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Robust cooperative car-parking: implications and solutions for selfish inter-vehicular social behaviour

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Abstract

Vehicular cooperation mechanisms are known to provide efficiency and scalability benefits but for the mechanisms to be human-centric, there is a need for them to be robust and resilient to anti-social behaviours such as deception. More specifically, decentralised vehicle-to-vehicle cooperation has been shown to be an effective and convenient approach to coordinate the use of dynamically changing common road resources such as car parking. However, the potential for selfish behaviour of some vehicles in the form of sending false information for self-benefit has a significant effect on the value of cooperation. In this paper, we investigate, via extensive simulations, the deception behaviour of malicious vehicles looking to park by sending false information in decentralized vehicle cooperation. Furthermore, Deception Detection Mechanisms (DDMs) are introduced and are shown to be valuable in ameliorating the effects of malicious vehicles. The work has broader implications for an open world of autonomous and adaptive systems with decentralized control and ownership which need to cooperate to use shared resources; they are susceptible to malicious behaviour, and hence, need to be built to be robust to such behaviour.

Keywords: Decentralized vehicle cooperation mechanism, Selfish behaviour, Deception detection mechanism

Introduction

The adoption of wireless communication in vehicles has received significant attention in academia and industry for its role in improving road safety and efficiency. Such communication provides a cooperative road environment, where vehicles can share their intentions and sensor information [1]; this contributes to establishing a feasible decentralized framework for coordinating the sharing of resources such as road infrastructure and car parking. Accordingly, there are international organization efforts to standardize vehicular wireless communication, for example, European Telecommunications Standards Institute (ETSI) and Society of Automotive Engineers (SAE) standards in Europe and the United States (US), respectively.

Decentralized cooperation mechanisms among vehicles are challenged by rapid changes in density and network topology, but there is a broad range of applications of

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vehicle-to-vehicle cooperation that can be made possible by such mechanisms. In addition, inter-vehicle cooperation can form the basis for smart social interaction among vehicles, instead of restricting the cooperation to mere dissemination or sharing of information. For example, in our previous work in [2], as will be explained briefly later, a decentralised car parking coordination mechanism called CoPark-WS (short for Co-operative Car PARKing with Walking and Searching time) was introduced based on vehicles cooperating without intervening car parking infrastructure, allowing resolving of contention for parking spaces and sharing of advice about occupancy of areas.

However, there is another side to a decentralized cooperation mechanism that can limit the benefits of cooperation, which is the selfish behaviour of some vehicles. The lack of a centralized authorised unit and the partial knowledge about the surrounding environment can provide an opportunity for selfish behaviours to improve one's own profit. Although the Institute of Electrical and Electronics Engineers (IEEE) 1609.2 standard proposed a security service to protect Wireless Access Vehicular Environment (WAVE) communication which can protect vehicles from spoofing and eavesdropping [3], the detection of specious transmitted information is also required in Vehicular Ad hoc NETworks (VANETs) [4].

There are two possible forms of selfish behaviours vehicles can experience in a decentralized cooperation mechanism:

1. One is when a vehicle plays a passive role, i.e. benefiting from receiving information from other vehicles, while not sending or forwarding useful messages to its neighbours, thereby, limiting the effect of vehicle cooperation or information sharing. There are various mechanisms which have been introduced to identify selfish devices in Mobile Ad hoc NETworks (MANETs) and VANETs via neighbours monitoring the device's actions and adopting reputation mechanisms, all this to encourage cooperation as in [5].
2. The other form of misbehaviour, which is more complicated than the first, is related to a vehicle sending false information with the objective of deceiving other vehicles in order to increase its chance of achieving its goal. For example, in a car park scenario, a vehicle can share false information about car parking space availability in a particular area to deceive other vehicles (mis-)leading them to search alternative areas, in order to enhance its own chance of getting a parking space in preferred areas. This is different from but related to the issues of message tampering and data trust in vehicle-to-vehicle communications [6], and false data injection or false event notification attacks [7].

Motivated by the need to address selfish behaviours while maintaining the benefits of cooperation, this paper aims to investigate the effect of selfish behaviour of vehicles looking to park by sending false information as studied within the framework of a decentralized car parking coordination mechanism (CoPark-WS).

The novel contributions of this paper are as follows:

- We provide a comprehensive analysis of the robustness of the decentralised cooperative parking approach (called CoPark-WS) based on extensive simulations, in

the case of varying proportions of participating vehicles and in the case of the second form of selfish behaviour above (i.e., when there are vehicles sharing false information); in particular, we quantitatively study the impact of misleading information shared by malicious vehicles (which we call *gang vehicles*) on a collection of vehicles within an area (e.g., a large carpark).
- We introduce a novel deception detection mechanism (DDM) to limit the effect of such selfish behaviour, using a mechanism to appropriately judge received advice messages. We show that DDM comprises a family of approaches (DDM-C, DDM-D and DDM-R) that relates to the extent of intervention required.

We believe our work is original in studying the impact of false information in cooperative parking scenarios, and in providing a mechanism to address this problem.

The remainder of this paper is organized as follows. Firstly, we will outline the context for cooperative vehicles, explaining key architectures and on-going work that will realize this notion. We will then describe CoPark-WS which relies on the ability of vehicles to cooperate via vehicle-to-vehicle exchanges to find parking effectively. Then, we will investigate, using extensive simulations, the influence of selfish behaviour in terms of vehicles working individually and in a group (as a gang) on CoPark-WS performance—we provide results to show the impact of fake messages by gang vehicles on parking behaviour. After that, a Deception Detection Mechanism (DDM) to ameliorate the situation is proposed, discussed and investigated—we provide results to show the improvements using DDM. Next, related work is reviewed. Finally, we conclude with future work.

Context-the advent of cooperative vehicles

Communication among vehicles is deemed to potentially increase traffic safety and efficiency [8, 9]. By providing information at long-range, the communication offers to the drivers (for non-fully automated vehicles) more time to process it and to react accordingly. For the connected and automated vehicle, it provides a redundant signal and complement the environment understanding outside of the sensors' view. Despite many deployment projects, the adoption of Cooperative Intelligent Transport Systems (C-ITS) is still limited. The eCall is the first application available; it has been standardised by the European Union after several implementations by car manufacturers and became mandatory for new vehicles from 31 March 2018[1]. The eCall will automatically send a message to the European emergency number in the event of a serious road accident, with information related to vehicle dynamics, as well as Global Positioning System (GPS) localisation.

In the United States and in Europe, the deployment of this technology depends on three progressive steps [10]: (Day 1) Awareness driving using status data (based on cooperative awareness and decentralized notification), (Day 2) Sensing driving via sensor data (using collective perception), and (Day 3) Cooperative Driving using intentions and coordination data (involving coordination or negotiation). These steps involve their respective services and use cases. The services relate to supporting

[1] see http://data.europa.eu/eli/reg_del/2017/79/oj, consulted 10/10/2019

communication; the use cases describe mobility and safety related applications. Day 1 applications have been extensively tested in the field and require simple message exchange that are standardised. Day 2 and 3 applications use more complex messages to extend the sensors' view of the vehicle or to coordinate themselves. The services are still not standardised and several use cases are being developed. The parking use case will build on such communication mechanisms, requiring additional standardized messages (not detailed in this paper).

In terms of connected and automated vehicle's architecture, the communications may interact with the system either at the sensing layer or at the decision layer (Fig. 1):

- The implementation of the first architecture, in real conditions, is recent. It benefits from the advances in communication devices to support the exchange of large quantities of data (such as images and raw sensors' signals). The exchange at this level enables applications such as cooperative perception [11] that relies on the fusion of signals from multiple vehicles and/or roadside equipment to provide an extended perception for automated driving as well as for a driver, or cooperative localisation [12] that relies on the close environment of the considered vehicle to provide better localisation.
- The second one is widespread. It has been initially described by [13] and is the foundation of numerous developments for vehicles acting together (platoon, cluster, merging, etc) as it allows exchange of (small sized) messages between vehicles and with the infrastructure to coordinate the movement of vehicles.

Building on the above architectures, one could envision vehicle-to-vehicle (v2v) message sets for the purposes of cooperative car parking, which we will detail in the next section. The following sections then consider the robustness of such cooperative mechanisms, in the face of fake or misleading messages and anti-social behaviour. Our work has broad implications for all such work involving cooperation via v2v messaging standards that are to come. Fake message injection in v2v communication has been considered in other road situations, as reviewed in [14], different from cooperative parking as we consider here.

Cooperative car parking

In general, a large number of people stream to work or to shopping areas at similar times (e.g., the rush hour). Consequently, a large number of vehicles could be cruising to find car park spaces at similar places, causing a built up of traffic, and with no means of cooperation, cars might compete with one another for similar spaces even if there are good alternatives available. Significant time is then used for parking. With the possibility for vehicles to 'chat' with each other and with infrastructure systems to increase their ability to observe their surroundings, eventually, improved safety and efficient use of road resources can be achieved. In this section, we describe how vehicle-to-vehicle communication can address the challenge of finding car park spaces with a large number of vehicles looking to park using a multiagent algorithm called *CoPark-WS*, first introduced in our previous work in [2].

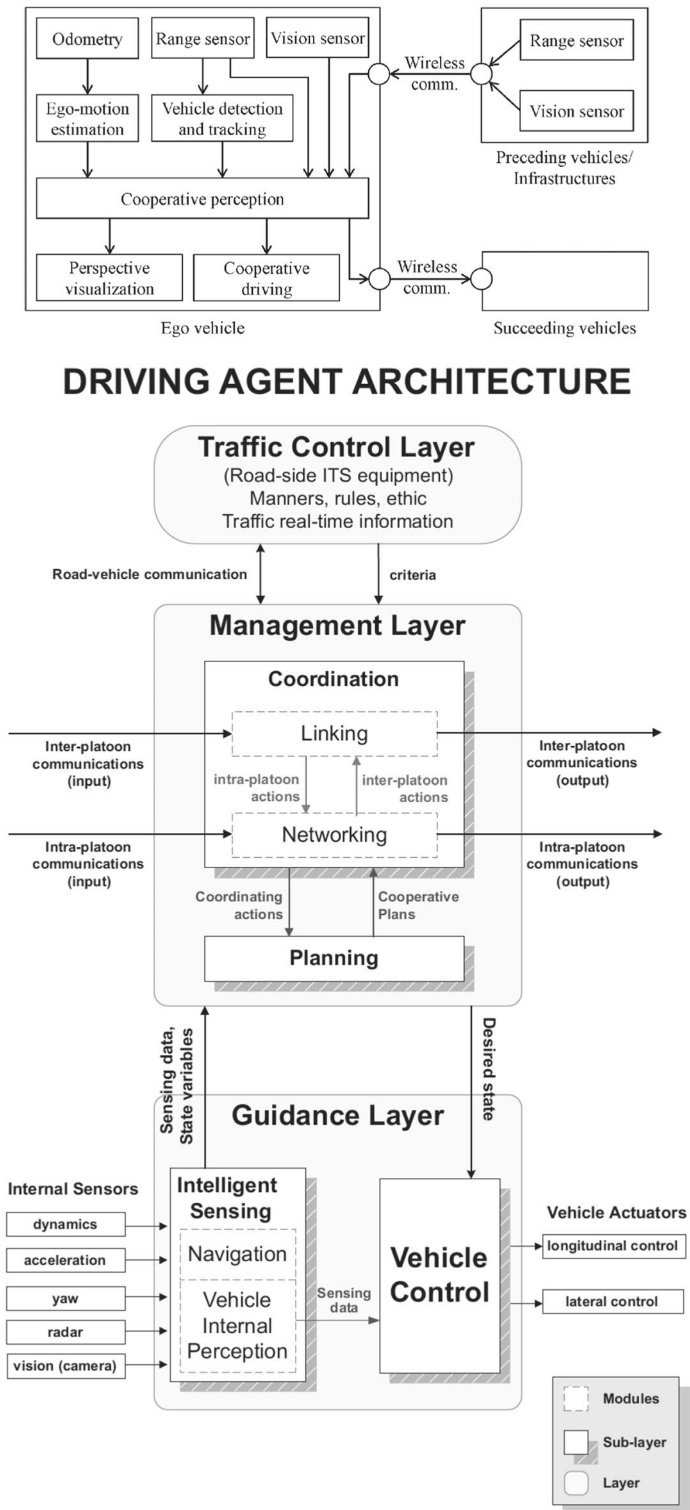

Fig. 1 Architecture for the use of communication in connected and automated vehicles, with an exchange of information at the sensing level (top, from [11]) and at the decision level (bottom, from [13])

CoPark-WS aims to provide a decentralized car park allocation mechanism in large car parks such as at an airport, mall or even a CBD area, assuming an absence of a centralized control unit, depending only on vehicle-to-vehicle cooperation. The vehicles attempt to reduce the searching time to find parking within acceptable levels of fairness with regard to distance to walk to the target building from the parked car, when a large number of vehicles enter the car park at nearly the same time (e.g., at peak hours) from different entrances. It is assumed a smart software agent is installed in the vehicles and vehicles have sensors to detect the parking spaces next to them, and vehicles have GPS navigation capabilities and the agents can cooperate with other agents. Also, it is assumed in our investigation that the vehicles start the searching journey with a static initial belief about parking occupancy patterns which can be inaccurate with respect to the current parking situation.

There are various ways discussed in the literature for predicting parking occupancy based on historical data. For example, occupancy can be estimated by receiving information from parked vehicles via a Road Side Unit (RSU) at the parking gate or by Floating Car Data (FCD). Regardless of the ways of collecting the initial information, in our study, we deliberately supposed that the early and the late coming vehicles all have the same initial belief about occupancy in order to demonstrate how CoPark-WS can deal with the partial and uncertain initial information. In the experiments, the car park area is set to be empty initially, for simplicity. The large car park is divided into equal sized areas. It is assumed that the number of slots in each area is S.

Lets look at our approach from the perspective of an agent (a vehicle). Let M and $O(k)$ represent the total number of areas and the number of *lost areas* with respect to an agent's belief at time k respectively, where a *lost area* is an area with no more vacant slots according to the agent's own current knowledge. Note that our approach is approximate and works with imperfect knowledge - hence, while vehicles work with the knowledge they have, and cooperate accordingly, our approach does not aim to achieve a globally optimal solution, but to improve on the situation of no-cooperation, that is, cooperation using CoPark-WS is better on average than no cooperation as we showed previously [2].

The vehicle, firstly, looks for an area that could be near to the destination (i.e., the building). A vehicle loses the chance to park in an area when the number of parked vehicles in the area is found to be S via information received from other vehicles or via deference to other competing vehicles closer to the area. Consequently, the vehicle will then have to select another area using a heuristic based on our proposed utility function (described later) and messages received from other vehicles. If the vehicle thinks that an area still has parking lots (based on information it has received from other vehicles and on information it gathered itself on the road segments the vehicle has so far traversed), the vehicle will keep going towards the target area and on arrival at the target area, starts to search for a slot within that area. Also, it is possible for a vehicle to lose when competing to get a slot in the target area, wherein, the vehicle has to select another area based on its recomputing of the utility function (applied to potential target areas), and changes its target to go towards a newly selected area.

The details with regards to a vehicle navigating within an area is demonstrated in Fig. 2. The list of areas is sorted in ascending order based on the distance to the building entry, and initially, an agent selects the first area (nearest to the entry), optimistically, as

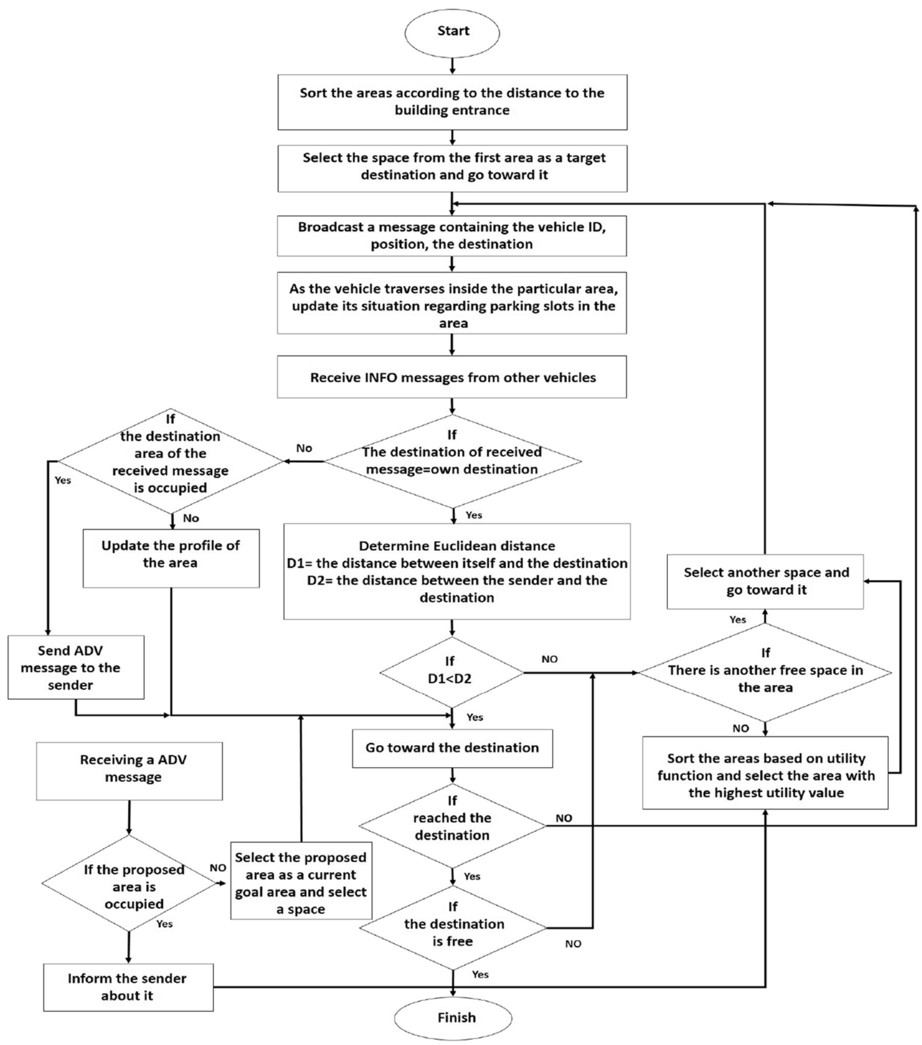

Fig. 2 The CoPark-WS flow chart: searching an area

a target area and goes towards it. In our decentralized approach, each agent adopts the broadcast mechanism to communicate with surrounding neighbours.

The first form of cooperation in CoPark-WS is represented by sharing intentions (i.e., a selected target area or parking space) through disseminating messages called INFO messages. It can be viewed as an extension or a potential addition to range of Cooperative Awareness Messages (CAMs) / Basic Safety Messages (BSMs) in Europe and US standards respectively. Besides containing a vehicle's spatial information (GPS information), vehicle identifier (ID), it includes the vehicle's intentions. There are two cases to be handled.

- Firstly, the agent finds that its own target area is different from that of the sender's, in which case a *demand value* of its target area i is computed by the following formula:

$$D_i(k) = MAX\{0, (\omega_i - \tau_i(k) - \rho_i(k))/\omega_i\} \quad (1)$$

where ω_i is the initial number of slots in area i (which is equal to S in case that vehicle had not visited the area before; otherwise, it is equal to the actual number of available slots at the visiting time, according to its own historical knowledge at time k), $\tau_i(k)$ is the number of vehicles looking to park in the area as determined by the agent based on received INFO (Information) messages at k, and $\rho_i(k)$ is the number of occupied slots in the area based on its own scanning of area i.

- Secondly, if the agent finds from an INFO message it received that the sender and itself have the same target area, the vehicle can determine its likelihood of getting a parking space in the target area by comparing the distance between itself and the target area, and the distance between the sender and the target area (i.e., via this heuristic). If it finds itself further, it determines if there are enough spaces in the target area to still accommodate itself if the sender gets there first. In case there is not enough, the vehicle then reassesses the available areas based on a utility function (given below) and selects another area that has the highest utility value as a new target area. Note that travel distance instead of Euclidean distance can also be used but our simulations here explore the Euclidean distance as a heuristic.

The key idea of computing a utility value is to evaluate areas according to the agent's preferences about distance to the building entry and the number of available areas.

The utility function will involve the availability ratio represented by

$$V(k) = \frac{M - O(k)}{M} \tag{2}$$

In addition, the agent's preference for an area i with regard to distance to the building, which is fixed, and distance to the vehicle's current position, which varies with time, are denoted by weights I_i and $J_i(k)$, respectively. The utility value of an area i at time k is computed as follows:

$$U_i(k) = \alpha * D_i(k) * V(k) * I_i + \beta * J_i(k) * (1 - V(k)) * (\omega_i/(\omega_i - \rho_i(k))) \tag{3}$$

where α and β are human factors and $\alpha + \beta = 1$; they are added to model the driver's personality in being bold (and tending to find a car park slot nearer to the building but at a higher risk of not finding one), or cautious (and tending to find any car park near to the vehicle's position even though far from the building).

In the case of vehicles already inside their target areas, the cooperation policy is different. Instead of contesting for an area in general, the vehicles will each select a particular slot and go towards it, sending INFO messages to announce to other vehicles about its goal (which is a target parking slot). A vehicle changes its target slot when it detects that the slot is occupied or, from an INFO message received, it finds that there is another vehicle intending to get to it and is nearer. In the situation where the area still has other free slots, the vehicle can select another slot. Otherwise, the vehicle will need to reassess the available areas based on the utility function and select an area with the highest utility value as its next target, as before.

Vehicles sending advice messages, which is a new type of vehicle-to-vehicle message related to CoPark-WS, is the second form of cooperation considered in CoPark-WS. Advice sharing is a strategy for vehicles to help each other. As mentioned earlier, a vehicle can know the target area of another vehicle when it receives an INFO message from that vehicle. Based on its own knowledge, the vehicle might know that the target area of the other vehicle is already fully occupied; the vehicle can then send a unicast message, called an ADV (advice) message to the other vehicle, informing it that its target area is occupied and also suggesting another potential target area to that vehicle. The area this vehicle suggests to the other in such a case is the second choice area of this vehicle (rather its own first choice, in aiming to reduce contention). The receiving advisee vehicle can accept the suggestion, or reject it in case it recognises the suggested area is occupied, in which case it can reply to the advisor vehicle about that.

Experimentation

Simulation tool and experiment configuration

We have used an integrated simulation environment, a combination of JADE [15] and SUMO [16] programs, for evaluating CoPark-WS's performance. JADE, which stands for Java Agent Development framework, is adopted to implement the agent behaviour (assumed to be installed in a vehicle) that makes decisions on behalf of the driver for selecting a parking slot, based on cooperation with other agents and on collecting physical information from attached sensors (e.g., about vacant slots near it). SUMO is used to model the road network and basic vehicle behaviour. Furthermore, we connect JADE and SUMO through the TraSMAPI interface (Traffic Simulation Manager Application Programming Interface) [17].

The connection between SUMO and JADE is based on a client-server approach by using the TCP socket protocol for exchanging messages. SUMO is provided with a tool called TraCI, which is an interface protocol that enables external applications to access and control the simulated transportation system elements such as vehicles, traffic light signals, and road sensors. TraSMAPI interacts with SUMO via TraCI. SUMO is used to create a car park area scenario and to model the vehicle movements. In addition, SUMO represents the server-side that provides real-time data of the running scenario to JADE and executes JADE requests; for instance, for changing vehicle routes and speeds. JADE, which represents the client-side, provides the agent programming environment for creating and programming agents corresponding to the "brains" of the vehicles. After establishing the connection, control will transfer to the listening mode for the client (JADE) commands, which is mapped to the permitted TraCI commands. Accordingly, the status response message which contains the required information is sent in response to the corresponding command. After launching SUMO, the car park scenario is loaded. After that, SUMO will change to the listening mode for receiving JADE request messages via the predefined port, which is set to 8820. More details of the simulation including source code are provided via the project Website.[2]

A simulated large car park representing a car park of size 1000×500 m area has been used to evaluate CoPark-WS with 120 distributed free parking slots. The default communication range of a vehicle is set to 300 m. Note that the simulated V2V communications

[2] https://sites.google.com/view/aliedanicode/.

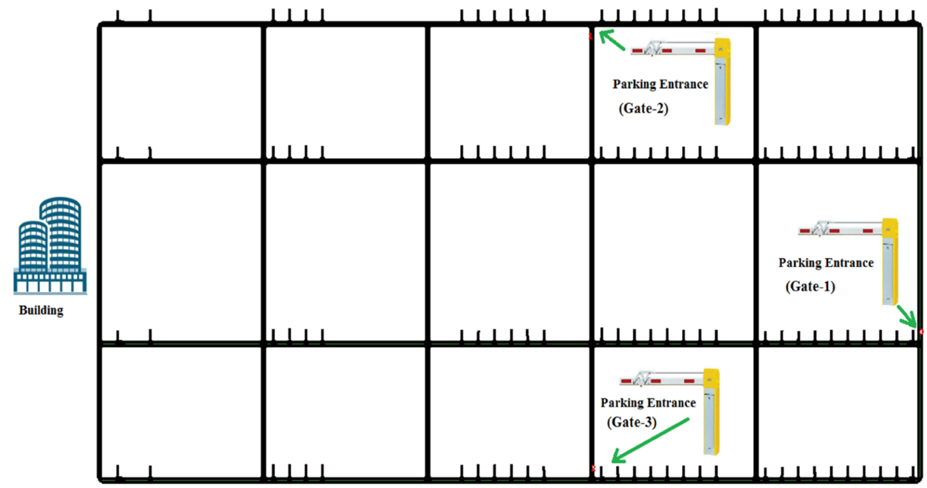

Fig. 3 The simulated car park area

could correspond to a real DSRC type V2V communications or 5G/LTE-V2V communications, but our simulation results are agnostic to this.

The designed car parking scenario attempts to capture the common characteristics of a large car park or an urban area (e.g., a CBD area). With the objective to assess CoPark-WS in various car parking circumstances, the position of the final destination and park entrance gates, in experiments, are considered in two car park structures. The first is shown in Fig. 3.

The building, representing the final destination, is located on one side of the car park, while the car park gates are located on the other side. Moreover, it is assumed that vehicles are entering via the three gates (Gate-1, Gate-2, and Gate-3) in a round robin manner and with IDs according to the entering order. For example, vehicles of ID 1,2, and 3 would enter via the gates Gate-1, Gate-2 and Gate-3, respectively.

The second car park structure is assumed in the experiments related to gang behaviour, as shown in Fig. 9. There are two parking entrances located on the car park area border with a distance of 1000 m between them, and the vehicles arriving in even-numbered order would enter from one gate, and the others from the second gate, while the final destination located on the opposite side in the middle. For the utility function, α and β are set to 0.6 and 0.4 respectively, to almost balance the intention of the individual between parking near the building or parking near where the vehicle currently is.

Proportion of participating vehicles

In this section, we evaluate the influence of CoPark-WS performance via computing the average searching time of vehicles looking to park with different percentages of equipped vehicles with wireless communication capability, implementing the CoPark-WS approach. The average searching time can be defined as the average time spent from entering the car park till obtaining a parking space. The times of equipped and non-equipped vehicles, as well as the average searching time for all vehicles, are obtained.

It is assumed that non-equipped vehicles use a greedy algorithm (which we call GD (Greedy)) with initial information of locations of car parking spaces.

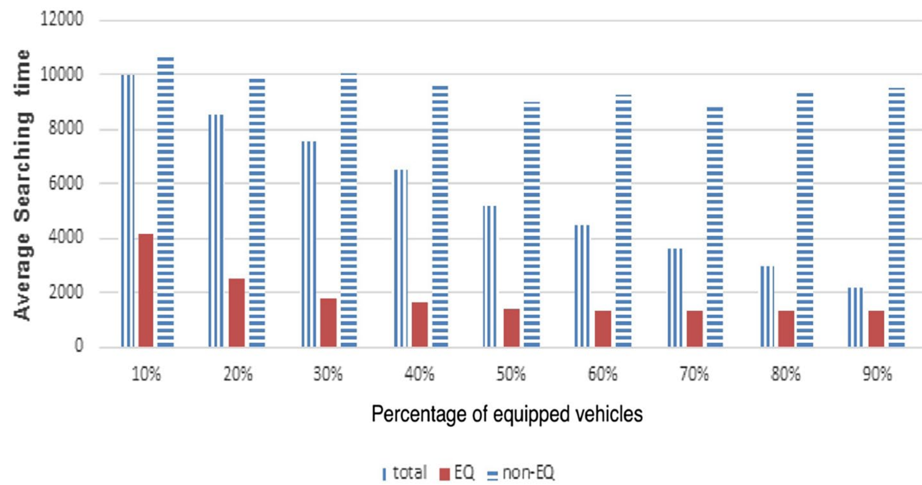

Fig. 4 The average searching time with averages for the equipped vehicles (EQ), non-equipped vehicles (non-EQ) and all vehicles using CoPark-WS (total)

Assumptions and settings. In GD approach, there is no cooperation and it depends on the driver's observation to find a parking space. It is assumed that the drivers can observe up to a range of 50 m. In addition, vehicles in the GD scenario aim only to park near the building entry without regard for the time spent to find a parking space. In this scenario, for a penetration rate of X%, i.e., it is assumed that the first X/10 of every 10 vehicles of a total of 100 vehicles is equipped with wireless communication capabilities and have the ability to cooperate. For example, in a situation where the rate is 30%, the first 3 vehicles of every sequence of 10 vehicles entering the park can cooperate.

Results. Figure 4 shows the average searching time with different penetration rates (i.e., different extents of cooperation), the average of the equipped vehicles (i.e., vehicles which cooperate as they are equipped with devices to do so), the average of the non-equipped vehicles (i.e., vehicles which cannot cooperate) and the average over all 100 vehicles. It can be seen that the equipped (cooperating) vehicles have a much lower average searching time than non-cooperating vehicles. The non-equipped vehicles took consistently longer to search for a parking space due to their selfish behaviour in trying to first park as near to the building as possible, unaware that many equipped vehicles had already parked there—upon finding those parking lots near the building occupied, the non-equipped vehicles then continue to search further. With an increasing percentage of equipped vehicles, there is a gradual decrease in the average searching time for all the vehicles, i.e., having more cooperative vehicles improves the situation for all, even the non-cooperating ones, to an extent. With more cooperation, the average searching time for the equipped vehicles decreases but only up to around 50%, after which the performance is fairly stable. This is because there is still a basic level of competition among the vehicles (equipped or not). It can be seen above that cooperative parking improves average searching time. The next section will study the effects of sending false information, via ADV messages, on the CoPark-WS approach.

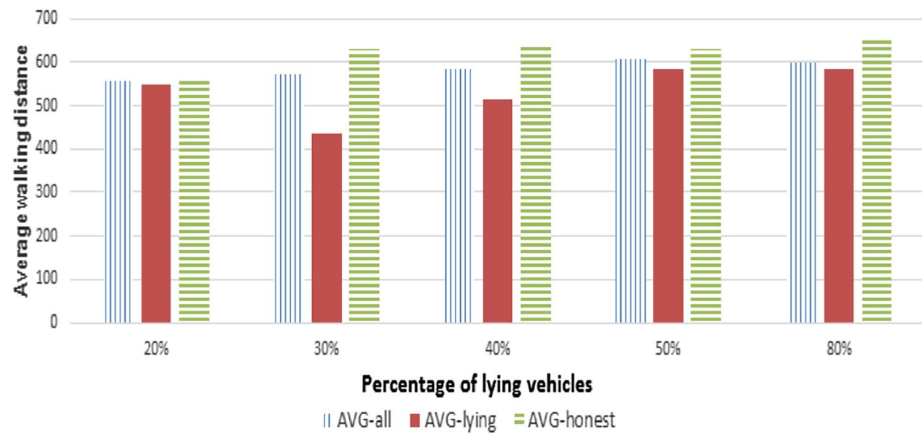

Fig. 5 The average walking distance to the building, taken over parked honest vehicles (AVG-honest), lying vehicles (AVG-lying) and all (honest and lying) vehicles (AVG-all) with 20%, 30%, 40%, 50%, and 80% of lying vehicles

Truthfulness of ADV messages

In this section, we attempt to find an answer to the question: *can the vehicles in CoPark-WS enhance the possibility of finding better car park spaces in their preferred areas by deceiving other vehicles through sending incorrect information in ADV messages?*

Assumptions and settings. With 80 vehicles implementing CoPark-WS with different percentages of lying vehicles, a number of simulation scenarios are executed. Note that, in this section, the lying vehicles are working individually and not part of a coalition. A lying vehicle's behaviour is modelled by sending ADV messages with incorrect information, i.e., to inform the other vehicles that are attempting to park in the same target area as itself that the area is occupied and suggest some other area. In the car park scenario, there are 120 parking slots distributed in a manner which gradually decreases in number towards the building. The vehicles with even *ID* numbers are selected as lying vehicles in different percentages.

Results. Figure 5 shows the average walking distance to the building entry of the honest vehicles, the lying vehicles and of all 80 parked vehicles, with different percentages of lying vehicles. With small proportions of lying vehicles (e.g., 20%), the average walking distance is similar for all types. The lying vehicles obtain benefits as they constitute more of the vehicle population, e.g., 30%, with a sharp drop in walking distance compared to 20% of lying vehicles. But moving up from 40% to 80% of lying vehicles, benefits decrease, till there is no more advantage from lying, when most vehicles are deceived into parking away from the building.

Figure 6 shows the walking distance of successively parked vehicles with varying numbers of lying vehicles. In normal situations, we expect the nearest slots to the building to be occupied first and, in time, the slots further away are occupied—the idea is that the "early birds get the worms". However, unfairly, with deceit, further away slots are occupied earlier when we have more lying vehicles, since vehicles which are lied to (i.e., are told that slots near the building have been occupied) will end up parking further away. It can be seen here that with more lying vehicles, the overall trend is to increase the walking distances, causing inefficiencies within the whole system.

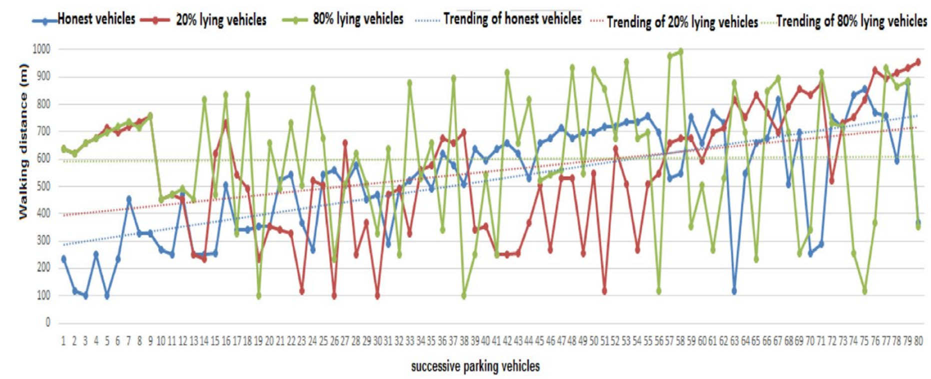

Fig. 6 The walking distances of successively parked vehicles of 80 vehicles with 0%, 20%, and 80% of lying vehicles

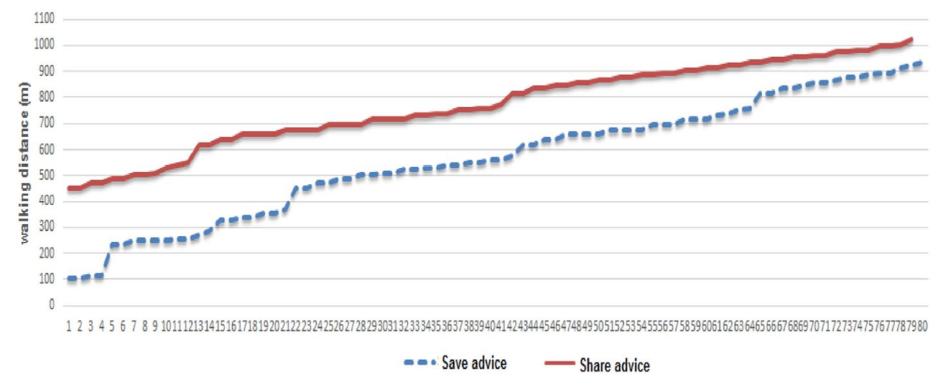

Fig. 7 The walking distances, in ascending order, of 80 parked vehicles, with (30%) lying vehicles and with two situations: save/keep advice they get or share the advice they get (passing them on). (Note that for the share advice case, one vehicle cannot at all find a parking space)

In the previous simulation scenarios, it is assumed that advisees keep the advised information, use the information themselves only, and only give advice according to their own experiences, i.e., they do not pass on ADV messages they received to other vehicles.

In the next scenario, we assume that the advisee can grant advice based on its own experience and also what is received from ADV messages (i.e., they pass on advice (ADV messages) they received). Figure 7 shows the walking distances of parked vehicles sorted in ascending order based on distance to the building entrance, with two situations: 30% of lying vehicles are passing on their advice to others, versus not passing on the advice they received. It is observed that the effect of untruthful advice when passed on leads to more vehicles being deceived and parking away from the building and one vehicle could not find a free space even when the number of slots (120) exceeds the total number of vehicles (80). The scenes for passing on advice (i.e., share) and not share (i.e., save) is given in Fig. 8, showing that passing on bad advice can quite radically affect the results, so that a cooperative approach is vulnerable to unchecked spreading of wrong advice.

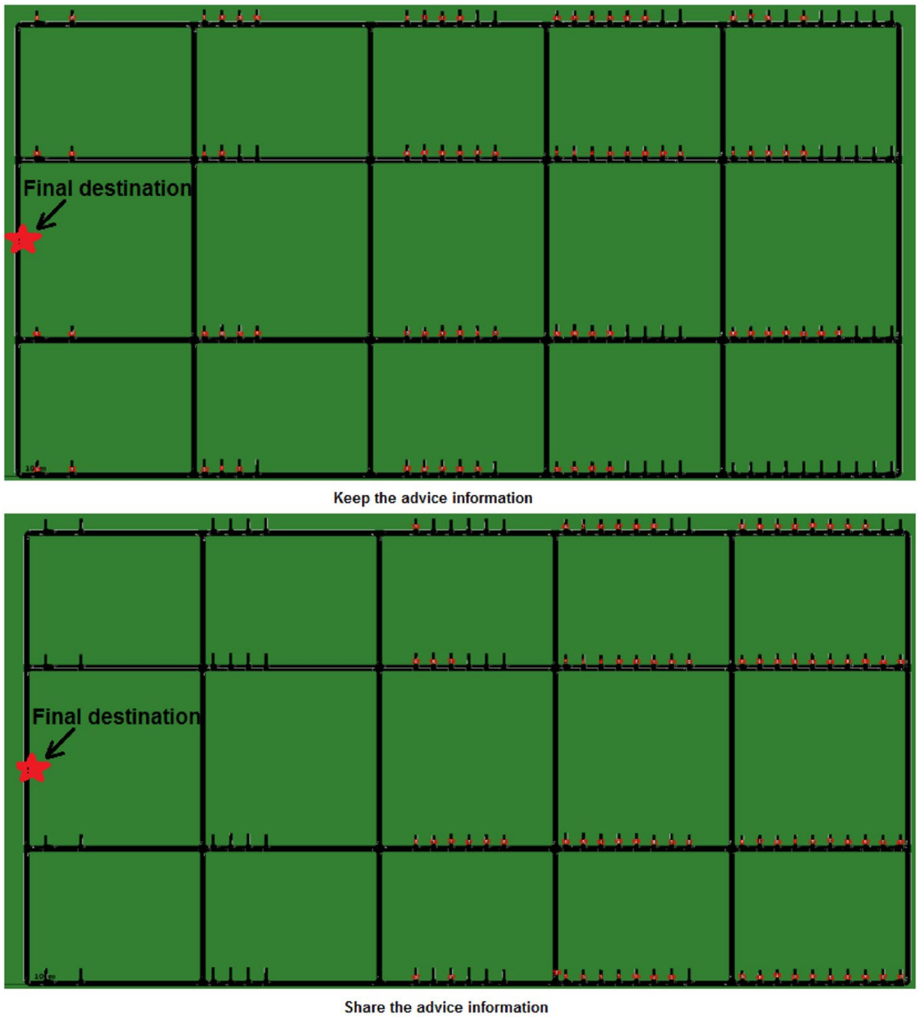

Fig. 8 The two scenes of parked vehicles with (30%) lying: not sharing (i.e., keeping) advice messages (top), and sharing advice messages (bottom). It can be seen that sharing bad advice leads to cars parked further away from the final destination

The impact of gang behaviour

In this section, we investigate the influence of selfish behaviour of a coalition (which we call a *gang*) of (in particular, self-driving peer-to-peer networked) vehicles that send false advice to deceive other vehicles (not in the gang) to get them to avoid going to a given chosen area (as chosen by the gang), in turn, enhancing the gang members' own opportunity to get better parking spaces closer to the final destination.

Assumptions and settings. The vehicles belonging to the gang accept truthful advice just from the gang members and ignoring messages from the others, while those not in the gang accept and take the advice of messages from any vehicle. With 80 vehicles in total, different gang sizes with different chosen area conditions are implemented. In general, in our simulation set up, it is assumed that there are two parking entrances located on the car park area border with a distance of 1000 m between them, and the vehicles arriving in even-numbered order would enter from one gate, and the others from the

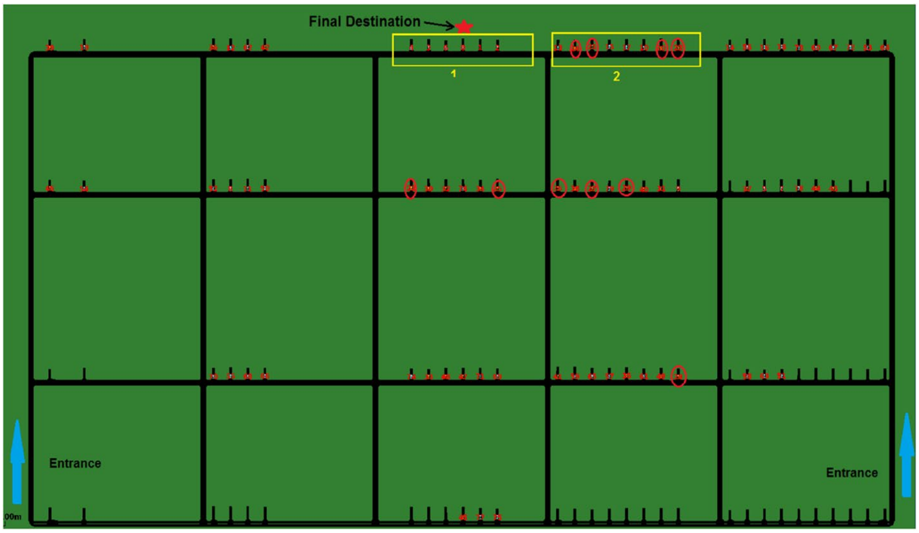

Fig. 9 The scene of parked vehicles in a normal situation

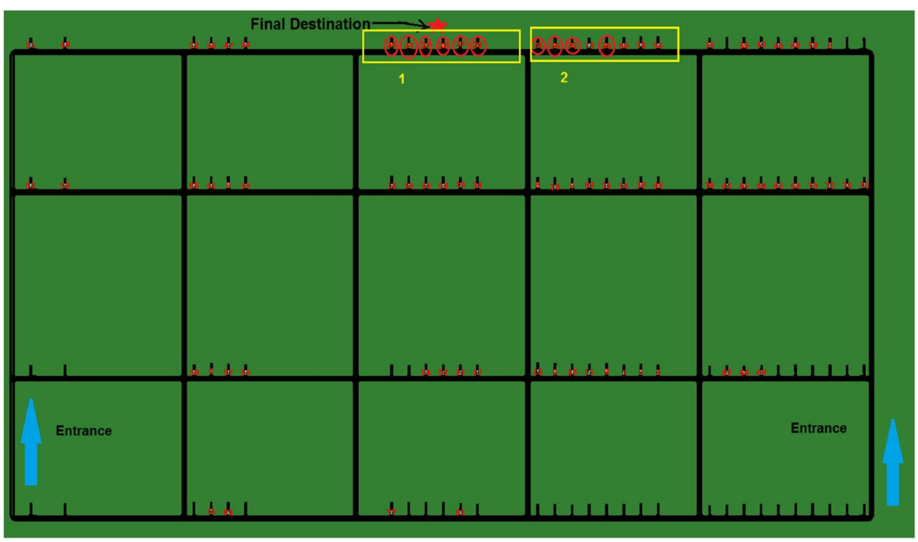

Fig. 10 The scene of parked vehicles with a gang of 10 members

second gate. Firstly, a gang with 10 members is implemented, comprising vehicles of order 20 to 29, which means they enter from both gates and they are not the vehicles entering the area early. The gang members lie by giving advice to other non-gang vehicles that the first two areas nearer to the final destination are fully occupied.

Results. Figure 9 shows a screen shot of the vehicles getting a parking space with the CoPark-WS algorithm in normal situation without gang members lying, where the gang vehicles with id between 20 and 29 are circled in red, and the two chosen areas are marked with yellow rectangles with numbers representing the first two favourite areas with regard to the distance to the final destination. Figure 10 shows the same scenario but gang members lying. It can be seen that all gang vehicles are parked in the two

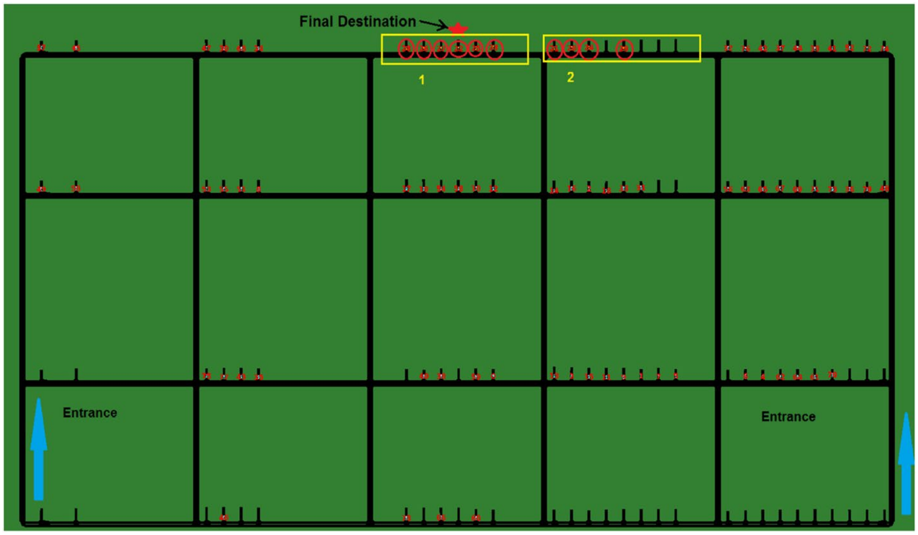

Fig. 11 The scene of parked vehicles with 10 gang members and sharing advice condition

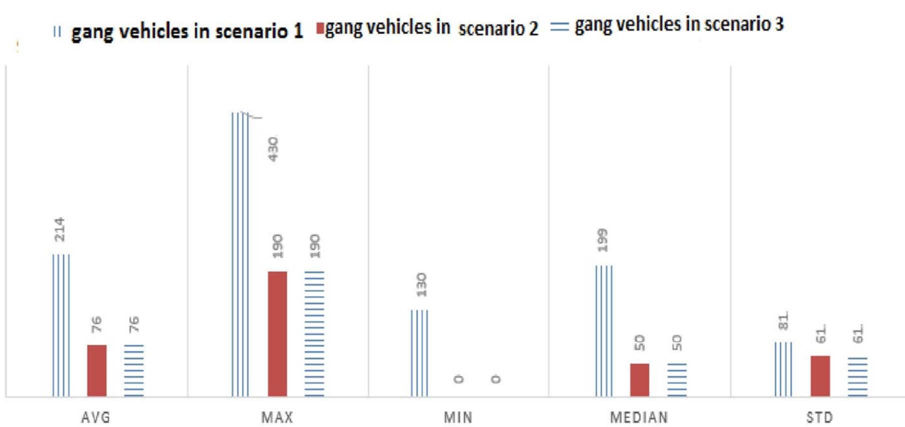

Fig. 12 The average, maximum, minimum, median, standard deviation values of the walking distances of 10 vehicles with IDs from 20 to 29 for gang vehicles in scenarios 1, 2, and 3

favourite/chosen areas; there are 14 parking spaces available in the two favourite chosen areas. The extra parking slots, i.e., the four parking spaces, are occupied by the vehicles coming in later (after all gang members have parked) which were not influenced by any false advice.

Figure 11 shows a similar scenario as in Fig. 10 but with sharing advice so that false advice messages of gang members continue to propagate even after the gang members have parked. The extra parking slots are still vacant as a result of the continued propagation of malicious advice even after all gang vehicles have parked.

Figure 12 shows the benefit of forming and being part of a gang which consists of 10 members by showing the average, maximum, minimum, median, and standard deviation values of the walking distance of the gang vehicles in normal circumstances, which means without gang behaviour (which we label as scenario 1), and of the gang vehicles

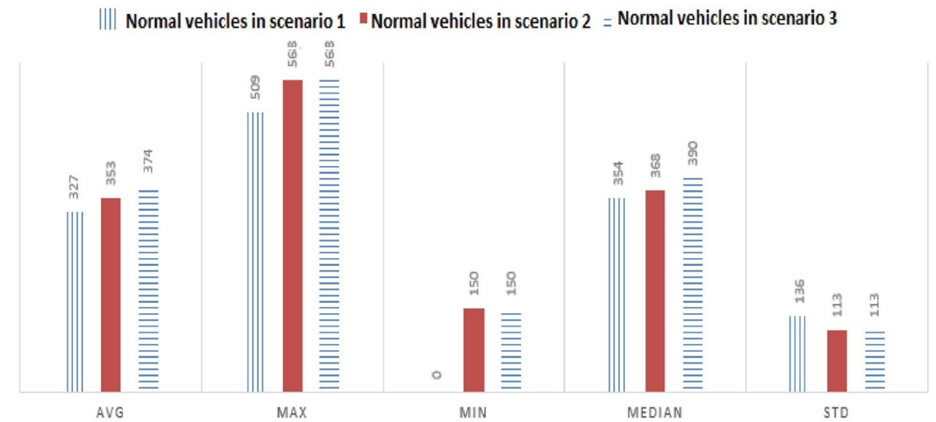

Fig. 13 The average, maximum, minimum, median, standard deviation values of the walking distances of 70 normal vehicles in scenarios 1, 2, and 3. Note the degrading in performance of non-gang cars due to the presence of gang behaviour

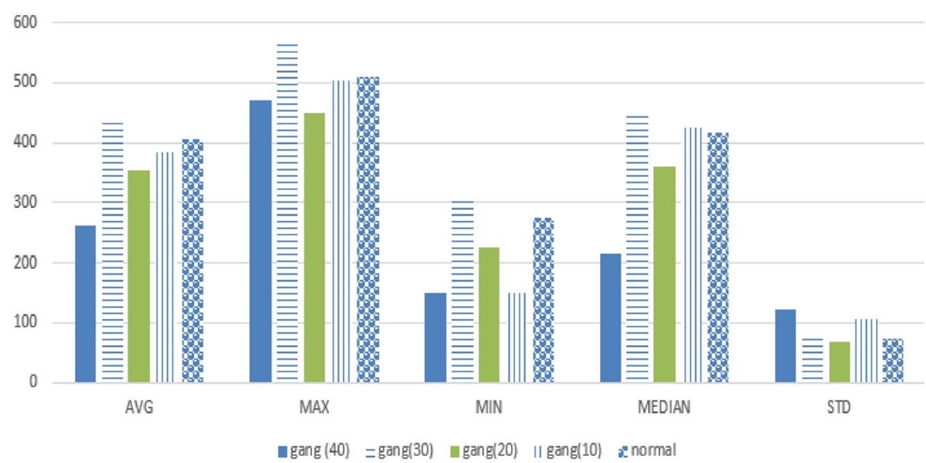

Fig. 14 The average, maximum, minimum, median, standard deviation values of the walking distances of the vehicles with IDs in the range from 50 to 59 and with various gang sizes: 10, 20, 30, and 40 members

when they collude with the above gang behaviour, in two situations: without (labelled as scenario 2) and with vehicles sharing advice (labelled as scenario 3). The gains of gang behaviour for individuals in the gang is clearly shown, as demonstrated by the reduced maximum, minimum and median values, and for the gang overall, as represented with average and standard deviation values. Figure 13 demonstrates the impact of the gang on the residual vehicles (normal vehicles), which consist of 70 vehicles, within the same situations as in Fig. 12. The effect of increasing the walking distance of non-gang vehicles can be observed, without and with sharing advice.

With extending the gang size, a vehicle's chance to get a parking space nearer to the building would be altered. In the simulation, we have gangs of sizes 10, 20, 30, and 40 members among 80 vehicles streaming into the car park in order of their IDs. The gang members's IDs are between (20–29), (20–39), (20–49) and (20–59) for gang size 10, 20, 30, 40 members, respectively.

Figure 14 shows the average, maximum, minimum, median and standard deviation value for vehicle IDs (50–59) with different gang sizes as described above. In general, the vehicles who are nearer to the gang members tend to get worse car parking (further from the final destination building) than the others. As shown, the values in the case of gang size 10 is near to the values in the normal (no-gang) situation as a result of the relatively large distance between these vehicles (IDs 50–59) and the gang vehicles. The walking distance values are generally reduced for vehicles 50–59 with gang behaviour of gang size 10 and 20 since the earlier vehicles which are nearer to the gang get bad advice and are parked further, so that, consequently, vehicles 50–59, coming in later, tend to get better car park spaces nearer to the building (the final destination). However, the vehicles 50–59 are badly affected in case of gang size 30 (since then, vehicles 20–49 are gang vehicles which are close to vehicles 50–59). Finally, when gang size is 40, vehicles 50–59 are themselves gang members and so they get the best values (lowered walking distances).

Deception detection and intervention

As shown from the preceding sections, sending false information would negatively impact on the chances of the normal (e.g., non-gang or truthful) vehicles in getting to park in the spaces in the chosen areas (i.e., nearer the building), in both situations of dishonest vehicles working: individually, or in a gang. Consequently, vehicles have to take into account these situations by verifying the received advice and cooperating with other vehicles to reduce the effect of deceitful vehicles.

The DDM approach

Here, we introduce a deception detection mechanism (DDM) to CoPark-WS algorithm in order to limit the influence of sending incorrect advice for selfish intents. It is a decentralized approach, which makes it more challenging without complete global knowledge of vacant parking spaces and so, there is a need to handle uncertainty. Our approach depends on vehicles integrating and validating received advice using our proposed Verified Function (VF) and a reputation mechanism to reduce the effects of bad vehicles. We will explore three DDM versions, namely, DDM-C, DDM-D and DDM-R which denotes detection mechanisms with key ideas Confirmation, Direct, and Rating, respectively. They differ in the way of handling the suspected vehicles.

At the beginning, the vehicles have to verify the content of received advice messages based on a heuristic function called VF, where VF is a linear combination as shown below:

$$VF(t) = a \times \Lambda(t) + b \times \sigma(t) \tag{4}$$

where $\Lambda(t)$ is a measure of the proportion of the distance between the vehicle itself to the target area (to which the received advice message refers) to the distance of the advisor (i.e., the sender of the advice message) to the target area. $\Lambda(t) = \frac{D1(t)}{D2(t)}$ where $D1(t)$ is the distance between the receiving vehicle (vehicle receiving the advice) and the target area and $D2(t)$ is the distance of the advisor to the target area. $\sigma(t)$ is the occupancy state of the current area where the vehicle is currently located, which is equal to the ratio of the number of occupied slots to the total size (slots) of the area. Both factors are

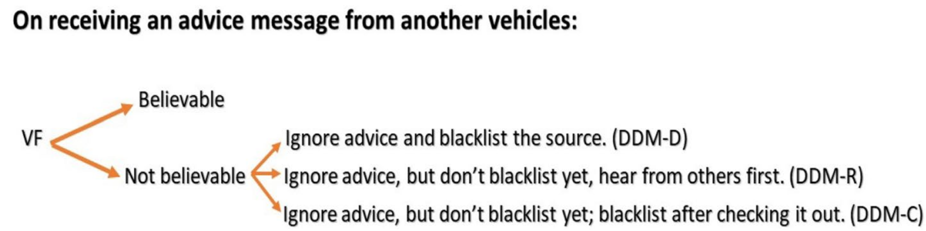

Fig. 15 The three DDM mechanisms compared, in summary

computed with regards to current time since their values vary with time. In addition, the weights a and b are used to weigh the factors in order to reflect their relative importance. In the following experiments, both values are set to *0.5*.

The objective of the VF function is to weigh the advisor's distance to the target area relative to the advisee's position, since the heuristic we consider here is that the one nearer would likely have more knowledge about the target area, and to consider the occupancy situation of where the advisee is located, which is used to predict the occupancy situation of the target area based on the spatial relationship between the areas—based on the heuristic: "if it is not busy where I am, it may not be busy where the target area is whatever the advice message says and I can distrust a message that says that the target area is busy". Hence, when receiving a message, a vehicle can compute the VF value of the message and if it is low or below a threshold, the vehicle could distrust the message.

Figure 15 illustrates the differences in the three DDM mechanisms when receiving a message. A message is considered not believable if the VF value is less than a given threshold value, and considered believable, otherwise—the higher the threshold, the more messages would be considered as bad, that is the more "skeptical" a vehicle is.

In case the VF value is less than a preset threshold value, in DDM-C, the vehicle would ignore the advice message (not to go to the target area) from an advisor vehicle, and keep going towards the target area. The vehicle will also broadcast a complaint about the advisor vehicle (announcing the vehicle ID of the fake message sender) if it finds that there are actually free slots in the target area. Subsequently, the received vehicles would add the name of the lying vehicle to its own blacklist, and cooperatively, broadcast the list to stop the impact of the bad vehicle on the others. The normal (non-deceitful) vehicles would discontinue cooperation with the bad vehicles through rejecting advice from them and not giving them advice. In this approach, all vehicles in the blacklist are considered "guilty" because they are added just after confirming that they lied. However, there is a delay to declaring them to be in the blacklists, especially with a large car park area, as the vehicles need to arrive at the target area to discover (and determine for themselves if what was said in the advice message was true) and time is needed for announcing the blacklists. Consequently, due to the delays, some vehicles might still compute VF values as being more than the threshold value for deceitful advisors, and fall victim to them.

However, in the DDM-D method, a vehicle takes a "suspicious" attitude and considers the advisor as deceitful just when the corresponding VF is less than the threshold and inserts the ID into the blacklist (without further verifying as in the case of DDM-C), and shares this with other vehicles, consequently, reducing the chance of gang

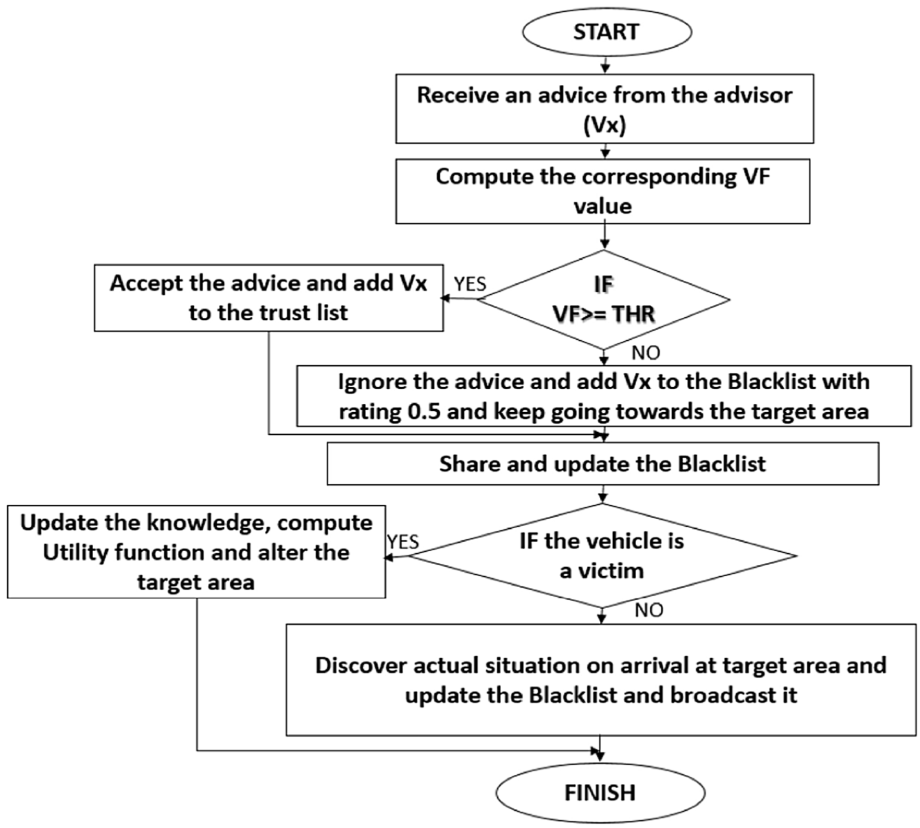

Fig. 16 The flow chart of DDM-R algorithm

members deceiving other vehicles. But at the same time, some honest advisors could be wrongly blacklisted for a period of time because the VF is a heuristic (which means it is not guaranteed to correctly classify vehicles as deceitful); the advisee vehicle then arrives at the target area and might find that it is really fully occupied, and subsequently, it has to correct this situation by announcing that the advisor is honest and has to remove that advisor from the blacklist (announcing the new blacklist). Hence, DDM-C takes the optimistic view of "innocent until proven guilty" and DDM-D takes the pessimistic view of "guilty until proven innocent".

On the other hand, the DDM-R, as shown in Fig. 16, attempts to increase the possibility of recognizing a bad vehicle before itself arriving at the target area (for verification) by adopting a rating mechanism. There are three categories for an advisor vehicle, which are good, suspicious, and bad. The vehicle classified as good and suspicious can send and receive advice. If a vehicle received an advice from a vehicle (say named Vx) and the computed VF value is larger or equal to the threshold value, the vehicle Vx will be considered as a good vehicle, adding its ID to the good-list and accepting the advice. Otherwise, the vehicles sees Vx as suspicious and a rating value of 0.5, inserts it into the blacklist, and still holding on the advice, the vehicle keeps going to the target area. While sharing the blacklist among vehicles, a vehicle can receive the blacklist of other vehicles (and might get to know what others think about

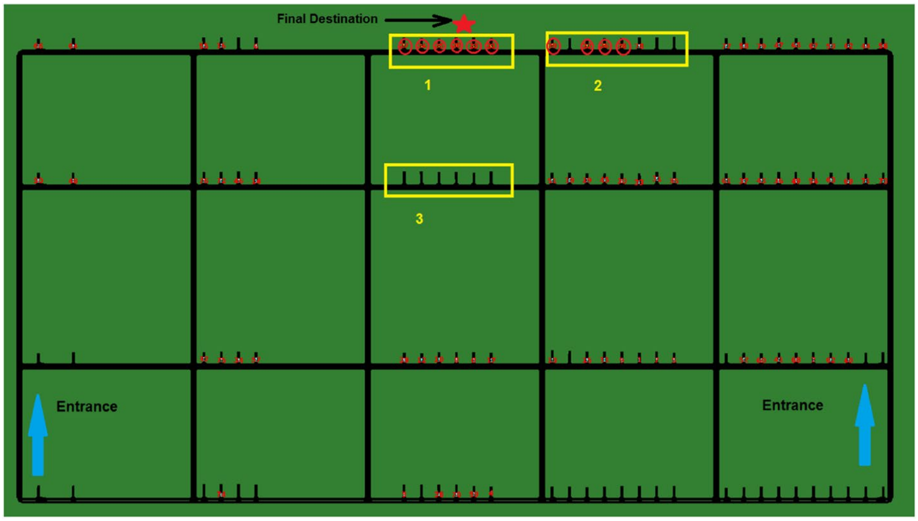

Fig. 17 The scenario of the gang "reserving" three areas (yellow rectangles) by sharing fake advice; this is without a deception detection mechanism in use—gang members circled in red and are all right in front of the final destination (assumed a building entrance)

Vx), so that Vx's classification can change to a bad vehicle when it finds that there is another vehicle also suspicious about Vx. Then, the vehicle can revise its plan and re-route its way in the case of finding out that it has been following the advice of a vehicle, now re-classified as bad, i.e., it finds that it is a victim accepting advice from a bad vehicle. The other condition where a vehicle can reclassify a suspicious vehicle as bad is when the advisee arrives at the target area and discovers that the advice in this situation is inaccurate, and before the advisee vehicle parks, it will announce about the bad vehicle. Note that our heuristics above are not necessarily fullproof and some vehicles might be wrongly reclassified as bad due to dynamic changes in the car park, but nevertheless, we investigate such an approach to address deceitful situations.

Experiments with DDM

Experimentally, we have investigated the proposed interventions mechanisms through comparing with the scenario without involving DDMs and with sharing advice among vehicles.

Assumptions and settings. The vehicles belonging to the gang accept truthful advice just from the gang members and ignore messages from the others, while those not in the gang accept and take the advice of messages from any vehicle. We experiment with 80 vehicles in total, 10 of which are gang members. In general, in our simulation set up, as before, it is assumed that there are two parking entrances located on the car park area border with a distance of 1000 m between them, and the vehicles arriving in even-numbered order would enter from one gate, and the others from the second gate.

Results. Figure 17 shows the scenario without a deception detection system. The gang consists of ten members, which are circled with red circles, declaring to the normal vehicles that areas 1, 2, and 3, which are marked with yellow rectangles are fully occupied and proposing other areas which are further from the building (though

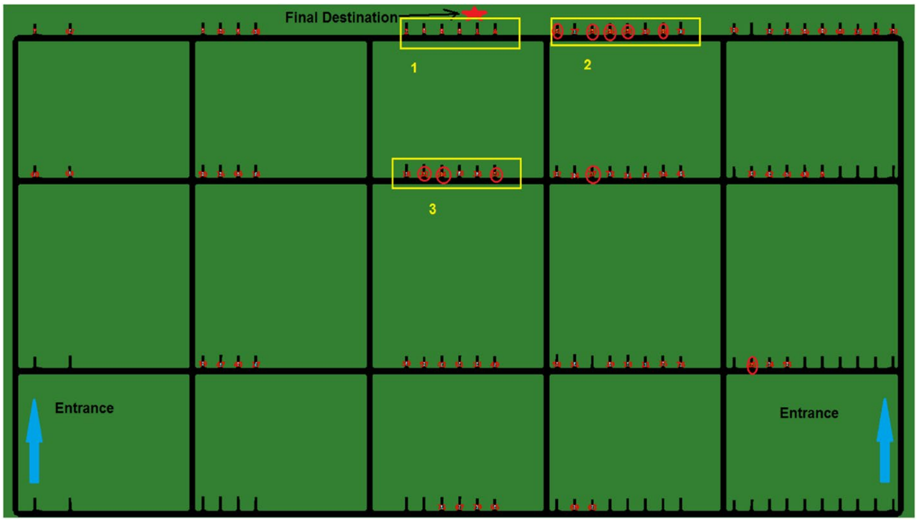

Fig. 18 The scenario of the gang "reserving" three areas with sharing fake advice but with DDM-D in place—gang members circled in red and it is no longer the case that all are right in front of the final destination (assumed a building entrance)

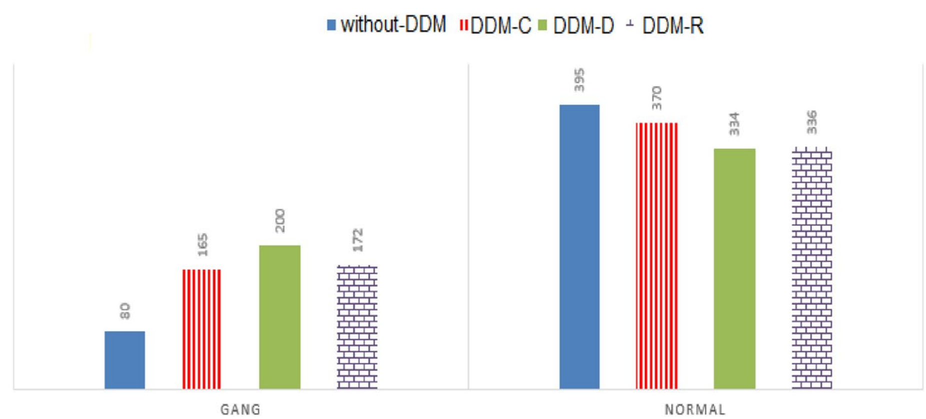

Fig. 19 The average walking distance (the lower the better for normal vehicles) of gang and normal vehicles without a DDM, and with DDM-C, DDM-D, and DDM-R mechanisms

there are vacant slots in areas 2 and 3). Interestingly, Fig. 18 illustrates a similar scenario but with implementing DDM-D. It can be seen that the normal vehicles can detect the bad gang vehicles at an early stage and, largely, the gang's advantage from sending fake advice messages is reduced.

Figure 19 shows the average walking distance (from where a vehicle is parked to the entrance of a building, i.e., the final destination) of gang vehicles and the normal vehicles in the following circumstances: without a deception detection mechanism, and with implementing the three DDM versions (DDM-C, DDM-D, and DDM-R). The gang attained the goal of capturing the parking spaces nearer to the building in the absence of a DDM with average walking distance equal to 80 m, far less compared to normal (non-gang) vehicles, with average distance 395 m. This situation is altered

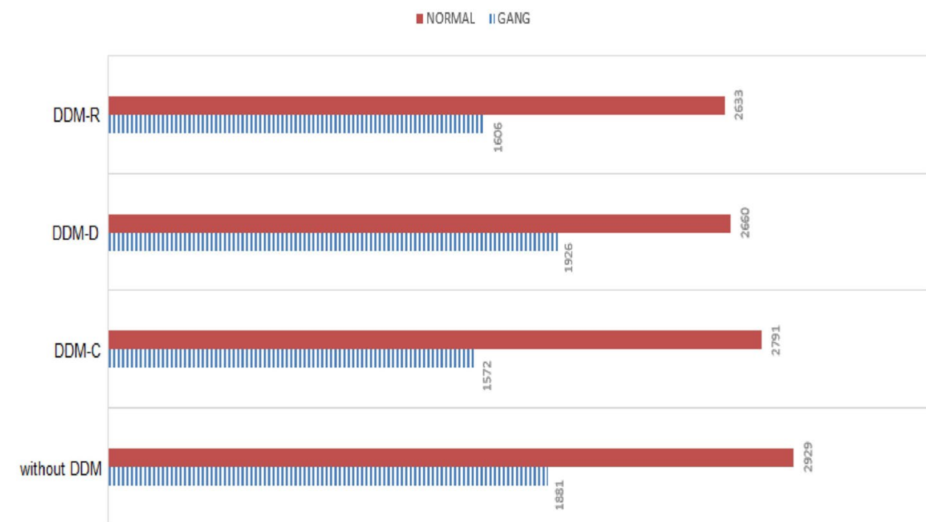

Fig. 20 The average arrival time of gang and normal vehicles in the cases without a DDM, and with DDM-C, DDM-D, and DDM-R mechanisms

by having the normal vehicles employ DDMs, and thereby, reducing the impact of gang deceit by allocating the parking spaces in a fairer manner (i.e., allocating the parking to who comes first or are nearer). There is an increase in the average walking distance for the gang members to 165 m, 172 m, and 200 m with DDM-C, DDM-R, and DDM-D, respectively. The normal vehicles obtain the parking slots with reduced average walking distances by applying DDMs, in particular DDM-D which recognizes the gang members at an early stage.

The arrival time of vehicles is explored in Fig. 20, where the arrival time is a combination of the time to find parking spaces and the walking time to reach the building. There is a decrease in average arrival time of normal vehicles with a DDM implemented compared to without a DDM, since overall, with a DDM, some normal vehicles do not have to circulate so much to find parking spaces. For the gang, a higher value is computed in the case without DDM because, even though their walking times are reduced, the gang members then need to traverse along the car park area to get to the parking spaces nearer the building. DDM-D is similar to without a DDM since while gang members are identified, and their effects reduced so that their walking time is increased as they park further, their time to park might be reduced as they might park sooner. Moreover, more vehicles tend to be classified as gang members sooner and perhaps inaccurately in DDM-D than in say DDM-C and DDM-R, so the benefits of cooperation might be reduced.

Furthermore, we evaluated the influence of the threshold value of the Verified Function (VF) on detecting bad vehicles—recall that messages with VF values below the threshold are considered bad and are ignored. Figure 21 describes the average walking time of gang and normal vehicles with DDM-D with different threshold values. For normal vehicles, this range of threshold values did not significantly affect performance. For gang vehicles, a threshold of 0.5 yielded the best performance for the gang. Higher thresholds tend to cause more messages to be rejected overall, so that

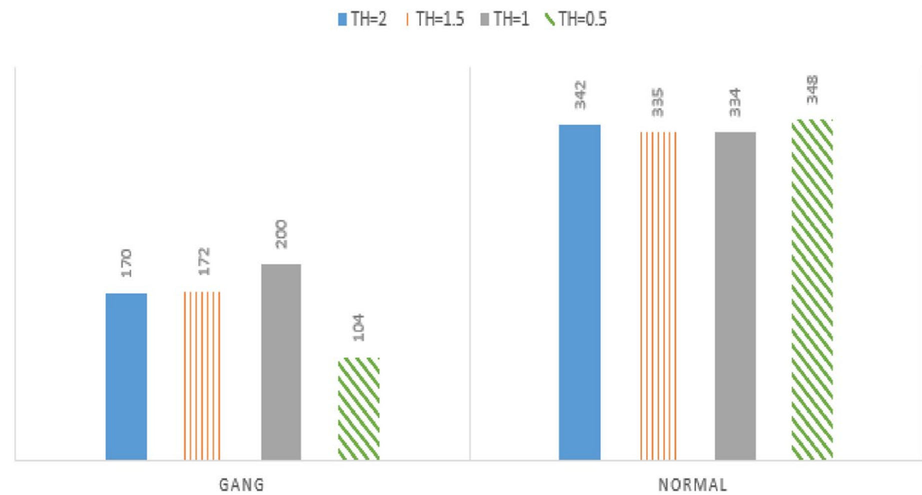

Fig. 21 The average walking distance of gang and normal vehicles in the case of normal vehicles applying the DDM-D mechanism with various threshold values: 0.5, 1, 1.5, and 2

gang members need to compete with everyone else, that is, the benefits of cooperation is reduced.

Related work

There are two approaches related to our deception detection mechanism to highlight. First, the false content in a message needs to be identified. Second, social actions of non-lying vehicles against lying vehicles are required to limit spreading of false messages and to discourage such selfish behaviour. With reference to validating the contents of received messages, in [4], a multisource filter method is introduced to validate message contents and to determine the importance of an event in terms of its proximity to the receiver based on the information collected from local sensors, as well as taking into account information received from the other vehicles and the RSU. Along similar lines, in [18], the Dempster-Shafer theory (DST) is used to combine an array of evidence under uncertainty and trust rating lists are shared among vehicles in order to evaluate the truthfulness of the vehicle and the information received. In [19], a mechanism is proposed to detect transmitted false information based on tracking the vehicle's trajectory after it has sent a message. The work in [20] proposes a framework to verify and amend the received information based on sensor information and cooperation with neighbours. However, there is a delay in validating and correcting the information. In [21], false messages (e.g., a false emergency message) in vehicular ad hoc networks are detected based on modelling the traffic flow using observation data aggregated from travelling vehicles, and determining if the observed flow is consistent with what would be expected (e.g., as a result of an emergency, if it had really occurred). In [22], false location messages from a vehicle are detected by estimating the vehicle's real location, via predicting its trajectory using multi-array 5G V2V localization. The second approach related to our work is community action against malicious vehicles. In [23], the effect of spreading messages about events in VANETs is studied, and the authors proposed a voting mechanism based on weighing the decisions received from neighbours using the number of hops that convey these decisions. In [24], a trust management scheme based on integrating the ratings among devices is introduced. In [25], a reputation mechanism in a peer-to-peer file sharing network is proposed to mitigate the number of downloading unauthenticated files; the work relies on assigning a global trust value for participants based on their history.

Our work is different from the literature reviewed above in that we investigate the cooperation in a dynamic physical environment. The vehicle validates the receiving messages by having partial knowledge of the surrounding car parking events and a blacklist reputation mechanism. In general, misbehaviour detection, including detecting fake or erroneous messages, can be based on plausibility and consistency mechanisms, as surveyed in [14], and our work falls into the plausibility mechanism category—our work is unique in dealing with misbehaviours in the context of cooperative parking.

The sending of false GPS readings is another factor that can affect the performance of CoPark-WS, when sending INFO messages. Indeed, the vehicles can send incorrect location information because of errors in computing due to attenuation of the GPS signals, or intentionally, to improve the chance of acquiring road resources. As in CoPark-WS, the vehicle can send false GPS data to deceive the other vehicles that it is nearer to the target parking space. Both situations can be handled similarly, to account for inaccuracies in the GPS readings, but we do not address this situation using experiments in this paper. In general, the precision of GPS plays a critical role in intelligent transportation systems and autonomous vehicles [26]. The quality of GPS readings can be in the error range of about 15 m which can affect advance driver assistance system and safety applications [27]. There have been different approaches to dealing with the GPS inaccuracies. One approach uses reference/anchor nodes to enhance GPS readings such as in [28] which considered the parked autonomous vehicles as anchor nodes; the work in [29] applied the Road Side Units in the car parking area as a source to computing the searching vehicle positions. The other approach is using data fusion algorithms to combine the GPS readings with the information of the attached sensors to vehicles such as camera and radar. Furthermore, cooperative localization uses the gathered information from other partners and own sensor information to improve the GPS accuracy, for example, the work in [27] depends on sharing the surrounding road constraints among vehicles. In [30], vehicles share location information of near physical objects, as reference nodes, to correct the GPS data.

Conclusion

In this paper, we have demonstrated that a deception detection and handling mechanism plays an essential role in a decentralized car parking environment, in situations where some vehicles may intentionally deceive their car parking competitors by sending false information.

Both individual and gang selfish behaviours were assessed against the CoPark-WS approach which relies on cooperation among vehicles. Our simulation based experiments showed that sending false advice messages can negatively impact the search behaviour, especially for honest vehicles. Consequently, a Deception Detection Mechanism (DDM) was proposed to enhance robust cooperation in CoPark-WS. We note that our methods are approximate and tolerant of errors in judging vehicles, and adaptable (via threshold values). Our DDM approach consists of two stages:

1. verifying the received messages based on a proposed heuristic function to judge plausibility, and
2. applying a reputation mechanism to reduce the effects of false advice messages and identifying the deceitful vehicles.

The impact of DDM on limiting the influence of malicious vehicles has been shown experimentally.

We note that the DDM approach does increase the number of messages due to the need to broadcast the blacklist, as shown in the lower part of Fig. 16. However, as in the normal CoPark-WS approach, each broadcast by a vehicle is to surrounding neighbours within a set transmission range (e.g., a preset DSRC range), and vehicles receiving the blacklist need not immediately re-broadcast the blacklist—hence, the sharing is done only opportunistically rather than aiming to share globally; in the worse case, even with a large enough transmission range, the broadcast is heard by all vehicles within close enough proximity of the broadcaster, and hence, the DDM approach is not expected to substantially increase network traffic. Detailed network traffic and complexity analysis will be future work.

Future work will also consider the following variations on the experiments we have done:

- we have used Euclidean distance in our simulations as a heuristic; further work could experiment with other distance measures including city-block distance or travel distances;
- so far, our simulations have considered arrival of vehicles and no vehicles leaving—this may increase the difficulty for later arriving vehicles to find parking; one could also consider vehicles leaving the carpark, thereby potentially causing traffic congestion, and to study how this would affect parking efficiency;
- the impact on search time due to peak hours, time-of-day usage of the car park, weekends, and festivals, can be examined, based on real city data; and
- the impact of the traffic in the areas leading into the car park can be examined.

Finally, while this work has focused on the specifics of cooperative car parking, our framework can be adapted for wider scale cooperation of smart vehicles, and to the open world of autonomous and adaptive systems. Future work will consider deception detection and intervention mechanisms for a broader range of cooperative behaviours for vehicles and other distributed cyber-physical systems. As mentioned, other work on plausibility analysis in inter-vehicle communications and to detect misbehaviours have been studied [14], and our framework for judging messages from vehicles and different forms of blacklisting, ranging from the cautious to the relaxed modes, could be explored in other cooperation contexts.

Abbreviations

DDM: Deception detection mechanism; ETSI: European Telecommunications Standards Institute; SAE: Society of Automotive Engineers; CoParkWS: Co-operative Car PARKing with Walking and Searching time; WAVE: Wireless Access Vehicular Environment; IEEE: Institute of Electrical and Electronics Engineers; MANETs: Mobile Ad hoc NETworks; VANETs: Vehicular Ad hoc NETworks; CITS: Cooperative Intelligent Transport Systems; v2v: Vehicle-to-vehicle; GPS: Global

Positioning System; CBD: Central Business District; RSU: Road Side Unit; FCD: Floating Car Data; CAMs: Cooperative Awareness Messages; BSMs: Basic Safety Messages; ID: Identifier; ADV: Advice; INFO: Information; GD: Greedy; VF: Verified Function.

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Competing interests
The authors declare that they have no competing interests.

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