Effective Real-Time Urban Traffic Routing: An Automated Planning Approach

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***Abstract*—One of the pivotal challenges presented to urban road traffic controllers is the effective utilisation of transport infrastructure, as a result of growing urbanisation, the finite network capacity, and of the increasing number of road vehicles. In this context, the arrival of connected vehicles present a unique opportunity for a fundamental change in urban traffic control. Urban traffic control approaches should then take an active role in integrating connected vehicles into the mobility ecosystem in order to maximise benefits.**

To support such integration, in this work we propose to leverage automated planning, a well-studied branch of artificial intelligence, to perform real-time traffic routing in urban areas. We describe the proposed approach, and we demonstrate its effectiveness using real-world historical data of a UK town.

***Index Terms*—Traffic Routing, Artificial Intelligence, Automated Planning, Urban Traffic Control**

I. Introduction

Over half of the world's population now lives in cities and global urbanisation continues at a steady pace. In the UK alone, the cost of congestion has reached nearly £8 billion in 2018 in lost time and fuel consumption,[1] and has become a major health threat that goes beyond the cardiac and respiratory systems [1].

In this context, the arrival of connected vehicles present an opportunity for a paradigm shift in urban traffic control. Connected vehicles can communicate, via appropriate protocols, with the infrastructure and with other vehicles [2]. In this work we focus on how urban traffic control can exploit the opportunities presented by the advent of connected vehicles to distribute traffic, hence reducing congestion and air quality issues while maximising the utilisation of the available infrastructure, in a controlled urban region.

Considering the broader context of intelligent vehicle routing [3], we address the problem of real-time routing by leveraging automated planning techniques. Automated planning is an extensively studied area of artificial intelligence (AI), and provides off-the-shelf highly-performant solvers and a set of standard languages that are capable of dealing with challenging problems from real-world applications. Notable examples include drilling [4], smart grid [5], underwater unmanned vehicles control [6], and mining [7].

In this work, we specify planning knowledge models using the numerical planning formalism, that can support complex reasoning with numbers and quantities at the network level, having a global view of the situation, e.g., positions and destinations of vehicles in the network, and expected paths, and can thus take informed (globally motivated) decisions that individual vehicles would not be able to take independently. Further, we introduce an architecture that allows to exploit planning for real-time traffic routing and that can lead to a fully autonomous centralised urban traffic controller.

To demonstrate the effectiveness of the proposed approach we test it, in simulation, on real-world traffic data of the Milton Keynes centre area – one of the largest town of the United Kingdom. The results indicate that the proposed approach is capable of reducing congestion and improving the exploitation of the available urban network by routing vehicles.

II. Background and Related Work

This section gives the necessary backgrounds on automated planning, and provides and overview of the work done in the vehicle routing field, particularly from an AI perspective.

A. Automated Planning

Automated planning is the area of AI that focuses on investigating approaches for generating plans, sequences of actions, that need to be performed to achieve predefined goals from a given initial state [8]. For producing plans and decisions rationally using symbolic reasoning, it has to have explicit knowledge of the environment and actions, a *domain model*, and description of objects, an initial state of the environment and goals, a *problem instance*. In numerical planning, The environment is represented by first-term logic predicates and numeric variables. Actions have preconditions, i.e., what has to hold in the state of environment prior action application, and effects, i.e., how the action application modifies the state of the environment. Both domain models and corresponding problem instances can be encoded in the PDDL language [9]. The combination of a domain model and a problem instance

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[1]https://inrix.com/press-releases/scorecard-2018-uk/

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is usually referred to as *knowledge model*, which incorporates all the information needed by a domain-independent planning engine to solve the described instance.

The development of domain-independent planners within the AI Planning community, motivated by the International Planning Competitions [10], has lead to a range of "off the shelf" technology that can be used in a wide range of applications: since they accept the domain and problem description in a standardised interface language and return plans using the same syntax, they can easily be leveraged as embedded components within larger frameworks, as they can be interchanged without modifying the rest of the system.

B. *Traffic Routing*

The problem of intelligent vehicle routing deals with finding routes for vehicles in the road network such that each vehicle has to reach its destination from its location of origin while optimising for specified criteria such as mitigating road congestion [3].

The standard approach, that is currently exploited in most urban areas, is to leave to drivers the decisions about the best route to follow. Drivers can decide to rely on satellite navigators but most of the decisions are based on the drivers experience and knowledge of the network.

Considering more intelligent approaches, the problem can be tackled from a centralised perspective, i.e., there is a central urban traffic controller having information about the routes of vehicles, and about the network conditions. On this basis, the controller can estimate how traffic flows will evolve in the near future. Vehicle routes can be hence calculated by taking into account such predictions, with the aim of maximising a general level of service for the overall network [11].

Another approach to intelligent vehicle routing is to consider decentralised approaches, where vehicles do not rely on a centralised system to decide the route to follow (see, for instance [12], [13]). In a decentralised approach, each vehicle has to decide in isolation, based on the information that it is able to collect on the network conditions and, in the case of connected vehicles, about the intentions of nearby vehicles. A decentralised approach is commonly exploited in satellite navigation systems (e.g., WAZE[2]), which, however, might lack of reliable information about the evolution of the road network conditions, or require strong vehicle to vehicle communication. Decentralised approaches are usually reactive, they determine the most promising route for a single vehicle taking into consideration the current state of the road network. Such approaches scale well, however, they lack the global perspective and might hence react, for instance, after some roads become congested.

A recent comparative study has considered various optimisation metrics, both centralised and decentralised [14]. The results of the study indicate that the most promising optimisation metric is road occupancy, i.e., the number of vehicles that are currently on a given road.

[2]https://www.waze.com/

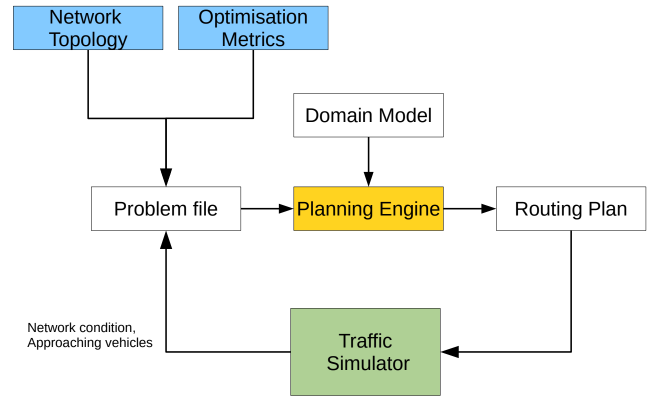

Fig. 1. An overview of the proposed architecture.

Taking a different perspective, artificial intelligence approaches based on planning has been proposed to tackle the intelligent vehicle routing problem by planning routes for a group of vehicles globally, rather than separately for each individual vehicle. Automated planning techniques can be used to in a centralised fashion to generate a plan for multiple vehicles. Preliminary works leveraging automated planning techniques in such a fashion aim for minimising the risk of road congestion [15] or satisfying air quality constraints [16]. The preliminary results presented in those works indicate that using the "global" planning approach is promising (e.g. roads might not become congested even in rush hours), although it might not scale well with an increasing number of considered vehicles and/or the size of the road network. We took inspiration from the work of Chrpa et al. [15] in terms of leveraging automated planning for intelligent vehicle routing. However, the approach that we present in this paper can perform real-time traffic routing, rather than the offline approach of Chrpa et al. Further, we consider a different planning formalism, namely numerical planning, that provides an excellent trade-off between computational complexity and accuracy of the knowledge models.

III. Proposed Approach

This section introduces the proposed architecture, and describes the knowledge model on which the approach relies.

A. *Architecture*

Figure 1 depicts the overall system architecture which has been designed in order to leverage automated planning for real-time vehicle routing in a urban area network. The planning engine, that is in charge of generating the overall routing plan for the vehicles approaching the controlled urban region, receives input (the knowledge model) under the form of a domain model and a problem file. The domain model describes the way in which the engine can generate the routing plans, and will be described in the next section. The problem file describes an instance to be solved, and must include the following information:

```
(:action drive-medium
 :parameters (?c - car ?r - link ?r2 - link)
 :precondition (and
    (>= (occupancy ?r2) (medium-level ?r2))
    (< (occupancy ?r2) (heavy-level ?r2))
    (at ?c ?r)
    (connected ?r ?r2)
      )
 :effect (and
    (increase (occupancy ?r2) 1.0)
    (not (at ?c ?r))
    (at ?c ?r2)
    (increase (total-cost) (cost-medium ?r2))
    )
)
```

Fig. 2. The *drive-to-medium* action in the PDDL language.

- The topology of the considered urban area network, in terms of links and legal traffic movements.
- The network condition: this is a "snapshot" of the state of the network.
- Information about approaching vehicles, in terms of entry point (initial position considered) and the destination to be reached.
- A metric to be optimised; i.e., the way in which the quality of the routing plan can be assessed and compared.

The goals (of a problem instance) are to have all the vehicles at their final destination. Once a problem has been solved, the generated routing plan is provided to the traffic simulator, that updates the path for the affected vehicles, and continues the simulation.

Please note that Figure 1 makes explicit reference to a traffic simulator, since we use a simulator for performing the experimental analysis of this work. However, in place of the traffic simulator, data from available sensors can be collected and enhanced (see for instance [17]) and provided as input to the system, and generated routing plans can be communicated to the vehicles via appropriate communication protocols.

B. Knowledge Model

We now present the engineered knowledge model that describes the controlled urban region (e.g. road network, positions of vehicles), the condition of the network, and the actions that the planning engine can use to route vehicles from their entry points to their destination points. The model is based on a micro-simulation model of road traffic [18], in other words, it considers traffic flows at the level of individual vehicles since routes are calculated for each vehicle individually.

In our encoding, the controlled region is represented as a set of unidirectional *links*. On the basis of the topology of the network to model, each link is characterised by its *length*, *occupancy*, and by the fact that it is *connected* to a subsequent link. Occupancy is specified in terms of vehicles (PCUs) that are currently occupying the link, either in movement or queuing. A link X is connected to a link Y if vehicles can move from X to Y via a junction. It is worth noting that the connected property is unidirectional so, for the sake of the above example, vehicles from Y are not allowed to move to X.

A link is also described in terms of its congestion levels. We designed a three-level system, corresponding to a link congestion being *light*, *medium*, or *heavy*. The level of congestion is defined via threshold values, specified in terms of occupancy of the link. Congestion levels play a pivotal role in our model, as they specify the "cost" of navigating via a link. Navigating via a link with a medium level of congestion costs more than navigating via the same link when it is lightly congested, and less than when it is heavily congested. Such costs are specified for each link via dedicated *cost-light / -medium / -heavy* predicates.

A vehicle is described by its position, via a dedicated *at* predicate that specifies the link the vehicle is currently navigating, and its destination.

Given the initial positions of the vehicles entering the controlled urban region, their destination, and the current network conditions, the planning engine has to find, for each of the vehicles, the path that minimises the overall cost. The process of navigating vehicles through the network is handled by a *drive-* type of actions, that allows a vehicle to move from a link to a connected one. There are three variants of this action: *drive-light*, *drive-medium*, and *drive-heavy*. The planning engine can select the appropriate one according to the level of congestion of the receiving link. The PDDL code of the *move-medium* action is shown in Figure 2. The action is specified by the preconditions that have to be satisfied before applying it. In particular, there are constraints on the current level of occupancy, and on the position of the vehicle. The effects of this action are that the vehicle is moved to the connected link $r2$ (according to the topology of the network), the occupancy of the connected link is increased by one PCU, and the overall cost of the plan is increased by the cost-medium value of the link. It is easy to notice that the action is not reducing the level of occupancy of the link r, but only increasing the occupancy of $r2$. This is because the numerical planning formalism has no notion of time, so by always increasing the occupancy our approach is forcing the planning engine to explore different routes in order to distribute traffic and minimise the overall costs.

As it is apparent, the knowledge model gives the planning engine an abstraction of the network and of the components that are part of a routing plan. For instance, it does not take into account traffic lights, the time needed for crossing junctions, etc. This has been done for the sake of reducing the computational complexity, and allowing the system to produce routing plans in a very limited amount of time.

A solution plan, which is the output provided by the planning engine, is a sequence of drive- actions that move each vehicle from its entry point to its destination, via a sequence of links. This plan can be parsed, in order to identify the route of each vehicles, that can then be provided to a traffic simulator –or to the actual vehicles.

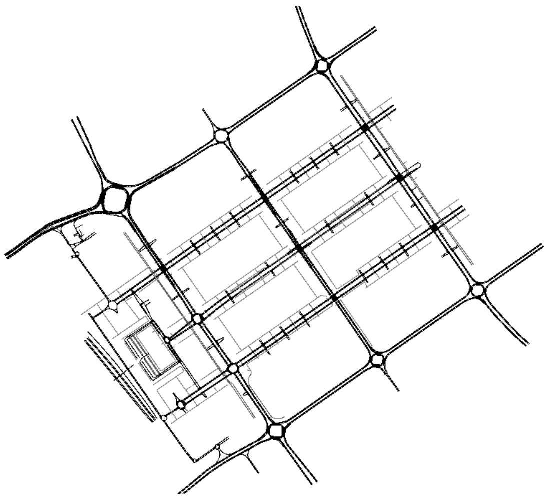

Fig. 3. The modelled central Milton Keynes urban area. During the simulated period of time, main traffic flows are from North to South-East, and from West to East. This is because large residential areas are located at North and West of the modelled region.

IV. Experimental Analysis

To investigate the empirical performance of the proposed planning-based approach for routing connected vehicles in urban areas under realistic traffic conditions, the network of Milton Keynes centre has been used. In particular, here we consider a SUMO microsimulation model [19], and the network is shown in Figure 3. Milton Keynes is a town of the United Kingdom, located about 80 kilometres north-west of London. Milton Keynes has a population of approximately 230,000. The model covers an area of approximately 2.9 square kilometres, and includes more than 25 junctions and more than 50 links.

The SUMO model simulates the morning rush hour, and has been built by considering historical traffic data collected between 8am and 9am on non-holiday weekdays. Data has been provided by the Milton Keynes Council, and gathered by sensors distributed in the region between December 2015 and December 2016. Traffic signal control information has been provided by the Council. The model has been calibrated and validated. During the morning rush hour, $1,800$ vehicles are entering the controlled region, and the main traffic flows are from North to South-East, and from West to East. This is because large residential areas are located at North and West of the modelled region

The framework presented in Figure 1 has been developed in Python, and uses the TRaCI interface to interact with the SUMO simulation environment, in order to get the current network status, the vehicles entering the network, generate the knowledge model, run the planning engine, parse the solution plan, and inform vehicles of the generated assigned route.

For every couple of origin-destination, described by the traffic flows of the model, traffic experts have identified reasonable links to be considered for routing. They did not provide complete paths, but only the set of links that they would consider for distributing traffic for the considered origin-destination couple. All the relevant links have been included in the topology, provided as part of the knowledge model to the planning engine.

For each link, congestion levels have been defined as follows. Light congestion corresponds to occupancy being less than 40% of link's capacity; a heavily congested link has occupancy above 70% of its capacity; medium level sits in between. Current occupancy is provided by the SUMO simulator. To provide the planning engine with a likely evolution of the traffic conditions, vehicles that are already in the network are considered as occupying 5 links at a time: the one they currently are, and the next 4. While this value can be set by the user, this specific value proved to work well for centralised routing [14], and has been identified via a set of preliminary tests. Further, it gives a rather pessimistic overview of the traffic conditions, forcing the system to distribute vehicles as much as possible.

The cost of navigating through a link is equal to the length of the link for light, $\times 10$ for medium, and $\times 100$ for heavy congestion. While these values are arbitrary, and can be modified by the user, the rationale is to force the planning engine to distribute traffic as much as possible, by making it expensive to select links that are already congested.

The simulation is run for 1 hour and then stopped. The presence of vehicles at entry links is checked every 5 seconds. For each set of experiments, the simulation is run five times and results are averaged, to account for non-determinism.

The well-known domain-independent planning engine LPG has been used [20]. It has been selected due to its wide use in real-world planning applications, and for its ability to quickly generate solution of increasingly good quality – according to the provided metric. The planning engine has been required to generate at most 3 solutions, and has been given at most 10 CPU-time seconds and 6 GB of RAM to run.

For the sake of contextualising the performance achieved by the proposed planning-based approach, we also report the results obtained by the best performing centralised and decentralised approaches introduced by Vallati and Chrpa and tested using the same urban region [14]. We will use the *Occupancy* (decentralised) and *n5-Occupancy* (centralised), as defined by the authors. In the remainder of this section we will refer to them as Decentralised and Centralised, for the sake of readability.

A. Results

The simulation results are summarised in terms of the following SUMO-calculated performance indices:

- number of departed (arrived) vehicles. Indicates the number of vehicles that entered the region (reached destination) during the simulation. A vehicle can enter the region if the entry link has enough space to accommodate it, otherwise it is assumed to be queuing outside the region.
- average speed (m/s) of the vehicles.
- average trip length (m) and duration (s). Length and duration reports the average measurement of the trips

TABLE I

PERFORMANCE ACHIEVED IN SIMULATION ON THE CONSIDERED URBAN REGION. DEFAULT INDICATES THAT NO TRAFFIC CONTROL IS IN USE. DEC, CEN, AND PLAN, STAND FOR RESPECTIVELY DECENTRALISED, CENTRALISED, AND PLANNING-BASED APPROACHES. BOLD INDICATES THE BEST PERFORMANCE.

	Considered Metrics			
	Default	Dec	Cen	Plan
Departed vehicles [#]	1669	1818	1860	**1895**
Arrived vehicles [#]	801	1628	1668	**1683**
Avg, speed [m/s]	0.58	4.62	**4.75**	4.38
Avg, trip length [m]	2297.35	2098.49	2049.49	**2043.34**
Avg, trip duration [s]	788.86	354.30	356.49	**353.87**
Avg, trip time loss [s]	622.12	**201.56**	207.18	204.95

of the vehicles to reach their destination from the entry point.

- Average time loss (s). This value indicates the time that has been lost due to vehicles queuing, or travelling at a very low speed.

As a first scenario for this experimental analysis, we consider the ideal case where all the vehicles in the modelled region are connected, and they are all following the provided route indications. This gives a clear figure of the potential impact of the routing approaches. Results are presented in Table I, and include the default performance of the network, achieved when no traffic routing control is in operation. In the Default settings, vehicles enter the network and follow their pre-calculated path to the destination, that does not take into account the network conditions. It should come as no surprise that the default leads to the worst possible performance with regards to all the considered metrics. Table I also shows the performance achieved by the best Centralised and Decentralised approaches, as for [14]. The presented results suggest that the proposed planning-based approach can effectively route traffic in the modelled region. In particular, the planning-based approach allows the largest number of vehicles to enter the region and to reach their predefined destination. It is also capable of finding a good tradeoff between average time loss and trip duration.

Results presented in Table I focus on the conditions inside the controlled region. An aspect that is not captured is that of vehicles that are approaching the region or trying to enter it. Figure 4 gives an overview of the vehicles that are waiting to enter the region, when the different real-time routing approaches are in charge. As expected, using no traffic routing quickly leads to very congested entry points, that do not allow traffic to enter and potentially leading to severe traffic issues on the surrounding areas. In some measure, however, this is also true for the Centralised and Decentralised approaches that we consider. After about 20 minutes (30 minutes), the Decentralised (Centralised) routing technique is failing to quickly move traffic away from the entry points, and the approaching vehicles are queuing just outside the controlled region, with average waiting times ranging between 20 and 40

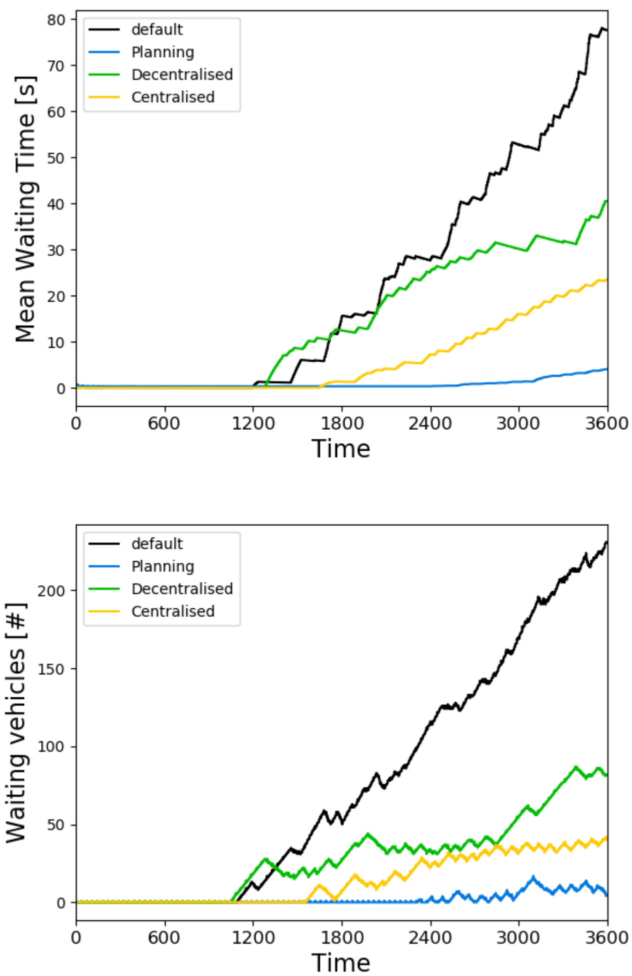

Fig. 4. Performance, in terms of mean waiting time (top) and number of waiting vehicles (bottom), achieved by the default (no traffic control), centralised, decentralised, and planning-based approaches on the modelled region. Waiting vehicles are outside the region, waiting to be able to enter via an entry point.

seconds by the end of the simulation. Similar figures are shown in terms of number of vehicles waiting to enter the region. In contrast, the proposed Planning-based approach demonstrates to be capable of maintaining entry links decongested, allowing more traffic to navigate the region and minimising the queues at the boundaries. It should be noted that, even though this is not modelled by the simulator, minimising the congestion on entry points is of pivotal importance, as they can have a knockout effect on exit points as well – i.e. worsening traffic conditions also inside the controlled region.

Finally, we consider a scenario where not all the vehicles are connected and follow the provided instructions. Results in Table II show how the considered approaches would perform if only 50% of the vehicles were following the given routing instructions. The proposed planning-based technique is still able to keep the entry points decongested, resulting in most of the vehicles being able to enter the controlled region. This

TABLE II
PERFORMANCE ACHIEVED IN SIMULATION ON THE CONSIDERED URBAN REGION, WITH A 50% PENETRATION RATE. DEFAULT INDICATES THAT NO TRAFFIC CONTROL IS IN USE. DEC, CEN, AND PLAN, STAND FOR RESPECTIVELY DECENTRALISED, CENTRALISED, AND PLANNING-BASED APPROACHES. BOLD INDICATES THE BEST PERFORMANCE.

	Considered Metrics			
	Default	Dec	Cen	Plan
Departed vehicles [#]	1669	1801	1807	**1879**
Arrived vehicles [#]	801	**1540**	1539	1501
Avg, speed [m/s]	0.58	**3.92**	3.66	2.71
Avg, trip length [m]	2297.35	2303.49	2280.03	**2264.40**
Avg, trip duration [s]	788.86	**434.01**	439.09	498.23
Avg, trip time loss [s]	622.12	**266.6**	273.26	333.14

leads to a tradeoff with regards to time loss, as vehicles that do not follow the given instructions can generate queues and congestion in some areas of the network. It is worth noting that the controller is unaware of whether a given vehicle will follow routing instructions: this can lead to unforeseen queues and congestion.

V. CONCLUSION

In this paper, we introduced a planning-based approach for real-time traffic routing with the aim of mitigating congestion in urban areas. We described the PDDL knowledge models needed by the technique, and presented a framework that could lead to a fully autonomous centralised urban traffic controller, able of communicating with vehicles and providing routing instructions according to a given objective function, and to the network conditions.

The experimental analysis considered the central Milton Keynes urban area in the morning rush hour. Data has been provided by the Milton Keynes council, and the SUMO model has been calibrated and validated. The experimental results indicated that: (i) the proposed planning-based approach is capable of effective real-time traffic routing; (ii) The planning-based technique is particularly good in decongesting entry points – minimising waiting time and queues of vehicles approaching the region; and (iii) even if only half of the vehicles are following routing instructions, the planning-based approach can have a remarkably beneficial impact on traffic. Notably, the proposed approach can be adapted to different urban networks by modifying only the corresponding part of the knowledge model.

We see several avenues for future work. First, we are interested in testing the proposed planning-based approach in different urban regions. We are interested in testing if, in cases where not all the vehicles are following the given instructions, it is possible to predict vehicles that are likely to participate, and adapt the routing accordingly. Finally, we envisage an integration of the proposed system which systems for intelligent traffic lights control [21], [22].

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