Towards reservation-based intersection coordination: an economic approach

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Abstract—Understanding and controlling a complex system like traffic is not a trivial task. To this aim, many market-based methods have been applied to the design and the management of such systems, by defining the “rules of the game” and trying to enforce a desired global outcome. We model traffic as a computational economy, where drivers trade with the intelligent infrastructure in a virtual marketplace, buying time and space to cross intersections when commuting through the city. We show how such mechanism influences the drivers’ behaviour, producing benefits for both the drivers (i.e. lower average travel times) and the road network (i.e. less congestions).

I. INTRODUCTION

A complex system is a system featuring a large number of interacting components, typically characterized by a nonlinear global behaviour, and whose properties cannot be completely explained by an understanding of its component parts. Understanding and controlling a complex system is not a trivial task, due to its large dimension, unpredictability, positive feedback effects and coupled component interactions.

To this aim, market-based methods [7] [16] have been applied to the design, management, evolution and control of complex (computational) systems. Such methods aim at generating and predicting a desirable system-level outcome when the behaviour of the single component of the system is not directly accessible nor under control. Mechanism design [8], auction theory [14], market-based resource allocation [15], prediction markets [12], are all methods that try to define the “rules of the game” in order to influence the behaviour of the single components and enforce system-wide properties.

Traffic is definitely a complex system [4]; millions of drivers every day commute from their homes to their respective workplaces and back, making autonomous decisions about route assignment and departure time selection, learning from their past experiences and influencing each other in both positive and negative ways.

In this paper, we study the effect of modelling traffic as a computational economy, where the drivers and the intelligent infrastructure trade in a virtual market, buying and selling space and time in order to move through the city. We show that this modelling affects the driver decision making for the route assignment, generating benefits for both the driver itself and the road network.

II. RELATED WORKS

The problems and challenges posed by the traffic and transportation domain have attracted scientists and experts from different fields, from traffic engineers, to control engineers and computer scientists. 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 or the adoption of control theory techniques, to the automation of the vehicles and the road infrastructure.

In [19] intelligent traffic lights learn via reinforcement learning the optimal signal plan, and also adapt to changes in traffic patterns by a meaning of context detection.

In [13] the coordination of traffic lights comes as a distributed constraint optimization problem, with the aim of creating “green waves” in a particular direction.

In [11] a novel mechanism for intersection control is introduced, where driver agents communicate with an intersection manager agent to make reservations of time and space within an intersection. Such a mechanism has shown in simulation a lot of potential to lower delays and increase throughput of intersections with respect to traffic lights.

III. TRAFFIC AS A COMPUTATIONAL ECONOMY

A. Motivation

The majority of intelligent control mechanisms found in literature usually considers the vehicles as mere “packets” that switch through a network. The best an infrastructure component can do in this case is optimizing its traffic flow, both locally or in a coordinated way. On the other hand, having a system-wide vision and trying to influence the driver behaviour to better allocate the common resource (i.e. the road network) is potentially a more effective approach (although extremely difficult). Computer-equipped autonomous vehicles will be a reality in the near future (cars that “park for you”
are already being sold\(^1\)). Together with the enrichment of the traffic management infrastructure with sensors and computing power, new possibilities for intelligent interactions between infrastructure and vehicles arise.

Furthermore, usually drivers are not penalized at all for the externalities that they cause to other drivers, in the form of congestion, and to the environment, in the form of pollution. A way to circumvent this problem is introducing money as a factor that must be taken into account by drivers when they make their decisions. In this way, choosing a route it is not only a matter of time, but also a matter of money, and if people usually are very patient in tolerating traffic jams, they are not so willing to waste their money.

A mechanism for internalizing the externalities caused by drivers may come in the form of congestion charges, a mechanism already deployed in many big cities such as London, Milan, Stockholm or Singapore. Although fixed congestion charges can in principle reduce traffic congestion, since they are fixed a priori they do not adapt to different traffic conditions. Nonetheless, such mechanism necessarily modifies the driver’s decision making. In [3] for example, the effect of congestion tolls is studied, where a control centre provides agents with a (noisy) estimation of the cost of choosing a certain route \(r\). The agents periodically update the heuristic information related to the available routes on the basis of the utility received in the past episodes.

B. Agent-based model

In this work, we draw upon the model of intersections proposed by Dresner and Stone [11], which aims at implementing a reservation-based mechanism to regulate intersections. In this work, an intersection is not regulated by traffic lights, rather by an intelligent agent that assigns reservations of space and time to the vehicles that want to cross the intersection. There are two kind of agents:

- **Intersection manager agent**, which manages the intersection and is responsible of the vehicles that want to cross the intersection.

- **Driver agent**, which autonomously drives the assigned vehicle.

When a vehicle is approaching the intersection, the driver agent requests the intersection manager agent to reserve the necessary time-space slots to safely cross the intersection. The intersection manager agent, provided with data such as vehicle ID, vehicle size, arrival time, arrival speed and type of turn, is able to simulate the vehicle transit through the intersection and so determine whether or not a request is in conflict with the already confirmed reservations. If the request is confirmed by the intersection manager agent, the driver agent stores the reservation details and tries to meet them, otherwise it will try again at a later time. If the driver agent realizes that the traffic conditions have changed and that it is not able to meet the constraints of its reservation, it can cancel the reservation and make a new one (see [11] for more details).

In a scenario where intersection manager agents assign reservations without any associated cost to the first requester, a driver has no incentive to prefer a particular intersection over another. In other words, when it starts to commute from its origin to its destination, it is likely to choose the route with the lowest (estimated) travel time.

In this work we model the traffic as a computational marketplace, where driver agents (i.e. buyers) must purchase the necessary reservations from the intersection manager agents (i.e. sellers), in order to cross the intersections. We assume that both agents are rational, and the formers want to minimize their expenditures, while the latters want to maximize their profits.

C. Trading model

The trading interactions that can occur between a driver agent and an intersection manager agent are:

- **Purchasing a reservation when approaching the intersection.** When a driver agent is approaching the intersection, it “calls-ahead” the intersection manager agent and requests a reservation, providing the necessary data to simulate its transit through the intersection. If the request cannot be satisfied, due to conflicts with the already confirmed reservations, the intersection manager agent refuses the reservation request. Otherwise, it replies with the price of the reservation (see (1)). Finally, the driver agent can refuse to purchase the reservation or accept and pay the fare.

- **Purchasing a reservation when stopped at the intersection.** If a driver agent was not able to purchase a reservation during the approaching phase, due to the traffic conditions, when it reaches the edge of the intersection it must stop. In this case, it is allowed to purchase a reservation in the “stopped-at-the-intersection” mode, whose price is determined by the price function (2).

- **Withdraw a reservation.** When a driver agent purchases a reservation, it tries to meet the constraints of the reservation, especially the arrival time. If it realizes that these cannot be met, due for example to changing traffic conditions, it can withdraw the reservation and be reimbursed (without cancellation fees).

D. Intersection manager agent model

The intersection manager agent, as a seller, is characterized by its price function, which depends on how much in advance the reservation is purchased and the use of the intersection. Formally, the price of purchasing at time \(t\) a reservation for time \(T\) is:

\[
F(x) = f^1(x) = p_{\min} + \frac{1}{\alpha \cdot q_{\text{free}} \cdot (1 + \beta \cdot x)} \tag{1}
\]

where \(p_{\min}\) is the minimum price, \(\alpha\) and \(\beta\) are parameters.

\(^1\)http://www valeo.com/innovation/en/home/driving-assistance/products/park4u.html
$q_{\text{free}}$ are the number of unsold cells\(^2\) at time $T$, and $x = (T - t)$. This function models the fact that the demand of the resource depends on the prices and on how much time in advance a resource is purchased [1], although more complex ones can be adopted. Such function has been used to study the pricing policy of flight companies, by tuning $\alpha$ and $\beta$ to map the actual prices. In this work, we adopt $p_{\text{min}} = 10$, $\alpha = 0.01$ and $\beta = 0.1$ in order to keep the price approximatively between 10 and 100.

In case that a driver is stopped at the intersection, the price function is modified as follows:

$$
F(x) = \begin{cases} 
    f^1(x) & x \in (0, 30) \\
    -p_{\text{min}} + \frac{1 + \ln(x/30)}{\alpha \cdot q_{\text{free}} \cdot (1 + 30 \cdot \beta)} & x \in [30, 60] \\
    -p_{\text{min}} + \frac{1 + \ln(60/30)}{\alpha \cdot q_{\text{free}} \cdot (1 + 30 \cdot \beta)} & \text{otherwise}
\end{cases}
$$

A driver must pay a positive price if it purchases a reservation within the next 30 seconds, otherwise it must pay a negative price (i.e. it is reimbursed) for purchasing a reservation beyond the next 30 seconds.

An intersection manager agent can be considered as an enterprise whose stocks are quoted in an indexed market. The value of a quote, updated every $\Delta T$ seconds, takes into account the number of sold reservations and the revenues earned in the time window $\Delta T$. More formally:

$$
Q(\Delta T) = \min\left(\frac{R(\Delta T)}{C(\Delta T)}, M\right)
$$

where $M$ is the maximum allowed value for a quote, $R(\Delta T)$ are the revenues earned in the last $\Delta T$, and $C(\Delta T)$ is the number of sold reservations in $\Delta T$. The stock quotes are published and regularly updated in the indexed market board, accessible to other intersection manager agents and driver agents. Like in real stock markets, the quote provides the buyers with all the information regarding the efficiency and quality of the seller, condensed in one single value. Furthermore, its historical trend provides further precious information about the dynamic of the seller in the market.

**E. Driver agent model**

The fact that a driver agent must purchase the necessary reservations to cross an intersection shapes its deliberation process. A driver is provided with an initial wealth that it must administrate with care if it wants to complete its trip. So it must decide with which intersection manager agent it wants to trade, which maximum amount of money it is willing to pay, with how much time in advance it want to buy the necessary reservations (giving that the driver agent does not know the price function of the intersection manager agent).

For simplicity we condense the whole deliberation process of a driver agents in the route assignment. The route assignment (also called route choice) is the selection of the route between an origin and a destination. It is the fourth step in the conventional transportation forecasting model [17]. A driver agent chooses the route applying the Dijkstra shortest path algorithm [9], where the weight of an edge $e$ is given by:

$$
w_e = \rho \cdot T_e + (1 - \rho) \cdot \frac{1}{1 + Q}
$$

where $T_e$ is the travel time at free flow on the edge $e$ (expressed in hours), $Q$ is the quote, and $\rho$ is a parameter that balances the importance of the travel time and the quote of the intersection manager agent. The route assignment function tends to assign a low weight i) to the shortest roads and ii) to the roads that are connected to the most valued intersections (i.e. those intersections whose respective intersection manager agents have the highest stock quotes).

The driver agent reasons about its route after crossing each intersection, by continuously re-planning its route and so reacting to the market fluctuations. The market-based information is not considered if the intersection has been already visited during the trip, to avoid jumping back and forth between a set of highly valuable intersections.

A driver must hold a valid and up-to-date reservation in order to cross an intersection. So if it detects that it cannot fulfill the details of a reservation, it can cancel such reservation and take the money back without any additional fee. If a driver had to pay money in concept of cancellation fee, this should be taken into account by the driver before the purchasing; depending on its risk aversion, a driver could try to purchase a reservation with more or less confidence about its estimation of the arrival time at the intersection. More risky drivers could benefit from early reservation and pay less money, assuming the risk of paying the cancellation fee if they cannot meet the reservation details.

**IV. Simulation environment**

To evaluate our approach we implemented a simulator based on the model of Schwertfeger [20]. The simulator is a hybrid mesoscopic-microscopic simulator, where the traffic flow on the roads is modelled at mesoscopic level, while the traffic flow inside the intersections is governed by a cellular automata-based microscopic simulator.

**A. Mesoscopic model**

In [20] the dynamics of a vehicle is governed by the average traffic density on the link it traverses rather than the behaviour of other vehicles in the immediate neighbourhood as in microscopic models.

A road network is modeled as a graph, where the nodes represent intersections and the edges represent the lanes of a road. An edge, also called stretch, is subdivided into sections (of typically 500 meters length) for which constant traffic condition is assumed. A vehicle that at time $t$ is driving on a section $s_j$ is characterized by its position $x^t_j \in [0, l(s_j)]$, where

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\(^2\)An intersection is modeled as a matrix, so a reservation is the set of cells occupied by the vehicle when crossing the intersection.
\( l(s_j) \) is the length of the section \( s_j \), and its speed \( v_j^t \). At each time step, a new target speed for each vehicle is computed, using the formula:

\[
\hat{v}_j^{t+\Delta t} = (1 - \frac{x_j^t}{l(s_j)}) \cdot u_j + \frac{x_j^t}{l(s_j)} \cdot u_{j+1}
\]

where \( u_j \) is the reference speed of section \( s_j \) and \( u_{j+1} \) is the reference speed of section \( s_{j+1} \). Such speeds are calculated taking into consideration the mean speed of the section and the vehicle’s desired speed. The mean speed of the section is calculated with a speed-density function \( U : \Phi \rightarrow \mathbb{R} \), that for a given section density \( \phi \) returns the section mean speed (for more details see [20]).

The equation above takes into consideration the fact that the closer is the vehicle to the next section \( s_{j+1} \), the more is the effect of the section reference speed on the vehicle target speed.

If the new target speed \( \hat{v}_j^{t+\Delta t} \) is higher (lower) than the current speed \( v_j^t \), the vehicle accelerates (decelerates) with a vehicle-type specific maximum acceleration (deceleration). The new speed is then denoted by \( v_j^{t+\Delta t} \). Finally, the vehicle position is updated using the formula:

\[
x_j^{t+\Delta t} = x_j^t + \frac{1}{2} (v_j^t + v_j^{t+\Delta t}) \cdot \Delta t
\]

If \( x_j^{t+\Delta t} \geq l(s_j) \), the vehicles is placed in the next section of its route, the densities for section \( s_j \) and \( s_{j+1} \) are updated accordingly, and the position is reset to \( x_j^{t+\Delta t} - l(s_j) \).

**B. Microscopic model**

The mesoscopic model described in section IV-A does not offer the necessary level of detail to model an intersection as in [11]. For this reason, when a vehicle enters an intersection, its dynamics switches into a microscopic, cellular-based, simulator, whose update rules follows the Nagel-Schreckenberg [18] model. The cell size is set to 5 meters, and for simplicity we assume that the vehicles cross the intersection at a constant speed, so that any additional tuning of parameters, such as slowdown probability or acceleration/deceleration factors, is not necessary.

**V. EXPERIMENTAL RESULTS**

The experimental setup is based on an instantiation of the simulation environment based on the city of Madrid (see figure 1, where each big dark vertex is an intersection). The aim of the experiments was measuring the effect of the market-based information on the deliberation process of the drivers. With the same experimental conditions, we compared travel times, covered distances and traffic densities when 1) the intersections are reservation-based only and when 2) the intersections participate in the computational marketplace.

We measured travel times and covered distances of 2744 drivers commuting along the North-South axis (from A and B to C and D), with 5368 (“noisy”) drivers commuting along the East-West axis (from X and Y to Z) and 2788 along the West-East axis (from Z to X and Y). All the drivers are generated in an interval of 10 minutes. We also measured the density and speed variations over time in the reference section \( s_r \), since it lays on the shortest path between the origin and the destination of vehicles under measurement.

**A. Driver metrics**

Table I and II show the average travel time and the average covered distance of the drivers under measurement. With the market-based information available to the drivers, the average travel time decreases by a 28%, while the average covered distance increases by a 9%. This was expected, since the route assignment now is affected by the market fluctuations, so that the drivers are spreaded along different routes. This reduces congestions but also increases the route length, since others, non-shortest routes, are likely to be selected.

Fig. 2 plots the travel time of the vehicles, ordered by the departure time. When the road network is not congested, the drivers can travel at free flow speed. so at the beginning of
the day there is no significative difference between the two experimental setups, due to the low traffic density. Then, as soon as the network starts to be congested, the travel time starts to increase linearly, although the travel time in the market-based scenario tends to increase less.

### B. Road network metrics

Another important metrics to evaluate the effects caused by the market-based modeling are the density and speed variations over time in the reference section $s_r$ (see Fig. 1). The section density is measured as $D_t/l(s_r)$, where $D_t$ is the number of drivers in section $s_r$ at time $t$, and $l(s_r)$ is the section length; the section speed is calculated as $\sum_{t \in \Delta T} v_t/\sum_{t \in \Delta T} 1$, where $\Delta T$ is the measuring period and $v_t$ is the speed of a driver entering the section at time $t$. The results are plotted in Fig. 3a and Fig. 3b respectively. In the first plot, it is noticeable that the section reaches a very congested state after approximately 1000 time steps, congestion that disappears in the market-based scenario. Accordingly to this fact, the section speed is in general higher in the market-based scenario, denoting a not congested section.

### C. Discussion

A market-based approach to intersection control has been outlined in [10], where the reservations are granted by a continually clearing combinatorial auction. The authors suggest that the revenues maximization operated by the intersection manager agent, as auctioneer, may generate higher throughput. The proposed mechanism aims at improving the efficiency of a single intersection, by replacing the first-come first-served mechanism, which is likely to be the bottleneck to further intersection efficiency improvements [21].

The effect of providing information to influence the driver decision making have been already studied in previous works. In [2] for example a traffic control center is in charge of processing data regarding the occupancy of the available roads and computing the optimal distribution. With this information, it provides manipulated information to the road users, with the aim of influencing their decision in several situations related to the Braess paradox scenario [5].

The experiments described in section V show that the information carried by the stock quotes affect the route assignment of the driver, which now is incentivated to prefer the most valuable intersections. The market fluctuations that are generated contributes to create a system in dynamic equilibrium by a matter of uneven development, where previously lowly valued “enterprises” increase their revenues and improves their quotes. Thereby the road network turns out to be continuously balanced and in dynamic equilibrium, so that on average the traffic density in a particular road tends to be lower. In this way, we take advantage of the reservation-based intersection control, which, for a given density, guarantees higher throughput and lower delays with respect to a traffic light system [11].

It is worth noting that the aforementioned improvements (i.e. lower travel times, lower densities . . . ) are a consequence of the driver agents deliberation process, which now is conditioned by the market. It deserves a further analysis the
possible effects engendered by the explicit coordination among intersection manager agents, as well as the effects of other control mechanism, like adaptive traffic lights.

VI. CONCLUSION

In this paper we studied the effect of modelling traffic as a computational economy, where driver agents and the intelligent infrastructure trade in a virtual market by buying and selling space and time to commute through the city. Starting from the assumption that driver agents are rational and are likely to save money, the market dynamics affects the driver agent decision making, contributing to generate benefits for both the driver itself and the road network.

The market-based scenario offers many possibility of extension. In the real life, drivers commute day by day and learn from their experience. Can be interesting to study the system behaviour in a co-learning setting, where both the drivers and the intelligent infrastructure learn from their experience; while drivers could learn the best route assignment, the intelligent infrastructure could learn the best pricing policies.

In the previous experiments, the money spent by the drivers to buy the reservations was “virtual” money, and all the drivers were initialized with the same amount of wealth. If the money was real money, the uneven distribution among more or less wealthy drivers could affect the system in a unpredictable way.

On the other hand, could be interesting keeping distinct the two assets, the traffic money and the real money, and establishing a *cap and trade* mechanism [6]; by fixing the daily traffic money available to the drivers, those that need to make a longer trip through the city must enter in a direct trading with other drivers, and exchange real money for traffic money. This approach should be evaluated under additional metrics (e.g. not only travel times but also emissions), because drivers could in this way be incentivated to not to use their private vehicles.

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