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FOCUS

Dispatching and rebalancing for ride-sharing autonomous mobility-on-demand systems based on a fuzzy multi-criteria approach

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Abstract
This paper presents an integrated approach, of a multi-criteria decision-making framework and fuzzy multi-objective programming to optimize dispatching and rebalancing for Ride-sharing Autonomous Mobility-on-Demand (RAMoD) systems, whereby, a fleet of self-driving electric vehicles are coordinated to service on-demand travel requests and eventually allowing multiple passengers to share rides. Specifically, the fuzzy analytical hierarchy process and the Fuzzy technique for order of preference by similarity to ideal solution are first integrated in order to analyze customer preferences, prioritize their attitudes toward autonomous vehicles, and then to rank fleet vehicles according to these prioritizations. Next, leveraging the ranks of vehicles, we introduce a new Multi-Objective Possibilistic Linear Programming (MOPLP) model, considering realistic constraints and handling the uncertain nature of some critical data affecting RAMoD systems. Three conflicting goals are considered simultaneously which are (i) to minimize the lost customer requests, (ii) to minimize the total transportation cost and (iii) to improve customer satisfaction. This MOPLP model is converted to an equivalent crisp MOLP through applying appropriate strategies and the goal programming method is called to solve this MOLP and find an efficient compromise solution. Finally, the applicability and efficiency of the proposed approach are presented through an illustrative example. Collectively, this work provides a unified framework for controlling and analyzing RAMoD systems, which includes a wide range of modeling options (e.g., the inclusion of the uncertain future demand), and provides the first correlation between the dispatching and rebalancing decisions, and the process of analyzing customer preferences toward autonomous vehicles.

Keywords Ride-sharing autonomous mobility-on-demand · Multi-criteria decision-making · Multi-objective possibilistic linear programming · Goal programming · Dispatching · Rebalancing

1 Introduction

The expansion of cities and the growth of population with a slowly adapting infrastructure and increased mobility demands, resulting in significant problems such as traffic congestion, air pollution, increased travel times and parking spaces. The urgent need to deal with these challenges has spurred the development of evolutionary transportation systems. Such an eventual solution will arguably involve the convergence of a number of emerging technologies. First, electric vehicles technology, which directly reduces pollution and promotes the usage of renewable energy. Second, one-way vehicle ridesharing systems, which are designed to bring together passengers with similar time schedules and itineraries (Agatz et al. 2012), have the potential to reduce road congestion and parking demand problems in the urban area.

Finally, the advancement of self-driving vehicles technology promises to further enhance safety, convenience, and mobility for people unwilling or unable to drive (Zhang et al. 2016). These key technologies lead to an emerging transportation paradigm commonly known as "Ride-sharing Autonomous Mobility-on-Demand" (RAMoD) systems, whereby self-driving shared electric vehicles service on-demand transportation requests.

Its multiple strengths have pushed several companies' toward RAMoD technology (Abduljabbar et al. 2019).

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Nevertheless, the optimal fleet scheduling and dispatching remain a key challenge, especially in the presence of asymmetric customer requests. This problem of imbalance arises in transportation systems when some stations/regions are more requested than others. At the end of such trips, vehicles will naturally accumulate in these stations/regions, thereby restricting the accessibility of the service on other stations/regions (Fricker et al. 2016). The significant requirement to cope with this trend has spurred the design of vehicle rebalancing processes, which consists of proactively repositioning empty vehicles in anticipation of future transportation requests.

In particular, travel demand forecasts are subject to a high level of variability, uncertainty and inaccuracies due to various external factors, such as traffic and weather. Accordingly, successful dispatching and rebalancing strategies in RAMoD systems must deal with such variability and uncertainty.

Even if several dispatching and rebalancing policies have been proposed, these research works assume either deterministic future demand or probabilistic demand forecasts, requiring specific knowledge on historical data. When statistical data are not available and/or incomplete, stochastic approaches may not be the better choice (Wang and Shu 2007). Simpler and less data-demanding than probability theory, the Fuzzy set theory (Zadeh 1965) and the possibility theory (Zadeh 1978) are very helpful to deal with epistemic uncertainty in RAMoD systems (Dubois et al. 2003).

Successful dispatching and rebalancing strategies should also hold promise for improving customer satisfaction. This goal is not only achieved by meeting demand requirements at each time period, but also by taking account of customer preferences toward autonomous vehicles services and options. Thus, for the design of an efficient strategy aiming to improve customer satisfaction, a better understanding of passenger preferences is necessary.

Due to the subjectivity and the inherent vagueness of human preferences, it is difficult to quantify them with exact numerical values. It is more desirable to specify these preferences using natural language (Zadeh 1975). In particular, Fuzzy set theory is very useful in tackling ambiguities arising in the process of linguistic evaluation.

Past research works tend to understand passenger's attitudes toward autonomous vehicles (Krueger et al. 2016; Beirigo et al. 2019; Cai et al. 2019), but they usually focus on the impact of traditional/functional travel factors (i.e., travel cost and travel time) and do not address the subjectivity of human preferences. Moreover, to the best of our knowledge passenger's preferences have never been explicitly integrated with the dispatching and rebalancing decisions.

In this research work, we target the aforementioned limitations reducing the applicability of RAMoD systems. Against this backdrop, we propose and test a novel dispatching and rebalancing strategy under realistic constraints and where the lack of some critical data is assumed to be fuzzy numbers. We show how such a strategy can be cast with a preliminary decision-making process. This preliminary process captures the vagueness and the subjectivity of the passenger's preferences and the decision maker's evaluations and leverages them to define efficient dispatching and rebalancing decisions to further improve customer satisfaction.

Specifically, contributions of this research work are fourfold: First, a new Fuzzy multi-criteria decision-making framework was proposed that leverages the Fuzzy AHP method for analyzing customer preferences and prioritize their attitudes toward autonomous vehicles. Based on this prioritization, the Fuzzy TOPSIS method is applied to rank fleet vehicles in terms of weights/importance. To the best of our knowledge, this fuzzy framework pioneers the consideration of customer preferences in the dispatching and rebalancing problem in the field of AMoD/RAMoD systems.

Second, it introduces a new multi objective possibilistic linear program to model the dispatching and rebalancing problem, which contemplates the various sources of uncertainty affecting AMoD systems. Notably, to our knowledge, it is the first time that the possibility theory and the uncertain optimization are exploited to meet the significant uncertainties in an AMoD system. Thirdly, to handle an effective decision about the aforementioned conflicting objective functions, goal programming approach is exploited, which combines the decision-makers' desire with the logic of optimization in mathematical programming to meet various goals (Pati et al. 2008). Finally, we show through experiments the usefulness and applicability of the proposed approach in the predefined area of Rambouillet.

The remainder of this article is arranged as follows. The next section illustrates the relevant literature. The theoretical background of this study is presented in Sect. 3 while Sect. 4 introduces the RAMoD dispatching and rebalancing problem. In Sect. 5, our three-phase Fuzzy approach for the problem under consideration is illustrated, numerical tests being presented in Sect. 6. A sensitivity analysis is performed in Sect. 7. Finally, concluding remarks and future works are the subject of Sect. 8.

2 Related literature

The issue of Autonomous Mobility on Demand (AMoD) systems has been addressed from several perspectives in the literature, ranging from simulation-based models to queuing-theoretical models and model predictive control (MPC) algorithms.

Simulation-based models (Chen et al. 2016; Levin et al. 2017; Hörl et al. 2019, 2021; Javanshour et al. 2019; Ortega et al. 2020; Poulhès and Berrada 2020) have the ability to capture transportation networks with very high precision, involving microscopic interactions and complex choice models, but are usually not expected to provide optimal solutions.

The analysis of AMoD systems with queuing network methods is commonly used for the routing and rebalancing problem. Driven by the real case study of Manhattan, Iglesias et al. (Iglesias et al. 2019) propose a Baskett Chandy Muntz Palacios (BCMP) queuing-theoretical framework (Baskett et al. 1975; Kobayashi and Gerla 1983) to deal with the routing and rebalancing problem. This framework captures passenger arrivals, congestion effects, vehicle routing, and the battery charge level of vehicles. The results provide novel tools to control and analyze performance metrics of AMoD systems. However, it is assumed that the number of passengers is static since passengers only switch their pick-up locations but do not leave the network. It is also assumed that each passenger travels alone: the problem of ride sharing is not addressed in this work.

(Wollenstein-Betech et al. 2020) provide a theoretical framework to design pricing and rebalancing policies for AMoD systems. The authors begin by describing the system using a fluid model consisting of queues of passengers and vehicles in each region. Then, they design an optimization framework to find optimal pricing and rebalancing policies given the endogenous travel demand rates. This framework aims to maximize profits while providing load balancing for customers and vehicles. The authors conduct two case studies of New York City to quantify the benefits of solving the joint problem of rebalancing and pricing over other approaches. The results suggest that the joint problem increases the total profit of the AMoD provider by 7–40%. However, this framework fails to deal with more realistic nonlinear travel demand functions.

Owing to their simplicity and their ability to include complex constraints, a number of papers model AMoD systems within a network flow model. For instance, in (Rossi et al. 2018), the problem of rebalancing vehicles and routing customers was modeled within a network flow framework. Within this model, the authors focus on control vehicle-to-vehicle interactions, which would lead to traffic congestion and decrease system performance. Nevertheless, travel demands are assumed deterministic and stationary, i.e., the rate of customer demands is modeled using deterministic value and does not change through time.

The work published by (Salazar et al. 2019a, b) explores the possibility of coordinating public transportation networks and AMoD systems by devising a multi-commodity network flow optimization model. The goal is to satisfy travel demand while maximizing the social welfare defined as the sum of the operational costs incurred by the various transportation modes and passengers' travel time. Based on real-world case studies of Berlin and New York City, the authors derive insights on the benefits of intermodal AMoD systems in terms of overall costs, travel time, and pollution emissions. However, it is important to highlight that this model is a time-invariant travel demand. That is, it is assumed that travel requests remain constant over the time horizon under analysis. Furthermore, the proposed model does not explicitly take into account the stochastic nature of the passenger arrival process and assume that AMoD vehicles transport only a single passenger at a time.

In (Wollenstein-Betech et al. 2021), the authors present a network flow model to optimize the routing and rebalancing strategies for intermodal AMoD systems, whereby self-driving vehicles provide on-demand mobility services jointly with public transit in mixed traffic (consisting of private and AMoD vehicles). The goal is to increase the quality of the service by decreasing the overall travel time while maintaining the availability of vehicles across the regions. The authors suggest that for significant levels of travel demand, pure AMoD systems can degrade the overall system performance owing to the additional traffic congestion arising from rebalancing flows. Using examples with the transportation sub-networks in New York City and Eastern Massachusetts the authors empirically showed that the combination of AMoD systems with public transportation systems, micromobility options, and walking can provide significant improvements in the overall travel times.

Reference (Ding et al. 2021) develops a combined operation scheme for AMoD system and Battery Swapping Station (BSS). The AMoD fleet operator manages the electric vehicles and determines rebalancing and swapping schedules. The operational behavior of the fleet is modeled as an expanded network flow model with the aim of maximizing the total profit. The BSS management problem is modeled as a mixed-integer linear program to optimize the refueling decisions of the depleted batteries. Simulation experiments demonstrate the effectiveness of the proposed integrated framework. However, the authors assume that customer requests are known and deterministic.

In contrast, MPC algorithms provide an efficient tool to leverage time-varying travel forecasts. This is way multiple

studies have been designed MPC approach to optimize vehicle scheduling in an AMoD system. This is a control technique, which consists of iteratively solving an open-loop optimization problem to produce a sequence of control actions up to a fixed horizon, and the first control action will be executed (Zhang et al. 2016).

In (Iglesias et al. 2018) a Model Predictive Control algorithm was designed for the dispatching and rebalancing problem. This framework leverages historical data and neural networks to build demand short-term forecasts model. Simulation using Didi data show that this strategy scales very well for large fleet sizes and outperforms state-of-the-art approaches by decreasing the mean passenger wait time by up to 89.6%. However, this MPC method was designed for a single-passenger configuration.

To account for forecast uncertainty, a stochastic MPC strategy focusing on vehicle dispatching and rebalancing was developed in (Tsao et al. 2018). The proposed controller was divided into two submodules: the first one allocates vehicles to existing passengers while the second redistributes empty vehicles around the city. Substantial performance gains in terms of reducing the average waiting time compared to state of the art non-stochastic strategies have been presented. However, the paper did not investigate whether ride-sharing systems can provide similar gains by forecasting uncertain future demand.

(Tsao et al. 2019) designed a real-time MPC framework to optimize the routes of both customers carrying vehicles and empty vehicles, with the goal is to improve social welfare i.e., a weighted combination of vehicle mileage and passenger travel time. Although the model has been designed to accommodate travel demands in a ride-sharing setting, all autonomous vehicles in this model are considered double-occupancy.

Theoretical queuing methods have the benefit of capturing the stochasticity of the passenger arrival process, making them suitable for efficient control synthesis (Salazar et al. 2018). These methods are founded on the "Jackson Network" premise (Jackson 1957), in which all-external arrivals at each queuing station in the transport network occur according to a Poisson process. This random process assumes constant occurrence rates for random variables. For instance, if we consider the specific random variable representing customer arrival time, according to Jackson Network, customers are arriving at a constant rate at pick up stations. In other words, this assumption disregards the time-variant nature of the customer arrival rates that happens on real transport networks (Javanshour et al. 2019). Thus, although queuing theoretical models can provide a practical solution to the complex issues of controlling and modeling AMoD systems, they prevent modelers from getting a realistic depiction of these transport networks as well as their potential impacts on the current urban contexts. In contrast, Network flow model and MPC algorithms provide an efficient tool to express complex constraints. However, the majority of existing research leverages a deterministic travel demand forecast. The few works taking into account for uncertainty on the short-term forecasts are mainly based on stochastic programming. In this regard, probability distributions are generally estimated from historical data. However, in real-life situations, providing exact probability distribution is very challenging and complex, especially if statistical data are incomplete, or are even unobtainable.

In this context, the Possibility Theory (Zadeh 1978; Dubois and Prade 2012) and the Fuzzy Sets Theory (Zadeh 1965) provide a highly efficient tool to deal with the uncertainties. Accordingly, they have been successfully applied to a variety of problems (Khemiri et al. 2017a, b; Zhang et al. 2019; Nemati and Alavidoost 2019; Petrovic and Kankaras 2020; De et al. 2020; Jain et al. 2020; Moghdani et al. 2020; Voskoglou 2020; Kane et al, 2021). Nevertheless, to our best knowledge, the only existing works exploring the potential of fuzzy logic for coping with uncertainty in AMoD/RAMoD systems are our previous works appeared as (Khemiri et al. 2020, 2020a).

In (Khemiri et al. 2020), a three-phase Fuzzy approach is developed to optimize dispatching and rebalancing for RAMoD systems considering the uncertain nature of the customer requests as well as two conflicting objectives simultaneously, namely, minimizing transportation costs and improving customer satisfaction. This work was extended in (Khemiri et al. 2020a) to design an integrated strategy for the dispatching, rebalancing, and charging problem. The optimal coordination of these different decisions has been shown to be effective in establishing optimal schedules for electric vehicle charging based on travel demand forecasts. The coordination of such decisions has shown its effectiveness in defining optimal schedules for vehicle charging given the uncertainty of demand forecasts.

There are some works in the field using hybrid approaches like the 2-opt local exchange guided discrete antlion optimization algorithm proposed by Barma et al. (2019) to solve the multi-depot vehicle routing problem, which is a variant of the vehicle routing problem. They have combined a meta-heuristic algorithm and an exact algorithm to address this problem. This amalgamation of techniques gives good results to deal with this NP-hard problem. However, the authors consider a homogenous fleet of vehicles and a deterministic customer request, which is not very realistic.

To position our proposed approach in the extended domain of AMoD systems, we use five criteria, namely the decision processes involved, the adopted modeling approach, the source of uncertainty on which the problem

is based, and whether the ride-sharing service and customer preferences have been addressed. Table 1 summarizes the papers presented above in accordance with these five dimensions. The majority of these papers are quite recent and divided mainly into three categories: queuing-theoretical models, simulation-based models, and MPC algorithms.0 It should also be pointed out that over 70% of the models studied are deterministic whilst less than 30% of the papers analyzed include only one source of uncertainty. This is a significant weakness since, although customer request is a significant source of uncertainty, the other sources of uncertainty can significantly affect the AMoD system. Moreover, the few works taking into account for uncertainty are mainly based on stochastic programming. Then these were followed by the models based on fuzzy logic. Although the ride-sharing service is a main challeng within AMoD systems, over half of the works studied feel to address this emerging transportation paradigm.

Another critical shortcoming of the dispatching and rebalancing strategies discussed above is that they consider

Table 1 Summary of the analysis of the literature according to four criteria

Paper	Process	Method	Source of uncertainty	RideSharing	Customer preferences
Chen et al. (2016)	Dispatching, Rebalancing, and charging	Simulation	–	–	–
Levin et al. (2017)	Dispatching and Routing	Simulation	–	X	–
Hörl et al. (2019)	Dispatching and Rebalancing	Simulation	–	–	–
Javanshour et al. (2019)	Rebalancing	Simulation	Demand	X	–
Ortega et al. (2020)	Daily activity plans of travelers	Simulation	–	X	X
Poulhès and Berrada (2020)	Dispatching	Simulation	–	X	X
Hörl et al. (2021)	Dispatching and Rebalancing	Simulation	–	X	–
Iglesias et al. (2019)	Routing, rebalancing and charging	BCMP queuing network model	Demand	–	–
Wollenstein-Betech et al. (2020)	Pricing and rebalancing	Dynamic fluid model	–	–	–
Rossi et al. (2018)	Routing and rebalancing	Network flow model	–	–	–
Salazar et al. (2019a, b)	Routing and rebalancing	Network flow model	–	–	–
Wollenstein-Betech et al. (2021)	Routing and rebalancing	Network flow model	–	–	–
Ding et al. (2021)	Rebalancing and charging scheduling	Network flow model and mixed-integer linear programming model	–	X	–
Iglesias et al. (2018)	Dispatching and rebalancing	MPC algorithm	–	–	–
Tsao et al. (2018)	Dispatching and rebalancing	MPC algorithm	Demand	–	–
Tsao et al. (2019)	Dispatching, routing and rebalancing	MPC algorithm	–	X	–
Khemiri et al. (2020)	Dispatching and rebalancing	Fuzzy multi-objective programming	Demand	X	–
Khemiri et al. (2020a)	dispatching, rebalancing, and charging	Fuzzy multi-objective programming	Demand	X	–
Barma et al. (2019)	Routing	Exact algorithm + meta-heuristic	–	X	–
This paper	Dispatching and rebalancing	MCDM and fuzzy multi-objective programming	Demand, Transportation cost	X	X

a homogeneous passenger base and fail to capture the considerable heterogeneity in customer preferences in terms of travel comfort, value of time, and diverse other opinions. The success of such emerging AMoD/RAMoD systems, nonetheless, depends on their ability to provide mobility services that adequately catering to the various customer preferences. That is to say, understanding customer preferences and perceptions toward autonomous vehicles is critical to design popular AMoD services and effective transport policies.

With the aim to further improve user's satisfaction, we propose in this paper a RAMoD solution able to capture individual travel preferences and integrate this critical data in the design of the dispatching and rebalancing decisions.

To achieve this goal, an integrated approach, of a multi-criteria decision-making (MCDM) framework and fuzzy multi-objective programming is developed. MCDM methods can provide an appropriate basis to capture customer preferences. While, the uncertain optimization method can be an appropriate tool to integrate these preferences in the decision process and model transportation networks with very high precision, especially in the presence of uncertain parameters. The two above-mentioned methods have been used with considerable success for a variety of problems. For instance, MCDM methods are used in various research works, focusing on the decision- and policy-making, to determine preferences when there are several alternatives defined on the basis of different attributes, which are usually conflicting. In order to find the most favorable alternative, intra- and inter-attribute comparisons are necessary (Lu and Ruan 2007). Some ideas are represented in these studies such as the combination of multiple methods and the usage of fuzzy sets instead of crisp ones to enhance the performance of the MCDM approaches and model the uncertainties. These methods are used in various fields and for various purposes including energy engineering (Lak Kamari et al. 2020; Abdel-Basset et al. 2021), supplier selection (Stević et al. 2020; Ulutaş et al. 2021; Ghasempoor Anaraki et al 2021), aggregating inputs (Sirbiladze 2021), biomedical problems (Zhang et al. 2020), waste management (Büyüközkan and Gocer 2017; Pamučar et al. 2021), public transport (Nassereddine and Eskandari 2017; Simic et al. 2021), project management (Jabbarzadeh 2018), software selection (Kaska and Tolga 2020), robotic (Liu et al. 2019), aeronautics (Chen 2016), supply chain management (Erceg and Mularifović 2019), neutrosophic decision (Edalatpanah 2020) etc.

Optimization problems under uncertainty are characterized by the need to make decisions without knowing all their effects. Such problems appear in numerous application areas and present several interesting design and computational challenges. Uncertain multi-objective optimization is an area of uncertain optimization involving more than one optimization goal. The uncertain parameters in such problems can be modeled as random variables for which probability theory can be exploited or as Fuzzy numbers to which Fuzzy set theory can be applied. Here, we limit ourselves to describe the essence of fuzzy multi-objective optimization, especially possibilistic multi-objective optimization. Many researchers took up the challenge of describing Fuzzy approaches for possibilistic multiobjective programming which is a research area of considerable practical relevance and which continues to evolve dynamically. These fuzzy approaches cover several fields, including transportation problem (Günay et al 2021; Das et al 2017, 2018), seaport-dry port network design (Tsao and Thanh 2019), water resource management (Wu et al 2021), electronic reverse logistics (Tosarkani et al 2020), Sustainable development (Ghaderi et al 2018), project management (Ehsani et al 2017), supply chain management (Tosarkani and Amin 2018) and the list is endless.

Owing to the success of the two above-mentioned methods, several research studies propose to integrate MCDM methods with possibilistic multi-objective optimization programs to deal with several challenging problems in various fields and for several purposes (Mohammedet al 2019; Mohammed 2020; Lahri et al. 2021). Despite that the reviewed literature revealed that such approaches have become fruitful in various fields of research, to our best knowledge, no solution framework for AMoD/RAMoD systems currently exists that leverages an integrated approach, of a MCDM framework and fuzzy multi-objective programming to build efficient dispatching and rebalancing decisions.

3 Theoretical background

3.1 Fuzzy set theory

Fuzzy set theory was first introduced by Zadeh (1965) as an extension of classical set theory. In ordinary set theory, an element either belongs or does not belong to the set, whereas in Fuzzy sets, elements have degrees of membership valued in the real interval [0, 1]. Hence, it has the advantage of representing the inherent imprecision and vagueness mathematically.

Triangular fuzzy numbers are used in this research work to deal with imprecise data and human judgments.

Some preliminary definitions are presented in the following:

Definition 1 A triangular fuzzy number (TFN) $\tilde{\boldsymbol{Z}}$ can be represented as a triplet of real numbers $(\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{c})$ and the following membership function:

$$\mu_{\tilde{Z}}(x) = \begin{cases} \dfrac{x-a}{b-a}, & a < x \le b \\ \dfrac{c-x}{c-b}, & b < x \le c \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where $\boldsymbol{a}$, $\boldsymbol{c}$, $\boldsymbol{b}$ stand for the lower bound, upper bound and modal value of the fuzzy number $\tilde{\boldsymbol{Z}}$ respectively (as Fig. 1).

Definition 2 Given two triangular fuzzy numbers $\tilde{\boldsymbol{Z}}_1 = (a_1, b_1, c_1)$ and $\tilde{\boldsymbol{Z}}_2 = (a_2, b_2, c_2)$, the operational laws of $\tilde{\boldsymbol{Z}}_1$ and $\tilde{\boldsymbol{Z}}_2$ are displayed as following (Kaufmann and Gupta 1988, 1991):

$$\tilde{z}_1 \oplus \tilde{z}_2 = (a1 + a2,\ b1 + b2,\ c1 + c2) \tag{2}$$

$$\tilde{z}_1 \Theta \tilde{z}_2 = (a1 - a2,\ b1 - b2,\ c1 - c2) \tag{3}$$

$$\tilde{z}_1 \otimes \tilde{z}_2 = (a1 \times a2,\ b1 \times b2,\ c1 \times c2) \tag{4}$$

$$\tilde{z}_1 \otimes r = (a1 \times r,\ b1 \times r,\ c1 \times r), \text{for each } r \in \mathbb{R} \tag{5}$$

$$\frac{\tilde{Z}_1}{\tilde{Z}_2} = \left(\frac{a_1}{c_2}, \frac{b_1}{b_2}, \frac{c_1}{a_2}\right) \tag{6}$$

$$(\tilde{z}_1)^{-1} = (a_1, b_1, c_1)^{-1} = \left(\frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1}\right) \tag{7}$$

Definition 3 Let $\tilde{\boldsymbol{D}}$ be the ($\boldsymbol{m}$*$\boldsymbol{n}$) matrix whose entries are from the fuzzy set. $\tilde{\boldsymbol{D}}$ is thus called a fuzzy matrix.

Definition 4 The linguistic variable is a variable whose value is not a number but sentence or word expressed in a natural or artificial language (Zimmermann 2011). This kind of expression is commonly used to represent human judgments and subjective appreciations of decision-makers. Linguistic variables can be converted into fuzzy numbers.

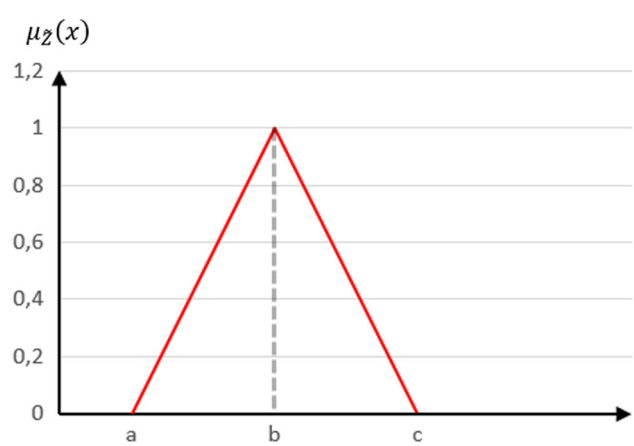

Fig. 1 The membership functions of the triangular fuzzy number

3.2 Fuzzy AHP

In MCDM techniques, the weights of the various criteria have an important role to play in providing information about the importance of the considered decision criteria (Roszkowaska 2013). Several models have been designed to evaluate these criteria weights. Some well-known approaches are Best Worst Method (BWM), Step-wise Weight Assessment Ratio Analysis method (SWARA), Full Consistency Method (FUCOM), Level-Based Weight Assessment (LBWA) model, and AHP method. The SWARA method has been applied in various kinds of studies due to its simplicity with few steps (Mansory et al. 2021; Cui et al. 2021). Its main drawback, however, is its inability to validate results through degrees of consistency (Pamucar et al. 2018). FUCOM, BWM, LBWA, and AHP are increasingly used recently because of their capability to determine the measurement of consistency. The FUCOM method (Pamucar et al. 2018; Ong et al. 2021; Popović et al. 2022) has a minimal number of pairwise comparisons among the previously mentioned approaches. However, the further calculation process of this method is quite complicated. The BWM method (Kumar et al. 2020; Khan et al. 2022) needs ($2n-3$) pairwise comparisons, which is double the number of pairwise comparisons needed by the FUCOM method. To determine the optimal weights of the criteria, the BWM method uses a nonlinear min–max model. However, a high number of pairwise comparisons makes the application of BWM significantly complicated (Zizovic and Pamucar 2019). Similar to the FUCOM method, the LBWA model (Žižović et al. 2019; Torkayesh et al. 2021) allows computing the weights with a minimal number of pairwise comparisons. Another strength of this method is that the increase in the number of criteria does not increase the complexity of the algorithm. But, besides these positive aspects, the LBWA model must highlight the flexibility in terms of further adjustments of the weight coefficients by the elasticity coefficient according to the decision maker's preferences (Saha and Roy 2021). The AHP proposed by Saaty (1987, 1990) and be widely used in the scientific literature (Karasan et al. 2019; Roy and Dutta 2019; Shaygan and Testik 2019; Akbar et al. 2020; Gündoğdu and Kahraman 2020; Yucesan and Gul 2020) is a multiple criteria decision analysis framework designed to facilitate structuring complex multiple criteria problems, and provide an objective strategy to choose the most appropriate among several alternatives for solving these problems. The AHP method is built on a hierarchical structure, and thus each criterion can be targeted in a more transparent and efficient way (Kumar et al. 2017). However, the AHP method becomes inadequate to face the ambiguity and the vagueness associated with human

subjective judgments. To deal with this drawback, this method has been extended by Chang (1996) for coping with uncertainty and subjectivity. This extension, called Fuzzy AHP, combines AHP and fuzzy set theory allowing, thus, more accurate and realistic descriptions of the decision-making process. Fuzzy AHP uses linguistic variables and fuzzy numbers to express the comparative judgments (or the relative importance of each pair of criteria).

In this paper, the Fuzzy AHP is chosen for its several advantages, including the relative simplicity with which it deals with multiple criteria. This decision-making tool is easy to understand and can efficiently process both quantitative and qualitative data. One of the main advantages of the AHP method is its acceptance of inconsistencies in perceptions/ judgments and its user-friendliness, as users can directly enter the judgment data without requiring cumbersome mathematical knowledge. The power of AHP lies also in its ability to decompose complex problems in the form of a hierarchy or a collection of integrated levels.

Consider the pairwise comparison matrix $\tilde{D} = \left(\tilde{z}_{i,j}\right)_{n*n}$:

$$\tilde{D} = \begin{bmatrix} (1,\ 1,\ 1) & (a_{12},\ b_{12},\ c_{12}) & \cdots & (a_{1n},\ b_{1n},\ c_{1n})(a_{1n},\ b_{1n},\ c_{1n}) \\ (a_{21},\ b_{21},\ c_{21}) & (1,\ 1,\ 1) & \cdots & (a_{2n},\ b_{2n},\ c_{2n}) \\ \cdots & \cdots & \cdots & \cdots \\ (a_{n1},\ b_{n1},\ c_{n1}) & (a_{n2},\ b_{n2},\ c_{n2}) & \cdots & (1,\ 1,\ 1) \end{bmatrix}$$

To calculate a priority vector of the fuzzy matrix $\tilde{D}$, we use the extent analysis method proposed by (Wang et al. 2008), which can outlined as follows.

Firstly, calculate the sum of elements in each row of the fuzzy matrix $\tilde{D}$ using fuzzy arithmetic operations:

$$\mathrm{RSi} = \sum_{j=1}^{n} \tilde{Z}_{i,j} = \left(\sum_{j=1}^{n} a_{ij},\ \sum_{j=1}^{n} b_{ij},\ \sum_{j=1}^{n} c_{ij}\right),\ i = 1, .., n \tag{8}$$

Secondly, normalize the row sums as following:

$$\tilde{S} = \frac{\mathrm{RS}_i}{\sum_{j=1}^{n} \mathrm{RS}_j} = \left(\frac{\sum_{j=1}^{n} a_{ij}}{\sum_{j=1}^{n} a_{ij} + \sum_{k=1}^{n}\sum_{j=1}^{n} C_{kj}}, \frac{\sum_{j=1}^{n} b_{ij}}{\sum_{k=1}^{n}\sum_{j=1}^{n} b_{kj}}, \frac{\sum_{j=1}^{n} C_{ij}}{\sum_{j=1}^{n} C_{ij} + \sum_{k=1}^{n}\sum_{j=1}^{n} a_{kj}}\right) \tag{9}$$

Thirdly, evaluate the degree of possibility of $\tilde{S}_{\mathrm{i}} >= \tilde{S}_{\mathrm{j}}$, which is defined as:

$$V\left(\tilde{S}_i \geq \tilde{S}_j\right) = \begin{cases} 1, & \text{if } b_i > b_j \\ \dfrac{c_i - a_j}{(c_i - b_i) + (b_j - a_j)}, & \text{if } a_j \leq c_i \\ 0, & \text{otherwise} \end{cases} \quad \mathrm{i, j} = 1, \ldots \mathrm{n} \text{ and } \mathrm{j} \neq \mathrm{i} \tag{10}$$

Fourthly, the degree of possibility of $\tilde{S}_{\mathrm{i}}$ the other $(n-1)$ fuzzy numbers is computed using the following equation:

$$V(\tilde{S}_i \geq \tilde{S}_j | j = 1 \ldots, n;\ j \neq i) = \min_{j \in \{1,\ldots,n\}, j \neq i} V\left(\tilde{S}_i \geq \tilde{S}_j\right) \tag{11}$$

Finally, the weight vectors of the fuzzy matrix $\tilde{A}$ is defined as:

$W = (w_1,\ w_2, \ldots,\ w_n)^T$ where:

$$wi = \frac{V(\tilde{S}_i \geq \tilde{S}_j | j = 1, \ldots, n; j \neq i)}{\sum_{k=1}^{n} V(\tilde{S}_k \geq \tilde{S}_j | j = 1, \ldots, n; j \neq k)}, i = 1, \ldots, n \tag{12}$$

3.3 Fuzzy TOSPIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a widely used Multi-Criteria Decision Method (Amin et al. 2019; Hu et al. 2019; Roy and Dutta 2019; Başhan et al. 2020; Rouyendegh et al. 2020; Yucesan and Gul 2020).

According to this method, the most appropriate alternative is decided on the basis of the minimization of the distance to the ideal negative solution (i.e., the alternative that minimizes benefit criteria and maximizes cost criteria) and the minimization of the distance to the ideal positive solution (i.e., the alternative that minimizes cost criteria and maximizes benefit criteria).

Fuzzy TOPSIS approach integrates the fuzzy logic to deal with imprecise information. This fuzzy version consists of the following six steps:

Step 1: Construction of the decisions matrix

Suppose a multiple criteria decision-making problem has $\boldsymbol{m}$ possible alternatives $A_i (i = 1, \ldots, m)$ and $\boldsymbol{n}$ criteria/attributes $C_j (j = 1, \ldots, n)$. The performance rating of each alternative with respect to each decision

criterion can be represented by the decision matrix $\tilde{D}$ as follows:

$$\tilde{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \left| \begin{array}{cccc} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & & \tilde{x}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{array} \right| \end{array} \tag{13}$$

where $\tilde{x}_{ij}$ indicates the rating of alternative $\boldsymbol{A_i}$ with respect to criterion $\boldsymbol{C_j}$ expressed by linguistic variables. The weight of the $\boldsymbol{n}$ decision criteria can be concisely expressed in vector format as formulation (14):

$$\tilde{w} = [\tilde{w}_1, \tilde{w}_2 \ldots \tilde{w}_n] \tag{14}$$

where $\tilde{w}_j$ represents the relative importance weight of the decision criterion $\boldsymbol{C_j}$.

In this work, $\tilde{x}_{ij}$ and $\tilde{w}_j$ ($i = 1,\ldots, m$ and $j = 1,\ldots, n$) are modeled by triangular fuzzy numbers given by:

$$\tilde{x}_{ij} = \left(a_{i,j},\ b_{i,j},\ c_{i,j}\right) \text{ and } \tilde{w}_j = \left(w1_j,\ w2_j,\ w3_j\right)$$

Step 2: computation of the normalized fuzzy decisions matrix

In some multi-criteria decision-making problems, the decision criteria can be assessed using different scales and measurement units. This step allows to transform them on a similar scale.

The normalization process depends on whether an attribute is a benefit decision criterion (to be maximized) or a cost decision criterion (to be minimized).

The normalized fuzzy decision matrix can be established as shown in Eqs. (15–17).

$$\tilde{R} = [\widetilde{r}_{ij}]_{m*n},\ i = 1, \ldots, m \text{ and } j = 1, \ldots, n \tag{15}$$

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right), j \in B \tag{16}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), j \in Co \tag{17}$$

Where $c_j^+ = \max_i c_{ij}$ if $j \in B$ and $a_j^- = \min_i a_{ij}$ if j $\in$ Co.

Step 3: computation of the weighted normalized fuzzy decisions matrix

The weighted normalized fuzzy decision matrix is calculated by multiplying the importance weights of the decision criteria by the normalized decision matrix according to Eqs. (18, 19).

$$\tilde{V} = [\tilde{v}_{ij}]_{m*n},\ \mathrm{i} = 1, 2, .., m;\ j = 1, 2, .., n \tag{18}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j \tag{19}$$

Step 4: determination of the fuzzy positive ideal solution and the fuzzy negative ideal solution

The fuzzy positive ideal solution (A^+) and the fuzzy negative ideal solution (A^-) can be computed respectively according to Eqs. (20) and (21).

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+) \tag{20}$$

$$A^- = \left(\tilde{v}_1^-, \tilde{v}_2^- \ldots \tilde{v}_n^-\right) \tag{21}$$

where $\tilde{v}_j^+ = \max_i \tilde{v}_{ij3}$; $\tilde{v}_j^- = \min_i \tilde{v}_{ij1}$; $\mathrm{i} = 1, .., m$; $j = 1, \ldots, n$

In the particular case where all criteria are evaluated using the same scale of fuzzy values, there is no need to normalize the fuzzy decision matrix, and the positive-ideal and negative-ideal solutions can be respectively calculated as:

$$A^+ = \left(\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+\right) = \left\{ \left(\max_i V_{ij3} | j \in B\right) \left(\min_i V_{ij1} / j \in Co\right) \right\} \tag{22}$$

$$A^- = \left(\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\right) = \left\{ \left(\min_i V_{ij1} / j \in Co\right) \left(\max_i V_{ij3} | j \in B\right) \right\} \tag{23}$$

Step 5: computation of the distance between each alternative, the fuzzy positive ideal solution and the fuzzy negative ideal solution

The distance from each alternative to the positive ideal solution is given as:

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+), \mathrm{i} = 1, .., m \tag{24}$$

Similarly, the distance from each alternative to the negative ideal solution is as follows:

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-), \mathrm{i} = 1, \ldots, m \tag{25}$$

where $\boldsymbol{D}(\ \tilde{z}_1, \tilde{z}_2)$ designates the distance between two fuzzy numbers $\tilde{z}_1$ and $\tilde{z}_2$, this is computed as in Eq. (26).

$$(D\tilde{z}_1, \tilde{z}_2) = \sqrt{\frac{1}{3}[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]} \tag{26}$$

Step 6: computation of the closeness index and ranking the alternatives

According to D^+ and D^-, a closeness coefficient (CC) is computed for each alternative as follows:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+}, \mathrm{i} = 1, .., m \tag{27}$$

This coefficient allows to rank alternatives in descending order so that the alternative with the highest closeness

index is the best choice.

The Fuzzy TOPSIS has strengths over other Multi-Criteria Decision methods because it has (1) a very simple computation process that can be implemented in a spreadsheet, (2) a scalar measure that simultaneously takes into account the best and the worst alternatives, (3) a sound logic that represents the rationale of human decision, and (4) performance measures that can be presented on a polyhedron.

3.4 Goal programming

The goal programming (GP) method originally developed by (Charnes et al. 1955) is one the most widely used method for solving multi-objective and multi-criteria decision-making problems (Chang 2007). It has been applied to many real-world problems in areas such as transportation, engineering, economics, marketing, supply chain design, energy efficiency, etc. (Romero 2004; Khemiri et al. 2017a; Aksaraylı and Pala 2018; Hu et al. 2018; Kaucic et al. 2020; Kilic and Yalcin 2020; Malik and Gupta 2020).

The popularity of this technique is directly linked to its mathematical models flexibility, robustness, and the ability to introduce a large number of system constraints (Dhahri and Chabchoub 2007).

Unlike linear programming, the GP method does not directly optimize objective functions. Instead, it aims to minimize the deviations between the realized results and the desired goals. GP can be formulated as follows:

$$\begin{aligned} &\underset{x\in A}{\text{Min}} \sum_{i=1}^{n} \left(\delta_j^+ + \delta_j^-\right) \\ &\text{Subject to:} \quad \begin{array}{ll} C_l(x) \le 0, & l = 1,2,\ldots,L \\ F_j(x) - \delta_j^+ + \delta_j^- = G_j & j = 1,2,\ldots,n \\ \delta_j^+, \delta_j^- \ge 0 & \end{array} \end{aligned} \tag{28}$$

where δ_j^+ and δ_j^- are the positive and negative deviations from the goal $\boldsymbol{G_j}$; $\boldsymbol{F_j(x)}$ is the level of realization of the objective function $\boldsymbol{j}$ (for j = 1; 2;…; n); $\boldsymbol{G_j}$ is the goal value of the $\boldsymbol{j}$th objective function and $\boldsymbol{C_l(x)}$ is a set of constraints.

In order to best reflect the preferences and desires of the decision-makers, a full range of extensions and variants of GP was proposed in the scientific literature. The two major GP forms are lexicographic and weighted Goal Programming (WGP). The distinguishing feature of the first variant is the existence of a certain number of priority levels. In turn, each priority level contains some undesirable deviations to be minimized. The WGP variant allows for direct trade-offs between all deviational variables by placing them in a normalized weighted single function (Jones et al. 2010). The general form of the WGP can represented by the following formulation:

$$\begin{aligned} &\underset{x\in A}{\text{Min}} \sum_{i=1}^{n} \left(w_j^+ \delta_j^+ + w_j^- \delta_j^-\right) \\ &\text{Subject to:} \quad \begin{array}{ll} C_l(x) \le 0, & l = 1,2,\ldots,L \\ F_j(x) - \delta_j^+ + \delta_j^- = G_j & j = 1,2,\ldots,n \\ \delta_j^+, \delta_j^- \ge 0 & \end{array} \end{aligned} \tag{29}$$

where w_j^+ and w_j^- are respectivly the weight factors for positive and negative deviations of the objective $\boldsymbol{j}$. These factors make it possible, on the one hand, to normalize the units of measurement of the various objectives, and on the other hand, to valorize each objective (Kettani et al. 2004).

In standard Goal Programming, the decision-maker is mainly called for establishing goals for the objectives, and his/her involvement in the decision-making process usually finishes at this stage. Thus, the weighted variant involves the decision-maker more than before by asking him/her not only to enter his/her preferences regarding the goals to be achieved for each objective but also to express his/her opinion regarding the importance given to each objective by means of the coefficients w_j. This issue can help to make a final decision that better reflects the structure of the decision maker's preferences.

Therefore, in order to benefit from these advantages, in this paper we use the WGP method to deal with a multi-objective decision-making problem.

4 Problem formulation

Despite the number of works that have investigated the potential of RAMoD systems, these various initiatives treat the problem with a specific focus on the high-density areas.

The FUI TORNADO project that we are working on aims to study the interaction between connected intelligent infrastructures and autonomous vehicles in a low-density environment where transport solutions are scarcer (Tornado 2020).

We consider an urban system discretized into a set of connected stations, where a fleet of autonomous vehicles fulfills on-demand transportation service. Each vehicle can provide a ride-sharing service to the passengers without exceeding their capacity. The fleet of self-driving vehicles is marked by a high degree of heterogeneity: different transportation costs and characteristics (sailing speed, capacity, Comfort, Safety, etc.).

In the context of the Tornado project, using a mobile application, the passenger is able to make a mobility

request from a pickup and drop off location in the predefined area of Rambouillet.

If there are available vehicles in the fleet, one of them will be chosen to accomplish this mobility demand. On the other hand, if there are no available vehicles, the user immediately leaves the transportation system without waiting time. Therefore, we adopt the passenger loss model, similar to (Zhang and Pavone 2016; Iglesias et al. 2019), where if all vehicles are unavailable upon the customer's request, the customer directly leaves the system. This modeling assumption is more involved in transportation systems where a high degree of service is desired (Iglesias et al. 2019).

Dispatching vehicles to accomplish mobility demands is done by the fleet manager. The vehicle will then drive the passenger to the desired destination while maintaining communication with the fleet manager in real-time to find optimal routes and track the information and status of the vehicle.

At the end of the trip, the fleet manager could be sending a mission to the vehicle to accomplish other mobility demands. It could also send a notification to rebalance itself or even to park in the drop-off station for a certain period of time.

For simplification purpose, it is assumed that each station has sufficient space so that incoming vehicles can directly be parked and recharge their batteries at all times. Further, it is assumed that people traveling as a group, must have the same pick-up and drop-off stations. It means, in this model, no detour will occur when picking up and dropping off passengers at different locations.

It is also worth mentioning that, due to several external factors, future customer demand is uncertain to the fleet management and will be estimated using fuzzy sets and possibility theory.

Finally, it is assumed that the time horizon is discretized into ordered periods.

5 Proposed approach

The suggested approach consists of three main phases namely analyzing customer preferences, ranking fleet vehicles and dispatching and rebalancing (see Fig. 2).

5.1 Phase I: analyzing customer preferences

Fleet vehicle selection is complicated by the fact that customer preferences must be taken into account in this decision-making process. Moreover, in practice, determining customer preferences is far from being an easy task. Our RAMoD system is able to query passengers for preferences using the ride request mobile application. The decision-makers take advantage of this available information for understanding passengers' attitudes toward autonomous vehicles service and selecting thereafter the right vehicles that will satisfy travelers.

5.1.1 Step 1: select the criteria used for fleet vehicle ranking

In this first step, the decision-maker must choose the preference attributes that will be used to evaluate the passengers' attitudes toward autonomous vehicles service and to evaluate thereafter the various vehicles.

We suggest in the following a list of preference attributes that can be adapted in order to fit with the strategy of the decision-maker as well as the specificity of a given real case.

- *Travel cost*: often considered as an important travel factor, which represents the total cost of the entire trip. This cost may be imprecisely known at the mid-term horizon; it will, therefore, be modelled by fuzzy numbers.
- *Vehicle speed*: the average speed of the vehicle can be calculated by dividing the total distance traveled by the travel time. There are many external factors that can affect the (average) speed of the vehicles such as traffic congestion and weather. It can also be significantly different according to the type of lanes (i.e., express lanes and local lanes) (Zoto et al. 2012).
- *Vehicle capacity*: the ability of the vehicle for carrying passengers. This attribute is of particular interest when we made with a ride-sharing system.
- *Comfort:* this factor concerns the passenger's level of comfort. According to (Telpaz et al. 2018), comfort is an important aspect of traveler experience. This is justified by the fact that a traveler's perception of a driverless ride is strongly based on the vehicle's driving style, especially in the complex road environment (headway gap, jerk, acceleration, deceleration, etc.)
- *Safety:* according to (Telpaz et al. 2018), the basic needs of passengers of self-driving vehicles is primarily that of protection and safety. Safety can be defined as a "state in which the system is not in danger or at risk, free of injuries or losses" (Sanz et al. 2015).
- *Accessibility for persons with reduced mobility*: the premise of AMoD systems is to provide on-demand transportation and 24/7 mobility to all, including persons with reduced mobility. Hence, we assume that this attribute is of particular interest in this kind of transportation system.

To deal with the inherent subjective nature of the last three criteria, we suggest that will be quantitatively evaluated according to an expert judgment.

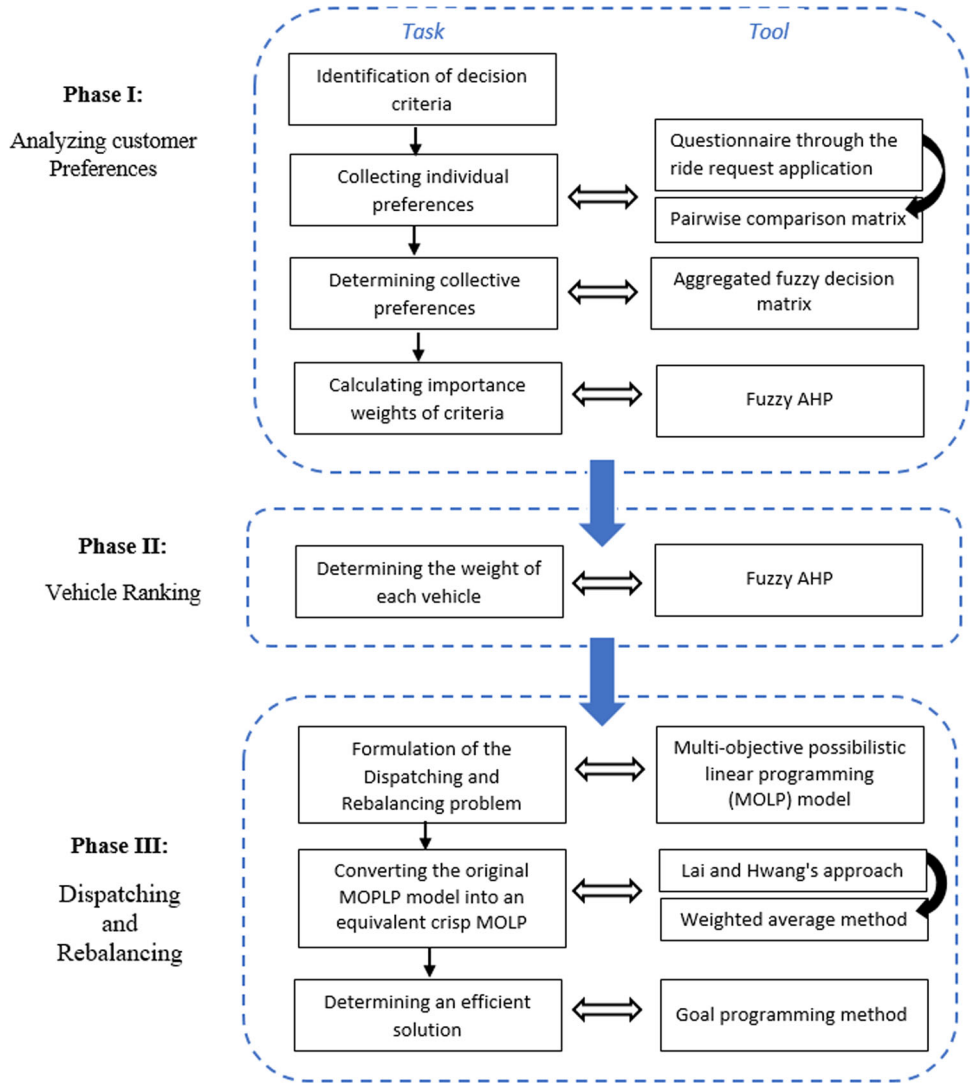

Fig. 2 Framework of the proposed approach

5.1.2 Step 2: Prioritization of vehicles evaluation criteria

In this step, the relative strengths of each criterion, from the perspective of an individual passenger, have been computed.

For the prioritization of individual preferences, passengers are queried through the ride request application and individual preferences are elicited by comparing the relative importance of two travel factors at a time.

After collecting these preferences, it would be coded as fuzzy comparison matrices. Fuzzy linguistic variables are used to indicate the relative importance of each pair of criteria and would subsequently be converted into fuzzy numbers.

Based on the pairwise comparison and triangular fuzzy numbers, the fuzzy comparison matrix is constructed as below:

$$\tilde{A} = \begin{bmatrix} \tilde{a}_{1,1} & \tilde{a}_{1,2} & \cdots & \tilde{a}_{1,n} \\ \tilde{a}_{2,1} & \tilde{a}_{2,2} & \cdots & \tilde{a}_{2,n} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{a}_{n,1} & \tilde{a}_{n,2} & \cdots & \tilde{a}_{n,n} \end{bmatrix}$$

where $\tilde{a}_{i,j}$ indicates the importance of criterion $\boldsymbol{i}$ over criterion $\boldsymbol{j}$, where $\boldsymbol{i = j = 1,\ldots n}$.

The number of matrices obtained at this phase depends on the number of passengers who agreed to answer the questionnaire through the ride request application.

5.1.3 Step 3: construct aggregated fuzzy decision matrix

5.1.3.1 Aggregation of the comparison matrix After the prioritization of the vehicle evaluation criteria was done, these individual passenger opinions should be fused to get a group opinion and estimate the collective preferences. In order to do that, we construct an aggregated fuzzy decision

matrix according to the definitions proposed by (Büyüközkan and Feyzıoğlu 2004; Vahidnia et al. 2008):

$$l_{ij} = \min_{k\in\{1,\ldots,p\}} \left(l_{ijk}\right) \tag{30}$$

$$m_{ij} = \left(\prod_{k=1}^{p} m_{ijk}\right)^{1/p} \tag{31}$$

$$u_{ij} = \max_{k\in\{1,\ldots,p\}} \left(u_{ijk}\right) \tag{32}$$

5.1.3.2 The measurement of consistency After the aggregation is done, the result must be controlled. This is achieved by calculating the consistency ratio (**CR**) for the aggregate comparison matrix. This parameter is used to directly evaluate the consistency of the pairwise comparison matrix and must be inferior to 0.1. In fact, it can be said that the collective preferences are acceptable and can be used later if and only if the **CR** is less than 0.1 otherwise, they will be not acceptable.

This consistency measure is obtained as per the following steps:

Calculate the maximum eigenvector $\boldsymbol{\lambda_{\max}}$ for the pairwise comparison matrix of order $\boldsymbol{n}$ using the formulae:

$$\lambda_{\max} = \max_{j}\left(\frac{L_j + U_j}{2 \times M_j}\right) \tag{33}$$

$$L_j = \frac{\sum_{i=1}^{z} l_{ij}}{\sum_{i=1}^{z}\sum_{j=1}^{z} l_{ij}};\ M_j = \frac{\sum_{i=1}^{z} m_{ij}}{\sum_{i=1}^{z}\sum_{j=1}^{z} m_{ij}};$$

$$U_j = \frac{\sum_{i=1}^{z} u_{ij}}{\sum_{i=1}^{z}\sum_{j=1}^{z} u_{ij}}$$

Compute the consistency index **(CI)** given by:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n-1} \tag{34}$$

The consistency ratio (**CR**) is then computed by dividing the **CI** by the random consistency index as follow:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RC}} \tag{35}$$

where RC is the average random consistency index computed from a significant number of simulation runs. The table of the average random consistency indexes of order 1–10 proposed by Saaty (1980) can be seen in Table 2.

5.1.4 Step 4: calculating importance weights of criteria

For analyzing customer preferences and fuzzy priorities, the fuzzy AHP process has been used in this study. AHP allows the complex decision of vehicle selection to be presented in a descending hierarchical structure from an overall goal of the objective to the various criteria contributing to the decision and so on until the last level of the hierarchy, which will include the different alternatives. Figure 3 illustrates the hierarchy of the considered problem. Specifically, the overall objective of this problem is to choose the best or most suitable autonomous vehicle in the fleet. To achieve this overall goal, six factors have been identified to constitute the second level. Finally, the third level represents the alternative vehicles.

At the end of this step, we can compute the weight vector $\boldsymbol{W} = (\boldsymbol{w_1}, \boldsymbol{w_2}, \ldots, \boldsymbol{w_n})$ of the $\boldsymbol{n}$ selected criteria, where $\boldsymbol{w_j}$ is the weight of the criterion $\boldsymbol{j}$.

5.2 Phase II: vehicle ranking (provide the weight of each vehicle)

At the second phase, the decision-maker compares all vehicles in the fleet under each of the decision criteria defined in the first step. As before, linguistic variables are used to express subjective appreciation and human judgments.

Assume there are $\boldsymbol{m}$ vehicles $\boldsymbol{V_i}$ $(\boldsymbol{i} = \mathbf{1, 2,\ldots}\boldsymbol{m})$, evaluated on $\boldsymbol{n}$ criteria $\boldsymbol{C_j} = (\boldsymbol{j} = \mathbf{1,..,}\boldsymbol{n})$. The rating of the vehicle with respect to the different criteria can be concisely represented by a decision matrix $\tilde{\boldsymbol{D}}$:

$$\tilde{\boldsymbol{D}} = \begin{array}{c} \\ \boldsymbol{V_1} \\ \boldsymbol{V_2} \\ \\ \boldsymbol{V_m} \end{array} \begin{array}{c} \begin{array}{cccc} \boldsymbol{C_1} & \boldsymbol{C_2} & \cdots & \boldsymbol{C_n} \end{array} \\ \left|\begin{array}{cccc} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & & \tilde{x}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{array}\right| \end{array}$$

If there is more than one decision-maker involved with the decision process, as is often the case, aggregation of the different decision matrices is made according to Eqs. (30–32). Then, we call the fuzzy TOPSIS method, considering the decision criteria defined in the previous phase and the fuzzy decision matrix $\tilde{D}$. At the end of this phase, we can compute for each vehicle $\boldsymbol{V_i}$, the relative weight $\boldsymbol{W_i}$.

5.3 Phase III: dispatching and rebalancing

5.3.1 Step 1: proposed multi-objective possibilistic linear programming model

5.3.1.1 Notations

- Set of indices

Table 2 Average random index (RI) based on matrix size adopted from (Saaty 2000)

n	1	2	3	4	5	6	7	8	9	10
RC	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

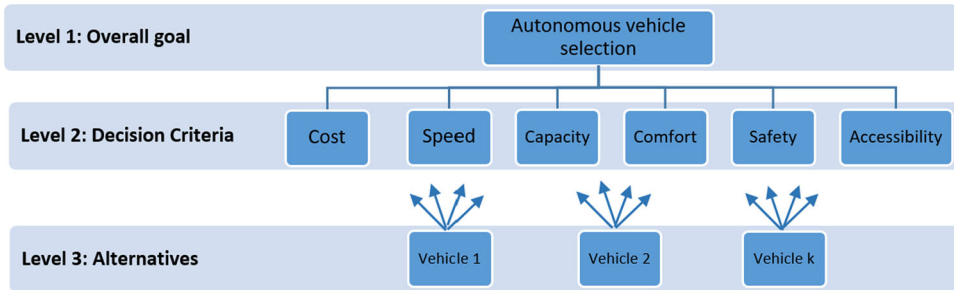

Fig. 3 Hierarchical structure of the considered autonomous vehicle selection problem

- S: overall number of stations in the considered urban environment ($s = 1, 2, \ldots, S$).
- V: overall number of autonomous vehicles in the RAMoD system ($v = 1, 2 \ldots V$).
- T: number of time periods in the planning horizon ($t = 1, 2 \ldots, T$).

- Fuzzy parameters:
  - $\widetilde{Cr}_{t,s1,s2}$: expected number of passengers who wish to travel from origin $s1$ to destination $s2$ departing at time t (i.e., customer trip demands).
  - $\widetilde{\mathrm{Tr_cost}}_v$: transportation cost of the vehicle v.
- Certain parameters:
  - W_v: relative weight of the vehicle v obtained from the previous stage.
  - Cap_v: capacity of the vehicle v for carrying passengers.
  - Sp_v: speed of the vehicle v.
  - $\mathrm{Dist}_{s1,\ s2}$: distance between stations $s1$ and $s2$ by taking the shortest way.
- Decision variables
  - $S_Cr_{t,s1,s2}$: the satisfied customer trip demands departing at time period t from station $s1$ to station $s2$.
  - $Local_init_{v,s}$: represents the initial availability of vehicle v at station s: if v is available at s in the first period, $Local_init_{v,s} = 1$ and 0 otherwise.
  - $Park_{v,t,s}$: Binary variable indicating if vehicle v is parked in station s during period t.
  - $Miss_{v,t}$: Binary variable indicating if vehicle v is on a mission during period t.
  - $Miss_R_{v,s1,s2,t1,t2}$: Binary variable indicating if vehicle v is on a rebalancing mission traveling from station $s1$ to station $s2$ beginning at period $t1$ and arriving at period $t2$.
  - $Miss_T_{v,s1,s2,t1,t2}$: Binary variable indicating if vehicle v is on a customer transport mission traveling from station $s1$ to station $s2$ beginning at period $t1$ and arriving at period $t2$.

5.3.1.2 Objective functions

- Objective 1: Minimizing the number of lost customer requests.

Minimize $\widetilde{\mathrm{LCr}}$

$$\widetilde{\mathrm{LCr}} = \sum_{t=1}^{T}\sum_{s1=1}^{S}\sum_{s2=1/s2\neq s1}^{S} \widetilde{\mathrm{Cr}}_{t,s1,s2} - S_\mathrm{Cr}_{t,s1,s2} \tag{36}$$

- Objective 2: Minimizing the total transportation cost.

Minimize $\widetilde{TC}$

$$\widetilde{\mathrm{TC}} = \sum_{t1=1}^{T}\sum_{t2=1}^{T}\sum_{s1=1}^{S}\sum_{s2=1/s2\neq s1}^{S}\sum_{v=1}^{V} \widetilde{\mathrm{Tr_cost}}_v^{*}\,(\mathrm{Miss_R}_{v,s1,s2,t1,t2} + \mathrm{Miss_T}_{v,s1,s2,t1,t2}) * \mathrm{Dist}_{s1,s2} \tag{37}$$

- Objective 3: Improving customer satisfaction.

Maximize CS

$$CS = \sum_{t1=1}^{T}\sum_{t2=1}^{T}\sum_{s1=1}^{S}\sum_{s2=1/s2\neq s1}^{S}\sum_{v=1}^{V} W_v^{*}\,\mathrm{Miss}_T_{v,s1,s2,t1,t2} \tag{38}$$

5.3.1.3 Model constraints

$$\sum_{s=1}^{S} \mathrm{Park}_{v,t,s} + \mathrm{Miss}_{v,t} = 1\ \forall v,\ t \tag{39}$$

$$\mathrm{Miss}_{v,t} = \sum_{s1=1}^{S}\sum_{s2=1/s2\neq s1}^{S}\sum_{t1\le t}\sum_{t2\ge t} \mathrm{Miss}_R_{v,s1,s2,t1,t2} + \mathrm{Miss}_T_{v,s1,s2,t1,t2}\ \forall v,\ t \tag{40}$$

$$\mathrm{Park}_{v,1,s} + \mathrm{Miss}_T_{v,s,s1,1,t1} + \mathrm{Miss}_R_{v,s,s2,1,t2} \le \mathrm{Local_init}_{v,s}\ \forall v,\ \forall s,\ \forall s1 \neq s,\ \forall s2 \neq s,\ t1 = 1 + (\mathrm{Dist}_{s,s1}/\mathrm{SP}_v),\ t2 = 1 + (\mathrm{Dist}_{s,s2}/\mathrm{SP}_v) \tag{41}$$

$$\text{Park}_{v,t,s} \leq \text{Park}_{v,t-1,s} + \text{Miss_}R_{v,s1,s,t1,t-1} + Miss_T_{v,s2,s,t2,t-1}$$
$$\forall v,\ s,\ s1,\ s2,\ t > 1,\ t1 = t - (\text{Dist}_{s1,s}/\text{SP}_v) - 1,$$
$$t2 = t + (\text{Dist}_{s2,s}/SP_v) - 1 \tag{42}$$

$$\text{Miss_}R_{v,s1,s2,t1,t2} \leq \text{Park}_{v,t1-1,s1} + \sum_{s3 \neq s1}^{S} \text{Miss_}R_{v,s3,s1,t3,t1-1} + \sum_{s4 \neq s1}^{S} \text{Miss_}T_{v,s4,s1,t4,t1-1}$$
$$\forall v,\ s1,\ s2,\ t1 > 1,\ t2 = t1 + (\text{Dist}_{s1,s2}/SP_v),$$
$$t3 = t1 - (\text{Dist}_{s3,s1}/SP_v) - 1,\ t4 = t1 - (\text{Dist}_{s4,s1}/\text{SP}_v) - 1 \tag{43}$$

$$\text{Miss_}T_{v,s1,s2,t1,t2} \leq \text{Park}_{v,t1-1,s1} + \sum_{s3 \neq s1}^{S} \text{Miss_}R_{v,s3,s1,t3,t1-1} + \sum_{s4 \neq s1}^{S} \text{Miss_}T_{v,s4,s1,t4,t1-1}$$
$$\forall v,\ s1,\ s2,\ t1 > 1,\ t2 = t1 + (\text{Dist}_{s1,s2}/\text{SP}_v),$$
$$t3 = t1 - (\text{Dist}_{s3,s1}/\text{SP}_v) - 1,\ t4 = t1 - (\text{Dist}_{s4,s1}/\text{SP}_v) - 1 \tag{44}$$

$$S_\text{Cr}_{t1,s1,s2} \leq \sum_{v=1}^{V} \text{Miss_}T_{v,s1,s2,t1,t2} * \text{Cap}_v \tag{45}$$
$$\forall s1,\ s2,\ t1,\ t2 = t1 + (\text{Dist}_{s1,s2}/\text{SP}_v)$$

$$S_\text{Cr}_{t,s1,s2} \leq \widetilde{\text{Cr}}_{t,s1,s2}\ \forall t,\ s1, s2 \tag{46}$$

$$S_Cr_{t,s1,s2} \geq 0 \text{ and integer } \forall,\ \forall s1,\ s2 \epsilon [1,\ S] \tag{47}$$

$$\text{Miss}_{v,t},\ \text{Park}_{v,t,s},\ \text{Miss_}T_{v,s1,s2,t1,t2},\ \text{Miss_}R_{v,s1,s2,t1,t2} \epsilon [0, 1]$$
$$\forall t,\ v,\ s,\ s1,\ s2,\ t1,\ t2 \tag{48}$$

Equation (39) models the two potential states each vehicle can take, namely, be on a mission between two stations and parked/wait at a station. Besides, this constraint guarantees that an autonomous vehicle can have only one state at a time.

During a vehicle mission, two possible actions can be carried out (1) travel empty in order to rebalance the system, and (2) transport customer(s) from one station to another. These actions are modelled through constraint (40), which also ensures that only one action can take place at one time by a vehicle.

When a vehicle v is on a rebalancing mission (i.e., $\text{Miss_}R_{v,s,s1,1,t1} = 1$), or a customer transport mission (i.e., $\text{Miss_}T_{v,s,s1,1,t1} = 1$) departing at the first period, it is essential that v was initially available at this station (i.e., $\text{Local_init}_{v,s} = 1$). Similarly, a vehicle $\boldsymbol{v}$ cannot wait in a station $\boldsymbol{s}$ during the first period (i.e., $\text{Park}_{v,1,s} = 1$) if and only if it is initially in this station (i.e., $\text{Local_init}_{v,s} = 1$). Equation (41) ensures that these rules are always respected.

These restrictions must be taken into account in the next periods (i.e., $t > 1$). This means that if a vehicle v has waited at a station s during a time period t (i.e., $\text{Park}_{v,t,s} = 1$), it is required that v is physically located in station s at the beginning of period t. Specifically, either the vehicle v 1) has waited at a station $\boldsymbol{s}$ during the last period (i.e., $\text{Park}_{v,t-1,s1} = 1$) or 2) has arrived at a station during the last period (i.e., $\text{Miss_}R_{v,s3,s1,t3,t1-1} = 1$ Or $Miss_T_{v,s4,s1,t4,t1-1} = 1$). Constraint (42) enforces the integration of this condition in the model.

In other words, when vehicle $\boldsymbol{v}$ is on a mission beginning from station $\boldsymbol{s1}$ at period $\boldsymbol{t1}$, it is necessary that $\boldsymbol{v}$ was physically located in $\boldsymbol{s1}$ at the beginning of this period (i.e., $\text{Park}_{v,t-1,s1} + \text{Miss_}R_{v,s3,s1,t3,t-1} + \text{Miss_}T_{v,s4,s1,t4,t-1} = 1$). Eqs. (43) and (44) guarantee the respect of this rule respectively for customer transport missions and rebalancing missions.

Constraint (45) limit the satisfied customer requests to the total capacities of the vehicles used for transporting passengers for each origin–destination pairs in each period.

Equation (46) ensures that vehicles transporting customer(s) between each origin–destination pairs in each period cannot transport more passengers than it has been requested.

Finally, limitations of variables are presented in Eqs. (47) and (48): $\boldsymbol{S_Cr_{t,s1,s2}}$ is an integer, while other decision variables are binary.

5.3.2 Step 2: an auxiliary multi-objective linear model

Fuzzy mathematical programming addresses two different issues: fuzziness and epistemic uncertainty. Fuzziness is modeled by fuzzy constraints while the lack of knowledge or epistemic uncertainty is modeled by fuzzy coefficients (Dubois et al. 2003; Mula et al. 2007).

The model proposed in the previous step jointly considers fuzziness (associated with the flexible constraint 46) and incomplete information in data (associated to: customer request and transportation cost). To deal with this fuzzy multi-objective linear programming model, we apply a two-step solution methodology. In the first step, the proposed model will be converted into an equivalent auxiliary crisp multiple objective linear model. Then, in the second step, an efficient compromise solution will be computed through interaction with the decision-maker. To do so, we apply in this section appropriate strategies for transforming the fuzzy total cost and lost customer requests objective functions as well as the soft constraint (46) into the equivalent crisp formulations.

5.3.2.1 Treating the imprecise objective functions In the scientific literature, several methods are developed to deal with imprecise objective functions (Luhandjula 1989; Sakawa and Yano 1989; Tanaka and Asai 1984; Tanaka et al. 1984; Lai and Hwang 1992). As stated by Hsu and Wang (2001), the first four approaches (Luhandjula 1989;

Sakawa and Yano 1989; Tanaka and Asai 1984; Tanaka et al. 1984) use restrictive assumptions and it is generally difficult to enforce them in practice, we then use the well-known Lai and Hwang's approach (Lai and Hwang 1992) which is also adopted by several researchers (Hsu and Wang 2001; Liang 2006).

Recalling customer trip demands $\widetilde{Cr}_{t,s1,s2}$ have triangular possibility distributions, the lost customer requests objective function $\widetilde{\mathbf{LCr}}$ should also have a triangular possibility distribution. In geometric terms, $\widetilde{\mathbf{LCr}}$ can be clearly defined by the three main points **($\mathbf{LCr^p}$,0)**, **($\mathbf{LCr^m}$,1)** and **($\mathbf{LCr^o}$,0).** Thus, in order to maximize the fuzzy objective, it is necessary to push these three corner points in the direction of the right-hand side.

As the vertical coordinates of the aforementioned points are always fixed at either 1 or 0, we're only looking at the horizontal coordinates. Therefore, the problem is to minimize $\mathbf{LCr^p}$, $\mathbf{LCr^m}$, and $\mathbf{LCr^o}$ simultaneously. According to Lai and Hwang's approach, in order to avoid the conflict resulting from the simultaneous minimization of these objectives, the process of maximizing the fuzzy objective function $\widetilde{\mathbf{LCr}}$ comes back to minimizing $\mathbf{LCr^m}$, maximizing ($\mathbf{LCr^m}$—$\mathbf{LCr^p}$) and minimizing ($\mathbf{LCr^o}$—$\mathbf{LCr^m}$).

In this way, the original fuzzy lost customer requests $\widetilde{\mathbf{LCr}}$ can be transformed into a three crisp objective as follows:

$$\text{Minimize}\ \mathrm{LCr}_1 = \mathrm{LCr}^{\mathrm{m}}$$

$$\mathrm{LCr}^m = \sum_{t=1}^{T}\sum_{s1=1}^{S}\sum_{s2=1/s2\neq s1}^{S} \mathrm{Cr}^m_{t,s1,s2} - S_\mathrm{Cr}_{t,s1,s2} \tag{49}$$

$$\text{Maximize}\ \mathrm{LCr}_2 = \mathrm{LCr}^m - \mathrm{LCr}^p$$

$$\mathrm{LCr}^m - \mathrm{LCr}^p = \sum_{t=1}^{T}\sum_{s1=1}^{S}\sum_{s2=1/s2\neq s1}^{S}\left(\mathrm{Cr}^m_{t,s1,s2} - \mathrm{Cr}^p_{t,s1,s2}\right) - S_\mathrm{Cr}_{t,s1,s2} \tag{50}$$

$$\text{Minimize}\ \mathrm{LCr}_3 = \mathrm{LCr}^o - \mathrm{LCr}^m$$

$$\mathrm{LCr}^o - \mathrm{LCr}^m = \sum_{t=1}^{T}\sum_{s1=1}^{S}\sum_{s2=1/s2\neq s}^{S}(\mathrm{Cr}^o_{t,s1,s2} - \mathrm{Cr}^m_{t,s1,s2}) - S_\mathrm{Cr}_{t,s1,s2} \tag{51}$$

Similarly, the original fuzzy total transportation cost can be replaced by the following crisp objective functions:

$$\text{Minimize}\ \mathrm{TC}_1 = \mathrm{TC}^m$$

$$\mathrm{TC}^m = \sum_{t1=1}^{T}\sum_{t2=1}^{T}\sum_{s1=1}^{S}\sum_{s2=1/s2\neq s1}^{S}\sum_{v=1}^{V} * \mathrm{Dist}_{s1,s2} \tag{52}$$

$$\mathrm{Tr_cost}^m_v * (\mathrm{Miss}_R_{v,s1,s2,t1,t2} + \mathrm{Miss}_T_{v,s1,s2,t1,t2})$$

$$\text{Maximize}\ \mathrm{TC}_2 = \mathrm{TC}^m - \mathrm{TC}^p$$

$$\mathrm{TC}^m - \mathrm{TC}^p = \sum_{t1=1}^{T}\sum_{t2=1}^{T}\sum_{s1=1}^{S}\sum_{s2=1/s2\neq s1}^{S}\sum_{v=1}^{V}\mathrm{Dist}_{s,s2}$$

$$(\mathrm{Tr_cost}^m_v - \mathrm{Tr_cost}^p_v)\left(\mathrm{Miss}_R_{v,s1,s2,t1,t2} + \mathrm{Miss}_T_{v,s1,s2,t1,t2}\right) \tag{53}$$

$$\text{Maximize}\ \mathrm{TC}_3 = \mathrm{TC}^o - \mathrm{TC}^m$$

$$\mathrm{TC}^o - \mathrm{TC}^m = \sum_{t1=1}^{T}\sum_{t2=1}^{T}\sum_{s1=1}^{S}\sum_{s2=1/s2\neq s1}^{S}\sum_{v=1}^{V}\mathrm{Dist}_{s1,s2}$$

$$(\mathrm{Tr_cost}^o_v - \mathrm{Tr_cost}^m_v)(\mathrm{Miss}_R_{v,s1,s2,t1,t2} + \mathrm{Miss}_T_{v,s1,s2,t1,t2}) \tag{54}$$

5.3.2.2 Treating the fuzzy constraint Recalling Eq. (46) in the original fuzzy model is a flexible constraint in which the fuzzy customer request $\widetilde{Cr}$ is compared to the crisp value S_Cr. One of potential resolutions for this flexible constraint is to provide crisp representative number for the fuzzy one. Then an auxiliary crisp constraint will be obtained.

In this paper, we adopt the well-known weighted average defuzzification method, originally introduced by (Lai and Hwang 1992) and successfully used in several researchers for its simplicity and efficiency (Wang and Liang 2005; Liang 2006; Torabi and Hassini 2009). To do so, the decision-maker must first determine the minimum acceptable possibility degree of occurrence for the imprecise/fuzzy parameter, α. Then, the fuzzy constraint (46) can be transformed into an auxiliary crisp one as follows:

$$S_\mathrm{Cr}_{t,s1,s2} \leq w_1\mathrm{Cr}^p_{t,s1,s2,\alpha} + w_2\mathrm{Cr}^m_{t,s1,s2,\alpha} + w_3\mathrm{Cr}^o_{t,s1,s2,\alpha}\ \forall \mathrm{t},\ \mathrm{s1},\ \mathrm{s2} \tag{55}$$

where $w_1 + w_2 + w_3 = 1$.

The weights w_1, w_2 and w_3 are commonly defined subjectively by the decision maker and represent respectively the weight of the most pessimistic value Cr^p, the most possible value Cr^m and the most optimistic value Cr^o.

As several relevant works (Lai and Hwang 1992; Liang 2006; Torabi and Hassini 2009), we adopt the concept of most likely values which uses the same minimum acceptable possibility degree and the same weights for all of the flexible constraints by setting these parameters as follows: $w_1 + w_3 = 1/6$; $w_2 = 4/6$ and $\alpha = 0.5$.

The purpose of using the above weighted values is that Cr^o is too optimistic and Cr^p is too pessimistic values of the fuzzy customer request $\widetilde{\mathrm{Cr}}$. Of course, these boundary values provided us boundary weights. On the other hand, the most possible value Cr^m is usually the most important one and thus should be assigned a higher weight (Lai and Hwang 1992).

5.3.3 Step 3: goal programming-based solution approach

In the previous step, the proposed MOPLP model was converted to an equivalent crisp one. For solving the resulting multi-objective linear programming model and finding an efficient compromise solution, we use here the Weighted Goal Programming approach, which is being increasingly applied in the scientific literature.

Accordingly, we can reformulate our GP problem that attempts to reduce the deviations between the realized results and the desired goals as follows:

$$\text{Minimize } F_{\text{GP}} = W^{+}_{Lcr_1}\delta^{+}_{Lcr_1} + W^{-}_{Lcr_2}\delta^{-}_{Lcr_2} + W^{-}_{Lcr_3}\delta^{-}_{Lcr_3} \; W^{+}_{Tc_1}\delta^{+}_{Tc_1} + W^{-}_{Tc_2}\delta^{-}_{Tc_2} + W^{-}_{Tc_3}\delta^{-}_{Tc_3} + W^{-}_{Cs}\delta^{-}_{Cs} \tag{56}$$

Subject to :

(39–45, 47, 48, 55)

$$\text{Lcr}_1 + \delta^{+}_{\text{Lcr}_1} = \text{Lcr}^{*}_1 \tag{57}$$

$$\text{Lcr}_2 + \delta^{-}_{\text{Lcr}_2} = \text{Lcr}^{*}_2 \tag{58}$$

$$\text{Lcr}_3 + \delta^{-}_{\text{Lcr}_3} = \text{Lcr}^{*}_3 \tag{59}$$

$$\text{Tc}_1 + \delta^{+}_{\text{Tc}_1} = \text{Tc}^{*}_1 \tag{60}$$

$$\text{Tc}_2 + \delta^{-}_{\text{Tc}_2} = \text{Tc}^{*}_2 \tag{61}$$

$$\text{Tc}_3 + \delta^{-}_{\text{Tc}_3} = \text{Tc}^{*}_3 \tag{62}$$

$$\text{Cs} + \delta^{-}_{\text{Cs}} = \text{Cs}^{*} \tag{63}$$

$$\delta^{+}_{\text{Lcr}_1}, \delta^{-}_{\text{Lcr}_2}, \delta^{-}_{\text{Lcr}_3}, \delta^{+}_{\text{Tc}_1}, \delta^{-}_{\text{Tc}_2}, \delta^{-}_{\text{Tc}_3}, \delta^{-}_{\text{Cs}} \geq 0 \tag{64}$$

where:

- $\boldsymbol{\delta^{+}_{k}}$ and $\boldsymbol{\delta^{-}_{k}}$ are respectively the positive and negative deviations from the target value of $\boldsymbol{k}$th goal.
- $\boldsymbol{w^{+}_{k}}$ and $\boldsymbol{w^{-}_{k}}$ are respectivly the weight factors for positive and negative deviations of $\boldsymbol{k}$th goal fixed by the decision-maker such that $\sum_k w_k = 1$.
- Lcr^{*}_1, Lcr^{*}_2, Lcr^{*}_3, Tc^{*}_1, Tc^{*}_2, Tc^{*}_3 and Cs^{*} are the goals calculated using the mathematical model with objective functions (38, 49–54) and respectively and constraints (39–45, 47, 48, 55).

6 Numerical example

In this section, we introduce numerical experiments to validate our proposed dispatching and rebalancing approach in the presence of imprecise travel demands. The tests are carried out with a fleet of 20 autonomous vehicles. The considered transportation network consists of a subset of Rambouillet's real road network, with 5 stations and 20 road links.

For all experiments, our approach was implemented using the optimization software LINGO.

The computational procedure is structured in three phases namely analyzing customer preferences, vehicle ranking, and dispatching and rebalancing.

6.1 Phase I: analyzing customer preferences

6.1.1 Step 1: select the criteria used for fleet vehicle ranking

The evaluation criteria to be considered in the model were identified by the decision-making team, based on their experiences and their strategies.

We suggest that the expert team choose the following decision criteria: total cost ($C1$), vehicle speed ($C2$), vehicle capacity ($C3$), comfort ($C4$), safety ($C5$) and accessibility for persons with reduced mobility ($C6$).

6.1.2 Step 2: prioritization of vehicles evaluation criteria

This step allows each passenger to specify his/her trip preferences and then coded these individual preferences as fuzzy pairwise comparison matrices. Here, we consider ten matrices coming from ten passengers (Tables 3, 4, 5, 6, 7, 8, 9, 10, 11, 12) by using the fuzzy scale provided in Table 13.

6.1.3 Step 3: construct aggregated fuzzy decision matrix

In the third step of the first phase, the aggregate comparison matrix is constructed (see Table 14) by using formulas (30–32). Then, the consistency test is carried out to evaluate the quality of the aggregated fuzzy decision matrix. This test demonstrates that the considered matrix is supposed consistent since the consistency ratio is equal to 0.077 (i.e., less than 0.10). Consequently, we can include this aggregated fuzzy decision matrix in the next steps.

6.1.4 Step 4: calculating importance weights of criteria

At this step of the decision procedure, the Fuzzy AHP method is called to calculate the weights of the decision criteria. By using formulas (9) and (10), we obtain:

$$S_{C1} = (0.08, 0.31, 0.63)$$
$$S_{C2} = (0.07, 0.26, 0.59)$$
$$S_{C3} = (0.05, 0.18, 0.51)$$
$$S_{C4} = (0.04, 0.13, 0.39)$$
$$S_{C5} = (0.04, 0.10, 0.29)$$
$$S_{C6} = (0.01, 0.02, 0.09)$$

Then, by appling formulas (10) and (11), the minimum degree of possibility of these values are:

$$V(S1 \geq S2, S3, S4, S5, S6) = \min(1, 1, 1, 1, 1) = 1$$
$$V(S2 \geq S1, S3, S4, S5, S6) = \min(0.91, 1, 1, 1, 1) = 0.91$$
$$V(S3 \geq S1, S2, S4, S5, S6) = \min(0.76, 0.84, 1, 1, 1) = 0.76$$
$$V(S4 \geq S1, S2, S3, S5, S6) = \min(0.64, 0.71, 0.89, 1, 1) = 0.64$$

$$V(S5 \geq S1, S2, S3, S4, S6) = \min(0.5, 0.57, 0.75, 0.87, 1) = 0.5$$
$$V(S6 \geq S1, S2, S3, S4, S5) = \min(0.06, 0.09, 0.21, 0.33, 0.43) = 0.06$$

Finally, by using formula (12), the weight vector of the six decision criteria is obtained:

$$W = (0.258, 0.236, 0.197, 0.165, 0.129, 0.16).$$

6.2 Phase II: vehicle ranking

At this second phase of the decision procedure, the linguistic terms and TFN were used by the decision-maker to evaluate the vehicles under each of the decision criteria separately. The Fuzzy comparison matrix established is presented in Table 15. This latter was used to construct the normalized fuzzy decision matrix (see Table 16) using the formulae (16) and (17).

Using the importance weights of the decision criteria calculated by Fuzzy AHP (i.e., vector $\boldsymbol{W}$) and the normalized fuzzy decision matrix, the weight normalized fuzzy decision matrix is established with formula (19). The resulting weighted evaluation matrix is given in Table 17.

The results obtained during the third and fourth stages, in particular, the distance of each vehicle from the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS), respectively, are shown in Table 18.

Based in Eq. (27), the closeness coefficient of each vehicle is calculated. Finally, these calculations led to overall outranking presented in Table 17.

6.3 Phase III: dispatching and rebalancing

6.3.1 Detailed results

We test the proposed dispatching and rebalancing strategy with a planning horizon divided into 10 periods. The discretization of time into small segments allows modeling the variation of customer requests over time. These customer requests, in turn, could be influenced by several external factors and will, therefore, be estimated using TFN, as shown in Table 19.

Figure 4 shows the results provided by the third phase of the decision procedure by reporting vehicle statues over time.

6.3.2 Discussion

We can see on Fig. 4 that, as intended, an autonomous vehicle can be on a rebalancing mission, be on a customer transportation mission and be parked in a drop-off station. For missions, pick-up and drop-off locations are also indicated in Fig. 4.

This latter also illustrates the relationship between customer request and the required fleet size. Indeed, we see that as customer demand increases, the number of vehicles involved increases until it reaches 100% during the last period.

The proposed approach is not only about the fleet sizing problem, but it also takes into account the composition of the fleet. An investigation of the impacts of the variation of customer requests on the fleet composition shows that for low demand levels, the fleet includes only the best-ranked vehicles with the lowest transport cost. However, increased customer demands require the inclusion of lower-ranked vehicles and/or vehicles with very high transportation costs.

For instance, during the first two periods, customer demand is satisfied with the best-ranked and least costly vehicles, which are V_1, V_2, and V_{20}.

The increase of the customer request in the third period results in an increase in the fleet size by integrating V_4. Although V_4 is ranked 5th, just after V_3, depending on the results of the previous phase, it was selected to be part of the fleet during this period before V_3. This is mainly due to the fact that V_3 has a high transport cost compared to V_4.

Similarly, to satisfy the increased customer demand during the fourth period, V_5 has been integrated into the fleet although the latter is ranked 8th after V_{10} and V_{19}, which are characterized by their very high transport costs.

We can observe that during the fifth period, V_{11} joins the fleet despite being more expensive and ranked lower than

Table 3 Passenger 1 fuzzy comparison matrix

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
$C1$	1	VH	H	H	H	M
$C2$	1/VH	1	M	M	VH	H
$C3$	1/H	1/M	1	H	VH	H
$C4$	1/H	1/M	1/H	1	H	VH
$C5$	1/H	1/VH	1/VH	1/H	1	M
$C6$	1/M	1/H	1/H	1/VH	1/M	1

Table 4 Passenger 2 fuzzy comparison matrix

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
$C1$	1	VH	VH	VH	VH	H
$C2$	1/VH	1	VH	M	H	M
$C3$	1/VH	1/VH	1	M	VH	P
$C4$	1/VH	1/M	1/M	1	M	VH
$C5$	1/VH	1/H	1/VH	1/M	1	VH
$C6$	1/H	1/M	1/P	1/VH	1/VH	1

Table 5 Passenger 3 fuzzy comparison matrix

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
$C1$	1	H	VH	H	VH	H
$C2$	1/H	1	VH	M	VH	M
$C3$	1/VH	1/VH	1	VH	VH	VH
$C4$	1/H	1/M	1/VH	1	M	P
$C5$	1/VH	1/VH	1/VH	1/M	1	VH
$C6$	1/H	1/M	1/VH	1/P	1/VH	1

Table 6 Passenger 4 fuzzy comparison matrix

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
$C1$	1	VH	VH	H	P	P
$C2$	1/VH	1	H	M	P	P
$C3$	1/VH	1/H	1	M	P	P
$C4$	1/H	1/M	1/M	1	M	M
$C5$	1/P	1/P	1/P	1/M	1	M
$C6$	1/P	1/P	1/P	1/M	1/M	1

Table 7 Passenger 5 fuzzy comparison matrix

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
$C1$	1	P	M	P	P	M
$C2$	1/P	1	VH	M	M	VH
$C3$	1/M	1/VH	1	P	P	P
$C4$	1/P	1/M	1/P	1	M	VH
$C5$	1/P	1/M	1/P	1/M	1	VH
$C6$	1/M	1/VH	1/P	1/VH	1/VH	1

Table 8 Passenger 6 fuzzy comparison matrix

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
$C1$	1	H	H	VH	M	M
$C2$	1/H	1	H	VH	M	VH
$C3$	1/H	1/H	1	M	P	M
$C4$	1/VH	1/VH	1/M	1	P	H
$C5$	1/M	1/M	1/P	1/P	1	VH
$C6$	1/M	1/VH	1/M	1/H	1/VH	1

Table 9 Passenger 7 fuzzy comparison matrix

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
$C1$	1	H	M	M	M	P
$C2$	1/H	1	M	P	P	P
$C3$	1/M	1/M	1	H	H	M
$C4$	1/M	1/P	1/H	1	H	M
$C5$	1/M	1/P	1/H	1/H	1	M
$C6$	1/P	1/P	1/M	1/M	1/M	1

Table 10 Passenger 8 fuzzy comparison matrix

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
$C1$	1	VH	M	VH	VH	H
$C2$	1/VH	1	P	H	M	VH
$C3$	1/M	1/P	1	VH	H	VH
$C4$	1/VH	1/H	1/VH	1	P	H
$C5$	1/VH	1/M	1/H	1/P	1	H
$C6$	1/H	1/VH	1/VH	1/H	1/H	1

Table 11 Passenger 9 fuzzy comparison matrix

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
$C1$	1	M	VH	H	M	H
$C2$	1/M	1	VH	H	M	VH
$C3$	1/VH	1/VH	1	M	P	M
$C4$	1/H	1/H	1/M	1	P	H
$C5$	1/M	1/M	1/P	1/P	1	VH
$C6$	1/H	1/VH	1/M	1/H	1/VH	1

V_{18}. This can be explained by the fact that the increase of the grouped customer requests involves more possibilities for grouping requests, which need autonomous vehicles with larger capacities, resulting in fewer trips and therefore lower transport costs. Given that V_{11} is characterized by a large capacity, it allows to better accommodate the grouped customer requests reported during the fifth period.

Table 12 Passenger 10 fuzzy comparison matrix

	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6
*C*1	1	P	P	P	P	VP
*C*2	1/P	1	VH	M	M	VH
*C*3	1/P	1/VH	1	P	P	M
*C*4	1/P	1/M	1/P	1	M	VH
*C*5	1/P	1/M	1/P	1/M	1	VH
*C*6	1/VP	1/VH	1/M	1/VH	1/VH	1

Table 13 Linguistics variables and fuzzy values

Very High(VH)	(8, 9, 10)
High (H)	(6, 7, 8)
Medium (M)	(4, 5, 6)
Poor (P)	(2, 3, 4)
Very poor (VP)	(0, 1, 2)

We can notice also that station S_5 is more on-demand than the other destinations during the fifth period. Consequently, at the end of this period, the vehicles used for these trips, which are the best-ranked ones with the lowest transport cost, are inevitably accumulate in S_5. However, in the next periods, trips departing from S_5 are not requested. This justifies the recourse to rebalancing missions from station S_5 to the requested stations.

The rebalancing decisions taken during T_6 and T_7 are guided by the minimization of the transportation costs and the improvement of customer satisfaction by promoting the use of the best-ranked vehicles with the lowest transport costs. On the contrary, these decisions were introduced during the 8th period to meet customer demands during the 9th period. Indeed, with the increase of the customer request during this period, all the vehicles were sent on transportation mission, even the lowest ranked and the most expensive ones.

Nevertheless, during the last period, the mobilization of all vehicles is still insufficient to meet customer demand, which exceeds the capacity of the fleet.

From these results, we can conclude that the dispatching and rebalancing decisions are very sensitive to the objectives of the minimization of transportation costs and the improvement of customer satisfaction while meeting customer requests.

7 Sensitivity analysis

Sensitivity analysis is a key issue in multiple criteria approaches, where all changes in the original data as well as in the preferences must be taken into account.

This section presents the results of sensitivity analysis based on the passengers' preference variation.

Table 20 illustrates the impact of these variations on the ranking of vehicles. In the first six tests, the passengers' preferences are assumed to be homogeneous. For example, in the first experiment, *C*1 is assumed to be the most important criterion for all passengers. The vehicles with the lowest cost are the highest ranked, namely *V*12, *V*10, and *V*13, while the *V*14 and *V*16 come in at the bottom of the ranking due to their significantly higher transportation costs. Similarly, for the second experiment, we assume that *C*2 is the most important criterion for all passengers. Therefore, the fastest vehicles in the fleet which are *V*3 and *V*4 come at the top of the list, while the slowest ones (i.e., *V*13 and *V*16) come at the bottom of the ranking. For test 7, criteria *C*2 and *C*3 are the most preferred criteria for the majority of passengers. Consequently, the fastest vehicles with a high capacity come at the top of the list. For test 8, the individual preferences of the passengers are oriented toward the *C*2 and *C*4 criteria. Thus, we find that vehicles with a good speed/comfort compromise appear at the top of the ranking. In experience 9, three criteria are referred by the passengers, which are speed, capacity, and comfort. Thus, the vehicles of the fleet presenting a good compromise about these three criteria are ranked at the top of the list. For test 10, the preferences of the majority of the passengers are oriented toward the speed criterion, while the rest prefer vehicles adapted to people with reduced

Table 14 Aggregate comparison matrix

	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6
*C*1	(1, 1, 1)	(2,00, 6.32, 10)	(2, 6.43, 10)	(2, 6.16, 10)	(2, 5.29, 10)	(0, 4.4, 8)
*C*2	(0.1, 0.16, 0.50)	(1, 1, 1)	(2, 6.82, 10)	(2, 5.39, 10)	(2, 5.25, 10)	(2, 6.26, 10)
*C*3	(0.1, 0.15, 0.50)	(0.10, 0.15, 0.50)	(1, 1, 1)	(2, 5.43, 10)	(2, 4.94, 10)	(2, 4.99, 10)
*C*4	(0.1, 0.16, 0.50)	(0.10, 0.18, 0.50)	(0.1, 0.18, 0.50)	(1, 1, 1)	(2, 4.59, 8)	(2, 6.65, 10)
*C*5	(0.1, 0.19, 0.50)	(0,10, 0.19, 0.50)	(0.1, 0.2, 0.5)	(0.13, 0.22, 0.5)	(1, 1, 1)	(4, 7.36, 10)
*C*6	(0, 0.21, 1)	(0,10, 0.16, 0.50)	(0.1, 0.2, 0.5)	(0.1, 0.15, 0.5)	(0.1, 0.14, 0.25)	(1, 1, 1)

Table 15 Fuzzy comparison matrix (Vehicle-Criteria)

V_i	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
V_1	(15, 20, 25)	(55, 60, 65)	10	VH	VH	VH
V_2	(18, 22, 26)	(58, 60, 62)	8	VH	VH	H
V_3	(20, 25, 30)	(60, 65, 70)	2	VH	VH	VH
V_4	(17, 19, 21)	(55, 65, 75)	1	VH	H	H
V_5	(2, 3, 4)	(25, 30, 35)	5	M	M	VP
V_6	(2, 4, 6)	(27, 29, 31)	4	M	VP	P
V_7	(8, 10, 12)	(25, 30, 35)	5	M	M	M
V_8	(7, 9, 11)	(27, 30, 33)	4	M	M	M
V_9	(12, 13, 14)	(30, 32, 34)	4	VH	P	VH
V_{10}	(1, 3, 5)	(10, 15, 20)	12	VP	M	VP
V_{11}	(2, 4, 6)	(12, 15, 18)	10	P	M	VP
V_{12}	(1, 2, 3)	(10, 15, 20)	1	VP	P	VP
V_{13}	(1, 4, 7)	(12, 14, 16)	2	P	VP	P
V_{14}	(22, 25, 28)	(25, 30, 35)	5	M	H	M
V_{15}	(15, 25, 30)	(15, 25, 35)	6	H	M	M
V_{16}	(22, 25, 28)	(10, 12, 14)	2	P	P	VP
V_{17}	(2, 5, 8)	(22, 24, 26)	2	M	VH	H
V_{18}	(12, 15, 18)	(10, 20, 30)	7	VH	M	P
V_{19}	(20, 22, 24)	(25, 35, 45)	8	M	H	VH
V_{20}	(7, 10, 13)	(50, 55, 60)	10	VH	H	M

mobility. Therefore, the vehicles with a good compromise between the C2 and C6 criteria and especially the fastest ones are placed at the top of the ranking as displayed in Table 20. Three criteria are also chosen by passengers in experience 13 which are speed, capacity, and safety. The fastest vehicles are the most popular, followed by high-capacity vehicles and then the safest vehicles. The analysis of the individual preferences revealed four criteria preferred by the passengers in experiment 14: $C6$ is the most requested criterion followed by $C2$, then $C5$, and finally $C1$. This analysis influenced the ranking of the vehicles. We find the vehicles with a good compromise concerning these criteria positioned at the top of the ranking, with special consideration of the vehicles adapted for people with reduced mobility. The passengers' preferences are very heterogeneous in the last experiment, so the weights of the different criteria are very close. Therefore the ranking reveals the vehicles with a good compromise of all decision criteria.

The vehicle rankings presented in Table 20 are in accordance with the vehicle occupancy rates presented in Fig. 5. For instance, in the first test where the passengers' preferences are oriented toward the cost criterion, the least costly vehicles are the most occupied. In the same way, for the five following tests where the preferences respectively

Table 16 Normalized fuzzy decision matrix

V_i	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
V_1	(0.25, 0.33, 0.5)	(0.92, 0.92, 0.92)	(0.83, 0.83, 0.83)	(0.8, 0.9, 1)	(0.8, 0.9, 1)	(0.8, 0.9, 1)
V_2	(0.16, 0.25, 0.5)	(0.92, 0.92, 0.92)	(0.66, 0.66, 0.66)	(0.8, 0.9, 1)	(0.8, 0.9, 1)	(0.6, 0.7, 0.8)
V_3	(0.08, 0.1, 0.13)	(1, 1, 1)	(0.16, 0.16, 0.16)	(0.8, 0.9, 1)	(0.8, 0.9, 1)	(0.8, 0.9, 1)
V_4	(0.09, 0.11, 0.14)	(1, 1, 1)	(0.08, 0.08, 0.08)	(0.8, 0.9, 1)	(0.6, 0.7, 0.8)	(0.6, 0.7, 0.8)
V_5	(0.071, 0.077, 0.08)	(0.46, 0.46, 0.46)	(0.41, 0.41, 0.41)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)	(0, 0.1, 0.2)
V_6	(0.2, 0.33, 1)	(0.45, 0.45, 0.45)	(0.33, 0.33, 0.33)	(0.4, 0.5, 0.6)	(0, 0.1, 0.2)	(0.2, 0.3, 0.4)
V_7	(0.16, 0.25, 0.5)	(0.46, 0.46, 0.46)	(0.41, 0.41, 0.41)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)
V_8	(0.33, 0.5, 1)	(0.46, 0.46, 0.46)	(0.33, 0.33, 0.33)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)
V_9	(0.14, 0.25, 1)	(0.49, 0.49, 0.49)	(0.33, 0.33, 0.33)	(0.8, 0.9, 1)	(0.2, 0.3, 0.4)	(0.8, 0.9, 1)
V_{10}	(0.03, 0.04, 0.05)	(0.23, 0.23, 0.23)	(1, 1, 1)	(0.0.1, 0.2)	(0.4, 0.5, 0.6)	(0, 0.1, 0.2)
V_{11}	(0.03, 0.04, 0.07)	(0.23, 0.23, 0.23)	(0.83, 0.83, 0.83)	(0.2, 0.3, 0.4)	(0.4, 0.5, 0.6)	(0, 0.1, 0.2)
V_{12}	(0.03, 0.04, 0.05)	(0.23, 0.23, 0.23)	(0.08, 0.08, 0.08)	(0.0.1, 0.2)	(0.2, 0.3, 0.4)	(0, 0.1, 0.2)
V_{13}	(0.12, 0.2, 0.5)	(0.22, 0.22, 0.22)	(0.16, 0.16, 0.16)	(0.2, 0.3, 0.4)	(0, 0.1, 0.2)	(0.2, 0.3, 0.4)
V_{14}	(0.056, 0.067, 0.08)	(0.46, 0.46, 0.46)	(0.41, 0.41, 0.41)	(0.4, 0.5, 0.6)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)
V_{15}	(0.042, 0.045, 0.05)	(0.38, 0.38, 0.38)	(0.5, 0.5, 0.5)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)
V_{16}	(0.07, 0.10, 0.14)	(0.18, 0.18, 0.18)	(0.16, 0.16, 0.16)	(0.2, 0.3, 0.4)	(0.2, 0.3, 0.4)	(0, 0.1, 0.2)
V_{17}	(0.25, 0.33, 0.5)	(0.37, 0.37, 0.37)	(0.16, 0.16, 0.16)	(0.4, 0.5, 0.6)	(0.8, 0.9, 1)	(0.6, 0.7, 0.8)
V_{18}	(0.16, 0.25, 0.5)	(0.31, 0.31, 0.31)	(0.58, 0.58, 0.58)	(0.8, 0.9, 1)	(0.4, 0.5, 0.6)	(0.2, 0.3, 0.4)
V_{19}	(0.08, 0.1, 0.13)	(0.54, 0.54, 0.54)	(0.66, 0.66, 0.66)	(0.4, 0.5, 0.6)	(0.6, 0.7, 0.8)	(0.8, 0.9, 1)
V_{20}	(0.09, 0.11, 0.14)	(0.85, 0.85, 0.85)	(0.83, 0.83, 0.83)	(0.8, 0.9, 1)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)

Table 17 Weighted normalized fuzzy decision matrix

V_i	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
V_1	(0.003, 0.013, 0.017)	(0.217, 0.217, 0.217)	(0.16, 0.16, 0.16)	(0.13, 0.15, 0.165)	(0.103, 0.116, 0.129)	(0.013, 0.014, 0.015)
V_2	(0.010, 0.012, 0.014)	(0.217, 0.217, 0.217)	(0.13, 0.13, 0.13)	(0.13, 0.15, 0.165)	(0.103, 0.116, 0.129)	((0.010, 0.011, 0.012)
V_3	(0.009, 0.01, 0.013)	(0.236, 0.236, 0.236)	(0.03, 0.03, 0.03)	(0.13, 0.15, 0.165)	(0.103, 0.116, 0.129)	(0.013, 0.014, 0.015)
V_4	(0.012, 0.014, 0.015)	(0.236, 0.236, 0.236)	(0.02, 0.02, 0.02)	(0.13, 0.15, 0.165)	(0.77, 0.09, 0.103)	(0.010, 0.011, 0.012)
V_5	(0.065, 0.086, 0.129)	(0.109, 0.109, 0.19)	(0.08, 0.08, 0.08)	(0.07, 0.08, 0.099)	(0.051, 0.064, 0.077)	(0, 0.002, 0.003)
V_6	(0.043, 0.065, 0.129)	(0.105, 0.105, 0.105)	(0.07, 0.07, 0.07)	(0.07, 0.08, 0.099)	(0, 0.013, 0.026)	(0.003, 0.005, 0.006)
V_7	(0.022, 0.026, 0.032)	(0.109, 0.109, 0.19)	(0.08, 0.08, 0.08)	(0.07, 0.08, 0.099)	(0.051, 0.064, 0.077)	(0.006, 0.008, 0.009)
V_8	(0.023, 0.029, 0.037)	(0.109, 0.109, 0.19)	(0.07, 0.07, 0.07)	(0.07, 0.08, 0.099)	(0.051, 0.064, 0.077)	(0.006, 0.008, 0.009)
V_9	(0.018, 0.02, 0.022)	(0.116, 0.116, 0.116)	(0.07, 0.07, 0.07)	(0.13, 0.15, 0.165)	(0.026, 0.039, 0.051)	(0.013, 0.014, 0.015)
V_{10}	(0.052, 0.086, 0.258)	(0.054, 0.054, 0.054)	(0.02, 0.02, 0.02)	(0, 0.02, 0.033)	(0.051, 0.064, 0.077)	(0, 0.002, 0.003)
V_{11}	(0.043, 0.065, 0.129)	(0.054, 0.054, 0.054)	(0.16, 0.16, 0.16)	(0.03, 0.05, 0.066)	(0.051, 0.064, 0.077)	(0, 0.002, 0.003)
V_{12}	(0.086, 0.129, 0.258)	(0.054, 0.054, 0.054)	(0.02, 0.02, 0.02)	(0, 0.02, 0.033)	(0.026, 0.039, 0.051)	(0, 0.002, 0.003)
V_{13}	(0.037, 0.065, 0.258)	(0.051, 0.051, 0.051)	(0.03, 0.03, 0.03)	(0.03, 0.05, 0.066)	(0, 0.013, 0.026)	(0.003, 0.005, 0.006)
V_{14}	(0.009, 0.01, 0.012)	(0.109, 0.109, 0.19)	(0.08, 0.08, 0.08)	(0.07, 0.08, 0.099)	(0.77, 0.09, 0.103)	(0.006, 0.008, 0.009)
V_{15}	(0.009, 0.01, 0.017)	(0.091, 0.091, 0.091)	(0.1, 0.1, 0.1)	(0.1, 0.12, 0.132)	(0.051, 0.064, 0.077)	(0.006, 0.008, 0.009)
V_{16}	(0.009, 0.01, 0.012)	(0.043, 0.043, 0.043)	(0.03, 0.03, 0.03)	(0.03, 0.05, 0.066)	(0.026, 0.039, 0.051)	(0, 0.002, 0.003)
V_{17}	(0.032, 0.052, 0.129)	(0.087, 0.087, 0.087)	(0.03, 0.03, 0.03)	(0.07, 0.08, 0.099)	(0.103, 0.116, 0.129)	(0.010, 0.011, 0.012)
V_{18}	(0.014, 0.017, 0.022)	(0.072, 0.072, 0.072)	(0.11, 0.11, 0.11)	(0.13, 0.15, 0.165)	(0.051, 0.064, 0.077)	(0.003, 0.005, 0.006)
V_{19}	(0.011, 0.012, 0.013)	(0.127, 0.127, 0.127)	(0.13, 0.13, 0.13)	(0.07, 0.08, 0.099)	(0.77, 0.09, 0.103)	(0.013, 0.014, 0.015)
V_{20}	(0.020, 0.026, 0.037)	(0.199, 0.199, 0.199)	(0.16, 0.16, 0.16)	(0.13, 0.15, 0.165)	(0.77, 0.09, 0.103)	(0.006, 0.008, 0.009)

Table 18 Computation of $D+$, $D-$, CC and outranking of vehicles according to Fuzzy TOPSIS

V_i	$D+$	$D-$	CC	Rank
V_1	5329	0674	0112	1
V_2	5364	0637	0106	3
V_3	5443	0559	0093	4
V_4	5485	0517	0086	5
V_5	5568	0439	0073	8
V_6	5651	0363	0060	16
V_7	5628	0374	0062	15
V_8	5641	0361	0060	17
V_9	5597	0405	0067	12
V_{10}	5539	0500	0083	6
V_{11}	5588	0424	0071	10
V_{12}	5718	0308	0051	19
V_{13}	5735	0311	0052	18
V_{14}	5619	0383	0064	14
V_{15}	5611	0391	0065	13
V_{16}	5824	0180	0030	20
V_{17}	5601	0413	0069	11
V_{18}	5578	0424	0071	9
V_{19}	5543	0458	0076	7
V_{20}	5363	0640	0107	2

centered on the criterion $C2$, $C3$, $C4$, $C5$, and $C6$, we can notice that the vehicles placed at the top of the ranking (in Table 20) are always the most occupied ones. For tests 7–13, the analysis of individual preferences has focused on two to three decision criteria which are aligned with the occupancy rates for these different tests. Thus, we can notice from the curves presented in Fig. 5 that the vehicles with a good compromise of the selected criteria have the highest occupancy rates. Despite the heterogeneity highlighted in the passengers' preferences in the two last experiments, the occupancy rate of the vehicles remains coherent with the ranking presented in Table 20. These findings demonstrate that the occupancy rate differs according to individual passenger preferences, as well as between vehicles.

Figure 6 also illustrates that there are significant variations from vehicle to vehicle in the average occupancy rate. We find at the first place $V1$ which showed an average occupancy of around 76%, followed by $V2$ and V20 where the average occupancy rate is about 71%. This is not unexpected because these vehicles present excellent performance for the most popular criteria, namely $C2$, $C4$, and $C6$. This differs from $V6$, $V13$, and $V12$ which have an average occupancy rate at around 17%, 15%, and 14% respectively. This low occupancy rate is due to poor performance, especially for the most popular criteria. We can

Table 19 Fuzzy Demand for each time period

		*T*1	*T*2	*T*3	*T*4	*T*5	*T*6	*T*7	*T*8	*T*9	*T*10
*S*1	*S*2	(0, 1, 2)	(3, 5, 7)	0	(0, 1, 2)	0	0	(10, 12, 14)	(2, 5, 8)	(4, 9, 17)	(10, 15, 20)
	*S*3	0	(1, 8, 9)	0	0	0	0	(4, 9, 17)	(0, 1, 2)	(8, 10, 12)	(11, 12, 13)
	*S*4	0	0	0	(4, 9, 17)	0	0	(7, 8, 9)	(2, 3, 10)	(4, 8, 12)	(12, 14, 16)
	*S*5	0	0	0	0	(0, 1, 2)	0	(0, 2, 4)	(1, 2, 3)	(10, 13, 16)	(15, 16, 17)
*S*2	*S*1	(0, 1, 2)	0	0	0	(3, 11, 13)	0	(0, 1, 2)	(6, 9, 18)	(2, 4, 6)	(4, 6, 8)
	*S*3	0	(4, 9, 17)	0	0	0	0	(0, 1, 2)	0	(1, 4, 7)	0
	*S*4	0	0	(7, 8, 9)	(3, 11, 13)	0	(6, 7, 8)	0	0	(6, 9, 18)	(0, 1, 2)
	*S*5	0	0	0	0	(0, 1, 2)	(3, 5, 7)	(3, 4, 11)	0	(1, 8, 9)	(1, 2, 3)
*S*3	*S*1	(0, 1, 2)	0	9	0	0	(3, 5, 7)	0	(0, 2, 4)	(0, 1, 2)	(10, 15, 20)
	*S*2	0	0	(3, 11, 13)	0	0	(3, 5, 7)	0	(6, 9, 18)	(1, 3, 5)	(3, 5, 7)
	*S*4	0	0	0	0	(2, 4, 6)	(3, 4, 11)	0	(3, 4, 11)	(0, 2, 4)	(15, 17, 19)
	*S*5	0	0	0	0	(7, 8, 9)	(10, 12, 14)	0	(3, 4, 11)	(1, 8, 9)	(15, 18, 21)
*S*4	*S*1	0	0	(0, 1, 2)	0	0	0	(2, 5, 8)	(6, 8, 10)	(3, 5, 7)	(2, 5, 8)
	*S*2	0	0	0	0	0	0	0	(1, 4, 7)	(1, 4, 7)	(2, 4, 6)
	*S*3	0	0	0	(4, 6, 8)	0	0	0	0	(3, 4, 11)	(6, 8, 10)
	*S*5	0	0	0	0	(18, 20, 22)	(3, 4, 11)	(5, 6, 7)	0	(2, 5, 8)	0
*S*5	*S*1	0	0	0	(1, 2, 3)	0	0	0	(3, 11, 13)	(3, 4, 11)	(3, 5, 7)
	*S*2	0	0	0	0	0	0	0	(2, 3, 10)	(1, 2, 3)	(10, 12, 14)
	*S*3	0	0	0	(3, 4, 11)	0	0	0	0	0	0
	*S*4	0	0	0	0	0	0	0	0	0	0

also notice that despite low transport costs, the average occupancy rate of these vehicles remains very low. This is justified by the fact that the cost is not a popular criterion for the passengers. The lowest average occupancy rate was observed for the *V*16, which has the worst performance in the fleet. These findings demonstrate that the average occupancy rate differs between vehicles, and it is coherent with the passenger preferences as well as the ranking of the vehicles.

8 Conclusion and future research work

The advance in transportation paradigms in the last decade has paved the way for the emergence of a novel transformational technology known as RAMoD systems. Such systems require an efficient mechanism to optimal schedule and rebalance activities of the fleet vehicles, which are impacted by various uncertainties. However, the scientific literature still reveals a lack of work to address these significant uncertainties. In addition, customer satisfaction is usually measured using traditional quantitative criteria such as travel time and waiting time. Nevertheless, quantitative criteria are not enough to reflect customer preferences. Therefore, an efficient combined quantitative and qualitative analysis becomes an important requirement for customer satisfaction.

This work proposes a new three-phase fuzzy approach to address the dispatching and rebalancing problem of RAMoD systems, which clubs a multi-criteria decision-making framework with a fuzzy multi-criteria objective program. At first, customers' preferences are captured and the fuzzy AHP method is used to analyze passenger's attitudes toward autonomous vehicles using qualitative and quantitative criteria. Thereafter, the fuzzy TOPSIS method is employed to evaluate the fleet vehicles. Next, we designed a new multi-objective possibilistic linear program that allows computing efficient dispatching and rebalancing decisions under dynamic environment assumptions.

Simulation results adopting the subset of Rambouillet's real road network, show the effectiveness of the proposed approach in terms of simplicity of implementation and ability to deal with uncertainty. These experiments show that the proposed strategy can produce efficient dispatching and rebalancing plans based on the passenger's preferences along with providing sufficient flexibility to deal with uncertain travel demand. They also show that the dispatching and rebalancing decisions are very sensitive to the passenger preferences.

This work leaves opens for considerable extensions for future research. First, the proposed approach can be

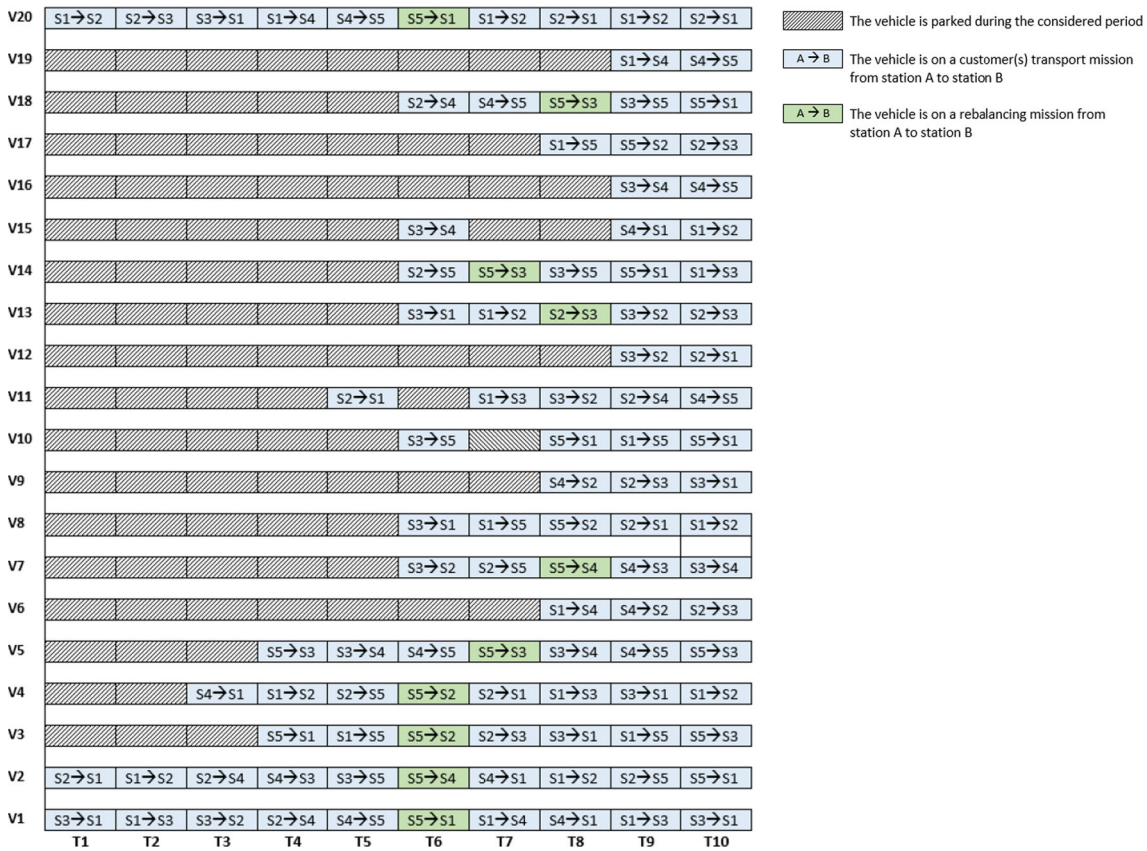

Fig. 4 Vehicle scheduling as a function of time

Table 20 Results of sensibility analysis: ranking of vehicle

Test 1	$V12 > V10 > V13 > V5 > V6, V11 > V17 > V8 > V20 > V7 > V9 > V18 > V1 > V4 > V15 > V2 > V19 > V3 > V14, V16$
Test 2	$V3 > V4 > V2 > V1 > V20 > V19 > V9 > V5 > V7 > V14 > V8 > V6 > V15 > V17 > V18 > V10 > V12 > V11 > V13 > V16$
Test 3	$V10 > V1, V11, V20 > V2, V19 > V18 > V15 > V5, V7, V14 > V6, V8, V9 > V3, V13, V16, V17 > V4, V12$
Test 4	$V1, V2, V3, V4, V9, V18, V20 > V15 > V5, V6, V7, V8, V14, V17, V19 > V11, V13, V16 > V10, V12$
Test 5	$V1, V2, V3, V17 > V4, V14, V19, V20 > V5, V7, V8, V10, V11, V15, V18 > V9, V12, V16 > V6, V13$
Test 6	$V1, V3, V9, V19 > V2, V4, V17 > V7, V8, V14, V15, V20 > V6, V13, V18 > V5, V10, V11, V12, V16$
Test 7	$V1 > V20 > V2 > V10 > V19 > V11 > V3 > V4 > V18 > V15 > V5 > V7 > V14 > V9 > V8 > V6 > V17 > V13 > V16 > V12$
Test 8	$V3 > V4 > V2 > V1 > V20 > V9 > V18 > V15 > V19 > V5 > V7 > V14 > V8 > V6 > V17 > V11 > V10 > V12 > V13 > V16$
Test 9	$V1 > V20 > V2 > V3 > V4 > V18 > V19 > V9 > V10 > V15 > V11 > V5 > V7 > V14 > V8 > V6 > V17 > V13 > V16 > V12$
Test10	$V1 > V2 > V20 > V3 > V19 > V9 > V4 > V17 > V18 > V15 > V14 > V10 > V11 > V8 > V5 > V6 > V13 > V16 > V12$
Test11	$V3 > V1 > V4 > V2 > V20 > V19 > V9 > V17 > V7 > V14 > V8 > V15 > V6 > V5 > V18 > V13 > V10 > V12 > V11 > V16$
Test12	$V1, V3, V9 > V2, V4 > V19 > V17 > V20 > V15 > V7, V8, V14 > V18 > V6 > V13 > V5 > V11, V16 > V10, V12$
Test13	$V1 > V2 > V20 > V3 > V4 > V19 > V10 > V14 > V5, V7 > V15 > V11 > V8 > V18 > V9 > V17 > V6 > V12 > V16 > V13$
Test14	$V3 > V1 > V2 > V4, V19 > V9 > V17 > V20 > V14 > V7 > V8 > V15 > V18 > V6 > V5 > V13 > V11 > V10 > V16 > V12$
Test15	$V1 > V2 > V3 > V20 > V19 > V4 > V17 > V14 > V10 > V15 > V18 > V7 > V11 > V8 > V9 > V5 > V6 > V16 > V12 > V13$

extended to take into account the routing problem with the capacitated road network. One of the purposes of this field is to introduce congestion-aware routing approaches (Rossi et al. 2018; Salazar et al. 2019a). Second, on the application side, we will focus on exploiting the high efficiency of the proposed approach in a number of cities with different urban infrastructures. Third, it may be advisable to add features to the RAMoD system presented

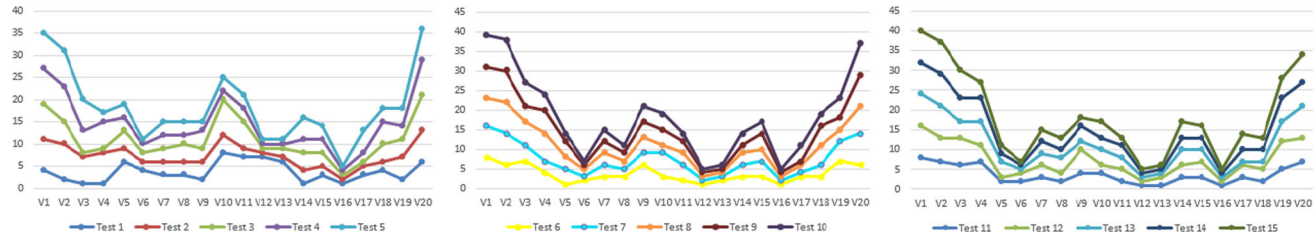

Fig. 5 Results of sensibility analysis: vehicle occupancy rates

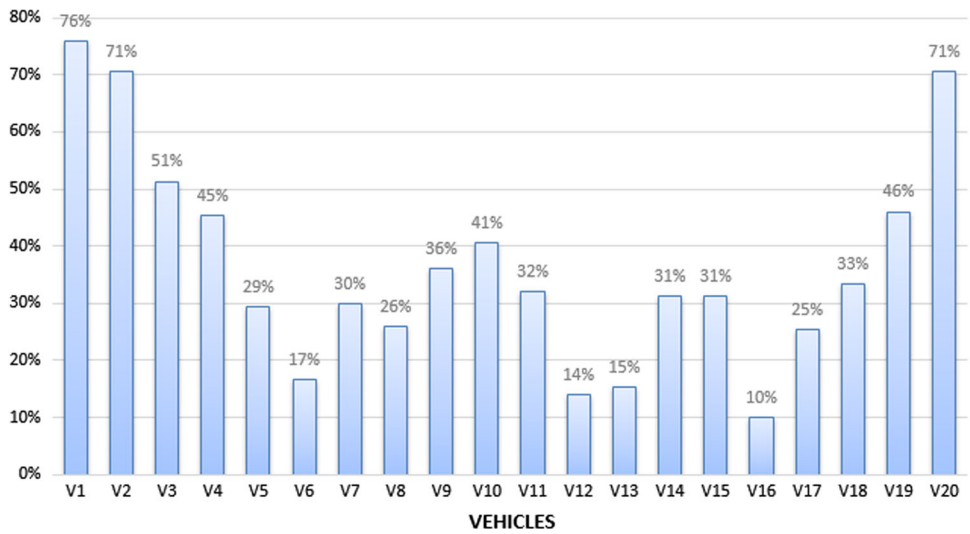

Fig. 6 Results of sensibility analysis: the average occupancy rate

here such as interactions with public transit and develop efficient dispatching and rebalancing policies for such an intermodal transportation system. Fourthly, we plan to study the interaction between large RAMoD fleets and the electric power network. Finally, we plan to integrate an additional constraint regarding customers' priorities. This approach may assign a higher priority to passengers with reduced mobility or those who have been waiting longer or give priority according to price incentives.

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Declarations

Conflict of interest The authors acknowledged that they have no conflict of interest.

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