Fleet dimensioning and scheduling in the Brazilian ethanol industry: a fuzzy logic approach

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Abstract: This work solves a real-world multi-depot vehicle routing problem (MDVRP) with a homogeneous fleet and capacitated depots. A pipeline company wants to establish a vehicle policy in order to own part of its fleet and serve its customers for a period of one year. The company also wants to know the schedule of the visits for collecting ethanol from 261 producers and taking it to their three terminals located in Brazil. This problem presents uncertain demand, since weather conditions impact the final crop and uncertain depot capacity. Due to the vagueness of managers' speech, this problem also presents uncertain travel time. In this paper, fuzzy logic is used to model uncertainty and vagueness and to split the initial instance into smaller ones. Besides solving a real-world problem with fuzzy demand, fuzzy depot capacity and fuzzy travel time, this paper contributes with a decision making tool that reports different solutions for different uncertainty levels.

Keywords: multi-depot vehicle routing problem; MDVRP; fuzzy logic; job scheduling; real-world problem; expert system.

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1 Introduction

The vehicle routing problem (VRP) has been studied for more than fifty years and it still presents many challenges especially regarding logistic systems (Laporte, 2009). It was first introduced by Dantzig and Ramser (1959) as a generalisation of the travelling salesman problem (TSP) presented by Flood (1956). The VRP consists of designing a number of vehicle routes so that each route starts and ends at the depot, the total demand of a route does not exceed a limit Q, and each customer is visited exactly once by a single vehicle (Juan et al., 2010).

Due to its combinatorial nature, VRP solutions are continuously studied because the personal computers that companies have access to still cannot viably solve exactly complex problems with more than 50 customers (Laporte et al., 2014). Heuristics have been proposed to solve VRP, such as route-first cluster-second (Willemse and Joubert, 2016; Todosijević et al., 2017), cluster-first route-second (Küçükdeniz et al., 2012; Ewbank et al., 2016), nature inspired algorithms (Prins, 2009; Mavrovouniotis and Yang, 2015; Teymourian et al., 2016) among others. Usually one of them overcomes the others for specific characteristics of the instances.

Real-world problems present several challenges and usually authors try different approaches to solve them (Liao, 2005). Some application examples are agriculture planning (Cohen and Shoshany, 2002; Edrees et al., 2003; Thomson and Willoughby, 2004), assembly task planning (Zha and Lim, 2000), transport terminal design (Abacoumkin and Ballis, 2004), and medical diagnosis (Kai and Hui-ping, 2009; Karabatak and Ince, 2009).

This paper presents a real-world problem with its several particularities and complexities. An ethanol pipeline company serves a wide area where it must collect ethanol and bring it to its terminals, which are inputs to their pipeline. The problem presented had to be solved in two parts. The first one is a multi-depot vehicle routing problem (MDVRP) with a homogeneous fleet and capacitated depots. The second one is that the company wanted to know how many vehicles it should have in order to attend all customers. The paper presents a final solution with which routes should be covered first for vehicles with multi routes. The approach chosen was to cluster-first route-second in order to simplify the model without giving up complexities such as demand uncertainties, uncertain depot capacity, and uncertain travel time.

This paper is organised as follows: Section 2 presents a contextual setting of the ethanol industry in Brazil. In Section 3, we present a literature review while in Section 4 the methodology is detailed. Section 5 presents the results of the algorithm which in turn are analysed in Section 6. Conclusions follow in Section 7.

2 Contextual setting

Investments in ethanol producers in Brazil were initiated in the early eighties when oil reserves were becoming scarce around the world (Brownstein, 1976). In the early 2000s, the Brazilian Government encouraged producers to develop alternative fuels to gasoline such as biogas and ethanol. Those incentives remained until recently when pre-salt oil reservoirs were found under several Brazilian offshore sites. Brazil is currently the second largest producer of ethanol in the world (Industry Statistics: 2015 World Fuel Ethanol Production, 2015), the ninth largest economy in 2015 (The World Bank, 2017) and the fifth largest country in world in area. Almost 90% of the Brazilian car fleet are hybrid, which means that vehicles can be fuelled with ethanol and or gasoline in any proportion. This represents more than 38 million cars (DENATRAN, 2017). Ethanol represented 33% of the overall fuel consumption of light vehicles (cars and small utility vehicles) in 2013 (Nascimento and Petraglia, 2016).

The north and northeast regions' producers distribute their ethanol output locally. The midwest, southeast, and south regions together account for 3.1 million square kilometres, which is equivalent to the eighth largest country in the world (The World Factbook, 2015; IBGE: Official Territorial Area, 2017). A single pipeline serves said area.

The midwest, southeast, and south regions have261 ethanol producers that send fuel to the pipeline mainly by truck. Figure 1 shows a schematic of the current pipeline, which is still under construction. Out of the many sections depicted in Figure 1, only the dark-painted ones are already built. Several companies run different sections of the pipeline. In this paper, we focus on three terminals operated by a single company: Uberaba, Ribeirão Preto, and Paulínia; these are currently the only inputs of ethanol to the pipeline system.

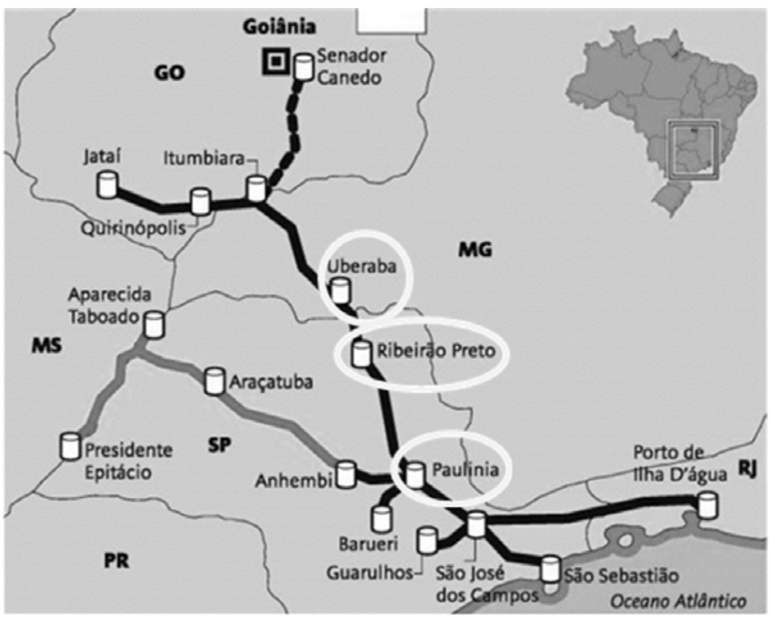
The terminals also act as depots since the company receives ethanol from local producers. Ethanol production is influenced by sugar cane's seasonality since the latter is ethanol's main raw material. The most efficient production season is from May to November (dry season).

The pipeline company would like to know which producers would be best served by which terminal and how. This problem comprises several sub-problems such as closed

VRP with homogeneous fleet and multi-depots with known location and uncertain demand (ethanol produced). In addition, each one of the three terminals had a different and uncertain capacity constraint because their storage tanks can undergo maintenance during periods of time. Another challenge was to determine which truck should run which routes. Finally, for each truck with multiple routes, the sequence to serve the routes should be determined, by solving a fuzzy scheduling problem based on subjective criteria.

This paper contributes to knowledge by solving a real-world problem with several approaches that consider uncertainty indifferent levels. The solution is not a 'single number', but a range of solutions for different levels of uncertainty by using Zadeh's extension principle.

Figure 1 Brazilian pipeline and the company's three terminals: Uberaba, Ribeirão Preto, and Paulínia



3 Literature review

Studies on MDVRP began in the early seventies (Tillman and Cain, 1972; Wren and Holliday, 1972) as a problem where customers must be served by more than one depot and not necessarily by the closest one. Vehicles must leave and return to the same depot and customers must be visited a single time by only one vehicle (Seidgar et al., 2016). This problem has been widely studied with a heterogeneous fleet (Salhi and Sari, 1997; Dondo and Cerdá, 2007; Salhi et al., 2014), but due to the nature of trucks used in the ethanol industry, this study considered a homogeneous fleet (Crevier et al., 2007; Pisinger and Ropke, 2007). Often MDVRP deals with the decision of where to locate depots, also known as the location-routing problem. In the present case, the locations of the terminals were already determined. Readers may refer to Drexl and Schneider (2013) for a broad literature review of the location-routing problem.

A variation of MDVRP is to consider time windows (Polacek et al., 2004), backhaul customers (Javad and Karimi, 2017) or uncertain demand (Solano-Charris et al., 2016). Samanta and Jha (2011) considered stochastic demand in MDVRP with a time window, solved by using a genetic algorithm. Hong and Xu (2008) used fuzzy logic to model MDVRP with a time window and fuzzy travel time. Juan et al. (2012) analysed MDVRP combining methods, including meta-heuristics, but considering unlimited depot capacity. Contardo and Martinelli (2014) considered MDVRP with capacitated depots and a homogeneous fleet. Rajmohan and Shahabudeen (2009) studied MDVRP with time windows by applying a two-phase solution. Initially they assigned customers to depots by using partitioning around medoids (PAM) and then solved each remaining VRP using ant colony optimisation. Seidgar et al. (2016) combined a hybrid solution of genetic and simulated algorithms with an imperialist competitive algorithm to solve the MDVRP.

Our ethanol real-world problem can be modelled as a MDVRP even though ethanol had to be collected from producers. Because this is a real-world situation, it presents simultaneously uncertain demand, uncertain travel time, and depots with uncertain capacity. In our literature review, we did not find reports of any similar problem with the same constraints and uncertainties.

Several authors modelled uncertainty into VRP using different techniques (Gounaris, 2013; Zhang et al., 2013; Cao et al., 2014; Jaillet et al., 2016), but few of them used fuzzy logic to model uncertainty on some constraints (Zheng and Liu, 2006; El-Sherbeny, 2011; Kuo et al., 2012). MDVRP has been widely studied in recent years, but studies modelling uncertain constraints remain scarce, especially using fuzzy logic (Montoya-Torres et al., 2015). Asl et al. (2012) used fuzzy logic to model a time window in order to minimise servicing time and distance travelled and to maximise service levels of a multi-objective MDVRP. Recently, Lau et al. (2009) used fuzzy adapted genetic algorithm to solve MDVRP, but with hard constraints.

A way to model uncertainty in any problem is applying the extension principle proposed by Zadeh (1978). Such principle allows for modelling uncertainty with fuzzy logic, by splitting input variables in different levels of uncertainty using alpha-cuts (Yager, 1986). The extension principle allows that the same modelling can be applied to over perform different approaches and combine results. This became very useful for our problem since it allowed us to analyse different levels of uncertainty while solving MDVRP and the job scheduling problem (JSP); this deals with the order of routes to be served by the vehicles assigned with multiple routes.

A JSP is an NP-hard problem and it is among the most difficult problems to solve (Jones et al., 1999; Behnamian et al., 2010). Nouri et al. (2016) performed literature review mainly focusing on job scheduling with transportation resources. Many authors used fuzzy logic to solve JSP (Behnamian, 2016). The problem presented in this paper refers to several JSP s with a single machine (the vehicle). We approached JSP using a fuzzy inference system (FIS).

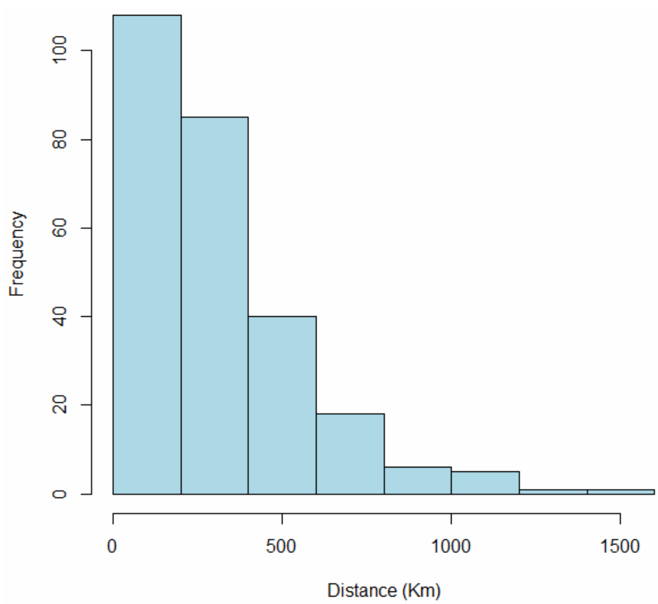
FIS is a decision making tool that allows to incorporate the judgement of experts into the model (Crockett et al., 2006; Öztürk, 2009). It accepts vague inputs that are subjected to a set of rules based on a previously defined expert's decision process and presents a single final result. Fahmy (2010) used FIS for scheduling a processor's tasks while Paul and Azeem (2010) applied FIS to minimise work-in-process inventory. Readers can find more details about FIS mathematical procedure in Takagi and Sugeno (1985).

Specifically about FIS applied to JSP, Caprihan et al. (1997) used Mamdani's method to analyse confidence levels and later Sun (1998) suggested a fuzzy ranking method to solve JSP using an original defuzzifier method. Lee et al. (2002) used fuzzy logic to model linguistic variables and solve fuzzy JSP.

4 Methodology

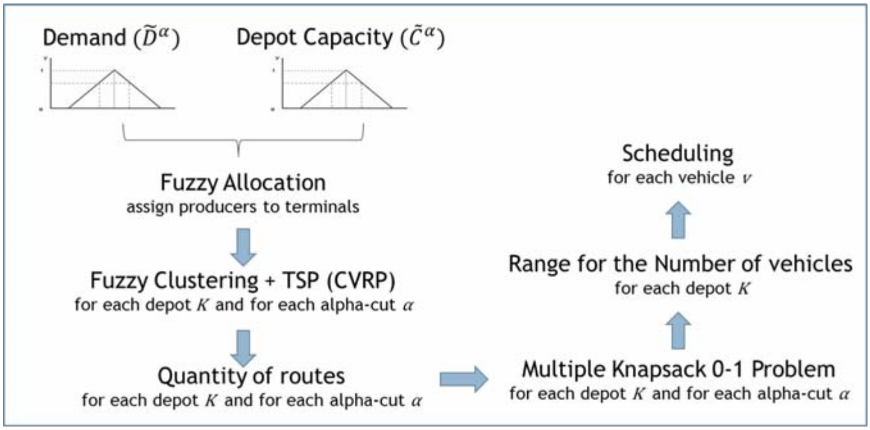
Due to a large number of customers and their distance to terminals, we initially classified ethanol producers according to the trip length and hence duration to serve each one based on an average speed of 40 km/h. Figure 2 presents the distribution of the distances from each producer to the closest terminal.

Figure 2 Distance from ethanol producers to closest terminal (see online version for colours)



Ethanol producers were classified into three groups: those that should receive daily visits, those receiving visits every two days, and finally those that should receive visits every three days. The same procedure presented in Figure 3 was applied for each group. We considered uncertain demand and depot (terminal) capacity by applying triangular fuzzy numbers (TFN) and allocated customers to depots. Then a capacitated vehicle routing problem (CVRP) was solved for each depot K determining the number of routes needed. A multiple knapsack 0–1 problem determined the number of vehicles that would serve which route and their assignment. Finally, the total number of vehicles was consolidated under Zadeh's extension principle and a job scheduling was solved for each vehicle with multiple routes.

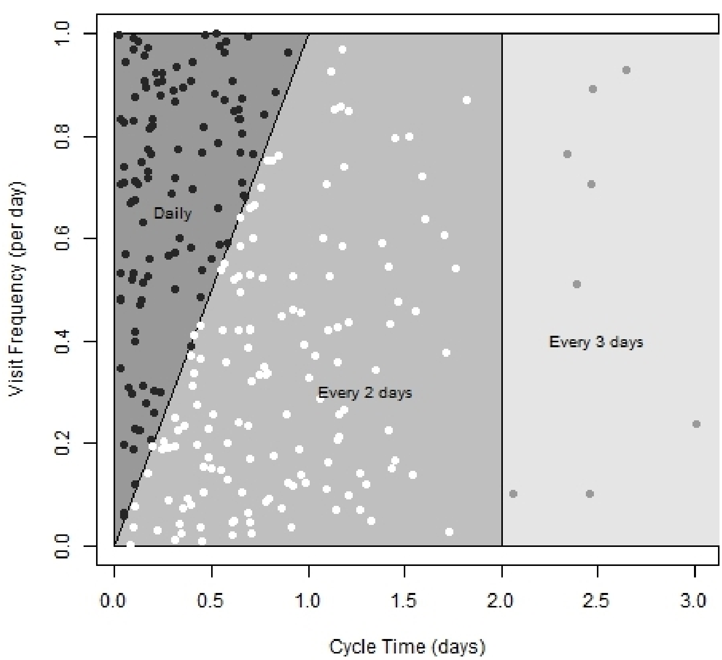
Figure 3 Schematic of methodology applied to solve real-world problem (see online version for colours)



4.1 Customers' classification

The classification considered two criteria: visit frequency and travel time in days. Travel time is how long a single visit to the producer would last when returning to the closest terminal while visit frequency represents how many visits a single producer could receive per day considering distance to the closest terminal and the average speed. Three groups arose from this classification, and they are represented in Figure 4: daily visits, visits every two days, and visits every three days.

Figure 4 Classification of customers by frequency of visits



4.2 Triangular fuzzy numbers

Yu and Jin (2011) modelled uncertain demand with fuzzy logic using TFN to describe demand possibilities.

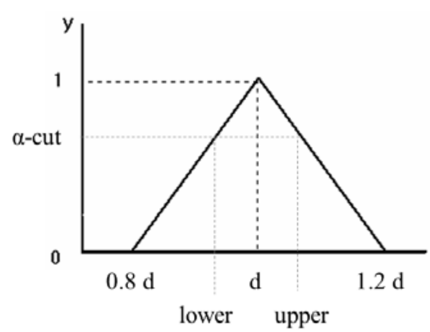
Let a TFN 'a' be represented by (a, $-\alpha$, a, $a + \beta$) where α and β correspond, respectively, to the spread to the left and to the right from a. If $\tilde{M}$ is a TFN expressed as $\tilde{M} = \langle a, \alpha, \beta \rangle$, its membership function is given by:

$$\mu_{\tilde{M}}(x) = \begin{cases} 0 & \text{for } x \le d - \alpha \\ 1 - \dfrac{d-x}{\alpha} & \text{for } m - \alpha < x < d \\ 1 & \text{for } x = d \\ 1 - \dfrac{d-x}{\beta} & \text{for } m < x < d + \beta \\ 0 & \text{for } x \ge d + \beta \end{cases} \tag{1}$$

The membership function is 1 when x is equal to the mean value m. In this paper, we assume that $\alpha = \beta = 0.20$ d, which means that the TFN is symmetric around its mean and has a margin of error of 20%.

Different values of the membership function will provide two other demand values: lower and upper demand. Those different membership values are the alpha-cuts and each one presented different ranges of demand. Figure 5 shows how an alpha-cut presents lower and upper demands. For mapping uncertainty, the authors considered seven different values of alpha-cut, $\alpha_{cut} \in \{0, 0.2, 0.4, 0.6, 0.8, 1.0\}$.

Figure 5 Triangular fuzzy number



4.3 Fuzzy allocation with TFN

Fuzzy allocation was solved with fuzzy mathematical programming to minimise the total distance from producer to the terminal; equation (2) presents the mathematical formulation. The problem considered fuzzy producer's demand and fuzzy depot capacity and also, that each producer should be assigned to only one depot, respectively.

$$\begin{aligned}
&\text{Min} \sum_{i=1}^{n} \sum_{k=1}^{m} D_{ik} X_{ik} \\
&\text{s.t.} \ \sum_{k=1}^{n} \tilde{K}_i X_{ik} \le \tilde{P}_k, \left(i \in \mathbb{N}_n\right) \\
&\sum_{i=1}^{n} X_{ik} \le 1, \left(k \in \mathbb{N}_m\right) \\
&X_{ik} \ \textit{binary}
\end{aligned} \tag{2}$$

where n is the number of producers, m is the number of depots, D_{ik} is the distance from producer i to depot k, $\tilde{K}_{ik}$ is the demand from producer i, $\tilde{P}_k$ is the capacity of depot k, and X_{ik} are decision variables stating if a producer i is assigned to a depot k (1) or not (0).

Substituting $\tilde{K}_i = \langle s_{ij}, l_{ij}, r_{ij} \rangle$ and $\tilde{P}_k = \langle t_{ij}, u_{ij}, v_{ij} \rangle$ and expanding fuzzy constraint into three inequalities, equation (2) evolves to equation (3):

$$\begin{aligned}
&\text{Max} \sum_{i=1}^{n} \sum_{k=1}^{m} d_{ik} x_{ik} \\
&\text{s.t.} \ \sum_{k=1}^{n} s_{ik} x_{ik} \le t_k \\
&\sum_{i=1}^{n} \left(s_{ik} - l_{ik}\right) x_{ik} \le t_k - u_k \\
&\sum_{i=1}^{n} \left(s_{ik} + r_{ik}\right) x_{ik} \le t_k - v_k, \left(i \in \mathbb{N}_n\right) \\
&\sum_{i=1}^{n} x_{ik} \le 1, \left(k \in \mathbb{N}_m\right) \\
&x_{ik} \ge 0 \left(i \in \mathbb{N}_n, k \in \mathbb{N}_m\right)
\end{aligned} \tag{3}$$

4.4 CVRP (fuzzy clustering + TSP)

The resulting instance from the fuzzy allocation consists of a CVRP. For each visit group and each depot, it is necessary to determine the routes that minimise the total distance travelled. The nature of the problem studied considered a homogeneous fleet of truck with capacity of 45 m^3.

Wolsey (1998) presented a mathematical formulation using subtour elimination constraints for the following CVRP:

$$\text{Min} \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} x_{ij} \tag{4}$$

$$\sum_{i=1, i \ne j}^{n} x_{ij} = 1, \forall j \in \{1, \ldots, n\} \tag{5}$$

$$\sum_{j=1, j \neq i}^{n} x_{ij} = 1, \forall i \in \{1, ..., n\} \tag{6}$$

$$\sum_{i \in S} \sum_{j \in S} x_{ij} \leq |S| - 1, \forall S \subset \{1, ..., n\}, 2 \leq |S| \leq n - 1 \tag{7}$$

$$\begin{aligned} &\sum_{i \in S} q_i \leq b, \forall S \subset \{1, ..., n\} \\ &x_{ij} \in \{0, 1\}, i = \{1, ..., n\}, j = \{1, ..., n\} \end{aligned} \tag{8}$$

where d_{ij} is the distance between customers i and j, q_i is the customer's demand, b is the constant for homogeneous fleet capacity, S is a subset of customers, and x_{ij} are the decision variables.

Equation (4) is the objective function that minimises the distance between nodes i and j, (5) and (6) are flow constraints, and (7) is the subtour elimination constraint. It enforces only one cycle with all n nodes. Equation (8) defines that the entire demand of a cycle that cannot exceed the truck's capacity.

As VRP is NP-hard (Karp, 1972), its solution computing time increases exponentially as the number of customers increase. To solve this problem while also considering uncertain demand, Ewbank et al. (2016) proposed to split the initial instance into smaller ones and solving them using an unsupervised fuzzy clustering approach. The fuzzy m-parameter adopted was equal to 2.02 as suggested by Ewbank et al. (2016).

4.5 Fuzzy multiple knapsack 0–1 problem

The fuzzy multiple knapsack problem is a development of the multiple knapsack problem considering fuzzy variables. In this case, the authors considered uncertainty average speed and uncertainty demand, fuzzifying those variables. The available time to perform the routes (limit time) can vary depending on day-by-day circumstances. To consider this uncertainty, the time limit was represented as a fuzzy number. Equation (9) presents the fuzzy mathematical formulation:

$$\begin{aligned} &\text{Min} \sum_{v=1}^{p} Y_v \\ &\text{s.t.} \sum_{r=1}^{p} \frac{\tilde{D}_j}{\tilde{S}} X_r \leq \tilde{H}.Y_v \left(v \in \mathbb{N}_r \right) \\ &\sum_{v=1}^{p} X_{vr} \leq 1, \left(r \in \mathbb{N}_r \right) \\ &X_{vr}, Y_v \textit{ binary} \end{aligned} \tag{9}$$

where p is the number of routes to be minimised, $\tilde{D}_j$ is the distance travelled of route r, $\tilde{H}$ is the time limit for using each vehicle, Y_v are binary decision variables stating if a vehicle v exists (1) or not (0), and X_{vr} are binary decision variables stating if a route r is assigned to a vehicle v (1) or not (0).

The development and solution of this linear programming problem is similar to the fuzzy allocation problem presented in Subsection 4.3.

4.6 Zadeh's extension principle

Zadeh's principle of extension is one of the most important tools in fuzzy set theory that allows transforming crisp mathematical concepts into fuzzy variables. It allows slicing the analysis into different levels of uncertainty. The description of Zadeh's extension principle (Niroomand et al., 2016) follows.

Let X be a Cartesian product of some universes $X = X_1 \times \ldots \times X_n$ and $\tilde{A}_1, \ldots, \tilde{A}_n$ be n fuzzy sets in $X_1, \ldots, X_n$, respectively. f is a mapping function from X to a universe Y such that $y = f(x_1, \ldots, x_n)$. Then the extension principle allows us to define a fuzzy set $\tilde{B}$ in Y by

$$\tilde{B} = \left\{ \left(y, \mu_{\tilde{B}}(y) \right) \middle| y = f\left(x_1, \ldots, x_n\right), \left(x_1, \ldots, x_n\right) \in X \right\}$$

where

$$\mu_{\tilde{B}}(y) = \begin{cases} \sup\limits_{(x_1, \ldots, x_n) \in f^{-1}(y)} & \min\left\{ \mu_{\tilde{A}_1}\left(x_1\right), \ldots, \mu_{\tilde{A}_n}\left(x_n\right) \right\}, f^{-1}(y) \neq 0 \\ 0, & \textit{otherwise} \end{cases}$$

where sup is a set of elements in $\mathbb{R}$ that result in positive value of the minimisation of memberships and f^{-1} is the inverse form of f.

4.7 Fuzzy scheduling

Scheduling is allocating limited existing resources for tasks with specific performance measures and targets (Behnamian, 2016). Fuzzy set theory provides better results in environments where the decision maker's judgement and experience may be used to improve models and where the information required to formulate those models are imprecise and vague (Schründer et al., 1994; Guiffrida and Nagi, 1998).

The fuzzy input variables used were the processing time of each route (procTime) and the distance from depot to the centroid of each route. The fuzzy output variable was 'priority', ranging from 1 to 10. The bending points where first and third quartile for each fuzzy variable. The t-norm and t-conorm methods used were 'minimum' and 'maximum', respectively. The defuzzifier method was the centroid method. For instance, Figure 6 presents fuzzy variables for visits that occur every two days, terminal Paulínia, lower demand, and alpha-cut 0.8. It also presents a three-dimensional surface summarising the FIS model. The same analysis can be done for any combination of those parameters.

Experts defined rules for this decision model, prioritising shortest processing time. They are listed below:

- IF procTime short AND distance short THEN priority high.
- IF procTime short AND distance long THEN priority low.
- IF procTime long AND distance short THEN priority low.

- IF procTime long AND distance long THEN priority low.

Figure 6 Fuzzy input and output variables and surface graphic about FIS model

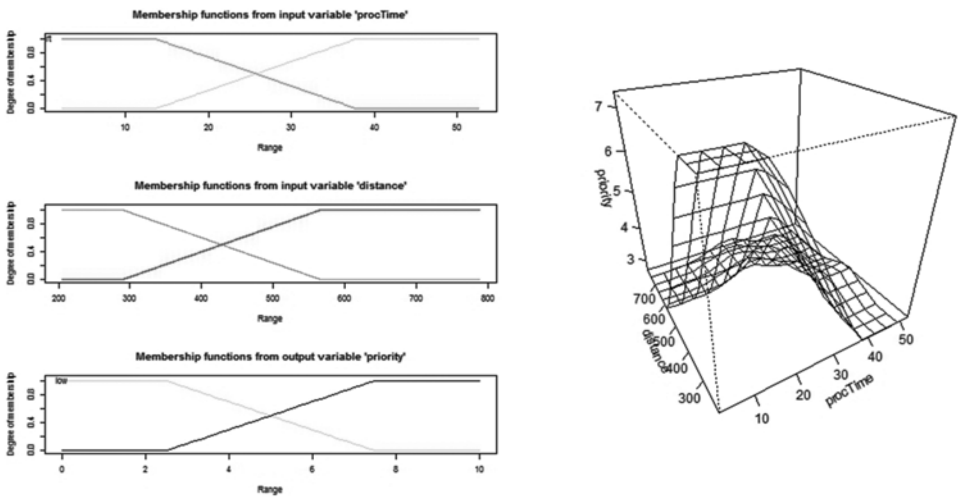


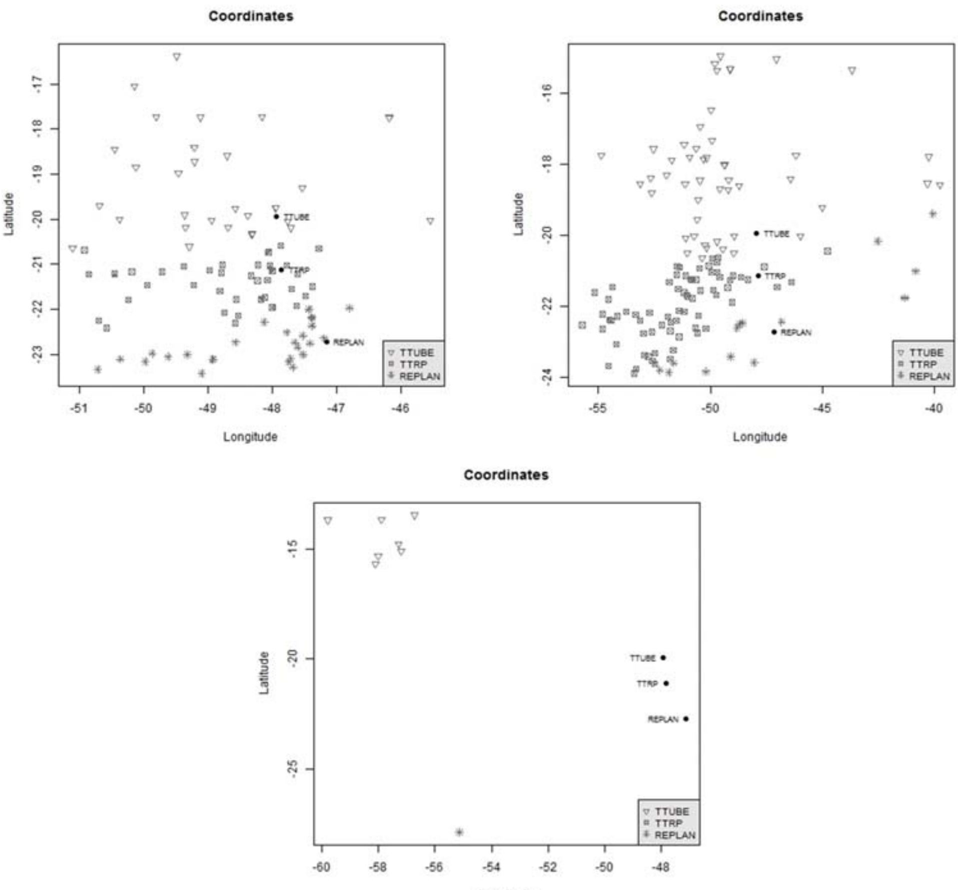
Table 1 Ethanol producers split by depot (terminal) and frequency of visit

Frequency of visit	*Uberaba (TTUBE)*	*Ribeirão Preto (TTRB)*	*Paulínia (REPLAN)*
Every day	34-37-41-46-58-61-73-80-81-82-90-92-93-99-104-105-106-112-117-118-124-154-168-169-171-180-205-215-218-249-253-254-259	2-8-9-11-12-15-17-22-29-32-49-50-65-85-88-89-103-107-113-115-116-134-155-156-162-167-173-174-175-178-185-186-191-192-193-197-198-202-203-216-217-224-233-235-236-237-238-239-241-252-256	13-14-18-19-21-30-33-44-51-54-62-94-95-96-109-126-127-136-160-170-182-183-184-206-208-214-223-226-248
Every two days	6-7-10-20-28-36-42-43-45-52-53-60-63-67-70-74-75-76-77-78-79-83-98-110-114-119-129-130-143-144-145-153-172-177-189-194-195-199-204-209-211-213-219-229-232-234-240-242-250-251-260	1-3-4-5-16-25-26-27-31-35-47-48-55-56-57-64-66-69-71-72-84-86-91-108-120-121-122-123-132-133-137-138-139-140-141-142-146-147-149-150-151-152-157-158-159-161-163-164-166-176-179-181-187-188-190-200-201-207-210-212-220-221-222-230-231-243-244-245-246-247-255-257-258-261	23-39-40-68-87-97-100-101-102-111-128-131-135-227-228
Every three days	24-38-59-125-148-165-225	NA	196

5 Results

All data used in this paper refer to 261 ethanol producers during the period of 2012/2013. Figure 7 presents how producers were classified considering frequency of visit and terminals. Table 1 identifies those producers.

Figure 7 Producers attended by each terminal for different visit periods: visits every day, every two days, and every three days



Each combination of parameters visit frequency, depot *k*, level of demand (minimal/lower or maximal/upper), and alpha-cut resulted in a CVRP. Each CVRP was then solved by using a two-step algorithm, splitting a larger instance into smaller ones and then rapidly solving them. FIS solved the JSP, attending different routes with the same vehicle. Its solution presented different results about the amount and composition of routes. This happened due to the variation of demand, representing its uncertainty. Due to space restriction, from now on we exemplify results for visits every two days, Paulínia terminal (k = 3), lower demand (minimal demand scenario), and alpha-cut 0.8 presented in Table 2.

Table 2 Aggregated routes for visits every two days, Paulínia terminal; lower demand, and alpha-cut 0.8

Vehicle #	*Routes*
1	120-58-121
2	71-65
	55
	35
3	68
4	54-51-49-10
5	18-19-53

6 Discussion

Classification of producers by attending distance was a step that turned an initially infeasible problem into a feasible one. The assignment of each customer to each terminal considered uncertain customer demand and uncertain terminal capacity, because of capacity fluctuations along the year. Results presented non-overlapped clusters with an elongated form, not necessarily an ellipse.

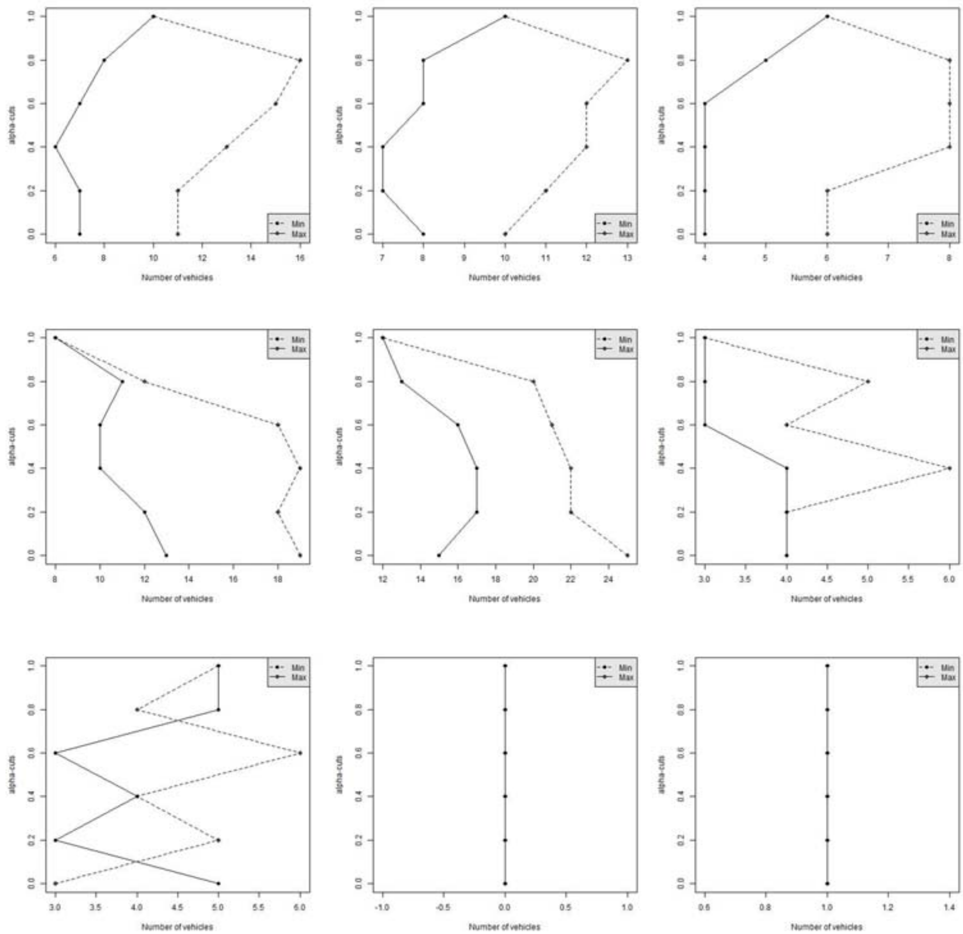
Results presented in Figure 8 show that scenarios with lower demand requested a higher number of vehicles than scenarios with higher demand after merging routes. Therefore, routes containing customers with large demands can be more easily merged into single vehicles than routes containing customers with lower demands. One reason for that could be that less than truckload (LTL) shipping takes more time to attend a larger number of customers. Although we might think that it is easier to group smaller demands, it also takes more time to attend said customers.

When analysing the frequency of visits, scenarios of visits every three days presented very different results when compared with other frequencies. This could be explained by the number of customers in each scenario. Terminals that would be visited every three days had only seven, none, and one customers respectively and large distances between them. Scenarios with daily visits and visits every two days presented more ‘expected’ results in terms of the shape of the figures. The latter presented a smaller number of vehicles as uncertainty decreases.

The nature of those instances provided longer time routes for high levels of uncertainty, which did not allow few vehicles as what happened with lower levels of uncertainty. Meanwhile, daily visit scenarios presented a higher discrepancy of results for intermediary levels of uncertainty. This could be explained by the increasing number of routes with a high level of vehicle usage for high and low levels of uncertainty. Those routes can be easily merged into a smaller number of vehicles.

Figure 8 is an important tool for decision makers since it allows for the determination of the size of a fleet, depending on a level of uncertainty. In other words, managers do not need to simulate different economic or political scenarios. Based on their experience, they simply have to estimate the level of uncertainty to get information about fleet size. In addition, they may quickly visualise different levels of uncertainty, allowing them to take strategic decisions based on how fast a scenario might change.

Figure 8 Quantity of vehicles per alpha-cut values



Note: The lines correspond to visit frequency (visits every one, two, or three days) and the columns correspond to each terminal.

A manager may decide the level of uncertainty to use based on the quality of the available information and on the experience of his contributors. With uncertainty in mind, managers can develop fleet policies such as how many vehicles a company must own and how many to contract. The idea of frequency of visits also contributes to the discussion about how many drivers to hire and the shift policy to use, which is limited to eight hours by Federal Brazilian law. We believe that the results presented here can be used in different but similar situations, not only in the ethanol distribution market.

7 Conclusions

This paper solved a real-world problem by breaking it into several optimisation problems as MDVRP, fuzzy knapsack problem, and fuzzy JSP. A large MDVRP instance was broken down into several smaller feasible ones with fuzzy demand, fuzzy travel time, and fuzzy capacitated depots.

The methodology proposed here was used to analyse several levels of uncertainty, providing a decision tool for decision makers and managers that handle distribution and fleet policies in their companies.

Future research could consider collecting anhydrous and hydrous ethanol from producers with a heterogeneous fleet or with vehicles that can carry both ethanol types simultaneously.

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