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A multi-objective optimization system for mobile gateways selection in vehicular Ad-Hoc networks☆

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ABSTRACT

Vehicular ad-hoc networks provide essential Internet services to users. In consequence, mobile gateways are deployed to guarantee access to the Internet for the entire network. However, the selection of the best gateway taking into account some constraints and trying to reach some high-level objectives is a significant issue in mobile gateways discovery. The number of connected client vehicles must be maximized while a fair load distribution must be performed. For this purpose, we propose a multi-objective optimization system for mobile gateways selection based on two models using different solving strategies allowing the decision maker to choose the adequate solution. The solving approaches are evaluated and compared, and the simulations prove its efficiency compared to that found in the literature. The results show the effectiveness of the system in supporting a decision maker in solving a gateway selection problem and finding a fair solution in case there are no user preferences.

1. Introduction

In Vehicular Ad-hoc Networks (VANET), communication is established within a group of vehicles within the range of each other, this kind of connection is called Inter-Vehicle Communication (IVC). Furthermore, vehicles communicate with stationary types of equipment within the scope usually called road equipment, and we say that it is a Roadside-to-Vehicle Communication (RVC). The primary purpose of these vehicular networks is to help drivers and interested authorities by providing relevant information about the road. VANET is a useful technique in the so-called Intelligent Transportation Systems (ITS) and plays a role in improving road security and guaranteeing passenger comfort. Among the current challenges in ITS, we cite implementing real-time optimization and efficient systems. As a result, advances in cloud computing are used in this domain to enhance the services provided by ITS. The combination of these two fields becomes a massive research effort in the recent past [1]. Thanks to this union, new concepts are emerging such as vehicular cloud which provides all the services required by the autonomous vehicles [2].

Nowadays, it is possible to optimize the traffic control in the road thanks to many proposed applications deployed by information technology developers. However, cloud computing with its scalable access to computing resources represents a suitable solution for combining the Internet advantages and the technology improvements used on roads. Indeed, massive investment in hardware is not needed to implement the applications if cloud computing is merged to VANET as in [3,4].

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In consequence, permanent access to the Internet for vehicles is mandatory to benefit from the advantages of applications which are designed to provide comfort and safety for drivers. A gateway discovery is necessary for selecting a gateway appropriately to provide information and data services to VANET users. Due to the high speed of vehicles, VANET users move quickly in and out of the communication range of a gateway. Thus, it is difficult to access services stably through a fixed gateway which is a road infrastructure component. This problem can be solved by using Mobile Gateways (MGs) which are vehicles with access to the Internet and provide access to the vehicles in need named Client Vehicles (CVs). In this paper, the research focuses on the gateway selection, since several parameters are involved, the determination of the appropriate MG becomes a critical problem to solve. In literature, most MGs selection solutions are based on reactive and proactive approaches where messages are sent between MGs and CVs. The main drawback of these solutions is the overload situation when the number of vehicles increases, therefore, cloud computing is used to remedy this problem. Based on an existing discovery system, we improve the quality of selecting an MG by adding more constraints and objectives. Indeed, unlike literature solutions, we consider some high-level objectives such as maximizing the number of connected vehicles and minimizing the traffic amount handled by MGs to avoid overload situations. Since our problem is suited to be modeled using multiple conflicting objectives; we use multi-objective optimization which proves to be an excellent way to find solutions that constitute a trade-off between the objectives. As a result, the decision maker will be in a better position to make a choice when such trade-off solutions are exposed. In this paper, we propose three approaches to solve the multi-objective problem. The weighted-sum approach is used in the case of a priori articulation of preferences. Game theory and constraint programming approaches are used in the case of no articulation of preferences.

The remainder of this paper is organized as follows. Section 2 presents some related works on VANET and multi-objective optimization. Section 3 addresses the problem and gives the adopted solving strategies by detailing the multi-objective optimization system we developed for gateways selection. Section 4 follows with simulations, discussion of results, and describes the performance evaluation of the proposed approaches compared to the literature solution. The paper concludes in Section 5 with a summary and some perspectives.

2. Background

2.1. Vehicular ad-hoc network

VANET environment attracts the attention of a high number of researchers and becomes a field of interest over the last several years. All the proposed applications providing useful or even crucial information to CVs (e.g., safety-related applications) need access to the Internet, and due to the mobility of vehicles and the dynamic nature of the network, this is considered as a big challenge. On another hand, the development of these networks engenders the deployment of new communication technologies for the transmission of data between vehicles from which we can take advantage of and connect a vehicle without access to the Internet. The vehicles interested in accessing Internet services from within the vehicular network can access the fixed gateways. These latter are part of road infrastructure such as Stationary gateways that are Access Points (AP) to WiFi, or WiMAX, or cellular networks Base Stations (BSS). However, this kind of connection can engender some access problems because of the velocity of vehicles, hence the need for using MGs. The idea of exploiting MGs located in the network addresses several issues in the fields of research which include the interoperability of communication protocol, the mobility support, the communication efficiency, the discovery of Internet gateways, the handover of connections from one gateway to the next, etc. Several studies were conducted to demonstrate that the idea of MGs has an excellent chance to succeed in providing global connectivity to vehicles on the road and such design is feasible using existing ITS radio technologies [5].

In this paper, the study involves one of the most important issues which is MGs discovery. There are mainly three approaches to the discovery process: *(i)* A proactive approach where the gateway periodically sends a message to other vehicles to signal its existence; *(ii)* A reactive approach where the vehicle may actively seek to connect to the Internet before receiving the gateway message; *(iii)* A proactive or reactive hybrid approach to minimize the disadvantages of proactive and reactive methods [6]. The authors in [7] propose a discovery mechanism which gives the best performance using the hybrid approach by decreasing the overhead. However, the selection of the appropriate gateway relies on several criteria involving the application requirements, the Quality of Service (QoS), and the stability of the path (i.e., multi-hop) to the candidate gateway, network availability and so on. In [8], the authors propose a service discovery protocol for vehicular ad-hoc networks which choose the most suitable Internet gateway among others with the help of fuzzy methods. This selection takes into account the geographical position, the number of clients using the current gateway and the available bandwidth to meet the needs of the application' s requirements. Moreover, this proposed protocol is based on a proactive approach. In [9], both the proactive and the reactive approaches are recommended for the system discovery, and the selection relies on the predicted link lifetime between the MG and the CV. This measurement is calculated based on the speed, the direction, the geographical location, and radio propagation range of the two nodes [10]. In all these works, a gateway selection consists of sending messages between vehicles, and the main drawback of these approaches is the overload situation when there are a high number of nodes in the network.

To fix the problem mentioned above, the study in [11] introduces a system discovery assisted by cloud computing. The authors suggest a scheme that uses two cloud servers namely Discovery as a Service Registrar which maintains information related to gateways and Discovery as a Service Dispatcher which is responsible for MGs discovery to meet the needs of vehicles requesting access to the Internet. Again, the MG offering most extended link lifetime with the CV is selected as the next-hop gateway. Similarly, the authors in [12] present a gateway controller that searches the position of the CV and determines a set of MGs close by the destination to forward the packets. The transfer is made by choosing the longest link lifetime path. In [13], VANET-Long Term Evolution (LTE) integrated network architecture is proposed where MGs are selected according to the transmission rate and the direction of vehicles. A new technique for gateway selection in VANET network merged to the LTE Advanced infrastructure is presented in [14,15]. The main novelty of this work is the consideration of the QoS of the transmitted traffic in selecting MGs. However, the selection of the appropriate gateway needs more criteria to based on, and more high-level objectives, such as the number of CVs connected to the gateway and the availability of bandwidth. That is why the authors in [16] propose a solution using the multi-criteria decision aid method Promethee to select the best gateway using the cloud-assisted gateway discovery system. The traffic amount handled by gateways is represented through the overload of the gateway and used as criteria for selection and not as objective. Hence, the weakness in this work is that there is no optimization in the selection procedure. In this paper, we still based on the system presented in [11], and we introduce a system relying on multi-objective optimization models.

2.2. Multi-objective optimization

Multi-Objective Optimization (MOO) consists of optimizing simultaneously many objectives related to a real-world problem. The major difficulty encountered in this kind of optimization is finding a trade-off solution among Pareto optimal solutions. A solution is called Pareto optimal when none of the objective functions can be improved in its value without affecting some of the other objective values. Indeed, the decision maker must be aware of some high-level information helping to order the objectives in term of importance to choose a solution. Therefore, an articulation of preferences can be used in the solving approaches. Based on the preferences related to the objectives, the methods for solving an MOO problem are mainly divided into three categories: *(i)* A priori articulation of preferences where the decision maker can order the objectives per pertinence using high-level information related to the problem. A relative importance vector is given to the optimizer, and one solution is generated (see Fig. 1); *(ii)* A posteriori articulation of preferences where the multi-objective problem is solved using the ideal optimizer. After the generation of a set of trade-off solutions, the decision maker can use high-level information to choose one solution (see Fig. 1); *(iii)* No articulation of preferences.

The most common method for solving MOO problems with a priori articulation of preferences is the Weighted Sum (WS) method where all objectives are combined in a single objective function using weights for each objective [17]. Posteriori articulation of preferences methods generate a set of solutions when it is difficult to determine an importance vector and to set weights for objectives; the decision maker can choose from some multiple solutions. Genetic algorithms represent a crucial tool in this case by determining the Pareto optimal set [18]. Nonetheless, if there is no articulation of preferences, which is often the case, methods that do not require any articulation of preferences are used. Among these methods, we cite the Nash bargaining approach which is a branch of Game Theory (GT) [19]. This strategy is a non-cooperative game and consists of two elements that are players and their utility functions such that each player is associated with one objective. Based on the Nash theory, each player seeks to improve the value of his objective and to avoid the worst value.

Evaluating the performance of algorithms is a significant issue in MOO. Indeed, solving methods provide Pareto optimal solutions which are difficult to compare due to the number of objectives. Evaluating an algorithm performance implies comparing the quality of output and also comparing the computational time. When it comes to single objective optimization, we compare two solutions by maintaining the smaller value (in case of minimizing the objective function) or the greater value (in case of maximizing the objective function). In MOO, some methods can be employed such as Pareto dominance as in [20], when solution s_1 strictly dominates solution s_2 (i.e., $s_1 \succ\succ s_2$) then s_1 is better than s_2 in all objectives. Solution s_1 dominates solution s_2 (i.e., $s_1 \succ s_2$) when the solution s_1 is not worse in all objectives and better in at least one objective. We say that s_1 weakly dominates s_2 (i.e., $s_1 \succeq s_2$) if s_1 is not worse than s_2 in all objectives. More often, we find some solutions that don't dominate other, and neither are dominated, in this case, we say that they are incomparable (i.e., $s_1 || s_2$).

2.3. Contribution

To the best of our knowledge, the most popular MGs selection methods are based only on the geographical position, the direction, and the velocity. However, other conflicting high-level objectives must be taken into consideration such as the whole network gain (i.e., the number of connected vehicles) and the traffic amount handled by MGs. Indeed, we aim at finding the best approach to select an MG for a CV taking into account some high-level information concerning the state of the network by maximizing the number of the connected CVs while minimizing the traffic amount handled by MGs. To do so, we propose an MOO system for gateways selection that helps a decision maker to choose a solution among a set of choices depending on his preferences; this system also gives a fair solution in case the decision maker does not set his preferences. Thus, the MOO methods proposed in this paper are considered as a new contribution to the area of MGs discovery in the vehicular ad-hoc network.

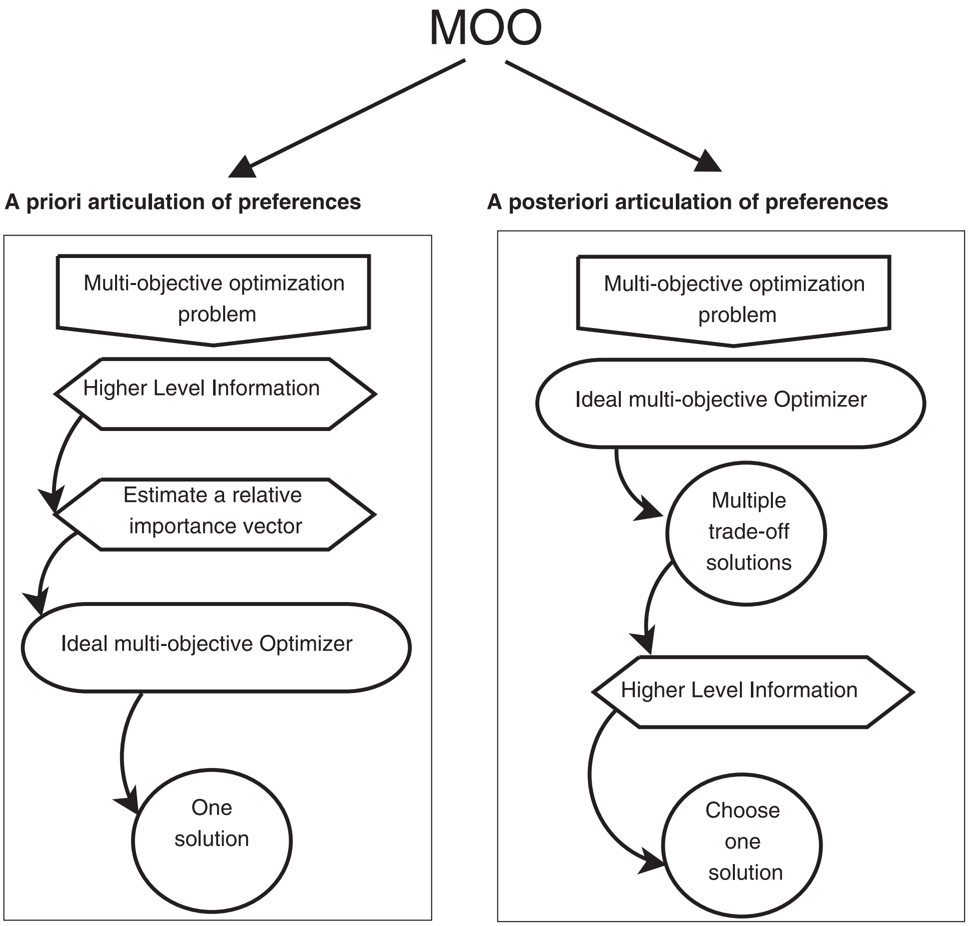


Fig. 1. Multi-objective optimization categories.

3. Problem formulation and solving strategy

3.1. System overview and methodology

The purpose of this study is selecting MGs in a gateway discovery system while maximizing the number of connected vehicles and minimizing the amount of traffic handled by each MG. A CV is a vehicle which wants to connect to the Internet, and an MG is a vehicle which can directly connect to the Internet. The discovery system is composed of two servers that provide services in the cloud. The first one maintains all information concerning MGs and the second one is responsible for affecting a CV to an MG. We propose a system that can be integrated into the second server which selects the appropriate gateway. Integer Optimization Problem (IOP) and Constraint Optimization Problem (COP) are the adopted models in the proposed system. By doing this, separating the formulation and the search strategy is guaranteed. The decision maker can add or remove constraints to the problem depending on the state of the network and can set his preferences regarding the objectives. To solve the IOP, we use the WS approach in the case of a priori articulation of preferences. The GT approach is proposed in case there is no articulation of preferences to solve the IOP. The COP is solved using the Backtracking algorithm. The decision maker can choose the solution depending on high-level information with the help of methods comparison and diagrams.

3.2. Integer optimization problem

3.2.1. Problem statement

VANET consists of a set of MGs which is represented by $\mathcal{MG}$ and a set of CVs in need to access the Internet which is represented by the $\mathcal{CV}$. The Euclidean distance between a CV $i \in \mathcal{CV}$ and a MG $j \in \mathcal{MG}$ is represented by d_{ij} such that:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \quad (1)$$

Let ω_i denotes the traffic amount requested by the CV i. D_i and D_j are, respectively, the directions of a CV i and a MG j such that $0 \le D_i,\ D_j \le 2\pi$ and V_i and V_j are respectively the velocities of the CV and the MG. Let r denotes the MG radio propagation range and V_{Max} denotes the maximum permitted velocity difference between a CV connected to an MG. Our contribution is to propose a solution to select MGs for the given CVs.

The relationship of CVs to MGs is represented through the binary matrix $\mathcal{X}(\mathcal{CV}, \mathcal{MG})$. If and only if the CV i is connected to the MG j, then $\mathcal{X}(i, j) = 1$, otherwise $\mathcal{X}(i, j) = 0$. We define the binary symmetric matrix $\mathcal{Y}(\mathcal{CV}, \mathcal{CV})$, if and only if $i_1 \in \mathcal{CV}$ and $i_2 \in \mathcal{CV}$ are connected to the same MG, then $\mathcal{Y}(i_1, i_2) = 1$, otherwise $\mathcal{Y}(i_1, i_2) = 0$. The problem of MG selection is represented through the following integer program:

$$\begin{cases} (2.1) \quad \mathbf{max} \ \sum_{i \in \mathcal{CV}} \sum_{j \in \mathcal{MG}} \mathcal{X}(i, j) \\ (2.2) \quad \mathbf{min} \ \sum_{i_1 \in \mathcal{CV}} \sum_{i_2 \in \mathcal{CV}} \omega_{i_1} \mathcal{Y}(i_1, i_2) \\ \mathbf{s.\ t.} \\ (2.3) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \forall j \in \mathcal{MG}, \mathcal{X}(i_1, j) + \mathcal{X}(i_2, j) \le 1 + \mathcal{Y}(i_1, i_2) \\ (2.4) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \forall j \in \mathcal{MG}, \mathcal{X}(i_1, j) - \mathcal{X}(i_2, j) \le 1 - \mathcal{Y}(i_1, i_2) \\ (2.5) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, d(i, j)\mathcal{X}(i, j) \le r \\ (2.6) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, |V_i - V_j|\mathcal{X}(i, j) \le V_{Max} \\ (2.7) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, |D_i - D_j|\mathcal{X}(i, j) = 0 \\ (2.8) \quad \forall i \in \mathcal{CV}, \sum_{j \in \mathcal{MG}} \mathcal{X}(i, j) = 1 \\ (2.9) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, \mathcal{X}(i, j) \in \{0, 1\} \\ (2.10) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \mathcal{Y}(i_1, i_2) \in \{0, 1\} \\ (2.11) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \mathcal{Y}(i_1, i_2) = \mathcal{Y}(i_2, i_1) \end{cases} \tag{2}$$

The first objective aims to maximize as much as possible the number of connected CVs in need to access the Internet. Meanwhile, the second one points at reducing the number of CVs connected to the same MG by minimizing the traffic amount handled by MGs of all the connected CVs. The constraints in the problem model are described as follows:

- Constraint (2.3) ensures that if $\mathcal{Y}(i_1, i_2) = 0$, i_1 and i_2 must not connect to the same MG.
- Constraint (2.4) ensures that if $\mathcal{Y}(i_1, i_2) = 1$, i_1 and i_2 must connect to the same MG.
- Constraint (2.5) ensures that if a CV i is connected to a MG j then i must be within the range of j.
- Constraint (2.6) ensures that if a CV i is connected to a MG j, then the difference between the two velocities must not exceed V_{Max}.
- Constraint (2.7) ensures that if a CV i is connected to a MG j, then they must have the same direction.
- Constraint (2.8) ensures that each CV must be connected only to one MG.
- Constraints (2.9) and (2.10) ensure that the matrices $\mathcal{X}$ and $\mathcal{Y}$ are binary.
- Constraint (2.11) ensures that the matrix $\mathcal{Y}$ is symmetric.

As a rule, it is more convenient to study and solve an optimization problem that aims to minimize or to maximize all the objectives. That is why, the integer program in Eq. (2) is reformulated and simplified in Eq. (3) as follows:

$$\begin{cases} (3.1) \quad \mathbf{min} \ \sum_{i \in \mathcal{CV}} \sum_{j \in \mathcal{MG}} (1 - \mathcal{X}(i, j)) \\ (3.2) \quad \mathbf{min} \ \sum_{i_1 \in \mathcal{CV}} \sum_{i_2 \in \mathcal{CV}} \omega_{i_1} \mathcal{Y}(i_1, i_2) \\ \mathbf{s.\ t.} \\ (3.3) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \forall j \in \mathcal{MG}, \mathcal{X}(i_1, j) + \mathcal{X}(i_2, j) \le 1 + \mathcal{Y}(i_1, i_2) \\ (3.4) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \forall j \in \mathcal{MG}, \mathcal{X}(i_1, j) - \mathcal{X}(i_2, j) \le 1 - \mathcal{Y}(i_1, i_2) \\ (3.5) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, d(i, j)\mathcal{X}(i, j) \le r \\ (3.6) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, |V_i - V_j|\mathcal{X}(i, j) \le V_{Max} \\ (3.7) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, |D_i - D_j|\mathcal{X}(i, j) = 0 \\ (3.8) \quad \forall i \in \mathcal{CV}, \sum_{j \in \mathcal{MG}} \mathcal{X}(i, j) = 1 \\ (3.9) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, \mathcal{X}(i, j) \in \{0, 1\} \\ (3.10) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \mathcal{Y}(i_1, i_2) \in \{0, 1\} \\ (3.11) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \mathcal{Y}(i_1, i_2) = \mathcal{Y}(i_2, i_1) \end{cases} \tag{3}$$

Table 1
Weighted-sum methods.

	α	β
WSA1	1	0
WSA2	0	1
WSA3	0.7	0.3
WSA4	0.3	0.7

In the next section, a solution based on a priori articulation of preferences is proposed to solve our problem.

3.2.2. Weighted-sum approach

The integer program is solved using the Weighted-Sum Approach (WSA) as presented in Eq. (4):

$$\begin{cases} (4.1) \quad \mathbf{min} \quad \alpha \sum_{i\in\mathcal{CV}} \sum_{j\in\mathcal{MG}} (1-\mathcal{X}(i,j)) + \beta \sum_{i_1\in\mathcal{CV}} \sum_{i_2\in\mathcal{CV}} \omega_{i_1} \mathcal{Y}(i_1,i_2) \\ \mathbf{s.\ t.} \\ (4.2) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \forall j \in \mathcal{MG}, \mathcal{X}(i_1,j) + \mathcal{X}(i_2,j) \le 1 + \mathcal{Y}(i_1,i_2) \\ (4.3) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \forall j \in \mathcal{MG}, \mathcal{X}(i_1,j) - \mathcal{X}(i_2,j) \le 1 - \mathcal{Y}(i_1,i_2) \\ (4.4) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, d(i,j)\mathcal{X}(i,j) \le r \\ (4.5) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, |V_i - V_j|\mathcal{X}(i,j) \le V_{Max} \\ (4.6) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, |D_i - D_j|\mathcal{X}(i,j) = 0 \\ (4.7) \quad \forall i \in \mathcal{CV}, \sum_{j\in\mathcal{MG}} \mathcal{X}(i,j) = 1 \\ (4.8) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, \mathcal{X}(i,j) \in \{0,1\} \\ (4.9) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \mathcal{Y}(i_1,i_2) \in \{0,1\} \\ (4.10) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \mathcal{Y}(i_1,i_2) = \mathcal{Y}(i_2,i_1) \end{cases} \tag{4}$$

The two objective functions must be arranged in order of importance to solve the integer program in Eq. (4). We define four weighted-sum methods with different preferences as detailed in Table 1. α and β take different values according to the importance of each objective function such that $\alpha + \beta = 1$. WSA1 solution minimizes only the first objective. Meanwhile, WSA2 solution aims at reducing only the second objective. The worst values of the first objective and the second objective functions are obtained using this two solutions, and are, respectively, $Obj1_{WORST}$ and $Obj2_{WORST}$. The WSA3 solution takes the first objective as a priority. Meanwhile, the WSA4 solution takes objective 2 as first choice. These two solutions aim to find a compromise between the different objectives. However, in the next section, we propose another trade-off solution without articulation of preferences.

3.2.3. Game theory approach

Game theory approach (GTA) is a trade-off solution which is applied to find a compromise between the first objective and the second one. To do so, we use the Nash bargaining approach and, the two objectives are considered as two players. The game is non-cooperative since each player aims at minimizing its objective without knowing the state of the other player. The first player seeks an objective value not better than $f^*(\mathcal{X},\mathcal{Y})$. On another hand, the second player should not wait for an objective better than $g^*(\mathcal{X},\mathcal{Y})$ (See Eq. (5) and Eq. (6)). However, it must be guaranteed that the two objective values should not be worse than $Obj1_{WORST}$ and $Obj2_{WORST}$, respectively for the player 1 and player 2.

$$\sum_{i\in\mathcal{CV}} \sum_{j\in\mathcal{MG}} (1-\mathcal{X}(i,j)) \le f^*(\mathcal{X},\mathcal{Y}) \tag{5}$$

$$\sum_{i_1\in\mathcal{CV}} \sum_{i_2\in\mathcal{CV}} \omega_{i_1} \mathcal{Y}(i_1,i_2) \le g^*(\mathcal{X},\mathcal{Y}) \tag{6}$$

In Nash bargaining theory, we aim to find an optimal point taking into account reference values which are the worst obtained values of the objectives such that:

$$f^*(\mathcal{X},\mathcal{Y}) \le Obj1_{WORST} \tag{7}$$

$$g^*(\mathcal{X},\mathcal{Y}) \le Obj2_{WORST} \tag{8}$$

The trade-off between the two objectives is obtained through Eqs. (5)–(8), and the following integer program:

$$\begin{cases} (9.1) \quad \mathbf{max} \ \ (Obj1_{WORST} - f^{*}(\mathcal{X},\mathcal{Y})) \times (Obj2_{WORST} - g^{*}(\mathcal{X},\mathcal{Y})) \\ \ \mathbf{s.\ t.} \\ (9.2) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \forall j \in \mathcal{MG}, \mathcal{X}(i_1,j) + \mathcal{X}(i_2,j) \le 1 + \mathcal{Y}(i_1,i_2) \\ (9.3) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \forall j \in \mathcal{MG}, \mathcal{X}(i_1,j) - \mathcal{X}(i_2,j) \le 1 - \mathcal{Y}(i_1,i_2) \\ (9.4) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, d(i,j)\mathcal{X}(i,j) \le r \\ (9.5) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, |V_i - V_j|\mathcal{X}(i,j) \le V_{Max} \\ (9.6) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, |D_i - D_j|\mathcal{X}(i,j) = 0 \\ (9.7) \quad \forall i \in \mathcal{CV}, \sum_{j\in\mathcal{MG}} \mathcal{X}(i,j) = 1 \\ (9.8) \quad \forall i \in \mathcal{CV}, \forall j \in \mathcal{MG}, \mathcal{X}(i,j) \in \{0,1\} \\ (9.9) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \mathcal{Y}(i_1,i_2) \in \{0,1\} \\ (9.10) \quad \forall i_1 \in \mathcal{CV}, \forall i_2 \in \mathcal{CV}, \mathcal{Y}(i_1,i_2) = \mathcal{Y}(i_2,i_1) \end{cases} \tag{9}$$

After we formulated our problem as an IOP where the objective functions and the constraints are linear, we propose a COP model in the next section.

3.3. Constraint optimization problem

3.3.1. Problem statement

In this section, we develop the gateway selection problem model using Constraint Programming. The primary process consists of, first, defining the variables and their corresponding domains and then, determining the constraints of the problem. If some criterion is to be optimized, the objective functions need to be specified. We model our problem as a COP as follows:

- A finite set of variables: $X = \{\mathcal{X}, \mathcal{Y}\}$.

  Where:

  $\mathcal{X}(\mathcal{CV}, \mathcal{MG})$ is a binary matrix. When the CV i is connected to the MG j, then $\mathcal{X}(i,j) = 1$, otherwise $\mathcal{X}(i,j) = 0$. $\mathcal{Y}(\mathcal{CV},\mathcal{CV})$ is a binary and symmetric matrix. When $i_1 \in \mathcal{CV}$ and $i_2 \in \mathcal{CV}$ are connected to the same MG, then $\mathcal{Y}(i_1,i_2) = 1$, otherwise $\mathcal{Y}(i_1,i_2) = 0$.

- A nonempty domain of possible values for each variable: $DOM(X) = D_{\mathcal{X}} = D_{\mathcal{Y}} = \{0, 1\}$
- A finite set of constraints:

  (C1). $\forall i_1, i_2 \in \mathcal{CV}^2,\ \forall j \in \mathcal{MG}$: $\mathcal{Y}(i_1,i_2) = 0 \Rightarrow (\mathcal{X}(i_1,j) = 0) \vee ((\mathcal{X}(i_2,j) = 0)$;
  (C2). $\forall i_1, i_2 \in \mathcal{CV}^2, \forall j \in \mathcal{MG}$: $\mathcal{Y}(i_1,i_2) = 1 \Rightarrow \mathcal{X}(i_1,j) = \mathcal{X}(i_2,j)$;
  (C3). $\forall i \in \mathcal{CV},\ \forall j \in \mathcal{MG},\ d(i,j)\mathcal{X}(i,j) \le r$;
  (C4). $\forall i \in \mathcal{CV},\ \forall j \in \mathcal{MG},\ |V_i - V_j|\mathcal{X}(i,j) \le V_{Max}$;
  (C5). $\forall i \in \mathcal{CV},\ \forall j \in \mathcal{MG},\ |D_i - D_j|\mathcal{X}(i,j) = 0$;
  (C6). $\forall i \in \mathcal{CV}$: $\sum_{j\in\mathcal{MG}} \mathcal{X}(i,j) = 1$;
  (C7). $\forall i_1 \in \mathcal{CV},\ \forall i_2 \in \mathcal{CV},\ \mathcal{Y}(i_1,i_2) = \mathcal{Y}(i_2,i_1)$;

- The objectives are:

  (Obj1). $\mathbf{min} \sum_{i\in\mathcal{CV}} \sum_{j\in\mathcal{MG}} (1 - \mathcal{X}(i,j))$
  (Obj2). $\mathbf{min} \sum_{i_1\in\mathcal{CV}} \sum_{i_2\in\mathcal{CV}} \omega_{i_1} \mathcal{Y}(i_1,i_2)$

  The constraints and the objectives in the COP model are described as follows:

- (C1) ensures that if $\mathcal{Y}(i_1,i_2) = 0$, i_1 and i_2 must not connect to the same MG.
- (C2) ensures that if $\mathcal{Y}(i_1,i_2) = 1$, i_1 and i_2 must connect to the same MG.
- (C3),(C4),(C5),(C6) and (C7) are the same as in the integer program in Eq. (3).
- (Obj1) and (Obj2) are the same as in the integer program in Eq. (3)

  To deal with this model, we propose hereafter a Constraint Optimization Problem solution.

3.3.2. Backtracking: A constraint optimization problem solution

There are mainly three solution strategies for solving a COP which are backtracking, dynamic programming, and local search. These algorithms are classified into two categories: complete and incomplete. Local search represents an incomplete algorithm which tries to find a solution if it exists and an approximation to the optimal solution. On another hand, backtracking and dynamic programming are complete algorithms which can be used to prove that the problem has no solution or to find an optimal solution. Dynamic programming requires an exponential execution time to find all solutions while backtracking works on only one solution at a time and require a polynomial time of execution. In what follows, we use Backtracking to solve the COP ensuring a minimal execution time. Backtracking algorithm consists of assigning values to variables, one by one, traversing through the domains such that the constraints are satisfied. The solution is represented by a vector containing all the assigned values of the variables. At each step where the constraints related to the concerned variables are not met, a return backward is carried out hence the name of backtracking. The problem is solved in a depth-first manner of the space to find a solution. Assuming that *Vector* is a solution to our COP by applying Backtracking, the steps of the generalized algorithm may be resumed in Algorithm 1. A starting point (i.e., a variable) is chosen to implement

Algorithm 1 Generalized Backtracking Algorithm.

$v \leftarrow$ CHOOSE VARIABLE($X = \{\mathcal{X}, \mathcal{Y}\}$)
$Vector \leftarrow \emptyset$
function BACKTRACK($Vector, v$)
    while $length(Vector) \neq length(X)$ **do**
        if ACCEPT($Vector \cup s$) **then**
            $Vector \leftarrow Vector \cup s$
            $v \leftarrow$ NEXT(v)
            BACKTRACK($Vector, v$)
        else
            $v \leftarrow$ ROOT(v)
            Backtrack($Vector, v$)
    return $Vector$

backtracking to our problem, *Choose Variable* function helps to start with one possible variable of many available variables in *X*. *Backtrack* function traverses all the variables recursively, from the root down, in depth-first order as mentioned before. At each variable *v*, the function checks whether the value $s \in DOM(X)$ can satisfy all the constraints and construct a valid solution, if yes the algorithm proceeds otherwise a reversal is performed, until *Vector* contains all instantiated values of all variables. *Accept* function returns true if *s* is a solution and false otherwise. *Root* function returns the root of a variable *v* while *Next* function returns the next candidate.

However, *Choose Variable* and *Next* functions play a crucial role in the progress of the algorithm. Indeed, the start of the procedure has an impact on the solution, and several methods have been proposed for ordering variables as an improvement to Backtracking strategy. In [21], a fruitful dynamic and adaptive variable ordering heuristic is proposed which is a combination of look-back and look-ahead schemes. This heuristic derives benefit from information about previous states of the search process. To do so, a weight is associated with each constraint, and it increases whenever the associated constraint is violated during the search. On another hand, the notion of the impact of a variable is introduced in [22]. The impact represents the importance of a variable for the reduction of the search space and using this concept the performance is improved. Indeed, measuring the impact with the observation of domain reduction during search proves to be a useful criterion for choosing variables. Based on the concept of the weight, each constraint $C(\mathcal{V})$ linked to a set of variables $\mathcal{V}$ has a weight $\psi(C)$, and the variable *v* is chosen using the domain size as extracted from [23] as follows:

$$min \frac{|D(v)|}{\sum_{v \in \mathcal{V}} \psi(C(\mathcal{V}))} \tag{10}$$

Based on the second strategy, we assume that $\mathcal{I}(v = i)$ is the impact of the decision $V = i$ as mentioned in [23]. The variable *v* is chosen as extracted from [23] as follows:

$$min \frac{\sum_{i \in D(v)} 1 - \mathcal{I}(v = i)}{\sum_{v \in \mathcal{V}} \psi(C(\mathcal{V}))} \tag{11}$$

To find an optimal solution, the approach is to solve a sequence of satisfaction problems using the described backtracking algorithm. For the sake of effectiveness, the AC3 algorithm is used to reduce the domains of the variables [24]. In the next section, the proposed MOO system for gateways selection is detailed.

3.4. Multi-objective optimization system for mobile gateways selection

An interactive MOO system for gateways selection is proposed to support decision making. This system helps a decision maker to select the best solution among a set of alternatives and is based on the models mentioned above. To select MGs, a decision maker can express his preferences regarding maximizing the number of connected CVs and minimizing the amount of traffic handled by MGs. These two objectives are conflicting, and the preferences can be set according to some high-level information that includes all information concerning the vehicular ad-hoc network. The proposed system is depicted in Fig. 2, it helps guiding the decision maker to explore the solutions with best match with his preferences through these three phases: *(i)* Construction phase; *(ii)* Resolution phase; *(iii)* Visualization phase. In the first phase, the decision maker

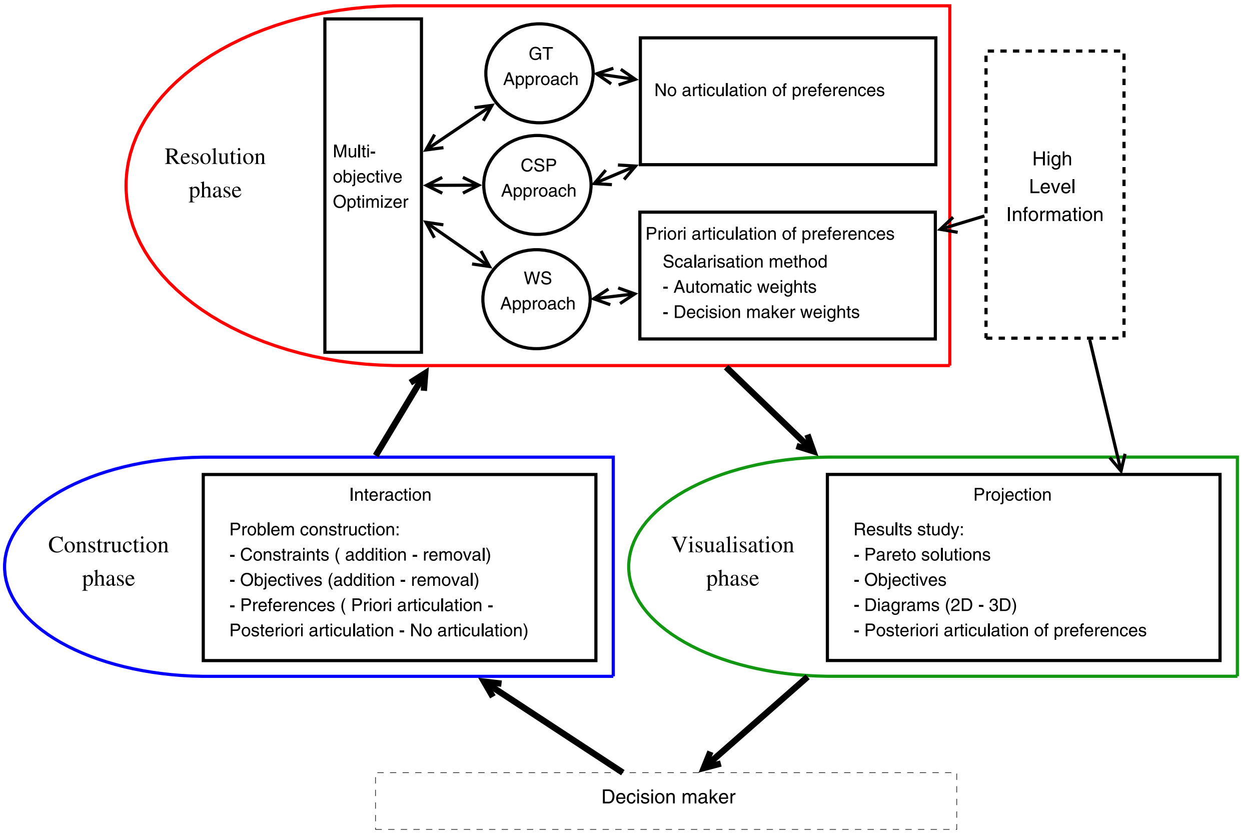


Fig. 2. Multi-objective optimization system for gateways selection.

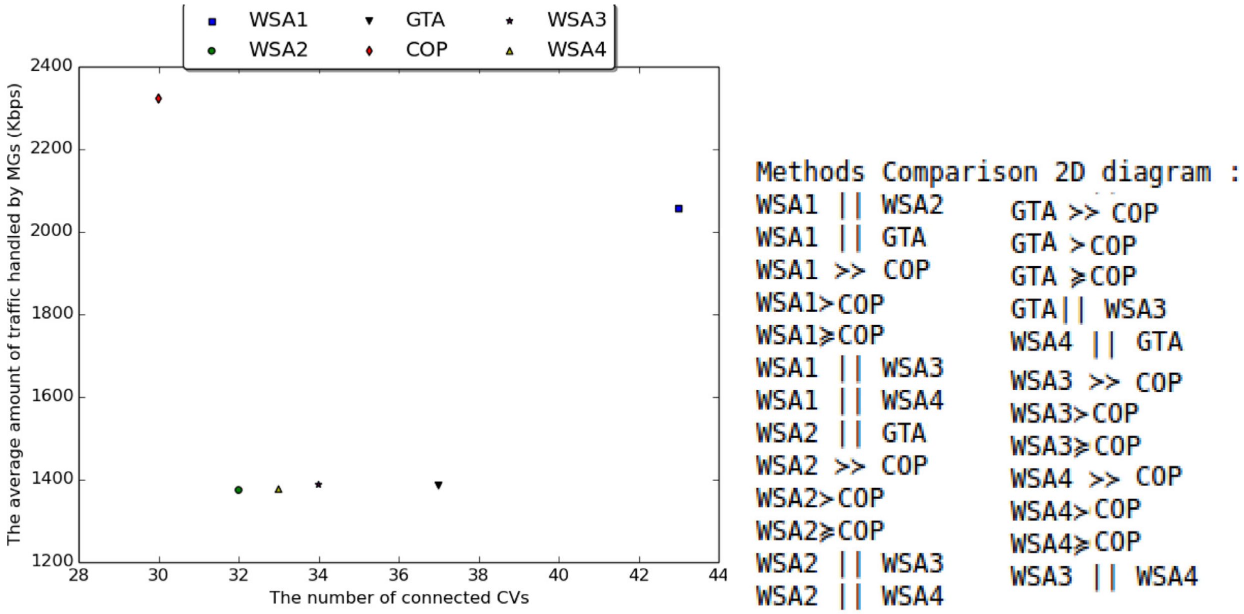
Table 2
Simulation parameters.

Parameter	Setting
Direction	$0 \leq \theta \leq 2\pi$
Velocity	0–20 m/s
X-coordinate	0–2000 m
Y-coordinate	0–2000 m
Z-coordinate	0 m
Transmission range	500 m

can interact with the system by constructing the problem, he adds or removes the constraints and sets his preferences. It can be a priori articulation of preferences, in this case, WS approach is used in the second phase or a posteriori articulation of preferences where all approaches are used. On another hand, if there is no articulation of preferences, GT and COP approaches are executed. In the resolution phase, the approaches are implemented and executed using a multi-objective optimizer. The high-level information represents the state of the environment containing CVs and MGs. In the last phase, the decision maker can study the problem using the projection of the possible solution according to his previous choice. He can choose one solution using high-level information with the help of 2D and 3D diagrams. This step may be considered as a posteriori articulation of preferences where the Pareto solutions are visualized according to the first objective, the second objective and the execution time. According to this three criteria, all approaches are compared using the comparison methods mentioned in Section 2.2.

4. Simulation results

In this section, the proposed approaches are evaluated through simulation. The MOO system for gateways selection is implemented using Python programming language. Gurobi Optimizer [25] is executed to solve GT and WS approaches whereas Mistral library [23] is used for solving the COP. Both of these tools prove to be highly efficient. In the simulation, the network containing CVs and MGs is randomly deployed, and the simulation parameters are shown in Table 2. We generate a random infrastructure in both x-axis and y-axis, for reasons of simplicity, we consider that z=0. We evaluate the perfor-



(a) 2D diagram (b) 2D comparison output.

Fig. 3. The system solutions projection using all approaches for objective 1 and objective 2.

mance of the proposed models (i.e., WSA1, WSA2, WSA3, WSA4, GTA, and COP) compared to the literature solution (i.e., The predicted link lifetime [10]) which we name PLET. The evaluation is performed according to the following metrics:

- Objective 1 which must be maximized and concerns the number of connected CVs;
- Objective 2 which must be minimized and involves the average of traffic amount handled by MGs;
- The execution time.

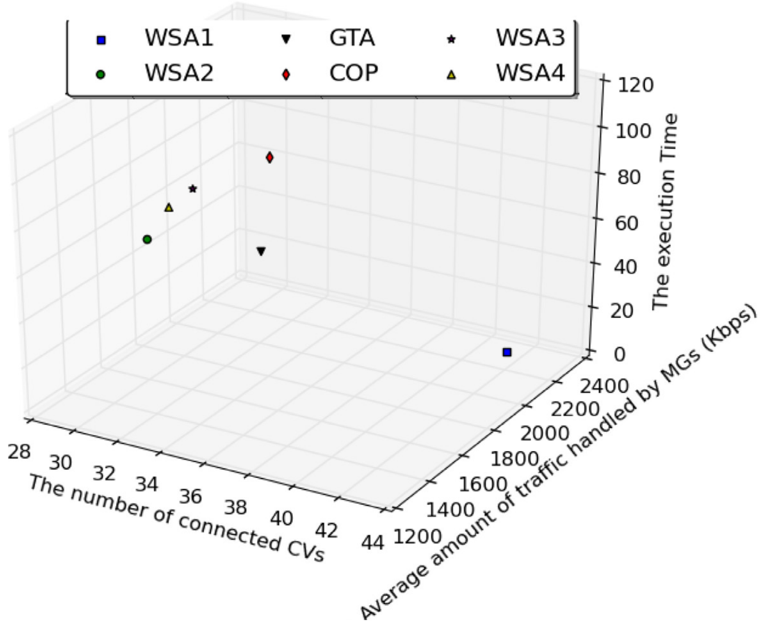
At first, we set the number of CVs to 50, and the number of MGs to 30 while V_{Max} and r remain fixed. Then, in the second simulation, the approaches are evaluated and compared with PLET solution by varying the number of MGs while the number of CVs is fixed to 50 and by changing the number of CVs while the number of MGs is set to 50.

4.1. A case study

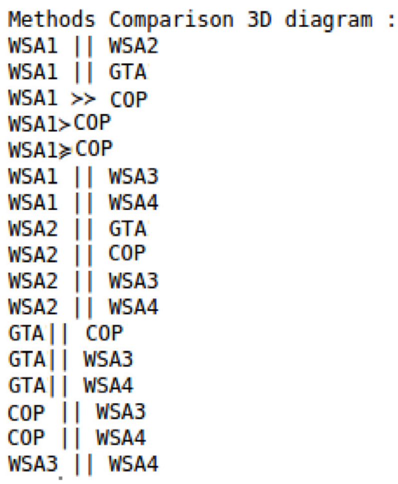
In this simulation, all approaches are executed for the same case study. The number of CVs is 50, and the number of MGs is 30. Fig. 3 and Fig. 4 represent the projection phase of our case study using all approaches. Fig. 3(a) shows a 2D diagram where the x-axis represents objective 1, and the y-axis represents objective 2. The methods comparison of this diagram is depicted in Fig. 3(b), WSA1, and WSA2 are incomparable, the first approach shows the best value concerning the first objective while the second approach shows the best value concerning objective 2, WSA1 is also incomparable to WSA3, WSA4, and GTA. WSA2 is incomparable to WSA3, WSA4, and GTA. WSA3 is incomparable to WSA4 and GTA. WSA4 is incomparable to GTA, and finally, all approaches strictly dominate COP. In Fig. 4(a), the 3D diagram is depicted, the x-axis represents the objective 1, the y-axis represents the objective 2, and the z-axis represents the time execution. Fig. 4(b) shows the output of this diagram methods comparison, as in Fig. 3(b), WSA1, and WSA2 are incomparable regarding the three metrics. In this case, all methods are incomparable to each other, and WSA1 strictly dominates COP. Otherwise, COP exhibits an excellent performance regarding the execution time.

4.2. The proposed approaches evaluation

In this simulation, we evaluate the proposed approaches implemented in the MOO system for gateways selection, and we evaluate the literature solution PLET. To do this, as mentioned earlier, we vary the number of MGs and fix the number of CVs; likewise, we change the number of CVs and fix the number of MGs. In this simulation results, each plotted point represents the average of 20 times of executions. The plots are presented with 95 confidence interval. In each execution, V_{Max} and r remain unchanged, so we vary all the other parameters. Fig. 5 shows the approaches evaluation using Mistral and Gurobi while changing the number of MGs from 30 to 55. The number of CVs is fixed to 50. Fig. 5(a) represents the objective 1 which increases while the number of MGs becomes high, this is due to the number of choices that increases. We notice that WSA1 shows the best performance concerning the number of connected vehicles after the solution PLET which

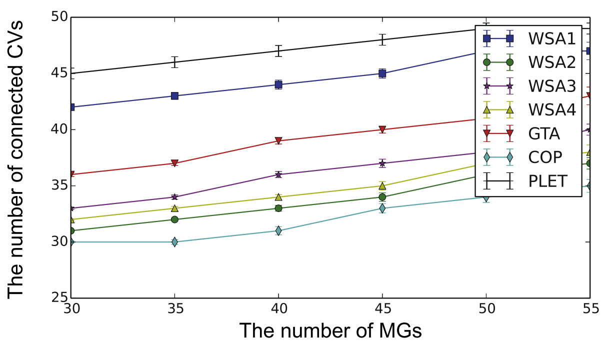


(a) 3D diagram

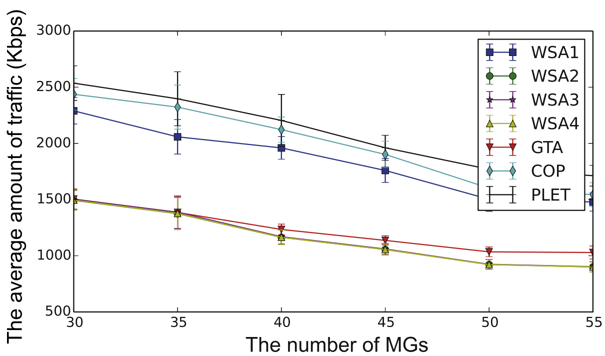


(b) 3D comparison output.

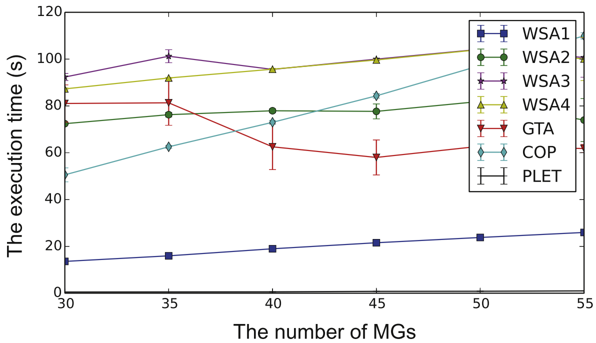
Fig. 4. The system solutions projection using all approaches for objective 1, objective 2, and the execution time.



(a) The number of connected CVs.

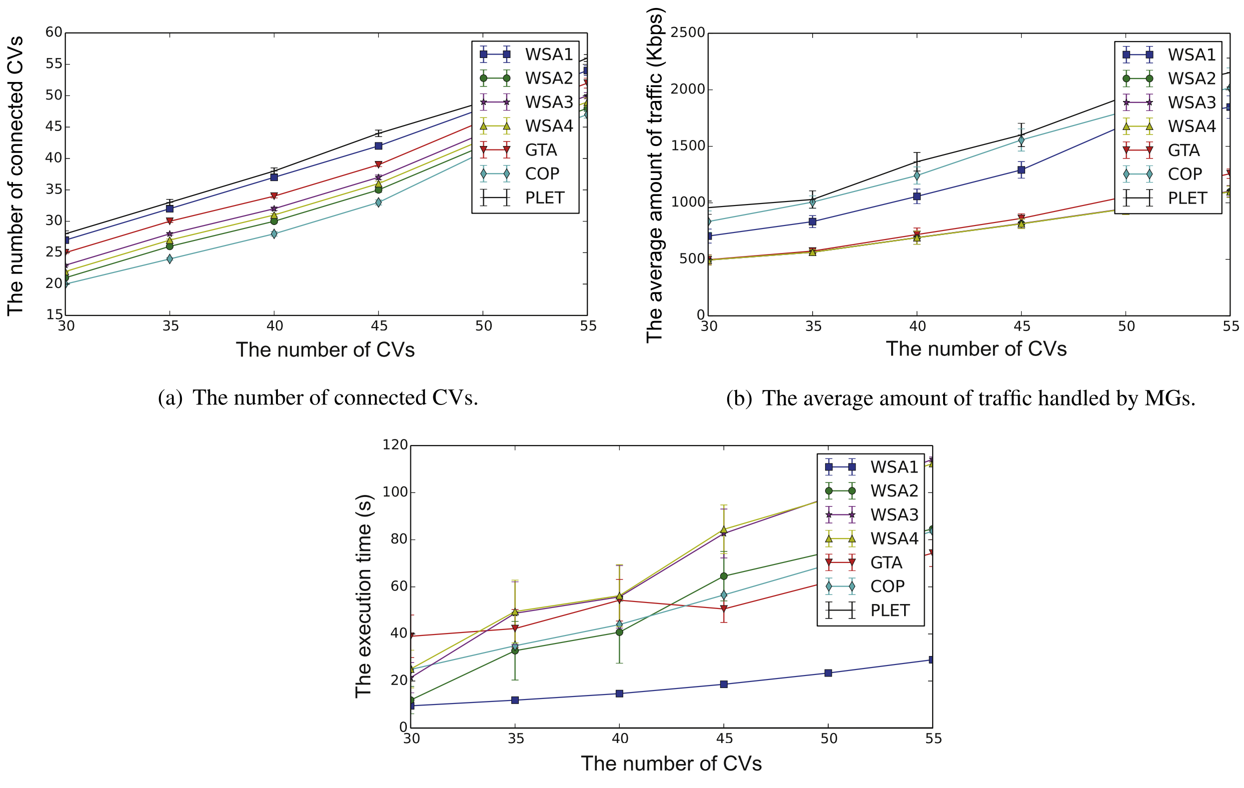


(b) The average amount of traffic handled by MGs.



(c) The execution time.

Fig. 5. Approaches performance using Mistral and Gurobi while varying the number of MGs.



(a) The number of connected CVs.

(b) The average amount of traffic handled by MGs.

(c) The execution time.

Fig. 6. Approaches performance using Mistral and Gurobi while varying the number of CVs.

connects all CVs except those out of range. Fig. 5(b) represents the average of the traffic amount of MGs, by varying the number of MGs the objective 2 decreases. WSA2 exhibits the best performance concerning this parameter, and PLET shows the worst performance. Fig. 5(b) shows the execution time of the proposed approaches and PLET solution. We notice that in general, it increases while the number of MGs grows. As depicted in this figure, PLET exhibits the best performance since there is no optimization. WSA1 shows the best value of execution time compared to the other approaches. Fig. 6 represents the evaluation of the proposed approaches and PLET solution while varying the number of CVs from 30 to 55 and fixing the number of MGs to 50. The graph of objective 1 is shown in Fig. 6(a), as in Fig. 5(a), WSA1 shows the best performance after the solution PLET. Moreover, objective 1 increases while the number of CVs becomes high. In Fig. 6(b), objective 2 is represented, and it increases by varying the number of CVs. Again, WSA2 exhibits the best performance and PLET has the worst values. Fig. 6(c) represents the execution time, and again, PLET exhibits the best performance concerning time. This simulation demonstrates the efficiency of each proposed model in achieving its key design goals compared to PLET solution; it is noticeable that WSA1 shows the best results regarding maximizing the number of connected CVs while WSA2 shows the best values regarding minimizing the amount of traffic handled by each gateway. WSA3, WSA4, and GTA reach them goals by finding a compromise between the two objectives, unlike COP that shows only better execution time in this case study.

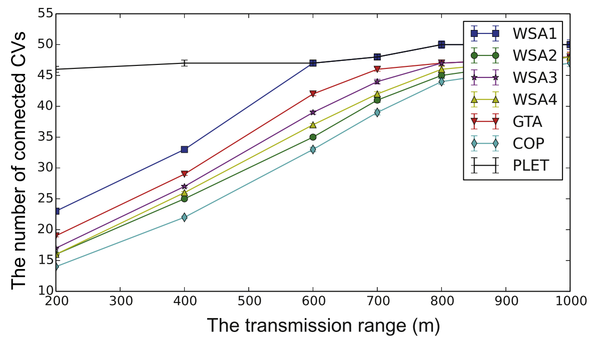
Table 3 displays the improvement percentage of objective 2 while maximizing the number of connected vehicles for the first simulation where we vary the number of MGs. The best reduction percentage regarding objective 1 is provided by WSA1 where the number of connected vehicles is reduced only to 5,63%, and the worst one is provided by COP by reducing the number to 32,04%. For objective 2, the best reduction percentage is performed by WSA2 which is 49,07% while COP has the worst one which is 6,42%. Table 4 represents the improvement percentage of objective 2 while maximizing the number

Table 3
The average amount of traffic handled by MGs improvement while maximizing the number of connected CVs and varying the number of MGs.

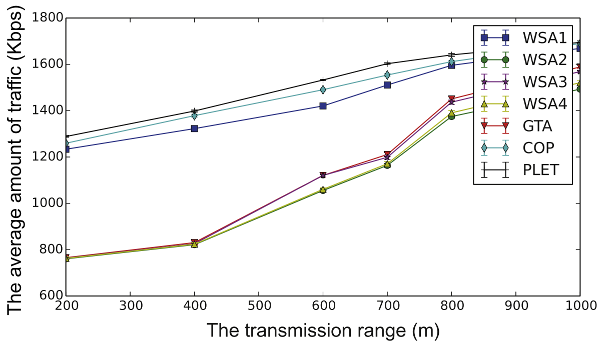
	COP	WSA1	WSA2	WSA3	WSA4	GTA
Objective 1	32,04% ↓	5,63% ↓	28,52% ↓	23,23% ↓	26,40% ↓	16,60% ↓
Objective 2	5,18% ↓	12,18% ↓	45,08% ↓	44,78% ↓	45,03% ↓	41,78% ↓

Table 4
The average amount of traffic handled by MGs improvement while maximizing the number of connected CVs and varying the total number of CVs.

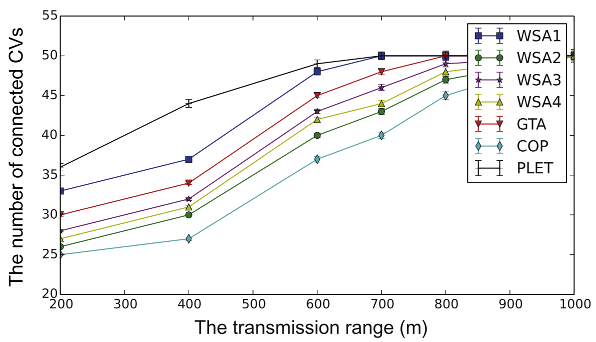
	COP	WSA1	WSA2	WSA3	WSA4	GTA
Objective 1	22,17% ↓	3,22% ↓	18,54% ↓	13,70% ↓	16,12% ↓	8,87% ↓
Objective 2	6,42% ↓	17,89% ↓	49,07% ↓	48,94% ↓	49,06% ↓	45,12% ↓



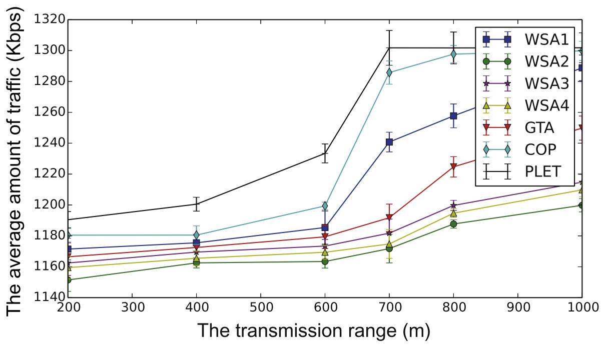
(a) Scenario 1: The number of connected CVs.



(b) Scenario 1: The average amount of traffic handled by MGs.



(c) Scenario 2: The number of connected CVs.



(d) Scenario 2: The average amount of traffic handled by MGs.

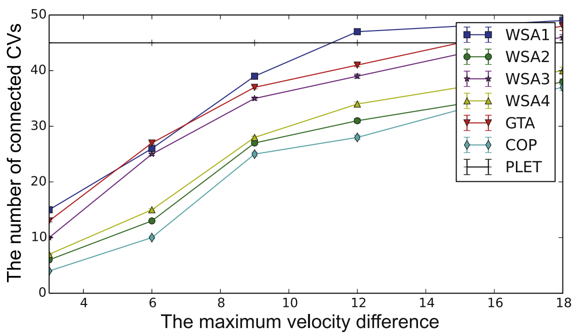
Fig. 7. The impact of the transmission range.

of connected vehicles for the second simulation where we vary the number of CVs. The percentage is 3,22% for objective 1 and is provided by WSA1 while COP has the worst percentage which is 22,17%. The best reduction value concerning objective 2 is performed by WSA2 and is equal to 49,07% while COP exhibits the worst percentage value which is 6,42%. In both simulations, all approaches improve the objective 2 by up to 49,07% while maximizing the first one by up to 3,04% of the difference to PLET solution.

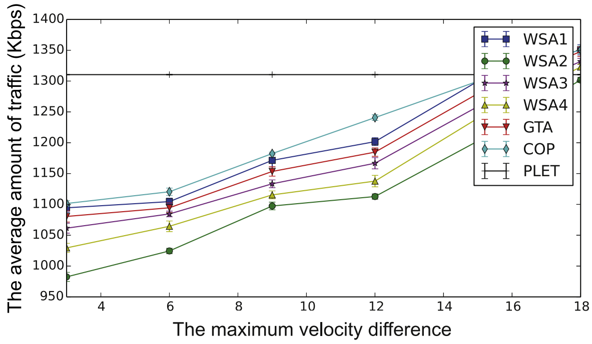
Finally, it is worth stressing out that the proposed approaches demonstrate its efficiency in helping a decision maker to realize the adequate mapping of CVs and MGs. Indeed with an articulation of preferences or without, the results prove that the solutions find the fair trade-off between maximizing the number of connected vehicles and minimizing the average amount of traffic handled by MGs.

4.3. The impact of the transmission range and the permitted velocity difference

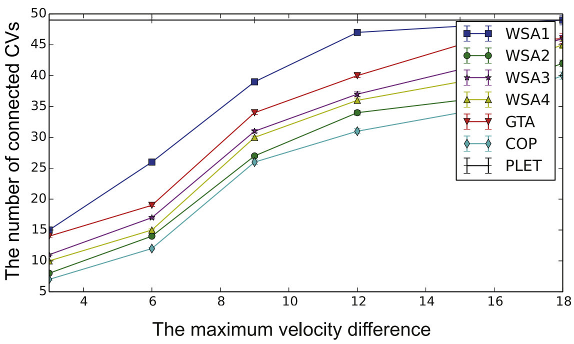
In this simulation, we consider two scenarios. In the first one, the number of CVs is 50, and the number of MGs is 30. In the second scenario, the number of CVs is fixed to 30, and the number of MGs is 50. We vary the transmission range r and the permitted velocity difference V_{Max} to study its impact on the number of connected CVs and the average amount of traffic handled by MGs. Each plotted point represents the average of 20 times of executions. The plots are presented with 95 confidence interval. Fig. 7 displays the impact of the transmission range. We notice that the number of connected CVs becomes higher when we increase the transmission range in both scenarios. Likewise, the average amount of traffic increases when the transmission range rises. However, when the number of MGs is large, the average amount of traffic is not as high as in the first scenario (See Fig. 7(b) and 7(d)). Fig. 8 presents the impact of the permitted velocity difference. Since PLET solution does not depend on this measurement, the result stills the same. Regarding the other solutions, the



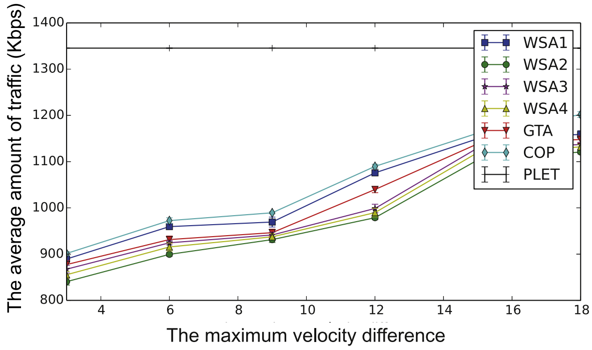
(a) Scenario 1: The number of connected CVs.



(b) Scenario 1: The average amount of traffic handled by MGs.



(c) Scenario 2: The number of connected CVs.



(d) Scenario 2: The average amount of traffic handled by MGs.

Fig. 8. The impact of the permitted velocity difference.

number of connected vehicles and the average amount of traffic handled by MGs increase while we vary the permitted velocity difference between CVs and MGs. Furthermore, the two metrics are more increasing in the first scenario. We notice that the transmission range and the permitted velocity difference have a significant impact on the number of connected vehicles and the average amount of traffic handled by MGs for all the proposed approaches.

5. Conclusion

Research proves the efficiency of mobile gateways in comparison to the fixed ones which are road infrastructure. Therefore, a suitable selection of gateways for vehicles in need of Internet access must be carried on. A multi-objective optimization system for mobile gateways selection is introduced to improve the gateways discovery system. This discovery system is assisted by cloud computing and affords to vehicles in need to access to Internet an appropriate gateway. Our proposed system consists of different models namely Integer Optimization and Constraint Optimization providing to the decision maker a palette of choices according to his preferences. This system also helps the decision maker by projecting results in 2D and 3D diagrams and using some comparative methods. The simulations show the performance of the system in comparing the different solving strategies, the effectiveness of the weighted sum method in the case of a priori articulation of preferences, the efficiency of the game theory approach in finding a trade-off between the conflicting objectives and the effectiveness of backtracking algorithm in term of execution time. These approaches are compared with the literature solution and prove to be effective in minimizing the traffic amount handled by each gateway while maximizing as much as possible the number of connected client vehicles. In future works, we intend on developing the system by integrating more constraints and objectives. We also aim at improving the system by making it autonomous. Indeed, without the intervention of the decision maker, the system may be more adaptive to the vehicular ad hoc network environment by proposing the best strategy for gateways selection and an automatic priori-articulation of preferences.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.compeleceng.2018.12.004.

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