A computational market for distributed control of urban road traffic systems

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Abstract—In the last decade, economic approaches based on computational markets have been proposed as a paradigm for the design and the control of complex socio-technical systems, such as urban road traffic systems. The control problem of an urban road traffic system can be modelled as a distributed resource allocation problem, in order to apply market-based techniques as solution method. In this work, we design a competitive computational market, where driver agents trade the use of the capacity inside the intersections with intersection manager agents. We show how the market dynamics influence the drivers’ behaviour, leading to a more efficient use of the urban road traffic system, in terms of lower average travel times and less congestion.

I. INTRODUCTION

Controlling a large-scale system such as an urban road traffic system is not a trivial task, due to its unpredictability and uncertainty. The optimal control of flows in any traffic network, including road traffic ones, is a well-known NP-hard problem [18], which means that the time required to find an optimal solution increases faster than polynomially with the network size. Due to this NP-hardness, traditional control techniques usually consist in an off-line search for the best control strategy for typical situations that traffic planners faced in the past. Unfortunately, fluctuations in dynamic systems are usually huge, and therefore the resulting control strategy is optimised for a situation that is true on average but that never occurs in any single instant [16].

To tackle this problem, a computationally viable option is an on-line and distributed control strategy. The majority of distributed control strategies found in literature usually consider the vehicles as anonymous particles of a traffic flow that a control policy cannot target individually. We claim that a tight integration between vehicles and control infrastructure with the aid of influencing the driver behaviour to better allocate the urban road network (i.e., the set of interconnected links of a city) is potentially a more effective approach. Furthermore, such an approach is complementary to distributed control strategies such as coordinated traffic lights [13][14][15][16].

Due to the scale of the (resource) allocation problem, a distributed formulation and solution method is needed. To this respect, it is very interesting to notice that markets perform distributed resource allocation also in rather complex environments. Indeed, markets as a solution method to solve distributed resource allocation problems have been applied to several socio-technical systems [7].

In the urban road traffic domain, the problem is to agree on an efficient allocation of an available resource (the elements of the road network) to consumers (the drivers). For this purpose, we can build an economic model where some public institution holds the resource (e.g., a city’s traffic management agency), and is willing to trade the right of using it in a marketplace by means of money. Drivers would then participate in this market so as to purchase the right of consuming a certain amount of the available resource.

In this paper, we take a multiagent approach to the problem of designing a competitive computational market for the distributed allocation of an urban road network. In particular, we assume the existence of a road traffic infrastructure where software agents act on behalf of the actors of the marketplace (the drivers and the traffic management operators).

The paper is structured as follows: in section II we introduce the context of our work. Section III presents our model of computational market for the control of an urban road traffic system. Section IV presents the simulation environment used to empirically evaluate our approach, while section V presents our experiments and the results obtained. In section VI we discuss the feasibility of our approach. Finally, in section VII, we conclude and point to future lines of work.

II. RELATED WORKS

The problems and challenges posed by the road traffic and transportation domain have attracted scientists and experts from different fields. The solutions proposed by the scientific community to alleviate traffic congestion and increase safety span from improving the management systems, by a major use of IT systems, to the automation of the vehicles and the road infrastructure.

In recent years, there is an increasing interest in applying agent-based techniques for traffic control [3][4][11][25]. Urban road traffic control appears to be a particularly promising application area for agent technology. In [14] intelligent traffic light agents create green waves in a particular direction by solving distributed constraint optimisation problems. In [15] the traffic light agents learn in a coordinated way the best signal plans. In [16] a self-organising approach is presented, which leads to emergent coordination patterns and achieves an efficient, decentralised traffic light control. Still, in these approaches only the entities that govern the intersection control devices (traffic lights) are modelled as agents, while drivers are only considered insofar as they are a part of the traffic flow through the road network.

On the other hand, other approaches focus on the behavioural modelling of drivers [1][21]. In this context, it is particularly interesting to study mechanisms that influence the driver behaviour so as to reduce travel time and/or congestion. Information-based network control strategies [12][19][22] can help agents avoid congested road sections to better distribute the traffic flow, but they can cause new problems when used by a large population of drivers [2].
Congestion charges [28] are another mechanism to influence the driver behaviour, aimed at penalising drivers for the externalities that they cause to the other drivers (congestion) and to the environment (pollution). Such mechanisms have been deployed in many big cities such as London [20], Stockholm [9] or Singapore [17]. Although fixed congestion charges can in principle reduce traffic congestion, since they are set a priori they do not adapt to different traffic conditions. Still, it is clear that the monetary incentive provides a more fine grained level of control than information-based control strategies. Consider the case in which a particular route A is congested, and a message (either on a variable message sign or from the on-board information systems) invites drivers to avoid route A and to deviate to the longest route B. If this message is trusted by the drivers, a high percentage of the driver population will deviate to route B, potentially causing new problems on that route. On the contrary, if it is announced that the route A has a price $p_A$, while the route B has a price $p_B$, with $p_A > p_B$, the drivers more concerned about prices will select route B, while those more concerned about their routing preferences will select route A. Thus, finding the right difference in prices at every moment can lead to a near optimal distributions of traffic load.

III. DESIGN OF A COMPUTATIONAL MARKET

A. Motivation

The objective of this work is designing a competitive computational market for the control of an urban road traffic system. Two types of actors are operating in this market: 1) software agents that act on behalf of human drivers and acquire the right to cross the intersections of an urban road network, and 2) intersection manager agents that govern the intersections and provide such rights. The ultimate goal of such a market is enhancing mobility and reducing travel times. The advantages of such an approach are manifold. Having the possibility of adjusting prices, intersection manager agents have a powerful lever to control a system whose components are otherwise hard to influence. Furthermore, the pricing policies have different effects on different groups of drivers (e.g., business drivers or leisure drivers [26]), thus allowing for control strategies targeted at specific types of drivers.

B. Infrastructure model

In our traffic infrastructure, each intersection is regulated by a traffic light that is governed by a software agent, embedded in the infrastructure (intersection manager from now on). An intersection manager is the supplier of the capacity of the intersection it manages, controlling the price of the supplied resource.

Vehicles are equipped with software agents that are configured to act on behalf of human drivers (driver agent from now on). Driver agents are capable of trading in the market with the intersection managers. To enable trading, we assume that driver agents and intersection managers have access to a shared communication medium.

We assume that at any time, driver agents have access to the current prices applied by the intersection managers in the network. Prices can be published and regularly updated in market bulletin boards.

Finally, we take for granted the availability of a trusted payment system\(^1\), allowing driver agents to securely transfer money to intersection managers.

C. Intersection manager model

In our model, each intersection manager competes with all the others for the provision of the resource it supplies. Our goal as market designers is to enforce the attainment of the general market equilibrium, a situation where the amount of resources sought by the buyers is equal to the amount of resources provided by the suppliers. The price vector $p^*$ that corresponds to the general market equilibrium is in general computed through a walrasian auction. This type of auctions, introduced by Walras in 1874 [27], involves a set of buyers $\mathcal{B}$ and a set of suppliers $\mathcal{V}$. The auction proceeds as follows. At time $t$, each buyer of the set $\mathcal{B}$ notifies to the suppliers of the set $\mathcal{V}$ the quantity of resources she is willing to buy, given the actual price vector $p^t$. In fact, the quantity of goods a buyer is willing to buy depends on the prices of such goods. Similarly, also the quantity of goods a supplier is willing to provide depends on the actual prices that such goods can be sold at in the market. With this information, each supplier computes the difference between the buyers’ demand for the resource she provides and the supply of such resource. If there is excess supply, the prices are lowered, whilst if there is excess demand the prices are raised. The new price vector $p^{t+1}$ is communicated to the buyers that iteratively compute the new demand. No transactions take place at disequilibrium prices, that is, the process continues until the equilibrium price $p^*$ is reached. The price $p^*$ is that price for which the total demand of all the buyers coincides with the total supply provided by all the suppliers. Only at that point the transactions take place and the resources are transferred from the suppliers to the buyers by means of money.

In our case, the buyers are the driver agents, the suppliers are the intersection managers, and the traded resource is the intersection capacity. More precisely, an intersection manager supplies capacity to the driver agents that want to cross the intersection $j$ coming from one of the incoming links. Be $L_j$ the set of incoming links of intersection $j$. For each incoming link $l^h_j \in L_j$, the intersection manager reasons over the following variables:

- Current price $p^t_j(l^h_j)$: It is the price that the intersection manager sets at time $t$ for vehicle passage through intersection $j$ from incoming link $l^h_j$.
- Total demand $d^t_j(l^h_j \mid p^t_j(l^h_j))$: It defines the number of vehicles, which the intersection manager observes at time $t$, that want to cross intersection $j$ from link $l^h_j$, given the current price $p^t_j(l^h_j)$.
- Supply $s^t_j(l^h_j)$: It defines the number of vehicles that the intersection manager can allow through intersection $j$ from incoming link $l^h_j$. It is constant and not time-dependent.

\(^1\)http://www.itsoverview.its.dot.gov/EPS.asp
Excess demand $z^*_j(l^h_j | p^*_j(l^h_j))$: It is given by the difference between the total demand at time $t$ and the supply, $z^*_j(l^h_j | p^*_j(l^h_j)) = d^*_j(l^h_j) - s^*_j(l^h_j)$.

Given the set of all intersection managers that are operating in the market, $\mathcal{J}$, we define the price vector $p^t$ as the vector of the prices applied by each intersection manager $j \in \mathcal{J}$ for the intersection capacity of each incoming link $l^h_j \in \mathcal{L}_j$:

$$p^t = [ p^t_1(l^h_1) \ p^t_2(l^h_2) \ldots p^t_{|\mathcal{J}|}(l^h_{|\mathcal{J}|}) ] \quad (1)$$

The market is said to be in equilibrium at price vector $p^*$ if $z^*_j(l^h_j | p^*_j(l^h_j)) = 0 \ \forall j \in \mathcal{J}, \forall l^h_j \in \mathcal{L}_j$, that is, if demand and supply are mapped by $p^*$.

To implement the Walrasian auction described at the beginning of this section, each buyer (i.e., driver agent) should communicate to the suppliers (i.e., intersection managers) the route that it is willing to choose, given the current price vector $p^t$. With this information, each intersection manager $j$ computes the total demand $d^*_j(l^h_j | p^t_j(l^h_j))$ as well as the excess demand $z^*_j(l^h_j | p^t_j(l^h_j)) \forall l^h_j \in \mathcal{L}_j$. Then, each intersection manager $j$ adjusts the prices $p^t_j(l^h_j)$ for all the incoming links $l^h_j \in \mathcal{L}_j$, lowering them if there is excess supply ($z^*_j(l^h_j | p^t_j(l^h_j)) < 0$) and raising them if there is excess demand ($z^*_j(l^h_j | p^t_j(l^h_j)) > 0$). The new price vector $p^{t+1}$ is communicated to the driver agents that iteratively choose their new desired route, on the basis of the new price vector $p^{t+1}$. Once the equilibrium price vector $p^*$ is computed, the trading transactions take place and each driver agent buys the required capacity from the intersection managers that govern the intersections that lay on the route chosen by the driver agent.

The Walrasian auction relies on several assumptions that make a direct implementation in the road traffic domain hard. For instance, the set of buyers is assumed to be fixed during the auction, which means that a new driver agent cannot join an auction until it ends. Also the fact that no transactions can take place at disequilibrium prices is a strong assumption: it is unreasonable for all the driver agents to wait for the equilibrium price to be reached before choosing the desired route and starting to travel. Finally a driver agent is usually able to transfer money to an intersection manager when it is spatially close to it, that is, when it is already travelling along its desired route.

Thus we implement a market that aims to enforce the attainment of the general equilibrium such as the Walrasian auction, but that works on a continuous basis, with driver agents that join and leave the market dynamically, and with transactions that take place at every moment. To continuously mapping demand with supply, each intersection manager applies the price update strategy sketched in Algorithm 1. At time $t$, each intersection manager $j$ computes, independently from each other, the excess demand $z^*_j(l^h_j | p^t_j(l^h_j))$ and updates the price $p^t_j(l^h_j)$ using the formula [6][27]:

$$p^{t+1}_j(l^h_j) \leftarrow \max \left[ \epsilon, p^t_j(l^h_j) \cdot \frac{d^*_j(l^h_j | p^t_j(l^h_j))}{s^*_j(l^h_j)} \right] \quad (2)$$

where $\epsilon$ is the minimum price and $s^*_j(l^h_j)$ is the (constant) capacity supplied by the intersection manager $j$ for the incoming link $l^h_j$. The definition of $\epsilon$ and $s^*_j(l^h_j)$ is an important design decision: 1) $\epsilon$ is the minimum price that an intersection manager charges for the use of the incoming link $l^h_j$ and 2) $s^*_j(l^h_j)$ is the number of vehicles above which the intersection manager considers that there is an excess demand and starts raising prices.

In many countries, providing a basic quality of service is seen as a state obligation that the citizens cannot be charged for, at least not directly. Drivers that travel through road network elements with low demand shall not incur in any costs, so we chose $\epsilon = 0$.

To define the supply $s^*_j(l^h_j)$, we rely on the fundamental diagram of traffic flow of link $l^h_j$ [10]. Let $\rho^\text{opt}(l^h_j)$ be the density\(^2\) that maximises the traffic flow on link $l^h_j$ (see Fig. 1). We chose $s^*_j(l^h_j) = 0.5 \cdot \rho^\text{opt}(l^h_j) \cdot ||l^h_j||$, where $||l^h_j||$ is the length of link $l^h_j$. In other words, the intersection manager considers that there is an excess demand on link $l^h_j$ when the density on that link reaches the 50% of the optimal density. This value, which has been selected experimentally, aims at making the intersection managers start to raise prices before reaching the optimal density. In this way, exceeding

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**Algorithm 1 Intersection manager price update**

01: $t \leftarrow 0$
02: for all $l^h_j \in \mathcal{L}_j$ do
03: $p^t_j(l^h_j) \leftarrow \epsilon$
04: initialise $s^*_j(l^h_j)$
05: end for
06: while true do
07: for all $l^h_j \in \mathcal{L}_j$ do
08: evaluate $d^*_j(l^h_j)$
09: $z^*_j(l^h_j) = d^*_j(l^h_j) - s^*_j(l^h_j)$
10: $p^{t+1}_j(l^h_j) \leftarrow \max \left[ \epsilon, p^t_j(l^h_j) \cdot \frac{d^*_j(l^h_j | p^t_j(l^h_j))}{s^*_j(l^h_j)} \right]$
11: end for
12: $t \leftarrow t + 1$
13: end while

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\(^2\)The density is the number of vehicles per unit length, expressed in veh/km
the optimal density, and thus causing congestion, occurs much more rarely, since increasing prices divert the drivers towards less congested (i.e., cheap) parts of the network.

D. Driver agent model

First, we informally define how the driver agent acts on behalf of the human driver that wants to travel from her origin to her destination, and then more formally in terms of choice set and decision-making functions.

When a human driver travels through an urban road network, she competes for the use of a scarce resource with the other human drivers. This resource is allocated through a market where driver agents and intersection managers participate as buyers and suppliers respectively. As said in section III-B, we assume that each vehicle is equipped with a driver agent that acts on behalf of the human driver. In particular, such personal agent is in charge of choosing a route $r$ and trading with the intersection managers that regulate the intersections of the route $r$. From the perspective of the driver agents, a route $r$ is characterised by two attributes: the travel time and the monetary cost. Each human driver has a private valuation of the wealth that she is willing to allocate when choosing a route $r$, defined by the variable $w_i$. We assume that the driver agent receives from the human driver the variable $w_i$ as input of its decision making process. Given the wealth constraint, the driver agent selects the most preferred route $r^*$, taking into consideration the other attribute of a route, that is, the travel time. To this regard, it is reasonable to assume that the lower the travel time, the higher the preference for that route for the human driver.

More formally, we model a route $r$ as an ordered list of links, $r = [l^1, \ldots , l^M]$, each of them characterised by two attributes, namely travel time at free flow:

$$TT_H(l^k) = \frac{||l^k||}{v_{\max}(l^k)}$$

and price:

$$K(l^k) = \begin{cases} \frac{p^h_j(l^h_j)}{l^h_j} & \text{if } l^k = l^h_j \in L_j \\ 0 & \text{otherwise} \end{cases}$$

where $||l^k||$ is the length of link $l^k$ and $v_{\max}(l^k)$ is the maximum allowed speed on link $l^k$. The price of link $l^k$ is not 0 only if the link $l^k$ is one of the incoming link of an intersection ($l^k = l^h_j$), in which case the price is $\frac{p^h_j(l^h_j)}{l^h_j}$. The summatory over all the links of $r$ gives the travel time at free flow and the price of the entire route $r$:

$$TT_H(r) = \sum_{k=1}^{M} TT_H(l^k)$$

$$K(r) = \sum_{k=1}^{M} K(l^k)$$

Different types of driver can be modelled based on the driver’s private valuation $w_i$: business drivers usually value time more than money, so they are willing to pay more for their desired routes than leisure drivers, who prefer to travel more cheaply.

Let $R$ be the set of all the routes available to driver $i$. The set $R$ is built using a k-shortest paths algorithm [29]. Given $w_i$, the driver agent builds the choice set $C \subseteq R$, composed of the routes at an affordable price:

$$C = \{r_1, \ldots , r_N \mid K(r_x) \leq w_i\}$$

To model the driver agent’s choice, we rely on neoclassical economic theory [5], assuming that a driver agent is able to compare two alternative routes $r_x$ and $r_y$ in the choice set $C$ using a preference-indifference operator $\succeq$. If $r_x \succeq r_y$, the driver agent either prefers $r_x$ to $r_y$, or is indifferent. Since the choice set $C$ is finite and the preference-indifference operator has the properties of reflexivity, transitivity and comparability, the existence of a route, $r^*$, which is preferred to all of them is guaranteed. Because of the three properties listed above, there exists a function:

$$U : C \to \mathbb{R}$$

such that

$$r_x \succeq r_y \Leftrightarrow U(r_x) \geq U(r_y) \forall r_x, r_y \in C$$

is guaranteed. Therefore, the route $r^*$ that is preferred to all of the alternatives in $C$ is:

$$r^* = \arg \max_{r \in C} U(r)$$

In summary, making a choice for a driver agent is equivalent to assigning a value to each alternative and selecting the alternative $r^*$ associated with the highest value.

In this work, the (normalised) function $U : C \to [0, 1]$ is defined by:

$$U(r) = \frac{M - TT_H(r)}{M - m}$$

where $TT_H(r)$ is the travel time at free flow,

$$M = \max_{r \in C} TT_H(r)$$

and

$$m = \min_{r \in C} TT_H(r)$$

In other words, given the set of routes at an affordable price, the driver agent always prefers the shortest route (with respect to travel time at free flow).

Once the choice is made, the driver agent notifies the human driver with the route that it selected. In this work we assume that the human driver follows the route proposed by the driver agent, and that the driver agent trades the capacity at each intersection that lays on the selected route $r^*$. The trading occurs when the vehicle is within the communication range of the intersection manager that governs the intersection, by transferring the corresponding amount of money.
A vehicle $i$ that at time $t$ is driving on link $l^k$ is characterised by its position $x_i^t \in [0, ||l^k||]$ and its speed $v_i^t$. At each time step, a new target speed for each vehicle is computed, using the formula:

$$v_i^{t+\Delta t} = \left(1 - \frac{x_i^t}{||l^k||}\right) \cdot u(l^k) + \frac{x_i^t}{||l^k||} \cdot u(l^{k+1}) \tag{15}$$

where $u(l^k)$ is the mean speed of link $l^k$ and $u(l^{k+1})$ is the mean speed of the next link of the route, $l^{k+1}$. The equation above takes in consideration the fact that the closer the vehicle is to the next link $l^{k+1}$, the greater the effect of the link mean speed on the vehicle target speed.

The target speed is the speed that a vehicle approaches, increasing or decreasing the current speed. Thus, if the target speed $v_i^{t+\Delta t}$ is higher (lower) than the current speed $v_i^t$, the vehicle accelerates (decelerates) with a vehicle-type specific maximum acceleration (deceleration). The new speed is then denoted by $v_i^{t+\Delta t}$. Finally, the vehicle position is updated using the formula:

$$x_i^{t+\Delta t} = x_i^t + \frac{1}{2} \cdot (v_i^t + v_i^{t+\Delta t}) \cdot \Delta t \tag{16}$$

If $x_i^{t+\Delta t} \geq ||l^k||$, the vehicle is placed in the next link of its route, the densities for links $l^k$ and $l^{k+1}$ are updated accordingly, and the position is reset to $x_i^{t+\Delta t} - ||l^k||$.

### V. EXPERIMENTAL RESULTS

Although our work is independent from the underlying road network, we chose to use a road network that resembles a real urban road network (see Fig. 2). The network is characterised by several freeways that connect the city centre with the surroundings and a ring road. Each big dark vertex in Fig. 2, if it connects three or more links, is modelled as an intersection regulated by traffic lights. We aimed at recreating a typical morning peak scenario, with more than 23000 drivers, endowed with a quantity of money $w_i$ randomly drawn from a uniform distribution, which travel from and to 7 destinations outside the city (marked as $O_1, O_2, \ldots, O_7$ in Fig. 2). To evaluate our approach we use two different types of metrics, related to the vehicles and related to the road network.

The vehicle-related metrics are the average travel time, the average speed and the moving average of travel time. The average travel time (for a given O-D pair) is given by $\sum_{i=1}^{N} TT(r_i)/N$ where $TT(r_i)$ is the real travel time experienced by the driver agent $i$ on its selected route $r_i$, and $N$ is the total number of driver agents for the given O-D pair. The average speed (for a given O-D pair) is given by $\sum_{i=1}^{N} ||r_i||/(TT(r_i) \cdot N)$, where $||r_i||$ is the route length. The moving average of travel time is intended to measure how the average travel time of the entire population of driver agents evolves during the simulation. This metric is initialised to 0, and once a driver agent $i$ concludes its trip, the travel time $TT(r_i)$ is computed and the moving average of the travel time $TT_{avg}$ is updated with the formula:

$$TT_{avg} = TT_{avg} + \frac{TT(r_i) - TT_{avg}}{n+1} \tag{17}$$
TABLE I: Average travel time (min): competitive market (CM) vs. traffic lights (TL)

<table>
<thead>
<tr>
<th>Origin</th>
<th>O1</th>
<th>O2</th>
<th>O3</th>
<th>O4</th>
<th>O5</th>
<th>O6</th>
<th>O7</th>
</tr>
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<tbody>
<tr>
<td>O1</td>
<td>TL</td>
<td>105.73</td>
<td>169.14</td>
<td>171.41</td>
<td>173.34</td>
<td>99.65</td>
<td>32.94</td>
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<tr>
<td></td>
<td>CM</td>
<td>34.23</td>
<td>51.37</td>
<td>83.1</td>
<td>81.22</td>
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<td>40.82</td>
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<tr>
<td>O2</td>
<td>TL</td>
<td>46.06</td>
<td>-</td>
<td>133.59</td>
<td>143.98</td>
<td>144.19</td>
<td>149.72</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>28.12</td>
<td>-</td>
<td>35.39</td>
<td>60.69</td>
<td>74.79</td>
<td>62.59</td>
</tr>
<tr>
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<td>TL</td>
<td>71.22</td>
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<td>-</td>
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<tr>
<td></td>
<td>CM</td>
<td>43.54</td>
<td>34.37</td>
<td>-</td>
<td>29.37</td>
<td>48.36</td>
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<tr>
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<td>85.4</td>
<td>81.98</td>
<td>51.09</td>
<td>-</td>
<td>42.25</td>
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<td></td>
<td>CM</td>
<td>77.12</td>
<td>62.53</td>
<td>41.77</td>
<td>-</td>
<td>53.12</td>
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</tr>
<tr>
<td>O5</td>
<td>TL</td>
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<td>80.6</td>
<td>68.73</td>
<td>-</td>
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<tr>
<td></td>
<td>CM</td>
<td>73.28</td>
<td>72.66</td>
<td>50.14</td>
<td>43.63</td>
<td>-</td>
<td>54.6</td>
</tr>
<tr>
<td>O6</td>
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<td>-</td>
</tr>
<tr>
<td></td>
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<td>67.07</td>
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<td>57.03</td>
<td>-</td>
</tr>
<tr>
<td>O7</td>
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<td>24.05</td>
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<tr>
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<td>52.84</td>
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<td>64.59</td>
<td>33.9</td>
</tr>
</tbody>
</table>

where \( n \) is the number of driver agents that have completed their trips.

The network-related metrics are the density variations at 7 critical points (marked as \( c_1, c_2, \ldots, c_7 \) in Fig. 2), which connect the freeways going downtown with the ring road.

The evaluation is performed by running the simulator with two different configurations: in the first one, the intersections are governed by intersection managers that, apart from regulating the vehicles’ crossing with traffic lights, compete in the market for the supply of the intersection capacity; in the second one, the intersections are governed by intersection managers that only regulate the crossing with traffic lights. In the following tables and figures we refer to the two configurations with the abbreviation CM (competitive market) and TL (traffic lights).

A. Vehicle-related metrics

Table I shows the average travel time of the drivers, according to their origin-destination pairs, when the system is only controlled by traffic lights (TL) compared with the system designed as a competitive market (CM). The competitive market in general reduces the average travel time, for almost every origin-destination pairs. Such reduction is specially noticeable for the route along the north-south axis, such as from \( O_1 \) and \( O_7 \) to \( O_2, O_3, O_4, O_5 \) and \( O_6 \). Nevertheless, the average travel time is slightly higher on the \( O_1-O_7 \) route. This is likely due to the topology of the network in use. In fact, the traffic on the northern part of the network is much lower than that in the southern part (see the density plots of Fig. 4(a) and 4(g)), since few origins are located in that area, so that selecting the shortest route\(^3\) is advantageous in that part of the network. On the other hand, the market fluctuations affect the route choice in the competitive market scenario, and therefore the driver agents are distributed along different routes, which reduces congestion but also increases the route length, since other non-shortest routes are likely to be selected.

In line with these results, table II shows that for 37 of 42 O-D pairs the average speed is noticeably higher when the system is designed as a competitive market (CM) compared to the system regulated only by traffic lights (TL).

To have a global idea of the impact of the competitive market on the travel time of the entire population of driver agents, we rely on the moving average of the travel time (Fig. 3). It is noticeable that at the beginning the travel time increases linearly for both settings. Then, when the number of driver agents that populate the network increases, the average travel time increases exponentially when the system is regulated only by traffic lights, while with the competitive market the increase is still linear.

B. Network-related metrics

Another important metric to evaluate the effects of the trading activity is the density variation over time at the critical points.

\(^3\)This is the expected behaviour of the drivers when the intersections are only regulated by traffic lights and there is no trading activity between driver agents and intersection managers.
In this paper we studied how the problem of controlling an urban road traffic system can be modelled as a competitive market, where driver agents and infrastructure agents trade the intersection capacity. The empirical evaluation showed how the market dynamics affect the driver agent decision making, contributing to generate benefits by means of lower average travel time and less congestion.

This work can be extended in different ways. For example, we assume that the exact prices applied by the intersection managers are available to the driver agents when they select the most preferred route. In reality, information takes time to spread through a network, so that the effect of this delay should be taken into account in the experiments. Also the road network topology could deserve special attention, if certain bottleneck intersections need specific modelling. In this case the intersection managers could be more sophisticated agents with more information available, in order to make more complex decisions than the price update of Eq. 2. Finally, the market can be enriched with different products offered by the intersection managers, such as discounts for usage at a particular time or daily subscriptions.

The behaviour of the competitive market must be analysed under different driver models. In the experiments described above we used a uniformly random population of drivers, since each of them always selects the shortest route at an affordable price. Still, other driver models can be conceived. For example, a driver could choose the route that minimises a weighted sum of the two attributes of the route (travel time at free flow and monetary cost). Given a set of driver agent profiles, we can sample one of them when we inject a driver agent into the system, thus generating different populations of drivers.

Another main line of work relies on intersection managers that act cooperatively in the marketplace. Such a cooperation would most likely be implemented through distributed learning behaviour in team of agents [24]. Although such adaptive cooperation schemes would be harder to design, they can help implementing the aforementioned market extensions in a more direct and effective manner.

VI. DISCUSSION

Although this work could sound far-fetched, we believe that an infrastructure such as that envisioned in this paper could be closer than we think. In fact, the continuous advances in software and hardware technologies will make possible a tighter integration between vehicles and infrastructure, as we assume in the scenario described in this work. For instance, the IntelliDrive initiative fosters research and development of technologies to directly link road vehicles to their physical surroundings, with the aim of improving road safety and operational efficiency. Therefore dynamic road pricing is one of the prospects for IntelliDrive. Data could be collectively transmitted to road users for in-vehicle display, outlining the lowest cost, shortest distance, and/or fastest route to a destination on the basis of real-time conditions.

VII. CONCLUSION

In this paper we studied how the problem of controlling an urban road traffic system can be modelled as a competitive market, where driver agents and infrastructure agents trade the intersection capacity. The empirical evaluation showed how the market dynamics affect the driver agent decision making, contributing to generate benefits by means of lower average travel time and less congestion.

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### TABLE II: Average speed (km/h): competitive market (CM) vs. traffic lights (TL)

<table>
<thead>
<tr>
<th>Origin</th>
<th>$O_1$</th>
<th>$O_2$</th>
<th>$O_3$</th>
<th>$O_4$</th>
<th>$O_5$</th>
<th>$O_6$</th>
<th>$O_7$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$O_1$</td>
<td>TL</td>
<td>11.7</td>
<td>5.65</td>
<td>6.95</td>
<td>7.24</td>
<td>15</td>
<td>35.13</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>27.44</td>
<td>21.07</td>
<td>16.86</td>
<td>16.56</td>
<td>23.76</td>
<td>26.52</td>
</tr>
<tr>
<td>$O_2$</td>
<td>TL</td>
<td>24.54</td>
<td>6.18</td>
<td>7.1</td>
<td>7.54</td>
<td>8.81</td>
<td>26.74</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>31.73</td>
<td>25.44</td>
<td>19.05</td>
<td>15.88</td>
<td>22.81</td>
<td>27.99</td>
</tr>
<tr>
<td>$O_3$</td>
<td>TL</td>
<td>15.37</td>
<td>14.66</td>
<td>9.03</td>
<td>9.2</td>
<td>11.43</td>
<td>14.43</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>23.59</td>
<td>25.03</td>
<td>27.53</td>
<td>16.85</td>
<td>25.76</td>
<td>25.68</td>
</tr>
<tr>
<td>$O_4$</td>
<td>TL</td>
<td>14.5</td>
<td>12.86</td>
<td>15.08</td>
<td>14.33</td>
<td>16.27</td>
<td>19.98</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>17.39</td>
<td>20.07</td>
<td>22.98</td>
<td>13.06</td>
<td>14.81</td>
<td>16.81</td>
</tr>
<tr>
<td>$O_5$</td>
<td>TL</td>
<td>11.1</td>
<td>9.97</td>
<td>9.01</td>
<td>7.84</td>
<td>-</td>
<td>15.91</td>
</tr>
<tr>
<td>$O_6$</td>
<td>TL</td>
<td>23.22</td>
<td>7.61</td>
<td>5.87</td>
<td>4.88</td>
<td>4.5</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>29.05</td>
<td>22.37</td>
<td>16.48</td>
<td>16.26</td>
<td>15.76</td>
<td>-</td>
</tr>
<tr>
<td>$O_7$</td>
<td>TL</td>
<td>44.95</td>
<td>11.89</td>
<td>7.77</td>
<td>6.71</td>
<td>6.47</td>
<td>22.12</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>40.03</td>
<td>35.39</td>
<td>24.97</td>
<td>19.1</td>
<td>18.25</td>
<td>34.67</td>
</tr>
</tbody>
</table>

points $c_1$ to $c_7$ (see Fig. 2). The results are plotted in Fig. 4(a) to Fig. 4(g). In all these figures, the constant curve labelled with $\rho_{\text{opt}}$ refers to the optimum density value that maximises traffic flow. In general, the density tends to be lower in the competitive market compared to the system regulated only by traffic lights. For example in $c_3$, the high density peak is absent, while in $c_1$, $c_4$, $c_5$ and $c_7$ the density variation shows the same trend over time. In $c_2$ and $c_6$, the density reaches the same value in both scenarios, but in the competitive market this density peak disappears with time, while normally this congestion would be present for more time. This is because the network is better balanced, since the price fluctuations force the demand to change towards less expensive intersections. Thus, the market dynamics contribute to create a system that continuously adapts to the current situation, in quest of a dynamic equilibrium, with unused intersections that become cheaper while congested ones become increasingly expensive.
TABLE III: Notation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( i )</td>
<td>Subscript for a driver agent</td>
<td>( TT_B(r)(h) )</td>
<td>Travel time at free flow of route ( r )</td>
</tr>
<tr>
<td>( j )</td>
<td>Subscript for an intersection</td>
<td>( K(r) )</td>
<td>Monetary costs of route ( r )</td>
</tr>
<tr>
<td>( R )</td>
<td>Set of buyers</td>
<td>( T_T(r)(h) )</td>
<td>Real travel time of route ( r )</td>
</tr>
<tr>
<td>( \psi )</td>
<td>Set of suppliers</td>
<td>( v_{\text{max}}(l_k)(km/h) )</td>
<td>Max allowed speed on link ( l_k )</td>
</tr>
<tr>
<td>( p^t )</td>
<td>Price vector at time ( t )</td>
<td>( \mathcal{R} )</td>
<td>Driver agent’s available route set</td>
</tr>
<tr>
<td>( p^* )</td>
<td>Price vector</td>
<td>( C )</td>
<td>Driver agent’s choice set</td>
</tr>
<tr>
<td>( J )</td>
<td>Equilibrium price vector</td>
<td>( \mathbb{R} )</td>
<td>Real numbers</td>
</tr>
<tr>
<td>( \lambda_j )</td>
<td>Set of incoming links of intersection ( j )</td>
<td>( \mathbb{C} )</td>
<td>Driver agent’s value for route ( r \in \mathbb{C} )</td>
</tr>
<tr>
<td>( l_i^b )</td>
<td>Incoming linking of intersection ( j )</td>
<td>( \rho_l (h) )</td>
<td>Density on link ( l_i )</td>
</tr>
<tr>
<td>( p^j_j^b(l_i^b) )</td>
<td>Price at time ( t ) of link ( l_i^b )</td>
<td>( \phi_l^f(h)(\text{veh}/km) )</td>
<td>Speed-density function for link ( l_i )</td>
</tr>
<tr>
<td>( d_j^j_j^b(l_i^b) )</td>
<td>Demand at time ( t ) of link ( l_i^b )</td>
<td>( \mu_l(h)(km/h) )</td>
<td>Speed at free flow on link ( l_i^b )</td>
</tr>
<tr>
<td>( s_j^j_j^b(l_i^b) )</td>
<td>Supply of link ( l_i^b ) (constant)</td>
<td>( u_l(h)(km/h) )</td>
<td>Mean speed of ( l_i^b )</td>
</tr>
<tr>
<td>( z_j^j_j^b(l_i^b) )</td>
<td>Excess demand at time ( t ) of link ( l_i^b )</td>
<td>( \rho_{\text{opt}}(h)(\text{veh}/km) )</td>
<td>Density that maximises the traffic flow on link ( l_i^b )</td>
</tr>
<tr>
<td>( c )</td>
<td>Minimum price</td>
<td>( \rho_{\text{opt}}^f(h)(\text{veh}/h) )</td>
<td>Maximum traffic flow on link ( l_i^b )</td>
</tr>
<tr>
<td>( r )</td>
<td>Route</td>
<td>( v_{\text{opt}}(h)(km/h) )</td>
<td>Mean speed at maximum traffic flow on link ( l_i^b )</td>
</tr>
<tr>
<td>( w_i )</td>
<td>Endowment of human driver ( i )</td>
<td>( v_i(h)(km/h) )</td>
<td>Position of vehicle ( i ) at time ( t )</td>
</tr>
<tr>
<td>( |l_i^b|(km) )</td>
<td>Length of link ( l_i^b )</td>
<td>( s_i(h)(km/h) )</td>
<td>Speed of vehicle ( i ) at time ( t )</td>
</tr>
<tr>
<td>( TT_B(l_i^b)(h) )</td>
<td>Travel time at free flow of link ( l_i^b )</td>
<td>( v_i(h)(km/h) )</td>
<td>Target speed of vehicle ( i ) at time ( t )</td>
</tr>
<tr>
<td>( K(l_i^b) )</td>
<td>Monetary costs of link ( l_i^b )</td>
<td>( \Delta t(h) )</td>
<td>Simulation time step</td>
</tr>
</tbody>
</table>

ACKNOWLEDGMENT

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Fig. 4: Vehicle density variation over time for critical intersections.
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