Exploiting Traffic Lights to Manage Auction-Based Crossing

Filippo Muzzini
Dip. Scienze Fisiche, Informatiche e Matematiche
Univ. di Modena e Reggio Emilia
Modena, Italy
filippo.muzzini@unimore.it

Nicola Capodieci
Dip. Scienze Fisiche, Informatiche e Matematiche
Univ. di Modena e Reggio Emilia
Modena, Italy
nicola.capodieci@unimore.it

Manuela Montangero
Dip. Scienze Fisiche, Informatiche e Matematiche
Univ. di Modena e Reggio Emilia
Modena, Italy
manuela.montangero@unimore.it

ABSTRACT

Auction-based crossing management approaches are used to design coordination policies for autonomous vehicles and improve smart intersections by providing differentiated latencies. In this paper, we propose and exploit an auction based mechanism for managing the urban traffic light infrastructure in which participant vehicles are either *equipped* or *non-equipped*. The difference between these two categories of vehicles is that only the equipped ones can actively participate to auctions through in-vehicle IoT-devices, i.e. they are able to communicate with the surrounding urban infrastructure. In this way, we aim to study the transitional period that will occur before the complete adoption of autonomous or strongly connected vehicles. Through extensive experiments and simulations, by comparing our mechanism to the traditional traffic light fixed-time-control approach, we studied the benefits and limitations, in term of waiting and trip times, when varying the subset of equipped vehicles and the available budget that can be used to participate to auctions.

CCS CONCEPTS

• **Computing methodologies → Model verification and validation**; **Agent / discrete models**; **Simulation evaluation**.

KEYWORDS

Autonomous vehicles, vehicle coordination, auction

ACM Reference Format:
Filippo Muzzini, Nicola Capodieci, and Manuela Montangero. 2020. Exploiting Traffic Lights to Manage Auction-Based Crossing. In *Proceedings of EAI International Conference on Smart Objects and Technologies for Social Good (GoodTechs '20)*. ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

The rapid growth of IoT [7]-based applications and related frameworks is opening all sorts of new opportunities. Smart mobility [9], for instance, will improve our driving experience in what are nowadays defined as *smart cities*. A smart city is an urban area enhanced with a pervasive technological infrastructure able to provide useful information in real-time with regards to traffic, city safety and current events. IoT-powered devices such as smartphones and next-generation vehicles are then responsible for collecting such data for processing. Focusing on smart mobility future development within the context of a smart city, we envision that autonomous vehicles will populate the streets, and will be able to take decisions about traffic by considering many different aspects such as the length of the path between origin and destination, the cost of the route, the driver needs, the state of current traffic and so on. Such decisions will be fostered by the surrounding smart city infrastructure and will be aimed at reduce travelling times, traffic congestion, pollution, driver stress and make cities a better place to live and work.

However, smart mobility needs proper design. In particular, *crossings* represent a challenge [1]: traditional traffic lights and precedence rules have been designed for a scenario in which vehicles were only human-driven and, thus, human characteristics and limitations are to be taken into consideration when devising mechanisms to clear crossings. On the one hand, traffic lights are fair because all vehicles will eventually pass the crossing by simply following a FIFO policy for each lane. However, FIFO policies tend to keep idle vehicles in case of no other vehicles coming from the intersecting lanes. On the other hand, precedence rules do not suffer from this problem, but they might sacrifice fairness. For instance, a STOP sign might keep a vehicle idle for a long time if a large number of vehicles keep coming from the lanes with priority. In other words, we can say that traffic lights keep vehicle latency's low, but are not work conserving, while precedence rules are work conserving but might incur in high latencies for some vehicles.

In a future in which all vehicles will be autonomous, more intelligent strategies for crossing management will be implemented. Such strategies will exploit all the interesting features and potentialities of such vehicles, provided that they all behave according to the same set of policies. This also includes not stopping at all at intersections, but rather dynamically adjust vehicle velocities to avoid collisions in crossings [6].

However, the transition from exclusively human-driven vehicles to exclusively autonomous vehicles will take time to conclude. Within a first transition period, human-driven vehicles will have to coexist with autonomous vehicles and, in a subsequent transition period, autonomous vehicles might act according to different policies. This might happen either because the city administration will experiment different co-existing policies or even due to the fact that different administrations might deploy different strategies.

In this paper, we tune our approach for dealing with the inevitable transition period in which streets are populated with both

GoodTechs '20, September 14–16, 2020, Cyberspace

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM…$15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

human-driven and autonomous or assisted vehicles. Indeed, human-driven vehicles are not to be expected to behave as autonomous ones: they are less reliable, less predictable, and human drivers can not execute driving instructions with the same precision and timing of autonomous ones.

Our work assumes the possibility to exploit already existing infrastructures, in particular traffic lights, to implement an auction-based policy to assign vehicles priorities at intersection crossings. More specifically of our scenario, traffic lights are used to give instructions to human drivers and coordinate them with autonomous vehicles through an auction based mechanism. Through extensive simulations we prove that out proposed mechanism incentives drivers to transition towards vehicles with autonomous driving capabilities. Our contribution is however twofold, because, by analyzing the performance of our policy, we also show a more general, important result: the FIFO nature of lanes at intersections jeopardizes efforts of single vehicles to win auctions placing high bids, thus frustrating attempts to reduce their trip duration.

The following of the paper is organized as follows: in Section 2 we present related work, in Section 3 we describe the simulated approach, in Section 4 we show experimental settings and results, finally we conclude in Section 5.

2 RELATED WORK

In this section we compare and discuss auction-based approaches for crossing management (Section 2.1) and more general mechanisms for coordination of autonomous vehicles (Section 2.2).

2.1 Auctions at Intersections

In one of the milestone papers exploiting auctions in crossings management [5], authors address the value of time of each vehicle, representing it by means of a wallet system for automatic bidding based on trip characteristics, driver-specified budget, and remaining distance to the destination. Moreover, they also address the optimization of the overall traffic. A more complex approach is adopted by Schepperle and Böhm [13]. They propose a two-step auction mechanism to manage vehicles at intersections, based on a second-price sealed-bid auction [15]: in the first step, only vehicles that can pass the intersections are involved, while in the latter step also the vehicles in the second place of the queue can bid, depending on the result of the first step for the preceding vehicle. Finally, Vasirani and Ossowski [14] propose a different approach to manage urban crossings, based on market-inspired rules.

We can highlight two main differences between this body of work and our contribution. First, we consider both *autonomous* vehicles and *human-driven* vehicles. Handling such a simultaneous presence is of paramount importance for coping with the transition from only human-driven vehicles to a traffic scenario only composed of autonomous vehicles. The need of studying the behaviour of a smart city in such a transitional period has been highlighted by both well-known and established literature [6] and more recent research contributions [2] [3]. Indeed, solutions designed exclusively for autonomous vehicles might not be adequate for human-driven ones, as human drivers might not be able to act as expected by the other actors of the system. Second, we enable *all* the vehicles waiting in a lane to participate to the auction, instead of only the vehicles located in the first position within a traffic light queue.

2.2 Coordination of Autonomous Vehicles

Pinciroli et al. [11] take into consideration the controllers embedded in ensembles of autonomous robots as a multi-agent system. They highlight the difference between smart devices and autonomous vehicles in navigation scenarios; the first ones feature little capability of interacting with the physical world, while this capability is generally exhibited by more complex robots and therefore by autonomous vehicles. To this purpose, the latter can exploit sensors and actuators by allowing the single agent to have an understanding of the surrounding environment through its sensors, to then act on it using its actuators. Their proposal relies on a *swarm language construct* that allows to categorize robots in swarms and to assign jobs to the swarms. The aim of their approach is to provide for *re-usability* and *predictability* of the coded behavior, which turn out to be very important aspects in the field of autonomous driving.

Murthy et al. [10] propose a simulated environment designed to have cars traveling in a highway, self-organize themselves in platoons with the final goal to reduce fuel consumption, by drafting off one another. This approach goes in the same direction of the previous one, hence it is aimed to achieve *re-usability* and *predictability* in a specific application scenario.

3 THE APPROACH

Our work is based on the approach proposed by Cabri et al. in [4], in which intersections already equipped with a traffic light are managed by means of auctions. This implies converting the traffic light functionalities to a new crossing management system. In our scenario we assume that autonomous vehicles and human-driven vehicles coexist. Moreover, vehicles might be *equipped* or *non-equipped* to participate to auctions at intersections. In the former case, vehicles are endowed with software and/or devices capable of autonomously participate to the auction. This is accomplished without the need of human drivers to take decisions. In case of non-equipped vehicles, they will not actively participate to auctions, but they will be allowed to go trough the crossing anyway by following directions given by traffic lights.

3.1 Crossings and Traffic lights

We assume that each crossing has its own management system that is run on a physical device that is placed at the crossing site and that can control the traffic light. The access to the crossing is regulated by the crossing management system by setting the next green light by means of an auction: vehicles in the lanes make their bids according to the budget they devoted to the current trip, and the lane with the total highest bid gets right to switch to a green light.

As in traditional traffic lights, the green lights dictates the lane whose vehicles are allowed to go through the crossing. Only one lane at the time displays the green light while all the other lanes display the red light and their vehicles must wait. We do not allow vehicles of different lines to be in the crossing at the same time, even if they do not have conflicting trajectories, to prevent incidents caused by possibly unpredictable behaviours of human drivers.

The green light has a minimum display time Γ, set to allow a safe crossing clearing by autonomous and human-driven vehicles.

3.2 Budgets

Equipped vehicles, either autonomous or human-driven, dispose of a budget in virtual coins that will be used to place bids when they reach the proximity of traffic lights. For each trip, autonomous vehicles allocate a part of their total budget according to how much they are willing to spend for the trip.

The choice of the amount of the budget for a specific trip can be set by drivers according to their needs, e.g., if they are in a hurry or not, or if they have to make some other trips before being able to get more budget. One might also foresee the possibility to define the trip budget according to an estimated arrival time. Eventually drivers will learn how to handle their budget, analogously to how we learned to manage our availability of GB of data for our smartphones.

3.3 Bids

When approaching an intersection with a traffic light, equipped vehicles participate to an auction. The traffic light collects the bids coming from vehicles in all the lanes for the whole duration of the current green light. At the end of this period of time, for each lane, the system computes the sums of the bids; the lane with the total highest bid wins so that the next green light for the next Γ time instants is awarded for that specific lane. For the sake of fairness, total bids coming from a lane having a green light are scaled down, to avoid starvation of the other lanes and to encourage alternation of the green light among different lanes.

Equipped vehicles compute their bids according to their route and their trip budget, analogously to what is done in [5]: at departure, final destination is selected and, thus, route is computed. Assume the route goes through $\mathcal{I}$ intersections for which a bid is necessary, and let $\mathcal{B}_t$ be the trip budget allocated for such route, then each bid is set to $\frac{\mathcal{B}_t}{\mathcal{I}}$. This bid choice prevents vehicles to run out of trip budget before reaching the end of the route. If a reroute occurs, a new bid amount is computed according to the new number of crossing in the new route and the remaining trip budget.

As for not equipped vehicles and for equipped vehicles that run out of budget, the system places bids for them, by computing the average of the bids received from all equipped vehicles that participate to that specific auction. In such a way such vehicles behave as an *average* equipped vehicle. If there are only non equipped vehicles, the auction is won by the lane with the largest number of vehicles.

4 EXPERIMENTS

We are interested in understanding if our reuse of existing traffic light might be useful not only in coordinating human-driven and autonomous vehicles, but also in reducing waiting times (latency) at crossing sites. Therefore, to test our proposal, we compare a situation in which traffic lights at crossings are used with the classical Fixed-Time Control (FTC) [12] approach to one in which traffic lights are used with the auction system described in the previous section.

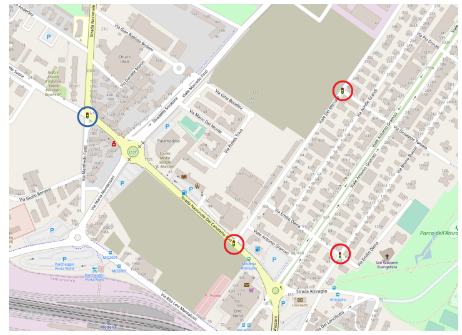


Figure 1: Modena Automotive Smart Area (MASA). The traffic light circled in blue is the only one really existing, those circled in red have been added for the sake of experiments.

4.1 Scenario

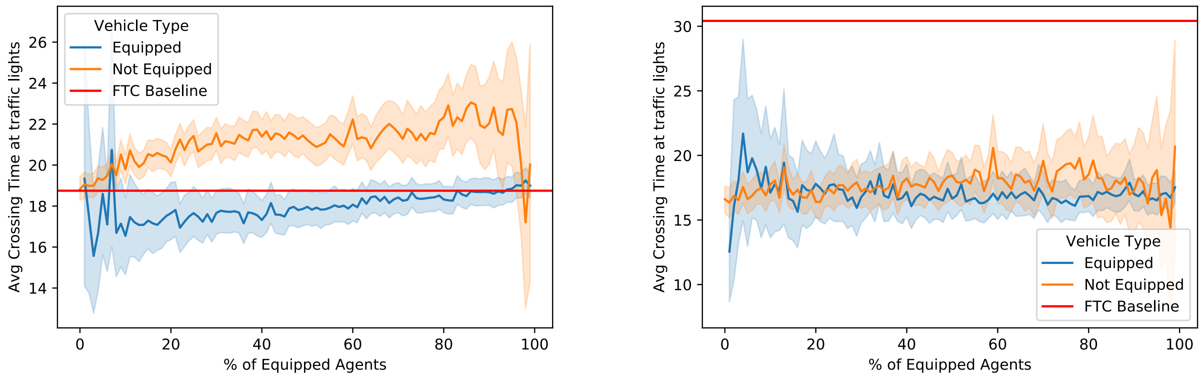
Our work is framed in the context of the CLASS Horizon 2020 project [1], whose goal is to deploy a 1 KM-wide smart urban area located within the city of Modena, in Northern Italy. Within this area and by exploiting a recently set up infrastructure with a wide variety of smart sensors, we can collect and process in real-time the vast amount of data on the urban traffic. Such data will be used to communicate to the connected vehicles. The latter are equipped with heterogeneous sensors/actuators and V2X connectivity so to enhance both driving experience and city overall safety. This is achieved by deploying advanced urban mobility applications based on a combination of data-in-motion and data-at-rest analytics to efficiently coordinate vehicles and the city computing resources.

The Map: The part of the city involved in the project, and that will be considered for the rest of this paper, is depicted in Figure 1. From now on, we will refer to this area with the acronym *MASA* (Modena Automotive Smart Area). In order to study the agents' behaviour on a more complex scale, we artificially added three traffic lights that are not present in the considered area (see Figure 1), and we reached a total of four traffic lights.

The Simulator: We reproduced the MASA area within the MATSim[2] multi-agent simulator for urban transportation [8]. Furthermore, we implemented and added to the MATSim simulator four additional modules for enhancing its ability to simulate smart city related scenarios. In particular, we implemented a *communication module* and a *smart agent module* in order to allow agents to send bids to traffic lights, a *perception module* in order to allow traffic lights to locate not equipped agents, and finally an *analysis module* to register values needed for the analysis.

Vehicles: The standard simulation population consists of 2000 agents with departure times spread during the 24 hours of the day. Each vehicle performs two trips a day, from home to work and back, and facilities (i.e. departure and destination locations) are randomly distributed all over the MASA map. Departure times follow a Gaussian's distributions (when departing from home the distribution has

[1] https://class-project.eu/
[2] https://www.matsim.org/



(a) 2000 vehicles **(b) 500 vehicles**

Figure 2: Average delays incurred by vehicles to cross the intersections with traffic lights during their trip, by varying the rate of equipped agents, grouped by Vehicles Type (equipped and non equipped). The red line indicates the average delay in the scenario with FTC policy. Bands around average delays represent the average confidence.

its peak at 9AM and on the way back the rush hour is set to 6PM), to simulate variations in daily traffic.

Budgets: Concerning vehicles individual budget, to simulate variability in budget disposal, each vehicle is associated to a class of budget among the following: *low budget*, with interval of possible values [1..28]; *average budget*, with interval of possible values [38..65]; *high budget*, with interval of possible values [75..101]. In our simulations, we set 1/3 of the vehicles in each budget class. The actual trip budget is randomly chosen within the previously assigned budget class range. The scaling factor for the bid of the lane with green light is set to ten.

Waiting times: We are interested in measuring the time spent by vehicles to cross the intersections with traffic lights during their trips. For this purpose we consider only the road segments before intersections with traffic lights and we measure the time elapsed between the instant a vehicle enters one segment and the instant the same vehicle leaves the same segment.

To understand how our approach performs, we set up two experiments within the MASA area:

Experiment 1. We measure delays of 2000 equipped and non equipped vehicles when using our crossing management system and varying the percentage of equipped vehicles. As a baseline we consider vehicle delays, under the same experimental settings, occurring when traffic light systems use the FTC policy.

Experiment 1bis. We repeat Experiment 1 by decreasing the number of vehicles down to 500, so to be able to study the impact on traffic light waiting times with a significant lower number of road users.

Experiment 2. We study how delays vary when varying the budget of a population sample and the size of the population with varied budget, under different conditions:

(1) 2000 vehicles, half equipped and half not equipped, with 200 of equipped vehicles getting their budget raised gradually up to twice the initial budget;
(2) 5000 agents half equipped and half not equipped, varying the percentage of agents that increase their budget and gradually doubling their budget;
(3) 2000 agents, gradually varying the percentage of agents that increase their budget up to 40% and gradually increasing their budget up to 2000%.

4.2 Experimental results

Experiment 1. Figure 2a shows the results of this experiment: the x-axis reports the percentage of equipped agents, whereas the y-axis shows the average delay due to waiting in line before crossing intersections with traffic lights. The blue line refers to equipped vehicles, the orange one to non equipped ones. Finally, the red line is the average delay when traffic lights implement the FTC policy. We observe that, except when the percentage of equipped vehicles is very small or very large, equipped vehicles incur into smaller delays than non equipped ones; in addition, the latency of the equipped vehicles in auction-managed crossings is smaller than when using the FTC policy. This result suggests that, during transition from non equipped to equipped, it is advantageous to be equipped.

On the other hand, when equipped vehicles are very few, it is difficult to determine whether being equipped is a real advantage or not. Delays might strongly depend on the specific traffic situations at intersection sites: whether the bidding vehicle is at the beginning or in the back of the lane, or whether the few actively bidding vehicles find themselves in the same lane and so on.

At the opposite side of the plot, we can observe that the situation seems to get worst for equipped vehicles than when the FTC policy is adopted, while the few non equipped vehicles gets a great advantage of being few. This result is not surprising for this setting: indeed the number of vehicles in the simulation is likely to fill all lanes at each crossing site, and the auction strategy might delay a lane for more than one round of green lights. This behaviour does not occur in the FTC strategy.

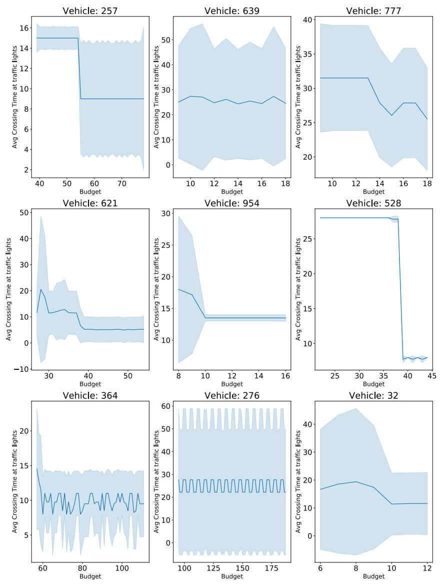


Figure 3: Avg waiting time at traffic lights (y-axes) during whole trip, when varying their budget (x-axes), for single vehicles.

Experiment 1bis. To test our last statement, we repeated the experiment with 1/4 of vehicles, namely 500, to see if intersection congestion might be the cause of such a small difference among the two policies when the percentage of equipped vehicles is high. Results in Figure 2b) show that, with lighter traffic, the auction policy always outperforms the FTC approach. Moreover, there is no great difference for equipped and not equipped vehicles. Motivation is to be sought in the fact that with light traffic and auctions, vehicles do not have to wait for green lights whenever the other lanes are empty.

Experiment 2.1 We run simulations gradually increasing the budgets of 10% of vehicles, and we analyze the variations in the delays occurred to the same vehicle along the same trip made at the same time of the day. Not completely unexpected, we observe that only 10% of the vehicles whose budged was increased had benefits in terms of reduced delays. We explain this phenomenon by observing that, even if a single vehicle has a very high budget, it can not enter the intersection before the vehicles ahead in the same lane, because intersection access is serialized. If these other vehicle bids are low, then one high bid alone might not be sufficient to win the auction against other lanes, even if in these other lanes there are no vehicles with high budget. This result clearly indicates that it might not be so easy to devise bidding policies to implement systems in which vehicles travelling with different urgency's are guaranteed to speed up their travelling time just by increasing their bids.

We deeper investigate those cases in which delays were reduced, looking for some reason why these cases are favourable. Figure 3 shows some representative examples of delays variations. In each plot, the x-axis reports the trip budget, while the y-axis the average waiting time at intersections with traffic lights.

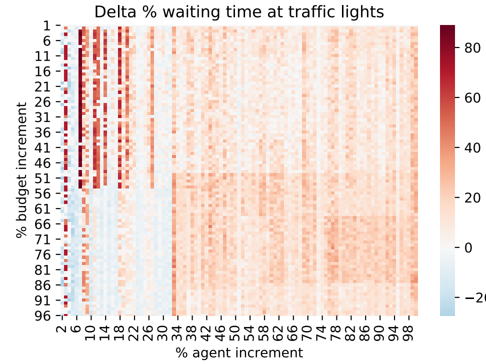


Figure 4: % of increase of waiting time at traffic lights.

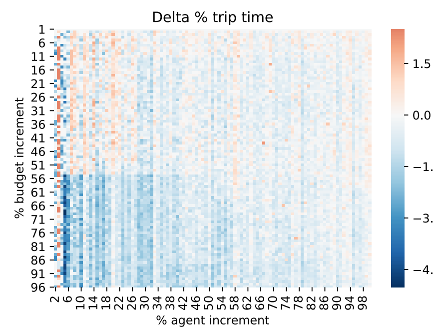
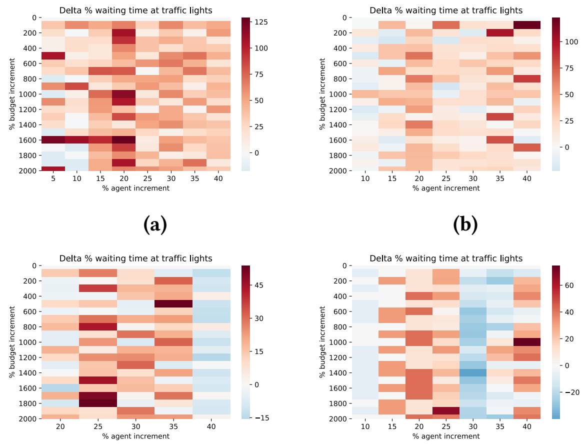


Figure 5: % of increase of trip time.

The majority of not shown plots resemble the behaviour of vehicle 639 (i.e., no significant variation), while for the others we have some that gets a benefit, and others that do not stabilize so well. However, with present experiments, we were not able to find a convincing explanation, in terms of number of intersections, starting budget and/or travelling times, to justify such different situations. The only hint we get is that when number of intersections gets smaller, the situation gets more stable when budget increases and it is more probable that are the some benefits, even with heavy traffic and small budget. Indeed, vehicles 257, 777, 954, 528 go through only one intersection per trip, while vehicles 364 and 276 go through two and three, respectively. Both vehicles 257 and 777 travel with high traffic (around 9AM and 6PM), but have very different starting (40 and 10, respectively) and final budget. On the other side, vehicles 639 and 954 have very similar starting budget (9 and 8 respectively), travel at similar times of the day (leaving home at 11AM and 10AM, respectively, and leaving work at 3PM and 4PM, respectively). However the former has a stable behaviour while the latter gets a benefit, and the only difference is that vehicle 639 has one extra intersection to go through.

Experiment 2.2 In this second experiment we measured the time that a vehicle waits for a green light during its trip and the total time of the trip. We report the result of those vehicles that cross at least 3 traffic lights during their trips, as these are the most significant ones. Figure 4 (resp. Figure 5) is a heat map in which



(a) (b)

(c) (d)

Figure 6: Single vehicle heat map, with increasing budget

we report the average of the percentages of the increase of the waiting times of vehicles (resp. percentage of increase of trip time), whit 5000 vehicles in a 24h time lap. On the x-axis there is the percentage of agents that increase their budget; on y-axis there is the percentage of budget increment. We observe that once over 30%-40% of vehicles have augmented budget, there is no real benefit in still augmenting budgets. On the other hand, up to 30% of vehicles with augmented budget, we have a somehow unexpected situation: it seems that a small increment of budget leads to even worsening waiting times and total trip times, while larger increments leads to some benefits. This might be determined by the heavy traffic condition of this simulation, or on the fact that the heat maps show average delays, or even because the budget increase was not enough to be determinant in some situations. Therefore, we set up the next experiment to have a better understanding of such results.

Experiment 2.3 We deeper analyzed waiting times at traffic lights, by running experiments with up to 40% of vehicles with a budget increase and gradually increasing the budget up to 2000%. We then looked at results for single vehicles. Figure 6 shows heat maps for four representative samples of the results, each corresponding to a different vehicle. We can see that very different situations might occur, with no real interesting pattern, on the contrary results seems rather random: (1) vehicles with high budges sometimes incur into large positive delta delays (es. 6.c with 1800% budget increase); (2) vehicles with a small increase incur into large negative delta delays (es.6.d with 200% budget increase); (3) when few (resp. more) vehicles have increased budged some vehicle have benefits (es 6.d with 10% increase - resp. es 6.d with 30% increase), but other definitely not (es 6.c with 30% increase - resp. es 6.a with 30% increase). Further investigation will be needed, but these results suggest that traffic conditions and vehicles routes are more determinant than budget.

5 CONCLUSIONS

In this paper we investigate the effectiveness of the auction based system proposed in [4] with respect to the standard traffic fixed-time light policy, also to achieve differentiated latencies. We show that there are benefits for vehicles to join the system for what concerns average waiting times at traffic lights. On the other hand, we show that the system fails in attaining differentiated latencies by differentiating vehicle budgets. Further investigations will be conducted to understand if such differentiated latencies are difficult to achieve because of the experimental settings or because the system intrinsically does not allow them.

ACKNOWLEDGMENTS

This work was supported by the EU H2020 program under the CLASS project, grant No. 780622.

REFERENCES

[1] M. Bertogna, P. Burgio, G. Cabri, and N. Capodieci. 2017. Adaptive coordination in autonomous driving: motivations and perspectives. In *IEEE Int. Conf. on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE)*. IEEE, 15–17.

[2] Giacomo Cabri, Luca Gherardini, and Manuela Montangero. 2019. Auction-based Crossings Management. In *Proceedings of the 5th EAI International Conference on Smart Objects and Technologies for Social Good* (Valencia, Spain) *(GoodTechs '19)*. ACM, New York, NY, USA, 183–188. https://doi.org/10.1145/3342428.3342689

[3] G. Cabri, L. Gherardini, M. Montangero, and F. Muzzini. [n.d.]. About Auction Strategies for Intersection Management when Human-Driven and Autonomous Vehicles Coexist. *Multimedia tools and applications,* to appear ([n. d.]).

[4] G. Cabri, F. Muzzini, M. Montangero, and P. Valente. 2020. Managing Human-driven and Autonomous Vehicles at Smart Intersections. In *in Proc. International Conference on Human-Machine Systems,* to appear.

[5] D. Carlino, S. D. Boyles, and P. Stone. 2013. Auction-based autonomous intersection management. In *Int. IEEE Conf. on Intelligent Transportation Systems*. IEEE, 529–534.

[6] Kurt Dresner and Peter Stone. 2008. A multiagent approach to autonomous intersection management. *Journal of artificial intelligence research* 31 (2008), 591–656.

[7] M. Furini, F. Mandreoli, R. Martoglia, and M. Montangero. 2017. IoT: Science Fiction or Real Revolution?. In *Proc. GOODTECHS 2016*. Springer International Publishing, 96–105.

[8] Andreas Horni, Kai Nagel, and Kay W Axhausen. 2016. *The multi-agent transport simulation MATSim*. Ubiquity Press London.

[9] A. Melis, S. Mirri, C. Prandi, M. Prandini, P. Salomoni, and F. Callegati. 2016. Crowdsensing for smart mobility through a service-oriented architecture. In *2016 IEEE Int. Smart Cities Conference (ISC2)*. IEEE, 1–2.

[10] D. K. Murthy and A. Masrur. 2016. Braking in Close Following Platoons: The Law of the Weakest. In *2016 Euromicro Conference on Digital System Design (DSD)*. 613–620. https://doi.org/10.1109/DSD.2016.78

[11] Carlo Pinciroli and Giovanni Beltrame. 2016. Swarm-Oriented Programming of Distributed Robot Networks. *Computer* 49, 12 (2016), 32–41.

[12] Holger Prothmann, Fabian Rochner, Sven Tomforde, Jürgen Branke, Christian Müller-Schloer, and Hartmut Schmeck. 2008. Organic Control of Traffic Lights. In *Autonomic and Trusted Computing*, Chunming Rong, Martin Gilje Jaatun, Frode Eika Sandnes, Laurence T. Yang, and Jianhua Ma (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 219–233.

[13] H. Schepperle and K. Böhm. 2007. Agent-based traffic control using auctions. In *Int. Workshop on Cooperative Information Agents*. Springer, 119–133.

[14] M. Vasirani and S. Ossowski. 2012. A market-inspired approach for intersection management in urban road traffic networks. *J. of Artificial Intelligence Research* 43 (2012), 621–659.

[15] W. Vickrey. 1961. Counterspeculation, auctions, and competitive sealed tenders. *The Journal of finance* 16, 1 (1961), 8–37.