A market-based approach to accommodate user preferences in reservation-based traffic management

Matteo Vasirani  
Centre for Intelligent Information Technology  
University Rey Juan Carlos  
Madrid, Spain  
matteo.vasirani@urjc.es

Sascha Ossowski  
Centre for Intelligent Information Technology  
University Rey Juan Carlos  
Madrid, Spain  
sascha.ossowski@urjc.es

ABSTRACT
Removing the human driver from the control loop by the use of autonomous vehicles and the integration of these with the traffic management infrastructure is a challenging long-term vision for the field of Intelligent Transportation Systems (ITS). Setting out from a recently proposed urban infrastructure that allows for autonomous vehicles to individually reserve space and time inside an intersection to safely cross them, multiagent approaches have been applied to simulate and to manage both single intersections as well as networks of intersections, achieving significant improvements in the drivers average travel times. However, these approaches do not take full advantage of the potential of vehicle-centric ITS, as they ignore the fact that different drivers may value their travel times quite differently.

In this paper we combine two different market-based mechanisms, acting at intersection level and at network level, respectively, to accommodate driver preferences in reservation-based urban traffic management. At intersection level, intersection manager agents assign space-time slots through combinatorial auctions, while at network level a pricing scheme, based on general market equilibrium, accounts for an efficient use of the available network resources. Our experiments show that this combined approach on the one hand allows drivers to effectively improve their travel times if they are willing to pay more money for their trip, while on the other hand the negative impact on social welfare (average travel times) is unnoticeable.

Categories and Subject Descriptors
I.2.11 [Artificial Intelligence]: Distributed Artificial Intelligence—Coherence and coordination, intelligent agents, multiagent systems

General Terms
Algorithms, Design, Experimentation

Keywords
Traffic and transportation, market-based mechanisms, combinatorial auctions

1. INTRODUCTION
Talk about autonomous vehicles that interact with an intelligent traffic infrastructure always sounds far-fetched, but such a scenario may be closer than we think. Indeed, removing (at least partially) the human driver from the control loop by the use of autonomous vehicles and the integration of these with the intelligent infrastructure is a challenging long-term vision for the field of Intelligent Transportation Systems (ITS). Autonomous vehicles are already a reality: two DARPA Grand Challenge and one DARPA Urban Challenge have been hitherto celebrated, where autonomous vehicles have successfully interacted with both manned and unmanned vehicular traffic in an urban environment. In line with this vision, the IntellIDrive initiative promotes research and development of technologies to directly link road vehicles to their physical surroundings. The advantages of such an integration span from improved road safety to a more efficient operational use of the transportation network.

However, the level of integration will most likely be limited by the individual needs and preferences of the human users of the vehicles, who will have the final say regarding the basic characteristics of their trips. Thus, managing next-generation integrated infrastructures for ITS means regulating a large-scale open distributed system populated by a huge number of autonomous, individually rational agents. This scenario is particularly well-suited for multiagent systems technology in an urban context, because management actions can target vehicles individually, instead of whole flows of traffic as, for instance, mechanisms based on the coordination of traffic light cycles do. To this respect, infrastructure facilities that allow each autonomous vehicle to reserve time-space-slots at interactions, so as to safely transit through them, have been studied both for single intersections and for networks of intersections. Still, these reservation-based regulation mechanisms do not consider the fact that different drivers have different preferences.

In this paper we present an economically-inspired policy for managing future reservation-based urban traffic management infrastructures that takes into account the drivers’ different valuations of their vehicles’ travel times. At the intersection level, vehicles compete for the right to cross intersections through combinatorial auctions, while at the network level a pricing scheme, based on general market equilibrium, accounts for an efficient use of network resources (time-space slots at intersections). In Section 2 we briefly outline previous work in the field. Section 3 evaluates our auction-based intersection control mechanism. Section 4 shows how a distributed pricing scheme, by setting the publicly-known reserve prices of the auctions, leads to a combined policy that allows vehicles to travel the faster through the network the more their drivers are willing to pay for the trip, with

2http://www.intellidriveusa.org
no significant social cost in terms of average travel times. Section 5 summarises the lessons that we have learnt.

2. PREVIOUS WORK

The applications of multiagent systems technology to the field of traffic and transportation are manifold [1]. In the context of urban traffic management, much work focuses on automation systems embedded in control devices that work at the operational level [19], as well as on distributed control [8] for traditional infrastructures. With the exception of some recent work [4] [16] [17], few authors have paid attention to the potential of a tighter integration of vehicles and control elements in future urban road traffic management infrastructures.

This paper sets out from the work of Dresner and Stone [4], who examine a minimally centralised infrastructure facility that allows for the control of intersections. In their model, an intersection is regulated by an intelligent agent, called the intersection manager, which assigns reservations of space and time to each autonomous vehicle, operated by a driver agent, intending to cross the intersection. When a vehicle is approaching an intersection, the driver agent requests the intersection manager to reserve the necessary time-space slots to safely transit through the intersection. The intersection manager, provided with data such as vehicle ID, vehicle size, arrival time, arrival speed, type of turn, etc., simulates the vehicle’s trajectory inside the intersection and informs the driver agent whether or not its request conflicts with the already confirmed reservations. If there is no such conflict, the driver agent stores the reservation details and tries to meet them; otherwise it may try again at a later time. Such an approach has shown, in a simulated environment, several advantages, because it may drastically reduce delays with respect to traffic lights.

3. TRAFFIC CONTROL: BEYOND FCFS

Any traffic control system is driven by the principle of optimising the use of the available resources. In the case of a single reservation-based intersection, this implies that the policy followed by the intersection manager for granting or rejecting the reservation requests should maximise the intersection’s throughput. In [18], for instance, Dresner and Stone’s first-come-first-served (FCFS) policy is compared to several other control regimes inspired by adversarial queueing theory in terms of the vehicles’ average delay. However, this metric ignores the fact that in the real world, depending on the context and their personal situation, people value the importance of travel times and delays quite differently. In this section we present a control policy for reservation-based intersections that relies on an auction mechanism, so as to allocate their resources to the agents that value them the most. We specify the auction design space (resources, bidding rules, clearing policy, etc.) and how the original protocol for intersection control proposed by Dresner and Stone is modified. In the following, we use the term bidder or driver agent to refer to the agent that operates an autonomous vehicle and submits bids to acquire a reservation request.

3.1 Auctioned resources

In our scenario, the auctioned good is the use of the space inside the intersection at a given time. An intersection is modelled as a discrete matrix of space slots. Be \( S \) the set of the intersection space slots, \( S = \{ s_1, s_2, \ldots, s_m \} \). Be \( t_{\text{now}} \) the actual time, and \( T(t_{\text{now}}) = \{ t_{\text{now}} + \tau, \forall \tau \in \mathbb{N} \} \) the set of (future) time steps. The set of items that a bidder can bid for is the set \( I = S \times T(t_{\text{now}}) \).

Due to the nature of the problem, a bidder is only interested in bundles of items over the set \( I \). In fact, a reservation request implicitly defines which space slots at which time the driver agent needs in order to transit through (see Figure 1). Thus, the items must be necessarily allocated by a combinatorial auction.

3.2 Bidding rules

The bidding rules define the form of a valid bid accepted by the auction. Note that the bundle of items the bid refers to is implicitly defined by the reservation request. Given the parameters arrival time, arrival speed, lane and type of turn, the auctioneer (i.e., the intersection manager) is able to determine which space slots at which time are needed. The only additional parameter that a driver agent must include in its reservation request is the amount of money that it bids...
In our scenario, a bidder is allowed to withdraw its bid and to submit a new one, if the new bid is greater or equal to the old one. This avoids that a bidder first acquires a reservation with an overpriced bid, and then iteratively tries to resubmit lower bids in order to obtain the same reservation at a lower price.

3.3 Auction protocol

The auction proceeds as a continuous alternation of two phases: bids collection and winner determination. The protocol (see Figure 3) starts with the auctioneer waiting for bids for a certain amount of time. Once the new bids are collected, they will form the bids set. Then the auctioneer executes the winner determination algorithm, and the winners set is built, containing the bids whose reservation requests are provisionally accepted. The auctioneer sends a CONFIRMATION message to all bidders that submitted the bids contained in the winners set, while a REJECTION message is sent to the bidders that submitted the remaining bids.

Then a new round begins, and the auctioneer collects new incoming bids for a certain amount of time. Once the new bids are collected, the bids set is built as the union of the new bids and the provisionally accepted bids (i.e. the winner of previous bidding rounds)\(^3\). After having executed the winner determination algorithm, the auctioneer sends a CONFIRMATION message to the bidders whose bid is in the winners set, unless such confirmation has already been sent in a previous round. For all the other bids, the auctioneer sends either a REJECTION message or a DECOMMIT message. The DECOMMIT message is sent to the bidders whose bids have been provisionally accepted in a previous round, but do not belong to the current winners set anymore.

\(^3\)We remark that even a bidder that submitted a winning bid is allowed to resubmit a new bid, which will replace the old one. This is because a driver agent may want to change its provisionally accepted reservation when it realises that it is unable to actually use the reservation due to changing traffic conditions.

This mechanism avoids that a low-valued bid, in the winners set at round \(k\), impedes the allocation of the disputed reservation to some high-valued bids, submitted at round \(k + n\). A bid can be de-committed as long as the driver agent that submitted the bid can safely decelerate and reach zero speed before the arrival time at the intersection\(^4\). At the end of any round, the auctioneer sends a CLEAR message to the bidders whose bids are in the winners set and cannot be de-committed. Notice that, in general, for driver agents approaching an intersection it is rational to treat their provisionally accepted bids as if they were cleared, as they can safely decelerate in case of a DECOMMIT.

3.4 Winner determination algorithm

Since the auction must be performed in real-time, both the bid collection and the winner determination phases must be time-bounded. This implies that optimal and complete algorithms for the winner determination problem (WDP), as those proposed by Leyton-Brown et al. [11] or by Sandholm [15], are not suited for this kind of auction. An algorithm with \textit{anytime} properties is needed, such as the stochastic local search proposed by Hoos et al. [7] that we have adapted to our scenario in order to manage the de-commitment of bids.

The algorithm starts initialising the set \(B\) with all bids (new ones and confirmed ones). The winners set \(W\) is initially empty, while the set \(C\) at first contains all confirmed bids. This condition is determined as follows: be \(v_a\) the arrival speed, \(b\) a deceleration factor, and \(t_a\) the arrival time at the intersection. The deceleration equation is defined by \(v(t) = v_a - b \cdot t\). Thus, the vehicle can safely reach zero speed before reaching the intersection if \(t = v_a/b < t_a\).

![Figure 3: Auction protocol](image-url)
Figure 4: Bid-delay relation ($\lambda = 10$, $\lambda = 20$, $\lambda = 30$). Please note the different scale of the y-axis in the three plots.

bids that cannot be de-committed. Once the initialisation has concluded, the algorithm executes the main loop. Within this loop, a stochastic search is performed for a number of steps equal to the number of bids contained in $B$. The set $A$, which at every step contains the candidate bids for the winners set, is initialised with the bids $C$ that cannot be de-committed. Then, with probability $wp$ (walk probability), a random bid is selected from the set of bids that are not actually in the candidate winners set ($B \setminus A$). Otherwise, with probability $1 - wp$, the highest and the second highest bids are evaluated. The highest bid is selected if its age (i.e., the number of steps since a bid was last selected to be added to a candidate solution) is greater or equal to the age of the second highest. Otherwise, with probability $np$ (novelty probability), the second highest is selected, and with probability $1 - np$ the highest is selected. Once the bid $b$ to be added to the candidate solution has been selected, the neighbourhood of $b$, $N(b)$, is evaluated. The neighbourhood of a bid $b$ is defined by the set of bids for bundles that share with $b$ at least one item. If the neighbourhood $N(b)$ does not contain any bid that cannot be de-committed, the bid $b$ is added to the candidate solution $A$ and all the neighbours of $b$ are removed from $A$. Finally, if the value of $A$ (i.e., the sum of the bids $\in A$) is greater than the value of the best-so-far winners set, $W$, the best solution found so far is updated.

3.5 Experimental results

To evaluate the auction-based policy, we simulate a single intersection with 4 incoming links of 3 lanes each. We simulate different traffic demands by varying the expected number of vehicles ($\lambda$) that, for every origin-destination pair (i.e., the 4 incoming links), are spawned in an interval of 60 seconds. We spawned vehicles for a total time of 10 minutes. In the following, we refer to the auction-based policy as CA and to the first-come-first-served policy as FCFS.

The main goal of this set of experiments is to confirm that the auction-based policy enforces an inverse relation between money spent by the bidders and their delay. The delay measures the increase in travel time due to the presence of the intersection. It is computed as the difference between the travel time when the intersection is regulated by the intersection manager and the travel time that would arise if the vehicle could travel unhindered through the intersection. We generated an artificial population of bidders whose initial endowment is drawn from a normal distribution with mean 100 cents and variance 25 cents, since the willingness to pay of human drivers is usually normally (or log-normally) distributed [6]. In this population, we inserted a set of driver agents, which we use as floating cars to evaluate their delay, endowed with 10, 50, 100, 150, 200, 1000, 1500, 2000 and 10000 cents. We also evaluated the auction-based policy with respect to the average delay of the entire population of driver agents. In all the experiments, we gave the intersection manager 1 second to collect the incoming bids and another second to execute the winner determination algorithm and return a solution. Regarding the parameters of the winner determination algorithm, we set the walk probability $wp$ and the novelty probability $np$ to 0.15 and 0.5, respectively. These values were reported by Hoos et al. [7] to give the best results in similar types of auction (number of bidders, expected size of bundles).

Figure 5 plots the relation between delay and bid value for different values of $\lambda$. There is a sensible decrease of the delay (between 30% and 40%) experienced by the driver agents which bid from 100 to 150 cents with respect to those that
Algorithm 2 Reserve price update

\[ t \leftarrow 0 \]

\textbf{for all } \( b_h \in \mathcal{L}_j \) \textbf{do}

\[ p_j^t(b_h) \leftarrow \epsilon \]
\[ s_j(b_h) \leftarrow initialValue \]
\textbf{end for}

\textbf{while} true \textbf{do}

\textbf{for all } \( b_h \in \mathcal{L}_j \) \textbf{do}

\[ d_j^t(b_h) \leftarrow evaluateDemand \]
\[ z_j^t(b_h) \leftarrow d_j^t(b_h) - s_j(b_h) \]
\[ p_j^t(b_h) \leftarrow updatePrice(\epsilon, z_j^t(b_h), s_j(b_h)) \]
\textbf{end for}

\[ t \leftarrow t + 1 \]
\textbf{end while}

bid less. Nevertheless, the delay reduction tends to settle for driver agents that bid more than 150 cents. This reflects the fact that as the traffic demand increases, the chance that even driver agents with high bids will not be able to travel through the intersection at the desired speed grows as well. Consider a vehicle with a wealthy driver who is in a hurry, travelling behind a vehicle that does not intend to allocate much money to acquire a reservation, and being too close to the intersection to overtake it. In such a case, even the highest bid would not be effective, because it would be impossible to actually make use of the reservation gained in the auction.

Figure 5 plots the average delay for different traffic demands (\( \lambda \in [1, 30] \)). When the traffic demand falls between 1 and 15 expected vehicles per minute, the performance of the CA policy and the FCFS policy is approximately the same. Still, when the traffic demand increases (\( \lambda \geq 20 \)), from the point of view of social welfare, the CA policy performs worse than the FCFS, with a noticeable increase of the average delay. Of course, this is not surprising, as the CA policy was designed to grant a reservation to the driver agent that values it most, rather than maximising the number of granted requests.

4. TRAFFIC ASSIGNMENT: A GENERAL EQUILIBRIUM PERSPECTIVE

As seen in the experiments of the previous section, for single reservation-based intersections under high demand, the CA policy entails a significant social cost, in terms of a greater average delay for the entire population of driver agents. For this reason, if we focus on a urban road network with multiple intersections, an integrated strategy is needed that combines traffic control and assignment, i.e. which distributes traffic flows over the network elements in line with their capacities, thus reducing the demand of potentially congested intersections.

4.1 Reserve price update strategy

From an economic perspective, an intersection manager is a supplier of reservations, which it then allocates through a combinatorial auction. Thus, it controls the reserve price of the auctioned reservations, i.e. the minimum price at which it is willing to sell [20]. Depending on the intersection usage, the intersection manager may apply pricing strategies and modify this reserve price.

Following the market metaphor, our intersection managers compete with each other for driver agents, raising prices in case of increasing demand or lowering them in case of decreasing demand. The pricing strategy is based on the general market equilibrium theory [2] [3]. The adaptive and concurrent pricing strategies applied by the intersection managers are in charge of computing in a distributed way the price vector \( p^* \) that corresponds to the general market equilibrium, a situation where the amount of resources sought by the driver agents is equal to the amount of resources supplied by the network.

Be \( \mathcal{L}_j \) the set of incoming links of intersection \( j \). For each incoming link \( b_h \in \mathcal{L}_j \), the intersection manager defines the following variables:

- Current reserve price \( p_j^t(b_h) \): the reserve price applied by the intersection manager \( j \) for the auctions that allocate the reservations to the driver agents of the incoming link \( b_h \).
- Total demand \( d_j^t(b_h | p_j^t(b_h)) \): represents the total demand at time \( t \), i.e., the number of driver agents on link \( b_h \) that are bidding for a reservation.
- Supply \( s_j(b_h) \): defines the supply of intersection manager \( j \) for the incoming link \( b_h \), i.e., the number of driver agents that intersection manager \( j \) wants to participate in each auction.
- Excess demand \( z_j^t(b_h | p_j^t(b_h)) \): the difference between the total demand at time \( t \) and the supply, \( z_j^t(b_h | p_j^t(b_h)) = d_j^t(b_h | p_j^t(b_h)) - s_j(b_h) \). We remark that the excess demand can be negative, when the demand is lower than the supply.

Given the set of all intersection managers that are operating in the market, \( J \), we define the price vector \( p \) as the vector of the reserve prices applied by each intersection manager \( j \in J \). To enforce the attainment of the general equilibrium, each intersection manager applies the reserve price update strategy outlined in Algorithm 2. At time \( t \), each intersection manager \( j \) computes, independently from other, the excess demand \( z_j^t(b_h | p_j^t(b_h)) \) and updates the price \( p_j^t(b_h) \) using the formula:

\[
p_j^{t+1}(b_h) \leftarrow \max \left\{ \epsilon, p_j^t(b_h) + \frac{z_j^t(b_h | p_j^t(b_h))}{s_j(b_h)} \right\}
\] (1)

where \( \epsilon \) is the minimum reserve price and \( s_j(b_h) \) is the number of driver agents that intersection manager \( j \) wants to participate in each auction. The definition of \( \epsilon \) and \( s_j(b_h) \) is a design decision that may affect the dynamics of the market: i) \( \epsilon \) is the minimum reserve price above which a bidder must bid to get a reservation and ii) \( s_j(b_h) \) is the number of vehicles above which the intersection manager considers that there is an excess demand and starts raising prices.

Vehicles travelling on network links with low demand shall incur in costs as low as possible, so we chose \( \epsilon = 0 \). To define the supply \( s_j(b_h) \), we rely on the fundamental diagram of traffic flow [12]. Let \( \rho^{opt} \) be the density that maximises the traffic flow on link \( b_h \). We chose \( s_j(b_h) = 0.5 \cdot \rho^{opt} \cdot ||b_h|| \), where ||\( b_h || \) is the length of link \( b_h \). In other words, the intersection manager considers that there is an excess demand when the density on link \( b_h \) reaches the 50% of the optimal density.
strategy, there is no need of communication between the intersection managers, since they are able to compute locally the total demand at time $t$, counting the number of driver agents that are bidding for a reservation.

### 4.2 Driver agent model

Differently from the single intersection scenario evaluated in Section 3, in case of a network of intersections we need a reasonable model for the vehicles’ route choice. We assume that driver agents have a model of the road network that enables the computation of the travel time at free flow. Furthermore, we assume that the intersection reserve prices are available to the driver agent, published on some sort of price index board. Each driver agent holds a private valuation of the bids that it is willing to submit to transit through the intersections of its chosen route, defined by the variable $b_i$. Given the monetary constraint, the driver agent selects the most preferred route $r^*$, taking into consideration the estimated travel time associated with the route. 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 $TT^{free}(l_k)$ and reserve price $K(l_k)$.

$$TT^{free}(l_k) = \frac{|l_k|}{v_{max}(l_k)} \quad (2)$$

$$K(l_k) = \begin{cases} p^j_i(l_k) & \text{if } l_k \in L_j \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where $|l_k|$ is the length of link $l_k$, $v_{max}(l_k)$ is the maximum allowed speed on link $l_k$, and $p^j_i(l_k)$ is the reserve price set by intersection manager $j$ that governs the intersection which the link $l_k$ is connected to. The sum over all the links of $r$ gives the travel time at free flow of the entire route $r$:

$$TT^{free}(r) = \sum_{k=1}^{M} TT^{free}(l_k) \quad (4)$$

Based on the bids $b_i$ that the driver agent plans to submit, the choice set $\mathcal{R}$ is given by those routes whose intersections have a reserve price lower than the bid $b_i$:

$$\mathcal{R} = \{ r_1, \ldots, r_N \mid K(l_k) \leq b_i \forall l_k \in r \} \quad (5)$$

Once the choice set is built, the driver agent selects the shortest route $r^* = \arg\min_{r \in \mathcal{R}} TT^{free}(r)$. Since the reserve prices change with time, a driver agent may react to the price fluctuations and rearrange its route on-the-fly.

### 4.3 Experimental results

To evaluate our approach, we use a hybrid mesoscopic-microscopic simulator. The traffic flow on road sections is modelled at mesoscopic level but, as a higher level of detail is required for reservation-based intersections, when a vehicle enters an intersection, its dynamic switches to a microscopic, cellular-based simulation, whose update rules follow the Nagel-Schreckenberg [13] model. Although our work is independent from the underlying road network, we chose a simplified topology of the urban road network of the city of Madrid (see Figure 6) for our empirical evaluation rather than an unrealistic, lattice-like, network. Each big dark vertex in Figure 6 that connects three or more links is modelled as a reservation-based intersection. We aimed at recreating a typical morning peak scenario, with more than 11000 vehicles that depart within a time window of 50 minutes from/to 7 destinations outside the city (marked with $O_1$ up to $O_7$ in Figure 6).

In our first experiment, the intersection managers apply the reserve price update strategy described in Subsection 4.1, and assign reservations to driver agents using the auction-based policy described in Section 3 (referred to as CA policy). The goal is to verify that our integrated policy effectively guarantees lower delays to driver agents that submit higher bids. For this purpose, we calculate the average increase of the vehicles’ travel times, defined as

$$\frac{TT^i_{real} - TT^i_{lower\,bound}}{TT^i_{lower\,bound}}$$

being $TT^i_{real}$ the observed travel time for vehicle $i$ from an origin to a destination, and $TT^i_{lower\,bound}$ the travel time from the same origin to the same destination if the vehicle could cross each intersection unhindered. For simplicity, we refer to the percentage increase of the travel time with the term normalised delay. Figure 7 plots the relation between bid value and normalised delay of the population of driver agents. As in the experiments of Subsection 3.5, it is possible to appreciate an inverse relation between these two quantities. The driver agents that submit bids between 150 and 200 cents reduce the delay of about the 50% with respect to those which bid less than 50 cents.

In a second experiment, we compared the CA policy to networks of intersections governed by the first-come-first-served control policy without assignment (FCFS). The aim is to evaluate the global performance (in terms of average

This ratio enables us to aggregate the results of driver agents even though they have different origins and/or destinations.

We assume that in this case the driver agents choose the shortest route from their origin to their destination.
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sections become cheaper while more demanded ones become
obtain a system in dynamic equilibrium where unused inter-
serve prices of the intersections’ auctions. As a result, we
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intersection level, intersection manager agents assign space-
vehicles in reservation-based urban traffic management. At
policy to accommodate the preferences of users of autonomous
5. CONCLUSIONS

In this paper we have presented an economically inspired
policy to accommodate the preferences of users of autonomous
vehicles in reservation-based urban traffic management. At
intersection level, intersection manager agents assign space-
time slots through combinatorial auctions, so as to give pri-
ority to vehicles whose drivers are willing to pay more. At
network level, a decentralised pricing scheme, targeting the
general market equilibrium, (implicitly) coordinates the re-
serve prices of the intersections’ auctions. As a result, we
obtain a system in dynamic equilibrium where unused inter-
sections become cheaper while more demanded ones become
more expensive, leading to a more efficient use of the net-
work resources. We have shown that vehicles whose drivers are
willing to pay more for their reservations are effectively
rewarded with lower travel time, while the social cost of our
policy when compared to FCFS is reduced and often even
compensated by the traffic assignment effects of our policy.
Our approach differs from other work on reservation-based
traffic management, such as [4] and [17], with regard to its
primary objective: instead of trying to improve the travel
time of everyone (social welfare), our management policy in-
tends to assign the available resources in the network to the
drivers that value them most (i.e., that are willing to pay
more for them). A similar objective underlies the work by
Schepperle and Bohm [16], although they do not account for
networks of intersections. In their work it is the intersection
manager that initiates a Vickrey auction, offering the earli-
est time slot to the first vehicles that are approaching the

![Figure 7: Relation between normalised delay and bid](image)

![Figure 8: Moving average of travel time](image)

Table 1: Average travel time (min): CA (upper) vs. FCFS (lower)

<table>
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<th>O₂</th>
<th>O₃</th>
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<td>20.74</td>
<td>12.07</td>
<td>7.47</td>
<td>-</td>
<td>10.05</td>
<td>21.36</td>
</tr>
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<td>O₂</td>
<td>32.16</td>
<td>30.61</td>
<td>21.53</td>
<td>8.83</td>
<td>-</td>
<td>10.77</td>
<td>17.65</td>
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<tr>
<td>O₃</td>
<td>24.46</td>
<td>27.24</td>
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<td>16.39</td>
<td>10.35</td>
<td>-</td>
<td>14.16</td>
</tr>
<tr>
<td>O₄</td>
<td>22.51</td>
<td>22.88</td>
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<td>15.73</td>
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<td>23.93</td>
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<tr>
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<td>23.25</td>
<td>56.42</td>
<td>34.99</td>
<td>31.23</td>
<td>11.99</td>
<td>-</td>
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</tbody>
</table>

Figure 7: Relation between normalised delay and bid

Table 1: Average travel time (min): CA (upper) vs. FCFS (lower)
also be relevant to this respect [5].

Another extension refers to the driver agent models used in the experiments. While we claim that the approach presented in Subsection 4.2 captures reasonably well individually rational behaviour for isolated trips, it is a matter of fact that most people travel repeatedly between specific locations (e.g., commuters). Driver agents could take advantage of this fact just as human drivers do, when they implicitly use historical information and past experiences to update the likelihood of selecting a specific route at a certain time [9]. Furthermore, a more sophisticated driver agent model should go beyond route choice and include, for instance, decisions on departure times [14].

Finally, in future work we will compare our management policy, based on one-to-many (combinatorial) auctions, to other economic models. For example, the market could be regulated by a continuous double auction, where many sellers (i.e., the intersection managers) place their sell-bids, and many buyers (i.e., the driver agents) submit their buy-bids, and the market continuously clears when a match between sell-bids and buy-bids is found. Also bargaining could be easily implemented in our scenario, with driver agents and intersection managers negotiating and agreeing on a mutually acceptable price.

6. ACKNOWLEDGMENTS

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7. REFERENCES