, and thus to solve real-life case studies. As this kind of real-world engineering system are too complex and difficult to be described in precise terms, imprecision is usually involved. Hence, fuzzy information is required to examine such system (Ghatee and Hashemi, 2009). Thus, interval and fuzzy perspectives are valuable to estimate real quantities, while fuzzy relations may give the basis for options selection through preference measures (Dehghan et al., 2008). In spite of the fact that the choice of these measure values in fuzzy logic is many times absolutely subjective and relies on decision maker's preference, it decreases the computation burden considerably when compared with stochastic programming approaches and is adequate for the uncertainty that lacks information (Tong et al., 2014a). For instance, in the proposed model, some considered costs are hard to be determined precisely as an exact value, such as the costs of installing and operating a warehouse, as well as a storage tank, and the cost per unit of capacity at warehouse. There exists ambiguity with regards to the exact value of each one of these costs, that is, the real cost ranges around an estimated value, but its exact value is not determined. As indicated by Pham and Yenradee (2017), fuzzy numbers can be used to estimate these costs by representing them under most likely, pessimistic and optimistic business conditions. Due to the importance of each supply chain to serve its markets, product demands are also estimated as fuzzy numbers in order to design a network structure that is more robust to their natural variability, as well as to avoid suboptimal logistics operation performance or even infeasible design (Tong et al., 2014a).

From this perspective, the present fuzzy programming approach contributes to the logistics operations and strategic design literatures in three important issues. Firstly, the network structure is optimally designed from scratch while the tactical operations are defined accordingly. Hence, the strategic and tactical decisions are fully integrated in the DOSC design problem representation. Secondly, the use of this fuzzy approach is in itself a contribution since uncertainty has been largely addressed through stochastic mathematical programming. Consequently, different sources of uncertainty can be more easily introduced into the optimization problem without increasing the computational burden. Thirdly and finally, a new real-life case study is proposed using an authentic database composed by the reliable information released by the government agencies in the country where the supply chain is located.

This paper is organized as follows. The optimization problem under uncertainty is characterized in Section 2. Fuzzy programming methodology to handle uncertainty in optimization problems is explained in Section 3. Fuzzy possibilistic models are proposed in Section 4. The real-life problem is illustrated in Section 5. The optimal strategic and tactical network plans are discussed in Section 6. Some conclusions are drawn in Section 7.

2. Problem description

The network design and distribution planning of the downstream sector of the oil supply chain is investigated in this study.

This location-transportation problem consists of the strategic planning of locating and building warehouses in predetermined geographical locations and the tactical planning of determining transport assignment and material flows along the network in order to satisfy the liquid fuels demand. To do so, a MILP model is proposed to optimize this problem, so that the optimal strategic and tactical planning establishes the best plan to transfer liquid fuels from refineries to local markets in a most economical direction, by simultaneously deciding the network structure, storage capacities, refining level, etc. The nominal formulation of this optimization problem can be stated as follows:

Given

- the sets of transportation modes, network entities, refined products and time periods,
- the locations of refineries and local markets, and also the possible locations of warehouses,
- the transportation arcs and the associated distances between each pair of network entities,
- the maximum refining capacities,
- the maximum storage capacities of tanks and their capacity rotations,
- the demand for liquid fuels by local markets,
- the investment costs inherent to warehouses and their tanks, as well as the respective operational costs, and also the cost per unit of capacity,
- the distribution costs.

Subject to

- uncertain network costs,
- uncertain demand for refined products,
- investment restrictions,
- logical constraints,
- capacity limitations,
- material balance requirements.

Determine

- the network structure,
- the network operations planning,
- the storage capacities,
- the storage levels,
- the refining levels,
- the transport assignment,
- the network flows,
- the demand fulfillment.

In order to minimize the total downstream oil supply chain cost.

This optimization problem is framed in a fuzzy mathematical programming approach to handle uncertainty in network costs and product demands.

3. Fuzzy programming approach

In real world programming problems, uncertainty comes from the vagueness and ambiguity about the true values of parameters. Fuzzy mathematical programming approach arises as an alternative to treat such uncertainties in an optimization framework (Ghatee and Hashemi, 2009). The main idea behind fuzzy programming is to model real world problems using a mathematical programming model comprising fuzzy parameters (Ghatee and Hashemi, 2009). As the coefficients in the objective function or constraints are ambiguous, this leads to define an ill-posed problem, and hence maximizing or minimizing this optimization problem is not appropriate. On the other hand, such problem can be transformed into a common mathematical programming by managing uncertainties regarding various interpretations of the problem, and then solved by an optimization technique (Liu and Liu, 2002). In this kind of fuzzy programming, the fuzzy parameters are considered as possibility distributions on parameters values and, for this reason, such case is also known as possibilistic programming (Inuiguchi and Ramík, 2000). Note that a possibility distribution represents the information level of someone in relation to some possible circumstances, either the present ones or the typical ones. The complete preordering of such circumstances distinguishes the most possible from the least possible situations. (Dubois and Prade, 2002).

From that perspective, consider a symmetric triangular fuzzy number A, defined by a center α and a spread w_α, i.e., $A = \langle \alpha, w_\alpha \rangle$, while the membership function associated to A, $\mu_A(r)$, gives the possibility degree that the event α is equals to r. In this context, $\mu_A(r)$ can be considered as a possibility distribution of the event α, which in turn can be regarded as a possibilistic variable restricted by the possibility distribution $\mu_A(r)$ (Zadeh, 1978). When parameters of a mathematical programming model are defined ambiguously as possibilistic variables like α, possibilistic linear functions between the model's variables are thus determined. In this way, note that the possibilistic linear function value is also ambiguous and defined by a fuzzy number, hence it cannot be uniquely determined (Liu and Iwamura, 1998). Therefore, optimizing such fuzzy mathematical programming model does not make sense. In order to make this possible, a specific interpretation can be introduced, i.e., particular relations $\rho(A;B) \in [0,\ 1]$, with A and B being fuzzy sets, can be used, being also known as indices defined by possibility and necessity measures (Inuiguchi and Ramík, 2000).

Under a possibility distribution μ_A of a possibilistic variable α of a fuzzy set A, possibility and necessity measures of the event that α is in a fuzzy set B are determined respectively by Eqs. (1) and (2) as below (Dubois and Prade, 1988; Inuiguchi and Ramík, 2000; Tong et al., 2014a):

$$\Pi_A(B) = \sup_r \min(\mu_A(r), \mu_B(r)) \tag{1}$$

$$\mathrm{N}_A(B) = \inf_r \max(1 - \mu_A(r), \mu_B(r)) \tag{2}$$

where μ_b refers to the membership function of the fuzzy set B. While the possibility measure, $\Pi_A(B)$, assesses the possibility degree that the possibilistic variable α restricted by the possibility distribution μ_A is in the fuzzy set B, the necessity measure, $\mathrm{N}_A(B)$, estimates the certainty degree of such event occurs (Dubois and Prade, 1988).

Let α be a possibilistic variable with a triangle membership function μ_A of a symmetric triangular fuzzy number A, so that α^p, α^m and α^o represent its pessimistic, most possible and optimistic values, respectively, and let B be a crisp (nonfuzzy) set of real number not greater than g, i.e., $B = (-\infty, g]$. Thus, possibility and necessity measures can be obtained respectively as shown in Eqs. (3) and (4). Note that the interpretations (in brackets) for possibility and necessity are obtained directly.

$$\begin{aligned}\mathrm{Pos}(\alpha \le g) &= \Pi_A((-\infty, g]) = sup\{\mu_A(r) \mid r \le g\} \\ &= \begin{cases} 0 & g \le \alpha^p \\ \frac{g-\alpha^p}{\alpha^m-\alpha^p} & \alpha^p \le g \le \alpha^m \\ 1 & g \ge \alpha^m \end{cases}\end{aligned} \tag{3}$$

$$\begin{aligned}\mathrm{Nes}(\alpha \le g) &= N_A((-\infty, g]) = 1 - sup\{\mu_A(r) \mid r > g\} \\ &= \begin{cases} 0 g \le \alpha^m \\ \frac{g-\alpha^m}{\alpha^o-\alpha^m} & \alpha^m \le g \le \alpha^o \\ 1 & g \ge \alpha^o \end{cases}\end{aligned} \tag{4}$$

Fig. 1 shows the possibility and necessity degrees to what extent α is not greater than g.

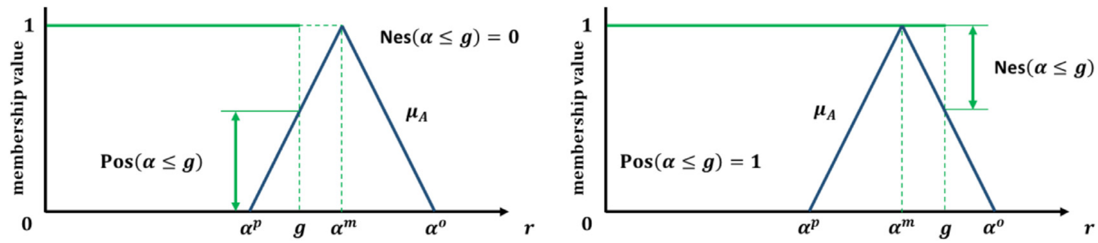

Fig. 1. Possibility and necessity degrees of $\alpha \le g$ (based on Inuiguchi and Ramík, 2000).

According to Das et al. (2007), possibility measure quantifies the best case of a fuzzy event, while necessity measure gives the worst case of that event. In order to establish a compromise between such measures, a Weighted Possibility and Necessity (WPN) measure is defined as below in Equation (5):

$$\mathrm{WPN}(\alpha \le g) = \rho \cdot \mathrm{Pos}(\alpha \le g) + (1-\rho) \cdot \mathrm{Nes}(\alpha \le g) \tag{5}$$

where ρ is an index that combines both measures. In a particular case, when $\rho = 0.5$, Liu and Liu (2002) called WPN as the credibility of that event – see Eq. (6) and observe the interpretation for credibility (in brackets):

$$\mathrm{Cr}(\alpha \le g) = \frac{1}{2} \cdot (\mathrm{Pos}(\alpha \le g) + \mathrm{Nes}(\alpha \le g)) = \begin{cases} 0 & g \le \alpha^p \\ \frac{1}{2} \cdot \frac{g-\alpha^p}{\alpha^m - \alpha^p} & \alpha^p \le g \le \alpha^m \\ \frac{1}{2} + \frac{1}{2} \cdot \frac{g-\alpha^m}{\alpha^o - \alpha^m} & \alpha^m \le g \le \alpha^o \\ 1 & g \ge \alpha^o \end{cases} \tag{6}$$

3.1. Possibilistic programming formulation

Consider the following possibilistic linear programming problem with fuzzy coefficients on objective function and constraints, i.e., Problem (7):

$$\begin{aligned} &\text{minimize} \sum_{j=1}^{n} \tilde{c}_j x_j \\ &\text{subject to :} \\ &\sum_{j=1}^{n} \tilde{a}_i x_j \le b_i, \forall i \in I \\ &x_j \ge 0, \forall j \in J \end{aligned} \tag{7}$$

where parameters $\tilde{a}_i$, $i \in I$, and $\tilde{c}_j$, $j \in J$, are possibilistic variables restricted by fuzzy numbers A_i, $i \in I$, and C_j, $j \in J$, respectively. In order to transform the fuzzy objective function and constraints into their crisp equivalents, a method proposed by Liu and Iwamura (1998) is employed and the following equivalent fuzzy programming problem under necessity/possibility/credibility constraints arises, as shown below in Problem (8):

$$\begin{aligned} &\text{minimize } U \\ &\text{subject to :} \\ &Pos/Nes/Cr\left(\sum_{j=1}^{n} \tilde{c}_j x_j \le U\right) \ge \theta \\ &Pos/Nes/Cr\left(\sum_{j=1}^{n} \tilde{a}_i x_j \le b_i\right) \ge \theta_i \\ &x_j \ge 0, \forall j \in J \end{aligned} \tag{8}$$

where θ and θ_i, $i \in I$, are predefined confidence levels for fuzzy constraints. Thus, the objective of the previous problem is to minimize U so that possibility, necessity, or credibility of the events in brackets is not less than the respective confidence levels θ and θ_i, $i \in I$. Also, Problem (8) can be cast as a linear formulation by employing Eqs. (3), (4) or (6) so as to determine a linear representation for the fuzzy programming problem under possibility, necessity or credibility constraints in that order. Then, Problem (9) is a linear formulation for the fuzzy programming problem under possibility constraints, however, the other reformulations are straightforward.

$$\begin{aligned} &\text{minimize} U \\ &\text{subject to :} \\ &U \ge \sum_{j=1}^{n} \left\{\left[c_j^p + \theta \cdot \left(c_j^m - c_j^p\right)\right] \cdot x_j\right\} \\ &b_i \ge \sum_{j=1}^{n} \left\{\left[a_i^p + \theta_i \cdot \left(a_i^m - a_i^p\right)\right] \cdot x_j\right\}, \forall i \in I \\ &x_j \ge 0, \forall j \in J \end{aligned} \tag{9}$$

4. Fuzzy possibilistic models

A MILP model is developed to handle the location-transportation problem under uncertainty in order to establish the optimal strategic and tactical planning for the downstream oil network. Strategic decisions include the installation and operation of warehouses and their storage tanks at predetermined potential locations along the supply chain, while tactical decisions encompass product flows, demand fulfillment and transport assignment. Network costs and products demand are treated as uncertain parameters restricted by a fuzzy number associated to a membership function.

Initially, the model is developed in a deterministic framework, and then reformulated into a chance constrained programming with fuzzy parameters. Later, the established chance constraints are converted into their crisp equivalents aiming to solve the proposed model.

4.1. Deterministic programming model

The deterministic formulation of the mathematical programming model for the location-transportation problem discussed before is presented hereinafter in Eqs. (10) to (21). Refer to Table A.1 in Annex A to consult the model notation.

$$\begin{aligned} \underset{x,y,z \in \mathbb{R}_+, v,w \in \{0,1\}, h,l \in \mathbb{I}_+}{\text{minimize}} & \sum_{j \in J, t \in T} V_j v_{j,t} + \sum_{j \in J, t \in T} W_j w_{j,t} + \sum_{j \in J, p \in P, t \in T} H_p h_{j,p,t} \\ & + \sum_{j \in J, p \in P, t \in T} L_p l_{j,p,t} + \sum_{j \in J, t \in T} Z_j z_{j,t} + \sum_{i \in I, j \in J, p \in P, m \in M, t \in T} F_{p,m} G_{i,j,m} x_{i,j,p,m,t} \\ & + \sum_{j \in J, k \in K, p \in P, m \in M, t \in T} F_{p,m} G_{j,k,m} y_{j,k,p,m,t} \end{aligned} \tag{10}$$

subject to:

$$\sum_{t \in T} v_{j,t} \le 1 \ \forall j \in J \tag{11}$$

$$h_{j,p,t} \le B \cdot v_{j,t} \ \forall j \in J, p \in P, t \in T \tag{12}$$

$$w_{j,t} \le \sum_{t' \le t} v_{j,t'} \quad \forall j \in J, t \in T \tag{13}$$

$$l_{j,p,t} \le B \cdot w_{j,t} \ \forall j \in J, p \in P, t \in T \tag{14}$$

$$l_{j,p,t} \le \sum_{t' \le t} h_{j,p,t'} \ \forall j \in J, p \in P, t \in T \tag{15}$$

$$\sum_{j \in J, p \in P, m \in M} x_{i,j,p,m,t} \le Q_i \ \forall i \in I, t \in T, (i,j,m) \in A_{i,j,m} \tag{16}$$

$$\sum_{i \in I, m \in M} x_{i,j,p,m,t} = \sum_{k \in K, m \in M} y_{j,k,p,m,t} \ \forall j \in J, p \in P, t \in T, (i,j,m) \in A_{i,j,m}, (j,k,m) \in A_{j,k,m} \tag{17}$$

$$z_{j,t} \le B \cdot w_{j,t} \ \forall j \in J, t \in T \tag{18}$$

$$\sum_{k \in K, p \in P, m \in M} y_{j,k,p,m,t} \le z_{j,t} \ \forall j \in J, t \in T, (j,k,m) \in A_{j,k,m} \tag{19}$$

$$\sum_{k \in K, m \in M} y_{j,k,p,m,t} \le R \cdot S_p \cdot l_{j,p,t} \ \forall j \in J, p \in P, t \in T, (j,k,m) \in A_{j,k,m} \tag{20}$$

$$\sum_{j \in J, m \in M} y_{j,k,p,m,t} \ge D_{k,p,t} \ \forall k \in K, p \in P, t \in T, (j,k,m) \in A_{j,k,m} \tag{21}$$

Equation (10) refers to the objective function and minimizes the total cost, including fixed and variable costs to install and operate warehouses and their tanks, and transportation costs to carry products over the chain. The first two terms represent respectively the fixed costs of installing and operating warehouses, as well as the next two terms denote the fixed costs for installing and operating tanks at warehouses. The fifth term is the variable costs depending on the volumes stored within tanks at warehouses. Finally, the last two terms refer to the primary and secondary distribution costs, respectively.

Constraint (11) establishes that just one warehouse should be installed at a specific location over the time horizon. Constraint (12) defines that tanks can be only installed in installed warehouses. Note that tanks will also be installed once along the time horizon when warehouses are installed. Constraint (13) assures that only installed warehouses can be operated. Constraint (14) ensures that tanks must be operated at operated warehouses, while Constraints (15) enforces that a tank can only be operated if it is installed. Constraint (16) limits the supply availability at refinery by its processing capacity. Constraint (17) controls the material balance at warehouses. Here, at the strategic and tactical levels, it is assumed that there is no accumulation of stock. Constraint (18) determines that the products can only be stored at an operated warehouse. Constraint (19) limits the products supply at warehouses by the volume stored there. Constraint (20) defines the quantity of tanks to be operated at warehouses. Constraint (21) guarantees that all demand is satisfied.

4.2. Chance constrained programming model with fuzzy parameters

The deterministic location-transportation problem is now cast as a possibilistic programming problem under possibility, necessity or credibility constraints. Aiming at this, the objective function (10) is reformulated into Eqs. (22) and (23), as well as Constraint (21) into Constraint (24). In this chance constrained programming model with fuzzy parameters, these ones comprise product demand and all costs under investigation, i.e., fixed installation and operation costs of warehouses and tanks, variable operation costs that depend on the respective volumes stored, and the transportation costs to move the products until the consumer markets. Note that fuzzy parameters are detached with tilde accent in the model shown below.

$$\underset{x,y,z,C \in \mathbb{R}_+, v,w \in \{0,1\}, h,l \in \mathbb{I}_+}{\text{minimize}} \ C \tag{22}$$

subject to: constraints (11)-(20)

$$\begin{aligned} \text{Pos/Nes/Cr}\Bigg(& \sum_{j \in J, t \in T} \tilde{V}_j v_{j,t} + \sum_{j \in J, t \in T} \tilde{W}_j w_{j,t} + \sum_{j \in J, p \in P, t \in T} \tilde{H}_p h_{j,p,t} \\ & + \sum_{j \in J, p \in P, t \in T} \tilde{L}_p l_{j,p,t} + \sum_{j \in J, t \in T} \tilde{Z}_j z_{j,t} + \sum_{i \in I, j \in J, p \in P, m \in M, t \in T} \tilde{F}_{p,m} G_{i,j,m} x_{i,j,p,m,t} \\ & + \sum_{j \in J, k \in K, p \in P, m \in M, t \in T} \tilde{F}_{p,m} G_{j,k,m} y_{j,k,p,m,t} \le C \Bigg) \ge \theta_{of} \end{aligned} \tag{23}$$

$$\text{Pos/Nes/Cr}\left(\sum_{j \in J, m \in M} y_{j,k,p,m,t} \ge \tilde{D}_{k,p,t} \right) \ge \theta_d \quad \forall k \in K, p \in P, t \in T, (j,k,m) \in A_{j,k,m} \tag{24}$$

Equation (22) aims at minimizing objective value C under the condition imposed by Equation (23) where the possibility, necessity or credibility for the total logistics costs being not greater than C is greater than or equal to the confidence level θ_{of} is considered. Also, Constraint (24) enforces that the possibility, necessity or credibility for the products delivered at markets being not greater than the respective demands is greater than or equal to the confidence level θ_d.

4.2.1. The deterministic counterparts

The chance constraints (23) and (24) can be converted into their respective crisp equivalents so that the proposed chance constrained programming with fuzzy parameters can then be solved. In this direction, both chance constraints are reformulated by employing Equation (3), so then the deterministic counterpart of the possibilistic programming problem under possibility measures is defined as can be seen in equations (25) to (27).

$$\underset{x,y,z,C \in \mathbb{R}_+, v,w \in \{0,1\}, h,l \in \mathbb{I}_+}{\text{minimize}} \ C \tag{25}$$

subject to: constraints (11)-(20)

$$\begin{aligned} & \sum_{j \in J, t \in T} \left\{ \left[V_j^p + \theta_{of} \cdot \left(V_j^m - V_j^p \right) \right] \cdot v_{j,t} \right\} + \\ & \sum_{j \in J, t \in T} \left\{ \left[W_j^p + \theta_{of} \cdot \left(W_j^m - W_j^p \right) \right] \cdot w_{j,t} \right\} + \\ & \sum_{j \in J, p \in P, t \in T} \left\{ \left[H_p^p + \theta_{of} \cdot \left(H_p^m - H_p^p \right) \right] \cdot h_{j,p,t} \right\} + \\ & \sum_{j \in J, p \in P, t \in T} \left\{ \left[L_p^p + \theta_{of} \cdot \left(L_p^m - L_p^p \right) \right] \cdot l_{j,p,t} \right\} + \\ & \sum_{j \in J, t \in T} \left\{ \left[Z_j^p + \theta_{of} \cdot \left(Z_j^m - Z_j^p \right) \right] \cdot z_{j,t} \right\} + \\ & \sum_{p \in P, m \in M} \left\{ \left[F_{p,m}^p + \theta_{of} \cdot \left(F_{p,m}^m - F_{p,m}^p \right) \right] \right. \\ & \left. \cdot \left[\sum_{i \in I, j \in J, t \in T} \left(G_{i,j,m} x_{i,j,p,m,t} \right) + \sum_{j \in J, k \in K, t \in T} \left(G_{j,k,m} y_{j,k,p,m,t} \right) \right] \right\} \le C \end{aligned} \tag{26}$$

$$\begin{aligned} & \textstyle\sum_{j \in J, m \in M} y_{j,k,p,m,t} \ge \left[D_{k,p,t}^p + \theta_d \cdot \left(D_{k,p,t}^m - D_{k,p,t}^p \right) \right] \\ & \forall k \in K, p \in P, t \in T, (j,k,m) \in A_{j,k,m} \end{aligned} \tag{27}$$

Note that upper indices p and m account respectively for the pessimistic and the most possible values for the respective fuzzy parameter.

Constraints (23) and (24) can be reformulated in accordance with Equation (4), and thus the deterministic counterpart of the possibilistic problem under necessity measures is determined, as shown in equations (28) to (30), where the index O on the fuzzy coefficients refers to their most optimistic values.

$$\underset{x,y,z,C\in\mathbb{R}_+,v,w\in\{0,1\},h,l\in\mathbb{I}_+}{\text{minimize}} \quad C \tag{28}$$

subject to: constraints (11)-(20)

$$\begin{aligned}
&\sum_{j\in J,t\in T}\left\{\left[V_j^m+\theta_{of}\cdot\left(V_j^o-V_j^m\right)\right]\cdot v_{j,t}\right\}+\\
&\sum_{j\in J,t\in T}\left\{\left[W_j^m+\theta_{of}\cdot\left(W_j^o-W_j^m\right)\right]\cdot w_{j,t}\right\}+\\
&\sum_{j\in J,p\in P,t\in T}\left\{\left[H_p^m+\theta_{of}\cdot\left(H_p^o-H_p^m\right)\right]\cdot h_{j,p,t}\right\}+\\
&\sum_{j\in J,p\in P,t\in T}\left\{\left[L_p^m+\theta_{of}\cdot\left(L_p^o-L_p^m\right)\right]\cdot l_{j,p,t}\right\}+\\
&\sum_{j\in J,t\in T}\left\{\left[Z_j^m+\theta_{of}\cdot\left(Z_j^o-Z_j^m\right)\right]\cdot z_{j,t}\right\}+\\
&\sum_{p\in P,m\in M}\left\{\left[F_{p,m}^m+\theta_{of}\cdot\left(F_{p,m}^o-F_{p,m}^m\right)\right]\right.\\
&\left.\cdot\left[\sum_{i\in I,j\in J,t\in T}\left(G_{i,j,m}x_{i,j,p,m,t}\right)+\sum_{j\in J,k\in K,t\in T}\left(G_{j,k,m}y_{j,k,p,m,t}\right)\right]\right\}\leq C
\end{aligned}\tag{29}$$

$$\begin{gathered}\textstyle\sum_{j\in J,m\in M}y_{j,k,p,m,t}\geq\left[D_{k,p,t}^m+\theta_d\cdot\left(D_{k,p,t}^o-D_{k,p,t}^m\right)\right]\\ \forall k\in K,\ p\in P,\ t\in T,\ (j,k,m)\in A_{j,k,m}\end{gathered}\tag{30}$$

The deterministic counterpart of the chance constrained programming under credibility measures is established, as shown in equations (31) to (33), by applying Equation (6) to chance constraints (23) and (24).

$$\underset{x,y,z,C\in\mathbb{R}_+,v,w\in\{0,1\},h,l\in\mathbb{I}_+}{\min} \quad C \tag{31}$$

subject to: constraints (11)-(20)

$$\begin{aligned}
&\sum_{j\in J,t\in T}\left\{\left[V_j^m+\left(2\theta_{of}-1\right)\cdot\left(V_j^o-V_j^m\right)\right]\cdot v_{j,t}\right\}+\\
&\sum_{j\in J,t\in T}\left\{\left[W_j^m+\left(2\theta_{of}-1\right)\cdot\left(W_j^o-W_j^m\right)\right]\cdot w_{j,t}\right\}+\\
&\sum_{j\in J,p\in P,t\in T}\left\{\left[H_p^m+\left(2\theta_{of}-1\right)\cdot\left(H_p^o-H_p^m\right)\right]\cdot h_{j,p,t}\right\}+\\
&\sum_{j\in J,p\in P,t\in T}\left\{\left[L_p^m+\left(2\theta_{of}-1\right)\cdot\left(L_p^o-L_p^m\right)\right]\cdot l_{j,p,t}\right\}+\\
&\sum_{j\in J,t\in T}\left\{\left[Z_j^m+\left(2\theta_{of}-1\right)\cdot\left(Z_j^o-Z_j^m\right)\right]\cdot z_{j,t}\right\}+\\
&\sum_{p\in P,m\in M}\left\{\left[F_{p,m}^m+\left(2\theta_{of}-1\right)\cdot\left(F_{p,m}^o-F_{p,m}^m\right)\right]\right.\\
&\left.\cdot\left[\sum_{i\in I,j\in J,t\in T}\left(G_{i,j,m}x_{i,j,p,m,t}\right)+\sum_{j\in J,k\in K,t\in T}\left(G_{j,k,m}y_{j,k,p,m,t}\right)\right]\right\}\leq C
\end{aligned}\tag{32}$$

$$\begin{gathered}\sum_{j\in J,m\in M}y_{j,k,p,m,t}\geq\left[D_{k,p,t}^m+\left(2\theta_d-1\right)\cdot\left(D_{k,p,t}^o-D_{k,p,t}^m\right)\right]\\ \forall k\in K,\ p\in P,\ t\in T,\ (j,k,m)\in A_{j,k,m}\end{gathered}\tag{33}$$

5. Case study

The proposed models are applied to optimize a real location-transportation problem under uncertainty based on the Brazilian oil network. Such logistics network includes 14 Brazilian state-owned oil refineries, 42 possible locations to receive a warehouse, 27 local markets and three transportation modes. Eight liquid fuels are considered, namely, gasoline C, hydrous ethanol, fuel oil, diesel, liquefied petroleum gases (LPG), aviation kerosene, jet fuel and illuminating kerosene (paraffin). Such liquid fuels must be transported by pipeline, tanker ships or tank trucks between refineries and potential warehouses, where they might be stored at specific tanks according to their properties. Later, they must be shipped by tank truck to reach the local markets. Also, maritime mode is considered to transfer products from warehouses to local markets at Northern region. Potential geographical locations are set in accordance with the real locations of the Brazilian state-owned oil terminals, while local markets correspond to the 26 Brazilian states and the Federal District, Brasília. Fig. 2 illustrates the potential locations to install a warehouse, and the local markets as the areas delineated on the map. Fig. 3 displays the locations of oil refineries. The planning horizon refers to a 6-year period, discretized into yearly cycles, from 2014 to 2019. The data set is composed by the information released by Agência Nacional do Petróleo, Gás Natural e Biocombustíveis (ANP, 2020), Petróleo Brasileiro S.A. (Petrobras, 2020) and Petrobras Transporte S.A. (Transpetro, 2020). In addition, Google Maps Platform were used to provide all the route distances. The detailed data set can be found in the supplementary material.

5.1. Fuzzy cases setting

In the fuzzy possibilistic problems, all costs under investigation and the demand for refined products are defined as a possibilistic variable α restricted by a triangle membership μ_A of a symmetric triangular fuzzy number A, whose pessimistic, most possible and optimistic values are represented by α^p, α^m and α^o, in that order. Following the literature, thus, α^m is assumed to be equivalent to α in the deterministic problem, whereas α^p and α^o to be 10% less and 10% greater, respectively. In turn, fuzzy constraints are hold with at least 80% confidence level, that is, θ_{of} and θ_d are all set to 80%. For details, see Inuiguchi and Ramík (2000), Das et al. (2007) and Tong et al. (2014a). Note that the level of conservativeness of the fuzzy solution can be adjusted by choosing either different confidence levels for the fuzzy constraints or different strategies (i.e., possibility, necessity or credibility measures) to solve the problem. In this way, the decision maker can test different alternatives to tackle uncertainty in his/her decision problem, so that the overall decision-making process is improved.

6. Results and discussion

All the MILP models were coded using GAMS 31.1.1 and solved with CPLEX 12.10 on Intel(R) Core(TM) i7-3540M CPU @ 3.00GHz and 8 GB RAM. Table 1 brings the computational results.

Table 1 shows that the problem size of all fuzzy possibilistic formulations is the same and increases by one constraint (e.g., Constraint (25) or (26)) and one continuous variable (i.e., C, the objective value) when compared with the nominal formulation. Also, the possibilistic model under possibility constraints is the least conservative, while the one under necessity constraints is the most conservative. These solutions reflect the decision maker's preference. Possibility measure reflects its optimistic sense, as long as necessity measure its pessimistic sense. Although the model under credibility constraints is not as conservative as the one under necessity constraints, it is still very conservative and returns a high total

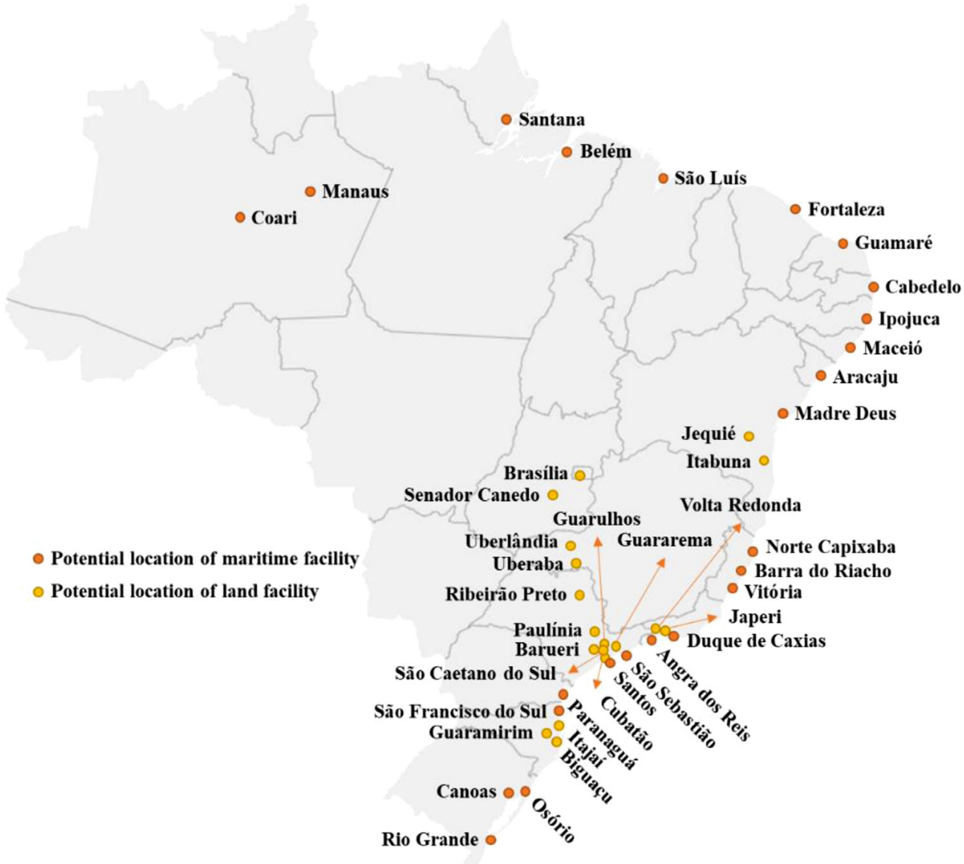

Fig. 2. Potential facility locations.

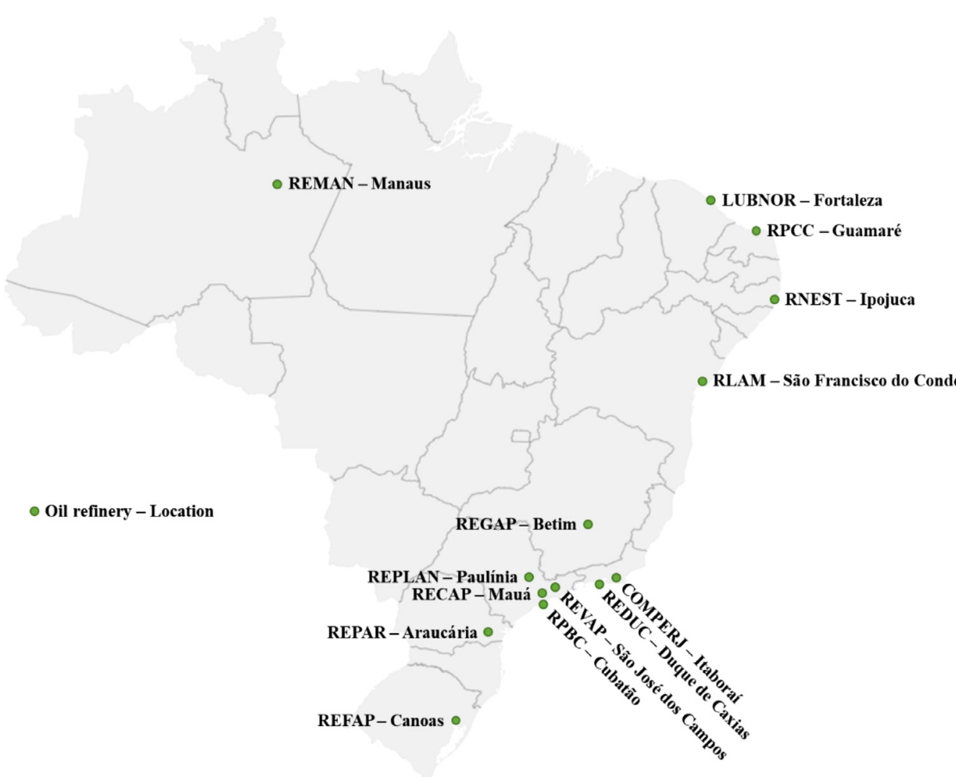

Fig. 3. Oil refineries locations.

Fig. 4. Locations selected to install a warehouse.

Table 1
Model statistics.

Model	Objective (G$)	Constraints	Variables		Time (s)	GAP (%)
			Continuous	Discrete		
Deterministic	106.611	12,259	91,189	4,536	1,599	0
Necessity	136.648	12,260	91,190	4,536	3,292	0
Credibility	128.735	12,260	91,190	4,536	3,623	0
Possibility	99.792	12,260	91,190	4,536	937	0

Table 2
Cost breakdown.

Cost (G$)	Facility installation	Tank installation	Facility operation	Tank operation	Volume storage	Primary transportation	Secondary transportation
Model							
Deterministic	0.136	0.655	0.165	0.687	1.812	52.037	51.118
Necessity	0.147	0.743	0.178	0.790	2.113	69.562	63.115
Credibility	0.145	0.726	0.176	0.764	2.036	65.060	59.828
Possibility	0.128	0.634	0.161	0.662	1.740	47.617	48.885

network cost. Hence, credibility measure inclines closer to a pessimistic sense. The cost breakdown of these models is presented in Table 2.

In general, the cost breakdown shows the major contribution of transportation costs to the total network cost. Note that, along the 6-year time horizon, tactically planning the network is more costly than planning it strategically. This means that costs related to distribution and storage activities are more expensive than those associated with facility location, capacity determination and resource operation.

6.1. Optimal network design

The deterministic model, as well as the necessity and credibility models, establishes the same optimal network design that includes 22 warehouses, while the possibility model comprises 21 warehouses, being the warehouse location at Uberaba the only difference. Fig. 4 presents the locations selected to house a warehouse. Bear in mind that Uberaba location is not included into optimal design defined by the possibility model. In most cases, the optimal design comprises 13 maritime facilities and 9 onshore facilities.

Table 3
Optimal storage capacity and number of tanks installed per product.

Model	Location	Capacity (m^3)	Hydrous ethanol	Gasoline C	Jet fuel	LPG	Fuel oil	Diesel	Aviation kerosene	Paraffin
Deterministic	Manaus	112,200	1	2	1	1	1	2	1	
	Santana	49,400		2		2		1		
	Belém	138,800	1	3	1	4	2	2	1	
	São Luis	116,600	1	2		3	2	2	1	
	Fortaleza	133,200	1	4		6	1	2	1	
	Cabedelo	103,800	1	3		4	2	1	1	
	Ipojuca	131,000	1	3		5	2	2	1	
	Maceió	59,400	1	1		2		1	1	
	Aracajú	59,400	1	1		2		1	1	
	Madre Deus	202,600	2	5	1	8	2	3	1	
	S. Canedo	317,600	6	6	1	8	1	6	1	
	Brasília	101,600	1	4		3		1	2	
	Barueri	548,800	4	21		29		7	6	
	Cubatão	170,000	7					4		
	S. C. do Sul	190,000	13				1	2		
	V. Redonda	215,000	2	6				5	1	
	D. de Caxias	369,800	6	12		9	1	5	3	1
	Uberaba	30,000		3						
	Vitória	256,600	1	2		3	1	8	1	
	Paranaguá	348,400	4	8	1	22	1	6	1	
	Biguaçu	171,400	1	6		12	1	2	1	1
	Canoas	202,600	1	7	1	8	1	3	1	
Necessity	Manaus	**102,200**	1	**1**	1	1	1	2	1	
	Fortaleza	**135,400**	1	4		**7**	1	2	1	
	Ipojuca	**143,200**	1	**4**		**6**	2	2	1	
	Madre Deus	**214,800**	2	5	1	**9**	**3**	3	1	
	S. Canedo	**319,800**	6	6	1	**9**	1	6	1	
	Brasília	**103,800**	1	4		**4**		1	2	
	Barueri	**608,200**	4	**23**		**31**		**10**	**2**	
	Cubatão	**165,000**	**14**					**1**		
	S. C. do Sul	**105,000**	**7**				1	**1**		
	V. Redonda	**230,000**	**3**	**3**			**1**	**6**	1	
	D. de Caxias	**322,000**	6	12		**10**	1	**3**	3	1
	Vitória	**281,600**	1	2		3	1	**9**	1	
	Paranaguá	**392,800**	4	**12**	1	**24**	1	6	1	
	Biguaçu	**268,600**	1	**12**	**1**	**13**	1	**3**	1	1
	Canoas	**196,000**	1	**8**	**0**	**5**	1	3	1	
Credibility	Manaus	**102,200**	1	**1**	1	1	1	2	1	
	Ipojuca	**143,200**	1	**4**		**6**	2	2	1	
	Madre Deus	**204,800**	2	5	1	**9**	2	3	1	
	S. Canedo	**319,800**	6	6	1	**9**	1	6	1	
	Brasília	**128,800**	1	**5**		**4**	1	2		
	Barueri	**628,200**	**2**	22		**31**		**10**	**7**	
	Cubatão	**190,000**	**14**					**2**		
	S. C. do Sul	**115,000**	**8**				1	**1**		
	V. Redonda	**220,000**	2	**4**				**6**	1	
	D. de Caxias	**332,000**	**7**	12		**10**	1	**3**	3	1
	Uberaba	**40,000**		**4**						
	Vitória	**281,600**	1	2		3	1	**9**	1	
	Paranaguá	**380,600**	4	**11**	1	**23**	1	6	1	
	Biguaçu	**258,600**	1	**11**	**1**	**13**	1	**3**	1	1
	Canoas	**198,200**	1	**8**	**0**	**6**	1	3	1	
Possibility	Barueri	**521,600**	4	21		**28**		**6**	6	
	Cubatão	**160,000**	**6**					4		
	S. C. do Sul	**215,000**	13				1	**3**		
	V. Redonda	**205,000**	**3**	**5**				5	**0**	
	D. de Caxias	**374,800**	**5**	**11**		9	1	**6**	3	1

To gain insights about the optimal network design, Table 3 shows the optimal storage capacity by elucidating the capacity determination at each location and the optimal number of storage tanks opened per product. The main differences between the deterministic model and each fuzzy model are highlighted in bold and green (positive deviations) or in bold and red (negative deviations), while the similarities between the deterministic and fuzzy cases were removed from the table. Note that the possibility case is too similar to the deterministic one, differing only in five locations that are all located in Southeast region, namely, Barueri, Cubatão, São Caetano do Sul, Volta Redonda e Duque de Caxias. Although the same locations are chosen in the different optimization problems, the storage capacities determined are quite different. For instance, Barueri warehouse is one of the most important installed warehouses and its capacity varies from 521,600 m^3 in the problem under possibility measures to 628,200 m^3 in the problem under credibility measures. The largest warehouses are established at Barueri, Paranaguá, Duque de Caxias and Senador Canedo, while the smallest ones at Uberaba, Santana, Aracajú and Maceió. In all, the warehouses located from Madre Deus upwards are small to medium size, while the others from Brasília downwards are medium to large size. Hence, larger warehouses are located near larger markets, where product demand is high. In contrast, smaller warehouses are close to smaller markets.

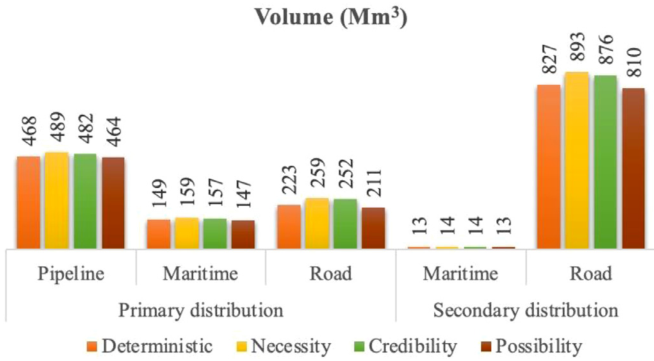

Fig. 5. Volume allocation to transportation modes.

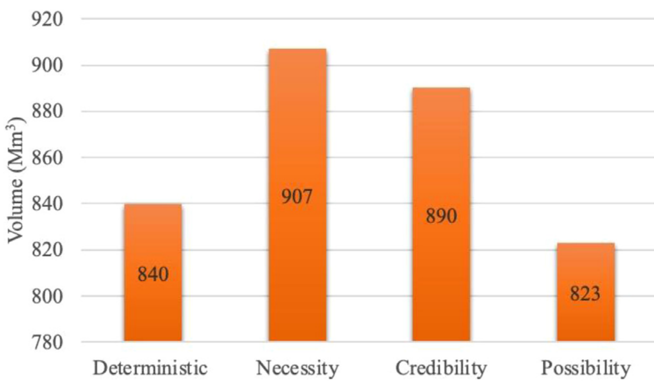

Fig. 6. Total volume passing through the network.

6.2. Optimal tactical planning

Fig. 5 shows the volume allocation for transportation modes in the primary and secondary distributions. In the primary transportation, from refineries to warehouses, the most commonly transportation mode assigned is pipeline, followed by road, and then by maritime. Differently, in the secondary transportation, road mode is majorly used to transfer products from warehouses to local markets. In this case, maritime mode is only employed in the Northern region, under circumstances where road mode is not available.

Fig. 6 depicts the total volume of refined products passing through the network along the planning horizon for each optimization model. Observe that the amount of products that passes through the primary distribution is the same as what is stored at all warehouses and transferred over the secondary distribution, as the logistics system is modeled as a direct network, where warehouses receive products from refineries and send them to local markets. The fuzzy model under possibility measures returns the lowest volume, while the other one under necessity measures the largest.

After analyzing both Table 3 and Fig. 6, some findings about the different network structures stablished by the fuzzy cases can be drawn. The results corroborate that the design of the network structure is directly influenced by the market demand, i.e., the total volume of products that is distributed across the network from refineries to warehouses to markets. Note that the least demand is associated with the possibility case (Fig. 6), which in turn installs less warehouses and storage tanks throughout the chain (Table 3). For this reason, the total cost for building the corresponding network is minimal. By contrast, the necessity case defines a larger network structure to satisfy the higher market demand, and, hence, the associated costs are maximum. Needless to say, since the credibility case is an average of both previous cases, the respective network structure and the inherent costs are something between these two extremes.

In general, the fuzzy programming under different measures (possibility/necessity/credibility) is adequate to optimally design and plan the downstream sector of the oil supply chain under uncertainty. Such measures refer to three different risk aversion strategies that enable the decision maker to further handle uncertainty in the decision-making process in the supply chain problems. Thus, there is not the most adequate fuzzy approach, but the conjoint usage of these decision-support tools provides the decision maker with all the necessary information to make better decisions.

7. Conclusion

In this paper, a mixed-integer linear programming model optimizes at a minimal cost the strategic and tactical planning for the downstream sector of the Brazilian oil supply chain. The network is designed by determining the strategic locations to hold warehouses, while their capacities are established by installing specific tanks for each product, and their operations are also decided strategically along the planning horizon. Logistics operations are considered as well, so that product flows, transport assignments and storage activities are handled tactically. Uncertainty is inserted into the optimization problem using fuzzy possibilistic programming under possibility, necessity and credibility measures, and thus costs and demands are treated as fuzzy numbers.

From the model results, the cost breakdown highlights the importance of the transportation cost, which is the most critical factor in the network costs. For such reason, the tactical plan is much more expensive than the strategic plan. All models select the same geographical locations, except Uberaba location that is not chosen by the possibility model. However, the capacity installed at each warehouse varies widely among the models. The larger warehouses are placed near larger markets, whose demand for refined product is higher. Pipeline is widely used in the primary transportation, while road in the secondary transportation. Maritime transport develops an important role in the transportation activity. The product flow across the network depends on the measure considered by the fuzzy model. For instance, possibility measure provides the lowest volume throughout the network, whereas necessity measure the highest.

Future works should extend the strategic planning to cope with other types of resources like manifold, pumps, arms, interfaces and pump stations. Further efforts must invest in a more accurate tactical planning in order to incorporate more details into the optimization problem, such as inventory management, transportation arc capacities, inter-warehouse transportation, crude oil purchase and international trade. A graph modeling approach could be employed to model the network aiming to better represent it in the optimization problem. In addition, different modelling approaches to improve the representation of uncertainty should be more explored in the strategic and tactical context. Within fuzzy programming context, a sensitivity analysis on the confidence level θ and the possibilistic variable α should be explored. As research direction, multistage stochastic programming and multistage adjustable robust optimization might be developed, while efficient solution techniques might also be formulated to handle the corresponding large-scale problems.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.compchemeng.2021.107373.

Annex A. Nomenclature

Table A1

Table A.1
Model notation.

Indexes and sets	
$m \in M$	transportation modes
$n, n' \in N$	network entities
$p \in P$	products
$t, t' \in T$	time periods
Indexes and subsets	
$i \in I \subseteq N$	refineries
$j \in J \subseteq N$	warehouses
$k \in K \subseteq N$	markets
Parameters	
$A_{n,n',m}$	arc between nodes n and n' using transport m
B	big number
$G_{n,n',m}$	distance between nodes n and n' per transport m
Q_i	capacity of refinery i
R	capacity rotations
S_p	tank size for product p
$D_{k,p,t}$	demand at market k for product p at time t
$F_{p,m}$	transportation cost per product p and transport m
H_p	cost of installing a tank for product p
L_p	cost of operating a tank for product p
V_j	cost of installing a warehouse j
W_j	cost of operating a warehouse j
Z_j	cost per unit of capacity at warehouse j
θ_{of}	confidence level for fuzzy costs constraint
θ_d	confidence level for fuzzy demands constraint
Variables	
Binary variables	
$v_{j,t}$	decision for installing a warehouse j at time t
$w_{j,t}$	decision for operating a warehouse j at time t
Continuous variables	
C	objective value
$x_{i,j,p,m,t}$	volume of product p carried by transport m at time t from refinery i to warehouse j
$y_{j,k,p,m,t}$	volume of product p carried by transport m at time t from warehouse j to market k
$z_{j,t}$	volume stored at a warehouse j at time t
Integer variables	
$h_{j,p,t}$	decision for installing tanks at warehouse j for product p at time t
$l_{j,p,t}$	decision for operating tanks at warehouse j for product p at time t

CRediT authorship contribution statement

Camilo Lima: Writing - original draft, Formal analysis, Investigation. **Susana Relvas:** Writing - review & editing, Supervision. **Ana Barbosa-Póvoa:** Writing - review & editing, Supervision.

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Update

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Corrigendum

Corrigendum to Designing and planning the downstream oil supply chain under uncertainty using a fuzzy programming approach'[Computers and Chemical Engineering 151 (2021) 107373]

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The authors regret

* Firstly, we do not understand why some equations/constraints are highlighted in blue throughout the text, while others not. For instance, Equation (22) is highlighted in blue within the main text, and thus linked to its formula. In contrast, Equation (10), for instance, is not highlighted, as well as not linked to its formula. The same occurs with Constraints (11), (12), …, (21). This problem occurs throughout the article, where several equations are not highlighted and not linked to its formulation;

* Equation 4 presents an error: inside the big bracket, the first term "0" is together with the interval "$g \leq \alpha^m$". They need to be separated. Please, see the error below:

$$\mathrm{Nes}(\alpha \leq g) = N_A((-\infty, g]) = 1 - sup\{\mu_A(r) \mid r > g\} = \begin{cases} \boxed{0g \leq \alpha^m} & \\ \frac{g-\alpha^m}{\alpha^o-\alpha^m} & \alpha^m \leq g \leq \alpha^o \\ 1 & g \geq \alpha^o \end{cases}$$

* Equation (23): the number 23 is not at the same line that the equation's formula is.

* Table 2 is not formatted adequately. There is an extra line, as seen below:

Cost (G$)	Facility installation	Tank installation	Facility operation	Tank operation	Volume storage	Primary transportation	Secondary transportation
Model							
Deterministic	0.136	0.655	0.165	0.687	1.812	52.037	51.118
Necessity	0.147	0.743	0.178	0.790	2.113	69.562	63.115
Credibility	0.145	0.726	0.176	0.764	2.036	65.060	59.828
Possibility	0.128	0.634	0.161	0.662	1.740	47.617	48.885

In fact, this name 'Model' needs to be at header, beside the name cost, as shown below:

Cost (G$) Model

* Table 3 presents the worst mistake. In the original manuscript, Table 3 has two different colours (green and red) to highlight some important information about the case study. Currently, the table is all in black. The table needs to present the following colours, as shown below:

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Model	Location	Capacity (m^3)	Hydrous ethanol	Gasoline C	Jet fuel	LPG	Fuel oil	Diesel	Aviation kerosene	Paraffin
Deterministic	Manaus	112,200	1	2	1	1	1	2	1	
	Santana	49,400		2		2		1		
	Belém	138,800	1	3	1	4	2	2	1	
	São Luis	116,600	1	2		3	2	2	1	
	Fortaleza	133,200	1	4		6	1	2	1	
	Cabedelo	103,800	1	3		4	2	1	1	
	Ipojuca	131,000	1	3		5	2	2	1	
	Maceió	59,400	1	1		2		1	1	
	Aracajú	59,400	1	1		2		1	1	
	Madre	202,600	2	5	1	8	2	3	1	
	S. Canedo	317,600	6	6	1	8	1	6	1	
	Brasília	101,600	1	4		3		1	2	
	Barueri	548,800	4	21		29		7	6	
	Cubatão	170,000	7					4		
	S. C. do Sul	190,000	13				1	2		
	V. Redonda	215,000	2	6				5	1	
	D. de	369,800	6	12		9	1	5	3	1
	Uberaba	30,000		3						
	Vitória	256,600	1	2		3	1	8	1	
	Paranaguá	348,400	4	8	1	22	1	6	1	
	Biguaçu	171,400	1	6		12	1	2	1	1
	Canoas	202,600	1	7	1	8	1	3	1	
Necessity	Manaus	102,200	1	1	1	1	1	2	1	
	Fortaleza	135,400	1	4		7	1	2	1	
	Ipojuca	143,200	1	4		6	2	2	1	
	Madre	214,800	2	5	1	9	3	3	1	
	S. Canedo	319,800	6	6	1	9	1	6	1	
	Brasília	103,800	1	4		4		1	2	
	Barueri	608,200	4	23		31		10	2	
	Cubatão	165,000	14					1		
	S. C. do Sul	105,000	7				1	1		
	V. Redonda	230,000	3	3			1	6	1	
	D. de	322,000	6	12		10	1	3	3	1
	Vitória	281,600	1	2		3	1	9	1	
	Paranaguá	392,800	4	12	1	24	1	6	1	
	Biguaçu	268,600	1	12	1	13	1	3	1	1
	Canoas	196,000	1	8	0	5	1	3	1	
Cr edi	Manaus	102,200	1	1	1	1	1	2	1	
	Ipojuca	143,200	1	4		6	2	2	1	
	Madre	204,800	2	5	1	9	2	3	1	
	S. Canedo	319,800	6	6	1	9	1	6	1	
	Brasília	128,800	1	5		4	1	2		
	Barueri	628,200	2	22		31		10	7	
	Cubatão	190,000	14					2		
	S. C. do Sul	115,000	8				1	1		
	V. Redonda	220,000	2	4				6	1	
	D. de	332,000	7	12		10	1	3	3	1
	Uberaba	40,000		4						
	Vitória	281,600	1	2		3	1	9	1	
	Paranaguá	380,600	4	11	1	23	1	6	1	
	Biguaçu	258,600	1	11	1	13	1	3	1	1
	Canoas	198,200	1	8	0	6	1	3	1	
Possibility	Barueri	521,600	4	21		28		6	6	
	Cubatão	160,000	6					4		
	S. C. do Sul	215,000	13				1	3		
	V. Redonda	205,000	3	5				5	0	
	D. de	374,800	5	11		9	1	6	3	1

* Some references are not correct, without the name of the consulting company. They are correctly shown below:

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- EY, 2019. Should oil and gas invest in what it knows or what it thinks will be? Ernst & Young LLP, pp. 1–20.

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