Fuzzy multi-objective optimization for Ride-sharing Autonomous Mobility-on-Demand Systems

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Abstract: In this paper, we propose a novel three-phase fuzzy approach to optimize dispatching and rebalancing for Ride-sharing Autonomous Mobility-on-Demand (RAMoD) systems, consisting of self-driving vehicles, which provide on-demand transportation service, and allowing several customers to share the same vehicle at the same time. We first introduce a new multi-objective possibilistic linear programming (MOPLP) model for the problem of dispatching and rebalancing in RAMoD systems considering the imprecise nature of the customer requests as well as two conflicting objectives simultaneously, namely, improving customer satisfaction and minimizing transportation costs. Then, after transforming this possibilistic programming model into an equivalent crisp multi-objective linear programming (MOLP) model, the Goal Programming (GP) approach is used to provide an efficient compromise solution. Finally, computational results show the practicality and tractability of the proposed model as well as the solution methodology.

1 INTRODUCTION

Nowadays, urban systems are characterised by the expansion of cities and by the growth of their population. This affects the current mobility trends marked by the continued growth of demand for personal mobility as well as the increasing of privately owned automobile.

This trend leads to many social and environmental severe problems including traffic congestion, increased travel times, air pollution as well as the growth of the greenhouse gas emissions, especially in the densely populated areas with limited space for parking and road infrastructure.

To deal with these problems, an efficient transportation system that responds to the mobility demands of people and that is more sustainable, reliable and efficient becomes essential.

In this context, Autonomous Mobility-on-Demand (AMoD) systems represent a very promising solution in meeting these needs. This emerging system is a fleet of self-driving electric vehicles designed to provide personal on-demand transportation service for passengers. AMoD systems offer many potential benefits such as minimizing pollution, avoiding the need for further routes and parking spaces. Moreover, autonomous vehicles may be safer than traditional vehicles as they can avoid accidents due to human errors, well known to be the main reason of traffic accidents.

These several advantages have led recently a number of works to investigate the potential of AMoD systems. A key challenge in this context is the design of dispatching strategies that entail to optimally assign the customers to vehicles, thus satisfying the customer's request at each given station and at each time period. To do this, the number of vehicles available at each station and each period must satisfy customer requests.

Nevertheless, when some stations are more in demand than others, at the end of the trip, vehicles will tend to be accumulated at these stations and become exhausted at others. This can lead to a spatial-temporal distribution of vehicles, which will probably not be in line with the distribution of the customer requests in the following periods.

Therefore, it becomes inevitable to devise efficient policies to deal with this problem of imbalance. Such rebalancing policies entail redistributing empty vehicles from overload stations to underloaded stations. However, AMoD systems might aggravate the congestion problem given the presence of these empty vehicles (Tsao et al., 2019).

This has prompted some AMoD systems to integrate the emerging transportation paradigm of ride-sharing to improve traffic flow.

Another important challenge is to deal well with rapidly varying customer requests, given several real-world constraints. Accordingly, it becomes mandatory to forecast customer requests to compute efficient strategies, having the robustness to inaccuracies and uncertainties due to several external factors such as traffic and weathers.

These various challenges have recently led to a considerable amount of studies to address the potential of AMoD systems. However, the majority of these researches do not allow easy to account for real-world phenomena such as the uncertain futures of customer demand, which limits their practical applications.

Although a few recent studies have been developed to cope with demand uncertainty, the latter are usually based on probability distributions, which requires knowledge of historical data. When such information was lacking, the Fuzzy Set Theory (Zadeh, 1978) and the Possibility Theory (Dubois and Prade, 1988; Zadeh, 1965) can help to handle epistemic uncertainty.

To the best of our knowledge, fuzzy logic has never been used to model the uncertainty in the context of AMoD systems.

The aim of this paper is to present a novel fuzzy approach for dispatching and rebalancing RAMoD systems. Specifically, the paper has three important contributions. First, it introduces a MOPLP model which contemplates the uncertainty affecting future demand. Two primary goals are considered simultaneously in the MOPLP model, namely, improving customer satisfaction and minimizing transportation costs. Second, in order to find an efficient compromise solution to the proposed MOPLP model, we suggest the exploitation of the well-known goal programming approach (Charnes and Cooper, 1961), which integrates the desire of the decision-maker with the logic of optimization to satisfy various goals (Pati et al., 2008). Third, we demonstrate the applicability of our proposed approach through numerical computations.

The remainder of this article is organized as follows. In the next section, we briefly review existing works and present their limitations. Section 3 illustrates some fundamental concepts used in this work. In section 4, we present the considered dispatching and rebalancing problem in RAMoD systems. In section 5, the proposed multi-objective possibilistic linear programming model for RAMoD systems is developed. In section 6, we exploit appropriate strategies for converting the proposed fuzzy model into an equivalent crisp one. Section 7 aims at finding an efficient compromise solution for the problem, thus exploiting the goal programming approach. We validate the proposed three-phase approach through numerical tests being exploited in Section 8. Finally, section 9 concludes the paper and provide future directions.

2 RELATED WORK

The problem of dispatching and rebalancing has received great attention over the last few years. The proposed studies can be classified into three main approaches, namely, simulation-based models; queuing-theoretical models and model predictive control (MPC) algorithms.

Simulation-based models (Hörl et al., 2018; Levin et al., 2017; Maciejewski et al., 2017; Javanshour et al., 2019) can accurately describe AMoD systems, but being unable to provide optimal solutions.

Queuing-theoretical models (Zhang and Pavone, 2015; Zhang and Pavone, 2016; Iglesias et al., 2019; Belakaria et al., 2019) have the advantage of capturing the uncertainty of the customer requests. These models are based on the Jackson network concept (Serfozo, 2012), in which all arrivals at each queuing station should follow a Poisson process (Moran, 1952). This concept assumes constant rates of occurrence of each random variable. That is, if the random variable is customer’s arrival times, it assumes customers arrive at stations at a constant rate (Javanshour et al., 2019). However, in reality, the customer arrival process for the various origin–destination pairs is time-variant nature. Therefore, we can deduce that the Queuing-theoretical models prevent the AMoD system modelers from capturing a realistic vision into these systems.

In contrast, Model predictive control (MPC) algorithms (Zhang et al., 2016; Alonso-Mora et al., 2017 ; Iglesias et al., 2018 ; Tsao et al., 2018 ; Tsao et al., 2019) can efficiently accommodate time-varying future demand. However, the majority of existing MPC algorithms assume that future customer demand is deterministic and the rare studies that accommodate uncertainty mainly suggest the use of stochastic programming. The probabilistic reasoning approaches are usually based on evidence/data recorded in the past. However, in many practical situations, this evidence/data is unavailable or subjectively specified, and the standard probabilistic approach would not be appropriate to deal with them. Thus, Fuzzy set theory and possibility theory provide an appropriate framework to handle uncertainty in such situations. Accordingly, it has been successfully used to model and treat uncertainties in many fields such as supply chain planning (Khemiri et al., 2017; Nemati and Alavidoost, 2019; Lima-Junior and Carpinetti, 2020), Business Process modelling (Yahya et al., 2017; Sarno et al., 2020), web services (Rhimi et al., 2016; Bagga et al., 2019), image processing (Ali and Lun, 2019; Nagi and Tripathy, 2020), etc.

Despite all this progress, the fuzzy logic and the possibility theory have never been exploited to handle uncertainties in AMoD systems.

To the best of our knowledge, this paper is the first one to leverage the strengths of such techniques and introduce a novel strategy for solving the dispatching and rebalancing decisions problem with imprecise travel demand in RAMoD systems.

In the next section, the basic concepts of the fuzzy logic are provided.

3 THEORETICAL BACKGROUND

This section briefly outlines the fuzzy set theory, the triangular fuzzy numbers and the goal programming method used in this paper.

3.1 Fuzzy set theory

Fuzzy set theory was originally introduced by Zadeh (Zadeh, 1965) to deal with the imprecision, uncertainty, and vagueness of subjective information.

From a mathematical point of view, a fuzzy set is characterized by a membership function. Such a function attributes to each object in the fuzzy set a specific grade of membership ranging from zero to one.

In this study, triangular fuzzy numbers are used to represent the imprecise data. As shown in Figure 1, a triangular fuzzy number $\tilde{Z}$ can be represented by the triplet (*a*, *b*, *c*) where *a*, *b*, *c* are the most pessimistic, the most possible and the most optimistic value of $\tilde{Z}$.

The triangular fuzzy number $\tilde{Z}$ can be represented by the following membership function:

$$\mu_{\tilde{Z}}(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ \frac{c-x}{c-b}, & b < x \leq c \\ 0, & x > c \end{cases} \quad (1)$$

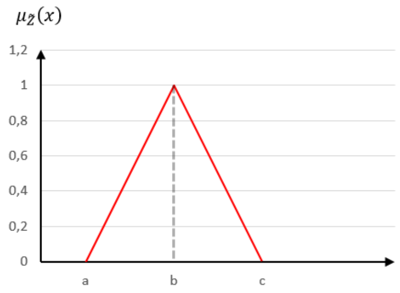

Figure 1: The triangular possibility distribution of $\tilde{Z}$

3.2 Goal programming

There are several methods in the scientific literature for dealing with multi-objective models. Among them, the goal programming (GP) method which is originally developed by Charnes et al. (Charnes and Cooper, 1961) and successfully used in several problems (Lee and Kim, 2000; Amin et al., 2019; Colapinto et al., 2020).

The popularity of this method is based on its mathematical flexibility, its robustness, and its accuracy.

The goal programming method consists in introducing for each criterion a goal to be achieved and to identify the solution that minimizes the sum of the deviations from these goals.

Several variants of the GP have been proposed in the literature. Here we use the Weighted Goal Programming (WGP) method. The WGP can be represented as follows:

$$\underset{x \in A}{\mathrm{Min}} \sum_{i=1}^{n} (w_i^+ \delta_i^+ + w_i^- \delta_i^-) \quad (2)$$

Subject to:

$$C_l(x) \leq 0 , \quad l = 1,2,..,L$$

$$F_i(x) - \delta_i^+ + \delta_i^- = g_i , \ i = 1,2,..,n$$

$$\delta_i^+ , \delta_i^- \geq 0$$

Where:

- $C_l(x)$ is the set of constraints.
- δ_i^+ and δ_i^- are respectively the positive and negative deviation from the target value g_i.
- w_i^+ and w_i^- are respectively the weight attached to the positive and negative deviation.
- $F_i(x)$ is the evaluation of the solution x against the criterion i.
- $\mathbf{g_i}$ is the aspiration level of the objective function i.

4 PROBLEM FORMULATION

Despite the major progress that has occurred in recent years, these various initiatives do not take into account the specificities of the low-density areas. In the Tornado Mobility research project (Tornado, 2020), that we are working on, the objective is to study the interaction between autonomous vehicles and connected intelligent infrastructures for serving mobility in low population density areas.

For this purpose, we consider an urban area discretized into multiple stations and served by several on-demand vehicles. Each vehicle can serve one or more passengers without exceeding their capacity. The considered fleet of vehicles is characterized by a high level of heterogeneity: transportation costs, speeds, and capacities of each vehicle can be different.

In the context of Tornado project, customers first request transportation from a pickup to a drop off location in the predefined urban area via a mobile application.

If there are available vehicles, one of them will be dispatched to drive this passenger towards its destination. Instead, if there are no available vehicles, the user instantly leaves the system (i.e. without any waiting time). Therefore, as in (Zhang and Pavone, 2016; Iglesias et al., 2019), our RAMoD system operate according to the passenger loss model. Such a model is well suited for systems where a high degree of service is desired (Iglesias et al., 2019).

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

For simplicity, it is assumed that each station has sufficient space so that vehicles can immediately be parked and recharged at all times.

Unlike traditional approaches, the proposed model does not assume complete knowledge about future customer demand; instead, it assumes that such critical parameters are estimated by the decision-maker using Triangular fuzzy numbers.

Finally, it is assumed that the time is discretized into an ordered set of time periods.

To deal with this challenging problem, we devise a three-phase approach, where the main steps are presented in Figure 2 and detailed in the following sections.

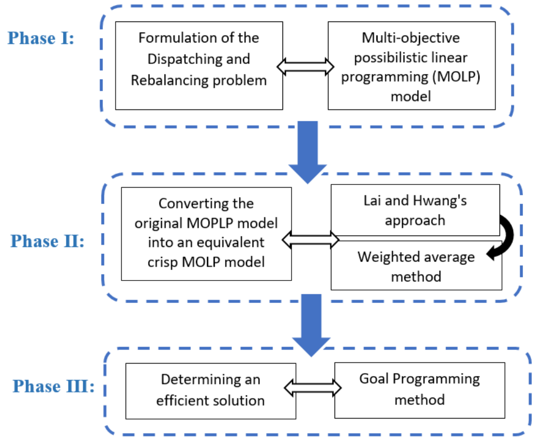

Figure 2: Framework of the proposed approach

5 PHASE I: PROPOSED MULTI OBJECTIVE POSSIBILISTIC LINEAR PROGRAMMING MODEL

5.1 Notation

- The set of indices
  - ***S***: Number of stations (s = 1, 2, …, S).
  - ***V***: Number of vehicles (v = 1, 2… V).
  - ***T***: Number of time periods (t = 1, 2…, T).
- Decision variables
  - $\boldsymbol{Miss_{v,t}}$: Binary variable indicating if vehicle *v* is on mission during period *t*.
  - $\boldsymbol{Park_{v,t,s}}$: Binary variable indicating if vehicle *v* is parked in station s during period *t*.
  - $\boldsymbol{Miss\_T_{v,s1,s2,t1,t2}}$: Binary variable indicating if vehicle *v* is on customer transport mission traveling from station *s1* to station *s2* beginning at period *t1* and arriving at period *t2*.
  - $\boldsymbol{Miss\_R_{v,s1,s2,t1,t2}}$: 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*.
  - $\boldsymbol{S\_Cr_{t,s1,s2}}$: The number of satisfied customer requests traveling from station *s1* to station *s2* departing at time period *t*.

- Certain parameters:
  - $\boldsymbol{Dist_{s1,\,s2}}$: distance between stations *s1* and *s2* (considering the shortest way).
  - $\boldsymbol{Cap_v}$: Transport capacity of the vehicle *v*.
  - $\boldsymbol{SP_v}$: speed of the vehicle *v*.
  - $\boldsymbol{Tr\_cost_v}$: transportation cost of the vehicle *v*.
  - $\boldsymbol{Local\_init_{v,s}}$: represents the initial availability of vehicle *v* at station *s*. If vehicle *v* is available at station *s* in the first periode, $Local\_init_{v,s} = 1$ and *0* otherwise.
- Fuzzy parameters:
  - $\tilde{Cr}_{t,s1,s2}$: number of customer requests who wish to travel from station *s1* to station *s2* departing at time period *t*.

5.2 Objective functions

- Objective 1: Improving customer satisfaction, which is to minimize the number of lost customer requests.

$$\text{Minimize } \tilde{LCr} = \sum_{t=1}^{T} \sum_{s1,s2=1}^{S} \tilde{Cr}_{t,s1,s2} - S\_Cr_{t,s1,s2} \quad (3)$$

- Objective 2: Minimizing the overall transportation cost.

$$\text{Minimize } TC = \sum_{t1,t2=1}^{T} \sum_{s1,s2=1}^{S} \sum_{v=1}^{V} Tr\_cost_v * (Miss\_T_{v,s1,s2,t1,t2} + Miss\_R_{v,s1,s2,t1,t2}) * Dist_{s1,\,s2} \quad (4)$$

5.3 Model constraints

$$S\_Cr_{t,\,s1,\,s2} \geq 0 \text{ and integer } \forall t,\ \forall s1, s2 \in [1, S] \quad (5)$$

$$Miss_{v,t},\ Park_{v,t,s},\ Miss\_T_{v,s1,s2,t1,t2},\ Miss\_R_{v,s1,s2,\,t1,\,t2} \in [0,1] \quad \forall t, v, s, s1, s2, t1, t2 \quad (6)$$

Equations (5) and (6) guarantees the non-negativity of the various decision variables: $S\_Cr_{t,s1,s2}$ is an integer, while other variables are binary.

$$\sum_{s=1}^{S} Park_{v,t,\,s} + Miss_{v,\,t} = 1 \quad \forall v, t \quad (7)$$

Equation (7) models the two possible states each autonomous vehicle can take namely parked at a station and be on a mission from one station to another. On the other hand, this constraint ensures that a vehicle can have only one state at any one time.

$$Miss_{v,t} = \sum_{s1,s2=1}^{S} \sum_{t1,t2 \leq t} Miss\_T_{v,s1,s2,t1,t2} + Miss\_R_{v,s1,s2,t1,t2} \quad \forall v, t \quad (8)$$

When a vehicle is on a mission, two possible actions can be achieved i) transport one or more customers from one station to another, and ii) travel without customers for rebalancing the system. These actions are modeled using equation (8), which also guarantees that the vehicle can only perform one action at a time.

$$Miss\_R_{v,s1,s2,t1,t2} \leq Park_{v,t1-1,s1} + \sum_{s3 \neq s1} Miss\_R_{v,s3,s1,t3,t1-1} + \sum_{s4 \neq s1} Miss\_T_{v,s4,s1,t4,t1-1}$$
$$\forall v, s1, s2, t1>1, t2 = t1 + (Dist_{s1,s2}/ SP_v), t3 = t-(Dist_{s3,s1}/SP_v) - 1, t4 = t1-(Dist_{s4,s1}/SP_v)-1 \quad (9)$$

$$Miss\_T_{v,s1,s2,t1,t2} \leq Park_{v,t1-1,s1} + \sum_{s3 \neq s1} Miss\_R_{v,s3,s1,t3,t1-1} + \sum_{s4 \neq s1} Miss\_T_{v,s4,s1,t4,t1-1}$$
$$\forall v, s1, s2, t1>1, t2 = t1 + (Dist_{s1,s2}/ SP_v), t3=t1-(Dist_{s3,s1}/SP_v)-1, t4 = t1-(Dist_{s4,s1}/SP_v)-1 \quad (10)$$

When vehicle *v* is on a mission traveling from station *s1* to station *s2* beginning at period *t1*, it is necessary that *v* is physically located in station *s1* at the beginning of period *t1*. In other words, either the vehicle *v* i) arrived at a station during the last period (i.e. $Miss\_R_{v,s3,s1,t3,t1-1}=1$ Or $Miss\_T_{v,s4,s1,t4,t1-1} =1$), or ii) parked at a station during the last period (i.e. $Park_{v,t-1,s1} =1$). The equations (9) and (10) ensure that this constraint is respected respectively for rebalancing missions and customer transport missions.

$$Park_{v,t,s} \leq Park_{v,\,t-1,s} + \sum_{s1 \neq s} Miss\_R_{v,s1,s,t1,t-1} + \sum_{s2 \neq s} Miss\_T_{v,s2,s,t2,t-1}$$
$$\forall v, s, t>1, t1=t-(Dist_{s1,s} / SP_v)-1, t2=t+(Dist_{s2,s}/SP_v)-1 \quad (11)$$

Equation (11) guarantees that if a vehicle *v* is parked at a station *s* during a time period *t* (i.e. $Park_{v,t,s} =1$), it is necessary that it be physically located in *s* at the beginning of *t* (i.e. $Park_{v,t-1,s} + Miss\_R_{v,s1,s,t1,t-1} + Miss\_T_{v,s2,s,t2,t1-1} =1$).

$$Park_{v,t,s} + Miss\_T_{v,s,s1,t,t1} + Miss\_R_{v,s,s2,t,t2} \leq Local\ init_{v,s}$$
$$\forall v, s, t=1, s1, s2, , t1=t+(Dist_{s,s1} / SP_v), t2=t+(Dist_{s,s2} / SP_v) \quad (12)$$

Equation (12) indicates that a vehicle may only be parked in a station *s* during the first period (i.e. $Park_{v,1,s}=1$) if it is initially available at this station (i.e. $Local\_init_{v,s} =1$). Besides, a vehicle *v* may only travel on a rebalancing mission (i.e. $Miss\_R_{v,s,s1,1,t1}=1$) or a customer(s) transport mission (i.e. $Miss\_T_{v,s,s1,1,t1}=1$) if it is initially available at this station ($Local\_init_{v,s}=1$).

$$S\_Cr_{t1,s1,s2} \leq \sum_{v=1}^{V} Miss\_T_{v,\,s1,\,s2,\,t1,\,t2} * Cap_{v} \qquad (13)$$
$$\forall s1, s2, t1, t2 = t1 + (Dist_{s1,s2} / SP_{v})$$

Equation (13) ensures that the number of satisfied customer requests traveling from station *s1* to station *s2* departing at time period *t1* can not exceed the total capacity of the vehicles transporting customers from station *s1* to station *s2* beginning at period *t1*.

$$S\_Cr_{t,\,s1,\,s2} \leq \tilde{Cr}_{t,\,s1,\,s2} \quad \forall t, s1, s2 \qquad (14)$$

Finally, equation (14) guarantees that vehicles transporting customer(s) from station *s1* to station *s2* beginning at time period *t* cannot transport more customers than it has been requested.

In this study, it is assumed that the imprecise customer demand in the first objective function and constraint (14) is modeled using a triangular-shaped possibility distribution. As explained in section 3, triangular possibility distribution $\widetilde{Cr}$ can be represented by the triplet (Cr^{p}, Cr^{m}, Cr^{o}) where Cr^{p}, Cr^{m} *and* Cr^{o} are the most pessimistic, the most possible and the most optimistic value of $\widetilde{Cr}$.

6 PHASE II: STRATEGY FOR PROCESSING THE FUZZINESS CUSTOMER REQUESTS

6.1 Treating the imprecise objective function

Given the imprecise customer's request coefficients in the first objective function, it is generally not possible to determine an ideal solution to the problem constrained by (3)-(14).

In the scientific literature, several approaches for identifying compromise solutions are proposed (Luhandjula, 1989; Sakawa and Yano, 1989; Tanaka and Asai, 1984; Tanaka et al., 1984; Lai and Hwang, 1992). As mentioned by Hsu and Wang in (Hsu and Wang, 2001), the first four approaches (Luhandjula, 1989; Sakawa and Yano, 1989; Tanaka and Asai, 1984; Tanaka et al., 1984) are based on restrictive assumptions and are generally difficult to implement in practice, we then use Lai and Hwang's approach (Lai and Hwang, 1992; Liang, 2006).

Since the imprecise customer demand has triangular possibility distributions, the $\tilde{LCr}$ objective function would also have a triangular possibility distribution. This imprecise objective is represented by the three important points $(LCr^{p}, 0)$, $(LCr^{m}, 1)$ and $(LCr^{o}, 0)$, geometrically. Therefore, minimizing the fuzzy objective can be achieved by pushing these critical points in the direction of the left-hand side.

According to Lai and Hwang's approach solving this problem becomes the process of minimizing LCr^{m}, maximizing $(LCr^{m} - LCr^{p})$ and minimizing $(LCr^{o} - LCr^{m})$. In this way, our first objective function can be transformed into a multiple crisp objective as follows:

Minimize $Z_1 = LCr^{m}$

$$LCr^{m} = \sum_{t=1}^{T} \sum_{s1,s2=1}^{S} Cr^{m}_{t,s1,s2} - S\_Cr_{t,s1,s2} \qquad (15)$$

Maximize $Z_2 = LCr^{m} - LCr^{p}$

$$LCr^{m} - LCr^{p} = \sum_{t=1}^{T} \sum_{s1,s2=1}^{S} (Cr^{m}_{t,s1,s2} - Cr^{p}_{t,s1,s2}) - S\_Cr_{t,s1,s2} \qquad (16)$$

Maximize $Z_3 = LCr^{o} - LCr^{m}$

$$LCr^{o} - LCr^{m} = \sum_{t=1}^{T} \sum_{s1,s2=1}^{S} (Cr^{o}_{t,s1,s2} - Cr^{m}_{t,s1,s2}) - S\_Cr_{t,s1,s2} \qquad (17)$$

6.2 Treating the fuzzy constraint

Recalling that equation (14) considers the situation in which the crisp left-hand side is compared to the fuzzy right-hand side. In this study, we implement the well-known weighted average method for dealing with this situation and approximating the $\tilde{Cr}$ parameter by crisp number. This method is originally introduced by (Lai and Hwang, 1992) and has been successfully used in several research studies (Wang and Liang, 2005; Liang, 2006; Torabi and Hassini, 2009; Khemiri et al., 2017a) due to its simplicity and efficiency in defuzzification.

To do so, we first need to determine a minimal acceptable possibility degree of occurrence for the fuzzy/imprecise parameter, α. Then the original fuzzy constraint (14) can be represented by a novel crisp constraint as follows:

$$S\_Cr_{t,s1,s2} \leq w_1\, Cr^{p}_{t,s1,s2,\alpha} + w_2\, Cr^{m}_{t,s1,s2,\alpha} + w_3\, Cr^{o}_{t,s1,s2,\alpha} \quad \forall t, s1, s2 \qquad (18)$$

Where $w_1 + w_2 + w_3 = 1$, and w_3, w_2 and w_1 denote respectively the weights of the most optimistic, the weights of the most possible and the weights of the most pessimistic of the fuzzy demand. In practice, the values of these weights, as well as the minimal acceptable possibility degree α, can be defined subjectively based on the knowledge and experience of the decision-maker.

In our work, we adopt the concept of most likely values, which is widely used in the literature (Lai and Hwang, 1992). According to this concept, the most pessimistic and optimistic values required a lower weight than the one assigned to the most possible value. Thus, as in (Lai and Hwang, 1992) we set these parameters to: $w_1 = w_3 = 1/6$; $w_2 = 4/6$ and $\alpha = 0.5$.

7 PHASE III: GOAL PROGRAMMING-BASED SOLUTION APPROACH

In the previous section, the original fuzzy MOLP model was converted into an equivalent auxiliary crisp multi-objective linear programming model. To deal with this multi-objective model, we use the Weighted Goal Programming (WGP) method, introducing specific weights for each criterion. Accordingly, we can reformulate our problem as follows:

Minimize F_{GP}

$$F_{GP} = W_{Z1} * \delta_1^+ + W_{Z2} * \delta_2^- + W_{Z3} * \delta_3^- + W_{Z4} * \delta_4^+ \quad (19)$$

Subject to:
(5) - (13), (18)

$$Z_1 - \delta_1^+ = Z_1^* \quad (20)$$

$$Z_2 + \delta_2^- = Z_2^* \quad (21)$$

$$Z_3 + \delta_3^- = Z_3^* \quad (22)$$

$$TC - \delta_{TC}^+ = TC^* \quad (23)$$

Where:

- Z_1^* is the goal calculated using the mathematical model with objective function (15) subject to constraints (5) - (13), (18) and δ_1^+ is the positive deviation from this goal.
- Z_2^* is the goal calculated using the mathematical model with objective function (16) subject to constraints (5) - (13), (18) and δ_2^- is the negative deviation from this goal.
- Z_3^* is the goal calculated using the mathematical model with objective function (17) subject to constraints (5) - (13), (18) and δ_3^- is the negative deviation from this goal.
- TC^* is the goal calculated using the mathematical model with objective function (4) subject to constraints (5) - (13), (18) and δ_{TC}^+ is the positive deviation from this goal.
- W_{Z1}, W_{Z2}, W_{Z3} and W_{Z4} are the importance weights of the various goals, usually determined by the decision makers such that $W_{Z1} + W_{Z2} + W_{Z3} + W_{Z4} = 1$.

8 SIMULATION RESULTS

In this section, we display two sets of simulation results to illustrate the validity and applicability of the proposed approach. First, we demonstrate that the dispatching and rebalancing problem in RAMoD systems can indeed be resolved using the proposed three-phase approach, especially in the presence of imprecise customer requests. Then, we compare the performance of our methodology with other dispatch strategies by varying customer demand over time.

For all experiments, we consider a fleet size of 15 autonomous vehicles and 5 stations. The planning horizon is decomposed into 10 periods. These periods correspond to 10 different predicted request demands with triangular distributions, synthesized in Table 1. Initially, the vehicles were distributed equally among the various stations, i.e. 3 vehicles for each station.

For reason of simplification, we consider that the travel time between two stations is one time step. The capacity of the vehicles is characterized by a high degree of heterogeneity which varies from a maximum capacity of a single passenger to a maximum capacity of 8 passengers. Additionally, we consider for simplicity that the weights of the various criteria are the same (i.e. $W_{Z1} = W_{Z2} = W_{Z3} = W_{Z4} = 1/4$).

For all simulations, the proposed approach has been implemented using the LINGO optimization package.

8.1 Detailed results for the proposed approach

Figure 3 summarizes the results provided by the proposed approach by detailing vehicle statuses according to the planning horizon. We remind that the vehicle can be parked at one station, be on a customer(s) transport mission and be on a rebalancing mission. For the last two states, the departure and arrival stations were also mentioned. These decisions are guided by the criteria of the customer satisfaction maximization and the transportation cost minimization at each period of the planning horizon.

Table 1: Fuzzy demand for each period

Si→Sj		**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**	**T8**	**T9**	**T10**
S1	**S2**	(0,1,2)	(0,1,2)	(0,1,2)	(4,5,6)	(1,2,3)	(3,4,5)	(6,8,10)	(4,5,6)	(4,5,6)	(1,3,5)
	S3	(1,2,3)	(0,1,2)	(0,1,2)	(2,3,4)	(1,3,5)	(1,2,3)	(4,5,6)	(2,4,6)	(3,5,7)	(4,5,6)
	S4	(0,1,2)	0	(2,3,5)	(2,4,6)	(2,3,4)	(4,5,6)	(4,5,6)	(2,4,6)	(3,6,9)	(2,3,4)
	S5	0	0	(1,2,3)	0	(2,4,6)	(2,4,6)	(2,4,6)	(10,12,14)	(6,8,10)	(2,3,4)
S2	**S1**	(0,1,2)	(0,1,2)	(1,2,3)	0	(1,2,3)	(6,7,8)	(1,2,3)	(1,2,3)	(6,8,10)	(2,5,8)
	S3	(0,1,2)	(0,1,2)	(3,4,5)	0	(0,1,2)	(1,2,3)	(3,4,5)	(1,2,3)	(1,2,3)	(2,4,6)
	S4	(0,1,2)	0	(0,1,2)	(0,1,2)	(3,4,5)	0	(1,3,5)	(1,2,3)	(3,5,7)	(4,5,6)
	S5	0	0	(0,1,2)	(3,4,5)	0	0	0	(1,2,3)	(3,5,7)	(4,5,6)
S3	**S1**	(1,2,3)	(0,1,2)	(2,4,6)	(1,4,7)	(1,2,3)	(2,5,8)	0	(3,4,5)	(3,5,7)	(10,13,16)
	S2	(0,1,2)	(0,1,2)	(1,2,3)	(2,4,6)	(1,2,3)	(0,2,4)	(1,2,3)	(0,1,2)	(0,1,2)	(2,3,4)
	S4	0	(0,1,2)	(1,2,3)	(2,4,6)	(1,2,3)	0	(3,4,5)	(1,2,3)	(1,3,5)	(2,5,8)
	S5	0	0	(1,2,3)	0	0	0	0	(2,3,4)	0	0
S4	**S1**	(0,1,2)	(0,1,2)	0	(0,1,2)	0	0	0	0	0	0
	S2	(0,1,2)	(0,1,2)	0	0	0	0	0	0	0	0
	S3	(0,1,2)	(0,1,2)	(0,1,2)	(5,7,9)	0	0	0	0	0	0
	S5	0	(0,1,2)	(0,1,2)	(1,2,3)	0	0	0	0	0	(2,5,8)
S5	**S1**	0	(0,1,2)	(1,3,5)	(0,1,2)	(1,2,3)	0	0	0	(1,2,3)	(1,2,3)
	S2	0	(0,1,2)	0	(0,2,4)	(1,2,3)	(1,4,7)	0	0	0	0
	S3	0	(0,1,2)	0	(3,4,5)	0	0	0	0	0	0
	S4	0	0	0	(1,3,5)	0	0	(3,5,7)	0	0	0

Indeed, we find that the increase in the cost of transporting a vehicle leads to not using it (i.e. staying parked in the station) if customer demand can be satisfied by vehicles with a lower transport cost. For example, for the first period, customer demands were satisfied with the various stations. In particular for station S3, this fuzzy demand has been satisfied by using V7 and V8 with the use of ride-sharing, while the V9 remains parked in S3 because it has much higher transport cost. Also during the second period, the vehicle V12 remains parked in the station S4 since customer demand has been satisfied by vehicles with a lower transport cost.

With the increase in customer demands during the third and fourth periods and guided by the criterion of maximizing customer demands satisfaction, all vehicles in the fleet were launched on missions, even the most costly ones.

However, beyond the fifth period, the mobilization of all vehicles remains insufficient to satisfy customer demand, especially when some stations are more in demand than others, at the end of the trip, vehicles are accumulating in these stations and depleting in the others. This justifies the use of rebalancing decisions from overloaded stations to under loaded stations.

The rebalancing decisions are also subject to the cost minimization criterion. Indeed, the least expensive vehicles will be assigned first to rebalancing missions

8.2 Performance of the proposed approach

To evaluate the performance of the proposed approach (D-R-RAMoD-Fuzzy), we conducted a simulation study comparing it to other dispatch strategies. These latter are concretely three versions of our proposed approach:

- **D-R-RAMoD-Perfect:** The dispatching and rebalancing approach proposed in previous sections based on an exact customer request as it appears in the data set as a "forecast" for the next 10 time periods. This is an efficient strategy to find the optimal dispatching and rebalancing policies for the case when the customer request is known in advance. Thus, it can be used for providing performance upper bounds of the system.
- **D-R-AMoD-Fuzzy:** This version uses the same model described in section 5 for single capacity vehicles (without the use of ride sharing).
- **D-RAMoD-Fuzzy:** This version is exclusively concerned with the “Dispatching” problem and vehicles do not rebalance in any situation.

The summary results of this comparison are presented in Figure 4, illustrating the number of lost customer requests for each dispatch strategies as a function of time.

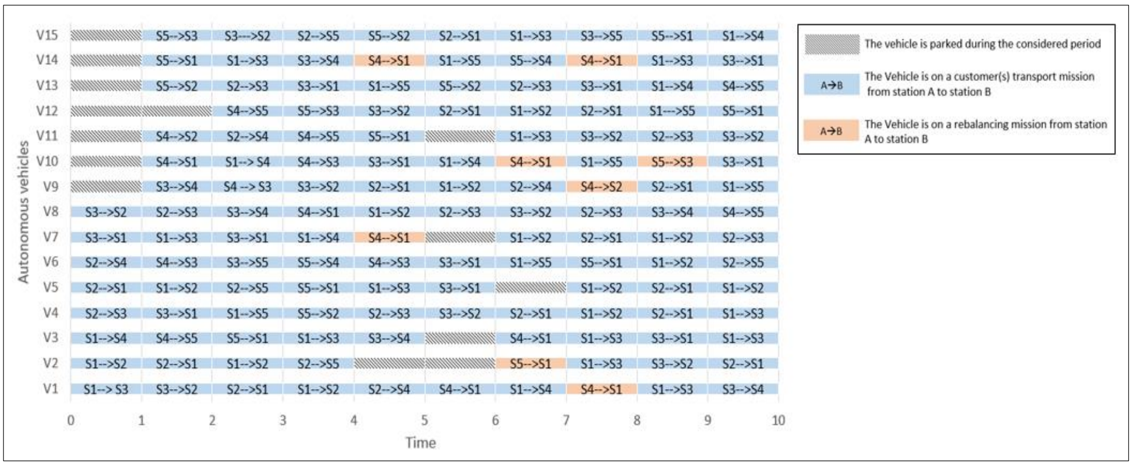

Figure 4: Vehicle scheduling as a function of time

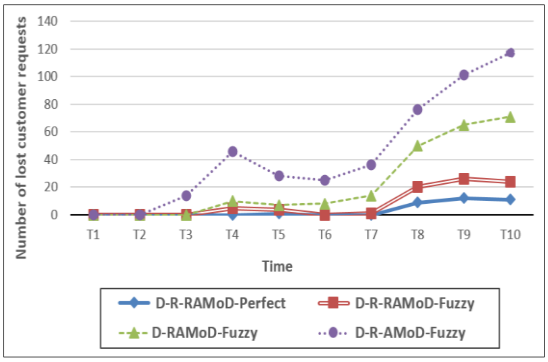

Figure 3: The number of lost customer requests for each dispatch strategies as a function of time

As expected, the strategy with exact customer requests has the best performance, with a minimum number of lost requests and a reduced transport cost.

The "D-R-AMoD-Fuzzy" strategy has the worst performance, with mean lost requests sixfold than that of "D-R-RAMoD-Perfect" strategy and multiplied by four compared to that of our proposed approach (i.e. "D-R-RAMoD-Fuzzy" strategy). This is not surprising, given that the single capacity strategy is here compared to the ride-sharing policies where the maximum capacity of vehicles is extended to eight.

We can also see the marked difference in performance between the "D-RAMoD-Fuzzy" strategy and the "D-R-RAMoD-Perfect" strategy from Figure 4 showing the number of lost customer requests at any given period. Notably, the "D-RAMoD-Fuzzy" strategy has significantly more lost customer requests at any given time period, with mean lost requests multiplied by four compared to the optimal strategy and multiplied by three compared to that of our proposed approach. This is also not unexpected, since we can gain much of performance by incorporating rebalancing trips ensuring a balance between the number of vehicles available in each station and customer requests.

A significant performance gain is attributed by incorporating rebalancing trips and the fact that several customers can share the same vehicle. Indeed, we can notice that out of 10 experiments, the proposed approach generates an optimal solution for six experiments. It also offers solutions that are very close to the optimal solution for the other periods with a deviation of 35%. This highlights the robustness of the proposed approach for operating the fleet and satisfying customers, even when forecasts of customer requests are uncertain.

9 CONCLUSION

Despite the significant advances in AMoD and RAMoD systems, the existing studies still display a lack of approaches dealing with the uncertainty affecting travel demand forecasts. The rare studies dealing with this drawback mainly suggest the use of stochastic programming that is usually based on the statistical data. However, in practice, historical data may not be reliable or even unavailable. Accordingly, these traditional programming models may not be the best tool to deal with uncertainty.

Thus, this work provides a new point of view on the problem of dispatching and rebalancing in the RAMoD systems by using a new alternative approach for managing uncertainty. Specifically, we first formulated the problem as a multi-objective possibilistic linear programming model in which customer requests are evaluated in an imprecise way using triangular possibility distribution. The proposed fuzzy formulation is then transformed to an equivalent crisp multi-objective linear programming model by combining appropriate strategies. In the third phase, the well known goal programming approach is being exploited to obtain a compromise solution. Through experiments, we show that the proposed approach has the capability to deal with realistic situations in an uncertain environment and provides an efficient decision tool for the dispatching and rebalancing decisions in RAMoD systems.

This work leaves opens for considerable extensions for future research.

First, the proposed approach can be extended in situations when RAMoD systems are faced with fluctuations of several parameters. This research area will require introducing forecasting models that are able to model not only the uncertain customer requests but also other critical parameters such as vehicle availability, costs, the states of charge of vehicles, etc.

Second, we plan to explore the integration of routing policies within a capacitated road network. This, in turn, can be subject to important uncertainties due to several external factors such as traffic congestion. Thus, the goal of this research axis is to devise a robust dispatching-rebalancing and routing policy that leverages forecasting parameters while considering the uncertainty that can arise in the road network.

Finally, further research can study the couplings that could occur between public transit and the AMoD systems.

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