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Policy-oriented Multimodal Auction-based Traffic Signal Control through Connected Vehicles

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ABSTRACT

This paper presents a novel auction-based traffic signal control mechanism aimed at optimizing multimodal traffic flow at signalized intersections through connected vehicles. The proposed framework, which utilizes a second price sealed bid auction mechanism, allocates green time dynamically based on user bids, incorporating policy-oriented modal priority. This approach addresses the limitations of current signal control systems by providing a computationally fast and distributable method that considers the priority hierarchy of traffic modes, thereby enhancing the efficiency and equity of intersection management.

Key innovations include a dynamic bid distance determination method and a modified bidding scheme that prioritize certain traffic modes according to predefined policies. The effectiveness of these methods is demonstrated through a case study focusing on bicycle prioritization at a real-world intersection in Bordeaux, France.

Simulation results indicate significant improvements in service levels for prioritized modes without substantially increasing delays for other users. The methods' flexibility for adaptation to different intersection configurations and computational feasibility ensure their applicability to a wide range of intersection types and traffic conditions. Our findings suggest that the sealed bid second price auction mechanism can be a useful tool for policymakers aiming to implement multimodal traffic priorities, contributing to reduced travel delays and more effective control at intersections.

Keywords: Multi-modal traffic control; Traffic priority; Traffic management; Traffic control; Auction

INTRODUCTION

Intersections in urban road systems are notable traffic bottlenecks that remain a crucial challenge to transport planners. Greater control of how different modes of transport negotiate their crossing could shape policy that reduces travel delays and environmental impacts.

The development of intersection control algorithms has aimed at a range of policy improvements in addition to the primary motivation of safety for conflicting movements. These include increasing efficiency by minimising vehicle delays, and maintaining equity in the distribution of intersection capacity amongst users (*1*). Some research has attempted to expand intersection optimisation to include alternative traffic modes (*2–4*). An established choice for such optimisation is Transit Signal Priority (TSP) (*5*). TSP allows traffic signal group timings to be adjusted when a bus (*6*), tram (*7*) or emergency service vehicle (*8*) sends a signal that it is approaching the intersection. The approach aims to minimise the delay of that service, although it often comes at the expense of increased delays for other users (*9, 10*). Considering essential metrics relating to emissions reduction, congestion, and accessibility, policymakers can assign modal priority according to a hierarchy of desirability (*11*). For instance, they may prefer to encourage travel with higher-occupancy buses or emission-free bicycles by targeted delay reduction.

The emergence of improved vehicle communication systems, including vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I), has provided opportunities to enhance intersection control with additional data that upgrades traffic and infrastructure coordination (*12, 13*). These can improve on pre-timed centralised control designs based on historical conditions, and basic adaptive or actuated strategies using low-resolution data (i.e. loop detector) (*14, 15*). The development of connected vehicles has led to the creation of control methods that utilise incentive mechanisms to push traveller behaviour towards what is best for the traffic system overall. These can include direct monetary transfers and credit schemes. Market theory-inspired auction-based control has received interest as a promising direction for such a mechanism (*16, 17*).

There are two main areas of research on auction-based control that differ on the involvement of signals (e.g. traffic lights). Firstly, there are non-signalised approaches primarily aimed towards self-driving vehicles, also known as Autonomous Intersection Management (AIM). Secondly, there are signalised approaches, that use high-resolution user data on state (i.e. speed, position) and preferences (i.e. value of time (VOT)) to optimise signal phases (*13*).

The AIM-based auction approaches control the crossing sequence of individual autonomous vehicles through the intersection (*13*). This can be done by vehicles bidding for access to discrete tiles of intersection space (*18*) or individual predefined trajectories (*19*). The computation time of the approaches are increased by the resolution of tiles and the evaluation of potential collisions between trajectories (*16*). With AIM-based approaches there is trade-off between the computational requirements and the level of model detail, which can limit the complexity of vehicle movements (*13*).

Signalised auction methods generally do not suffer from the computational trade-off issue (*20*). Some methods have treated signal phases as auction participants, bidding for green time using loop detector data to measure the vehicle queues for each movement (*21*). These approaches lack the input of individual user preferences, so they do not account for heterogeneity in user VOT (*22*). This has been improved on in other studies that consider auctions held by intersection managers on behalf of road users bidding for each directional flow, incorporating individuals' information (*23*).

The auction types used in signalised auction-based control have mostly lacked consideration of incentive compatibility (i.e. truthful bidding). Performance levels of auction-based schemes that do not incorporate this are at risk of deterioration over time, losing any initial advantages (*24*). The mechanism of auction used is important, as it must incentivise participants to bid their actual valuation for crossing the intersection, so strategic misreporting cannot lead to a personal gain (*25*). First-priced sealed bid auctions have commonly been used in signalised control (*26*). In this type of auction, bidders submit sealed bids, and the highest bidder wins the item and pays the price they bid. It is not incentive compatible as, by bidding less than their true valuation, bidders can ensure they achieve a surplus benefit if they win. Also, by guessing the bids of others, the best strategy may be to not bid their actual valuation. The use of incentive-compatible auction mechanisms has mostly been limited to unsignalised approaches. These include Second Price Sealed Bid (SPSB) auctions (*27*), also known as a Vickrey, and combinatorial auctions under the Vickrey–Clarke–Groves (VCG) mechanism (*28*).

One key recent example of incentive-compatible signalised control is the work by Iliopoulou *et al.* that uses SPSB (*24*). In a second-price auction, the highest bidder wins but pays the amount of the second-highest bid. This type of auction is incentive-compatible because bidders have no reason to bid anything other than their actual valuation. Since the payment is based on the second-highest bid rather than the first, bidding truthfully ensures that a bidder wins if and only if their valuation is the highest. The winner maximises their benefit without the need for strategic manipulation.

In Iliopoulou *et al.*, the work presents a method that is easy to implement and transfer to different intersection layouts, accounting for varying numbers of lanes serving each movement (*24*). The method includes dynamic bidding that accounts for delay accumulation, such that drivers bid more the longer they have been waiting. Promising results were found regarding its ability to reduce delays when applied to a simple artificial intersection. However, it was limited to a single mode of traffic. Based on a review of the existing literature, it appears the most advanced incentive-compatible auction-based signalised control schemes have not investigated the role of traffic mode priority in their operation. How the priority of different modes could be established through the market-based mechanism remains an open research question.

In this work, we extend the current state of the art in auction-based signalised intersection control into multimodal traffic. We propose a SBSP auction mechanism for green time allocation that includes dynamic user bids with modal priority. We show the effectiveness of such an approach in changing the level of service experienced by different traffic modes when one is selected for priority. Importantly, the mechanism is computationally feasible and transferable to any intersection. The specific contributions of this work are:

- We introduce an improved auction mechanism for green time allocation at signalised intersections. The key innovation being it is able to express prioritization of different travel modes, in line with exogenous travel policy.
- We present a dynamic bid distance determination approach that embeds policy principles through a varying bid distance calculation for different modes.
- We further introduce a modified dynamic bidding scheme, where bids of prioritised modes are post-processed by the auctioneer in order to express policy concerns.
- We compare the two proposed approaches, highlighting under which conditions and assumptions these can be employed effectively to express priority policy.

The proposed auction-based control is evaluated using a test case intersection based on a real-world road system in Bordeaux, France. It is compared against the current fixed-time signal control used by the local traffic management authorities. Our tests focus on priority allocation for bicycles, although our methodology is generic and can be applied to one or more modes, so long as these can be ranked in a defined hierarchy of importance.

The remainder of the paper is structured as follows. Firstly, the conceptual framework is presented and the proposed auction mechanism with modal priority is described. Then, the alternative ways of expressing modal priority are compared together with fixed-time control using simulation. Lastly, a final section presents the conclusions of the work and directions for future research.

METHODOLOGY

Conceptual framework

This work envisions widespread connected vehicle use across modes, with reliable V2I communication and sufficient penetration for intersection control mechanisms. Smartphone technology suffices if infrastructure ensures adequate capacity and coverage. We consider the different traffic signal phases as auction participants, obeying specific constraints to maintain safety (e.g. minimum green times). As in the work of Iliopoulou *et al.*, the auction process determines which phase should be active next and set to green (*24*). Wallet agents are assumed to represent road users, irrespective of travel mode, bidding on their behalf to capture their characteristics (e.g. VOT, impatience, mode) and dynamics. These bids are communicated to an intersection manager, which executes the auction. The auction process can be evaluated in real-time due to its lightweight nature, ensuring its responsiveness.

In the following section, we describe an extension of the approach employed in (*24*) to include multimodal priority while maintaining the desirable properties of market-inspired mechanisms (e.g. incentive-compatibility). We consider an intersection comprised of a set of lanes L that accommodate M movements, which are served by the set of green phases S. Each phase $s \in S$ serves a subset of movements $M_s \subset M$, with the subset of respective lanes serving that phase denoted by $L_s \subset L$. For clarity, the notation used is summarised in Table 1.

Policy-oriented bidding distance determination

Determining which vehicles can participate in the bidding process is crucial for the efficiency of any traffic auction scheme (*29*). This can be done by setting a bidding distance, with any vehicle within the limit allowed to take part in the auction. This aspect might also be employed to enact alternative policies to prioritise different modes of transport. In a policy-oriented bidding distance determination, the various types of dedicated lanes at a junction (e.g. cycle, bus, etc.) can be provided with varying default (i.e. minimum) bidding distances for vehicles approaching the intersection. This intends to change number of vehicles bidding in those lanes and thus the size of the total bids, influencing the outcome of the auctions in favour of the signal phases they are part of. This assumes only the prioritised vehicles travel on the dedicated lanes, further research is needed for application to shared mode lanes.

At each time step t, a new auction is triggered and an initial bidding distance factor is determined based on the average waiting time for each lane l with a red light indication. Subsequently, the proposed bidding distance per lane is calculated as the sum of a fixed component of the lane type-specific default bidding distance $\hat{d}^{b,u}$ and a variable component depending on the current waiting time observed. In order to avoid strategic misreporting, the waiting time is not reported directly by the users, but measured through connected vehicle capabilities and assumed adequately precise. Finally, to ensure that the same bidding range applies to all vehicles waiting in

Symbol	Definition
A^t	Set of bidding phases at time t
C^t	Set of bids at time t
D_s^t	Set of bidding distances for phase s at time t
K_l^t	Set of vehicles in lane l at time t
L	Set of lanes l
L_s	Subset of lanes serving phase s
M	Set of movements
M_s	Subset of movements served by phase s
N_l	Set of bidding vehicles per lane l
S	Set of phases s
U	Set of lane types u
J	Set of vehicle types j
H	Set of weighting factors h
T	Set of time steps t in time horizon
b_i^t	Bid amount for bidding vehicle i at time t
$\hat{d}^{b,u}$	Default bidding distance for lane type u
d_l^t	Bidding distance per lane l at time t
e_s^t	Active duration of phase s at time t
$G_s^{\max}$	Maximum green duration for phase s
G_s	Minimum green duration for phase s
G^{ext}	Green time extension for repeat winning phase
m_i	Movement of bidding vehicle i
s_i^t	Traffic light phase for bidding vehicle i at time t
VOT_i	Value of time for user of bidding vehicle i
Y_s	Yellow phase duration corresponding to green phase s
$P_i(w_i^t)$	Impatience function for user of bidding vehicle i
q_l^t	Number of vehicles in queue in lane l at time t
r	Auction payment of vehicle i at time t
ρ	Saturation headway
v_i^t	Speed of bidding vehicle i at time t
w_i^t	Waiting time for bidding vehicle i at time t
x_i^t	Distance from intersection of bidding vehicle i at time t
h^j	Bid weighting factor for vehicle type j

TABLE 1: Notation and Definitions

lanes serving a specific phase s, the maximum of the values in the set D_s^t is divided by the number of corresponding lanes and assigned as the bidding distance for all lanes in L_s. The process is outlined in Algorithm 1.

Bidding scheme

In the proposed approach, users are assumed to have a known VOT, yet are allowed to increase their bid relative to their waiting time as it accumulates at the junction. In this way, we consider dynamic bidding behaviour at each time step. The concept of user impatience and the bidding

Algorithm 1 Bid Distance Calculation

for each phase $s \in A^t$ **do**
  if $e_s^t == 0$ **then**
    for each lane l in L_s **do**
      if $q_l^t > 0$ **then**
        $z_l^t = \frac{\sum_{i \in K_l^t} w_i^t}{q_l^t}, \quad l \in L_s$
      else
        $z_l^t = 0, \quad l \in L_s$
      end if
    end for
  end if
end for
for each phase $s \in A^t$ **do**
  if $e_s^t > 0$ **then**
    for each lane l in L_s **do**
      $d_l^t = \hat{d}^{b,u}, \quad u \in U$
      $d_l^t \rightarrow D_s^t$
    end for
  else
    for each lane l in L_s **do**
      $d_l^t = (a + \frac{z_l^t}{\sum_{k \in L} z_k^t})\hat{d}^{b,u}, \quad l \in L, u \in U$
      $d_l^t \rightarrow D_s^t$
    end for
  end if
  for each lane l in L_s **do**
    $d_l^t = \frac{argmax(D_s^t)}{|L_s|}, \quad l \in L$
  end for
end for

rules are similar to those outlined in (*24*). The impatience function yields a scaling factor between a minimum of 1 and maximum of 2 to multiply the user's bid by depending on their current waiting time. The impatience factor is calculated as follows:

$$P_i(w_i^t) = min(P_i^{max}, 1 + \frac{1}{1 + e^{-\alpha_i^1 * (w_i^t - \alpha_i^2)}}), \tag{1}$$

where α_i^1 governs the impatience of the user (i.e. the larger α_i^1 is the more impatient the user is) and α_i^2 is the time where the impatience function becomes 1.5. These parameters essentially describe user behaviour and have user-specific values assumed to be uniformly distributed within a specific range. We assume that these parameters can be declared by the user at the start of their trip, along with their VOT. The wallet agent can then compute bids automatically based on current conditions. It should be noted that the developed function increases the initially declared VOT, thus the user's lowest bid is bounded by their declared VOT.

Bid calculation

As in the work of Iliopoulou *et al.*, the bid for each user is calculated based on the current traffic light phase, as well as their VOT, impatience and waiting time (*24*). There are two cases to consider:

(i) For users who are currently in a queue at the red light, the time needed to cross through the intersection depends on their location at the queue n_i^t and the saturation headway ρ.

(ii) For users who have entered the lane-specific auction bidding distance and face a green light indication, the time needed to cross the intersection depends on their current speed v_i^t and distance x_i^t from the junction.

For these cases, the bid calculation is then as follows:

$$b_i^t = \begin{cases} P_i(w_i^t) \cdot \rho \cdot n_i^t \cdot VOT_i, & \text{if } s_i^t = \text{red} \\ P_i(w_i^t) \cdot v_i^t \cdot x_i^t \cdot VOT_i, & \text{if } s_i^t = \text{green} \end{cases} \tag{2}$$

As the minimum default bidding distance can be varied for different lanes, this may lead to situations where a vehicle is part of a winning bid but the distance is too large for it to cross in time. Although this did not occur for the distance values tested in the case study, this is a potential issue that needs investigation and could potentially be avoided by varying the minimum green time or setting a maximum distance. In the proposed method, vehicles only pay for a winning bid if they cross the junction, so they are not charged twice. Due to hysteresis phenomena that may be observed in traffic light queues, if a vehicle facing a green light indication has a speed of zero, its bid is calculated based on the red light case.

Bid boosting

To implement priority with the different vehicle modes j, a weighting factor h^j is applied to the bid calculation. Such that:

$$\bar{b}_i^t = h^j * b_i^t \tag{3}$$

An adapted version of the second-price sealed-bid auctioning mechanism applied in the work of Iliopoulou *et al.* is then executed based on these weighted bids (Algorithm 2) (*24*). The winning phase W is selected based on the total weighted bids $\bar{c}_s^t$ for the phase s. The runner-up Z is then selected as the phase that has the highest unfactored bid c_s^t below the winning phase's unfactored bid, such that any bid larger than the winning phase in the unfactored set is *not* eligible. The payments r^t are then scaled with the ratio of the runner-up to the winning phases' unfactored total bids. This additional form of second-price auction might negatively affect incentive compatibility, the effects of which will be the object of further investigation.

Algorithm 2 Adaptive Traffic Signal Control

$t \leftarrow 0$
Set G_s, G_s^{max}, G^{ext}, Y_s, $A^0 = S$
while $t < T$ **do**
  Determine bidding vehicles per lane N_l based on Algorithm 1
  Run second-price sealed-bid auction
    Collect bids from bidding vehicles based on Eqs. (1), (2)
    Calculate bids for each phase,
      $c_s^t = \sum_{i|x_i^t \leq d_l^t, i \in N_l, m_i \in M_s} b_i^t, \quad c_s^t \in C^t, s \in A^t$
    Calculate weighted bids for each phase,
      $\bar{c}_s^t = \sum_{i|x_i^t \leq d_l^t, i \in N_l, m_i \in M_s} b_i^t \cdot h^j, \quad \bar{c}_s^t \in \bar{C}^t, s \in A^t, h \in H, j \in J$
    Determine auction winner from weighted bids
      $W = \arg\max(\bar{C}^t), \quad W \in A^t$
    Determine the runner-up to the winning phase
      $Z = \arg\max_{e \in \{o|C_o^t < C_W^t\}} C_e^t, \quad C_W^t \subset C^t$
    Determine payments, $r_i^t = b_i^t \cdot \frac{\sum_{k|m_k \in M_Z} b_k^t}{\sum_{o|m_o \in M_W} b_o^t}$
  if W $\neq$ currently active phase **then**
    Activate yellow phase for Y_s seconds
    $t = t + Y_s$
    Activate green phase W for G_s seconds
    $t = t + G_s$
  else
    Extend green phase W for G^{ext}
    if $e_s^t > G_s^{max} : A^t = S \backslash W$ **then**
      $t = t + G^{ext}$
    end if
  end if
end while
Terminate

In the following section, the two techniques of implementing priority through the auction process are investigated separately on a real road junction in Bordeaux, France. One through changes to the bidding distance calculation, named mode-dependent adaptive Lane Bidding Distance adjustment, and the other through boosting bids in the auction process, named Bid Boosting. A policy of providing priority to bicycle traffic is investigated for both. For the Lane Bidding Distance adjustment, this is done by varying the default bid distance for cycle lanes while keeping the other default bid distances fixed at 10m. For the Bid Boosting approach, this is done by varying the bid weighting factor for the bicycles while keeping the factor for all other vehicle classes fixed at one.

In all simulations, the parameters are set as follows: the minimum green time (G_s) is 15 seconds, the maximum green time (G_s^{max}) is 40 seconds, the green time extension (G^{ext}) is 5 seconds, and the yellow time (Y_s) is 3 seconds, with vehicles allowed to pass during the first 1 second of the yellow phase.

RESULTS

In this section, we test our methodology using a simulated intersection model constructed from data collected in the city of Bordeaux, France. We first introduce the test scenario, highlighting its characteristics. Then, we showcase our results, comparing the performance of the proposed policy-oriented auction-based mechanism, under a range of parameter values and assumptions, with those of a fixed-time controller calibrated to emulate that currently deployed.

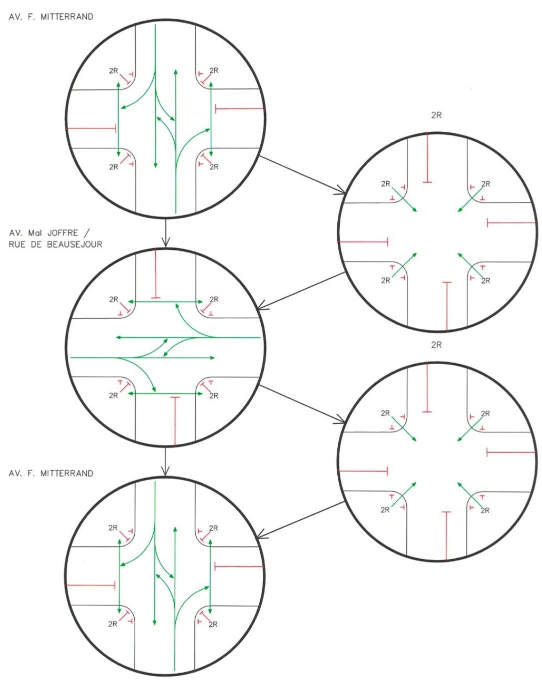
Case study: bicycle prioritization on Bordeaux intersection

To set up a virtual pilot of the intersection control, we create it in AIMSUN simulation software. The test intersection is replicated in as much detail as possible, including lane configuration and measurements, movements, pedestrian crossings and dedicated / shared bicycle infrastructure. The resulting simulated intersection is shown in Fig. 1a, with the simulation platform overlayed on an aerial view. The traffic light phasing diagram for the intersection is shown in Fig. 1b, this displays the movements associated with each phase.

The municipality of Bordeaux carried out a data collection campaign during April 2024 to determine demand patterns during morning (07h45–08h45) and evening (16h45–17h45) peak hours. Data was collected for the following modes: cars, heavy goods vehicles (HGVs), public transport, motorcycles, bicycles and pedestrians. A summary of the collected data, for morning and evening peak respectively, is shown in Fig. 2 (a-b), in Passenger Car Equivalent (i.e. UPV in French) units. The total number of vehicles and the distribution between the modes is shown in Table 2. Given the sizable share of bicycle traffic both in morning and evening peak, this intersection is suitable to validate our proposed priority allocation mechanism. We set up our simulation model with these origin-destination demand matrices and conducted replications for both morning and evening peak scenarios.

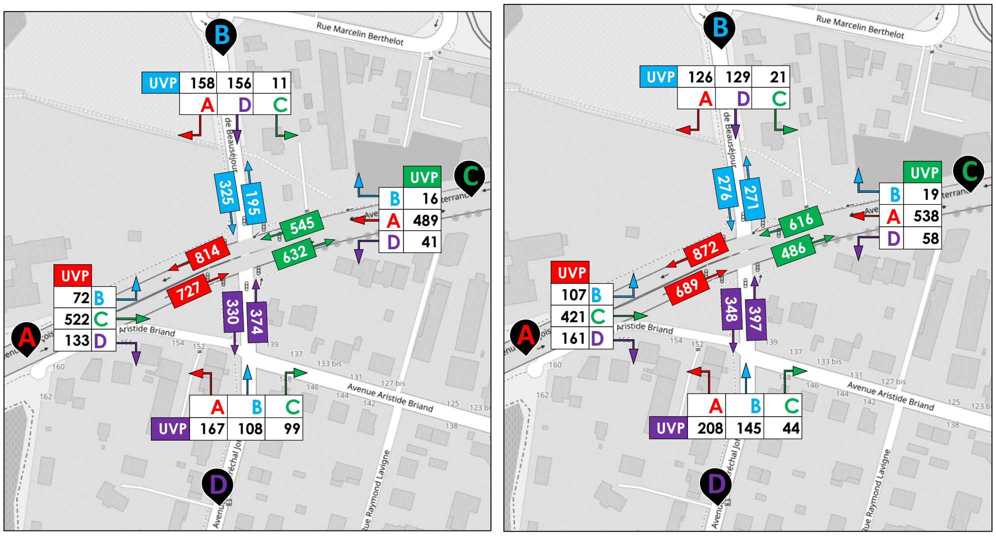
To establish a basis for accurate comparison, we implemented a fixed-time intersection controller as the baseline scenario. Its phases and their combinations replicated those implemented in the local intersection traffic controller, considering a maximum cycle length of 90 seconds. The controller in operation at the intersection operates on a variable cycle length. This means that during extended cycles, certain movements may receive more green light time based on real-time data from loop detectors and bicycle push buttons. Our choice of a fixed-time controller was made due to business confidentiality constraints preventing replication of the proprietary deployed

(a)



(b)

FIGURE 1: (a) Case study intersection as replicated in the AIMSUN simulation software; (b) Case study phasing diagram.



(a) Morning Peak Hour

(b) Evening Peak Hour

FIGURE 2: Travel demand for representative morning and evening peak hour traffic for the test case intersection. Movements between the branches of the intersection are in Passenger Car Equivalent (i.e. UVP in French) units. Data collected by municipality of Bordeaux in April 2024.

TABLE 2: Vehicle Distribution During Peak Hours

Time Period	Total Veh.	Cars (%)	PT (%)	HGVs (%)	Motorcycles (%)	Bicycles (%)	Pedestrians (%)
Morning	2213	81	0.7	0.7	6	12	0
Evening	2170	85	0.05	0.004	4.6	10	0

controller.

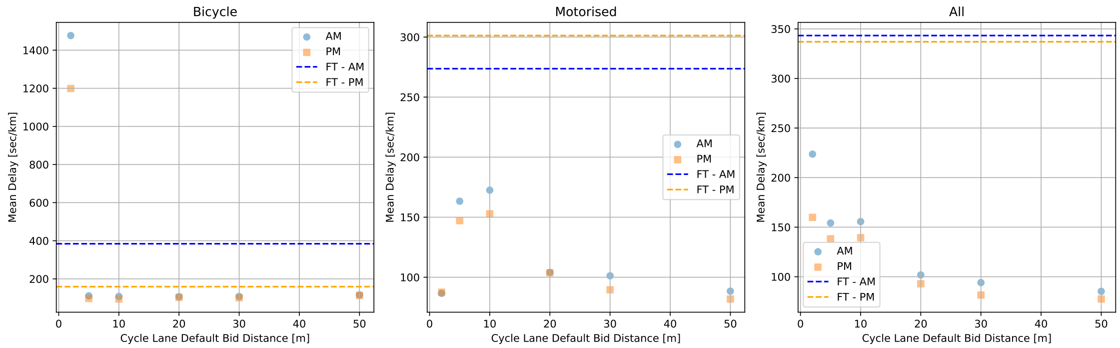
To simulate our proposed auction-based control approach, we employed AIMSUN's Python interface, to make an externally controlled traffic light plan, which operates based on Alg. 1 and 2.

Simulation results

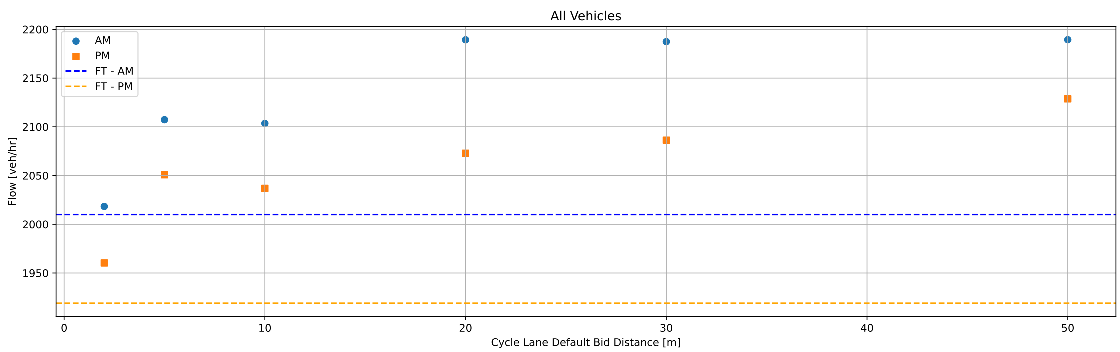
In this section we showcase results for the case study intersection using priority allocated by mode-dependent adaptive Lane Bidding Distance adjustment (Fig. 3 (a-d)), and priority allocated by Bid Boost (Fig. 4 (a-d)). These two approaches are compared to the performance of the current Fixed Time (FT) controller in operation. We collect the following metrics for each priority allocation mechanism, for separate vehicle classes (bicycle, motorised) and joint together (i.e. all), and for both for the morning (AM) and evening (PM) peak hour demand profiles:

- Mean vehicle delay [s/km]
- Total vehicle flow [veh/h]
- Mean realised auction payment [EUR]

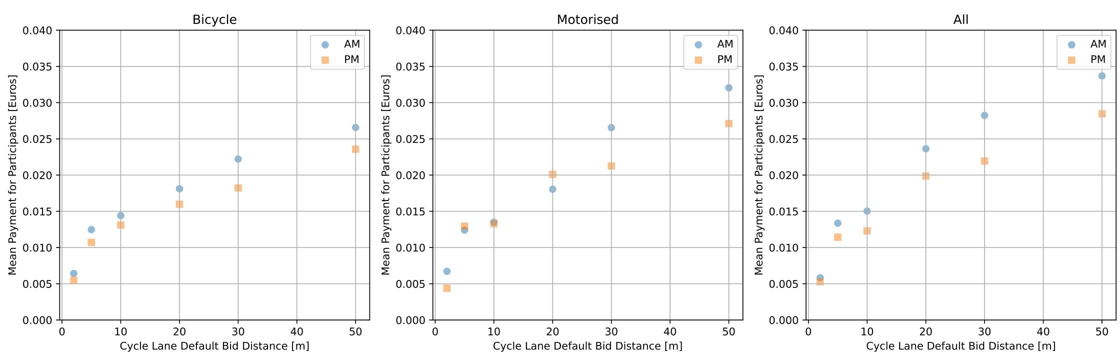
In Fig. 3a, it can be seen that when bicycle default bid distance is 2m, the bicycles are effectively not able to compete in the auction and they experience much larger delays than the



(a) Mean vehicle delay [sec/km] per individual mode and all together, FT is the result for Fixed Time controller.

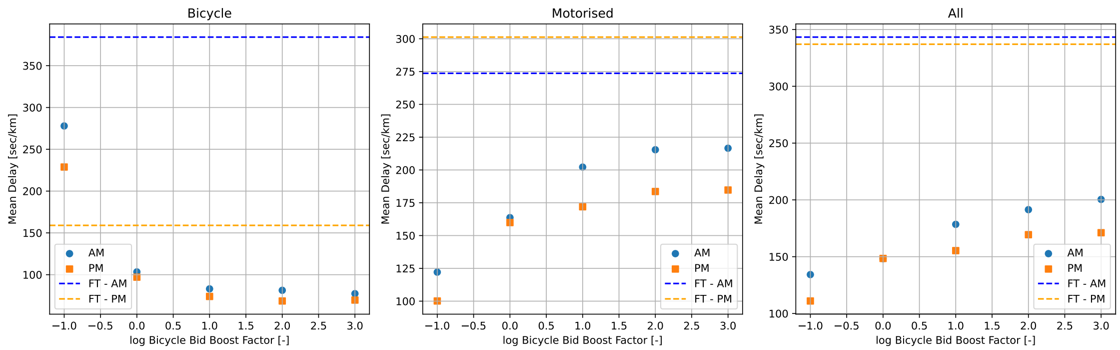


(b) Vehicle flow [veh/h] per individual mode and all together, FT is the result for Fixed Time controller.

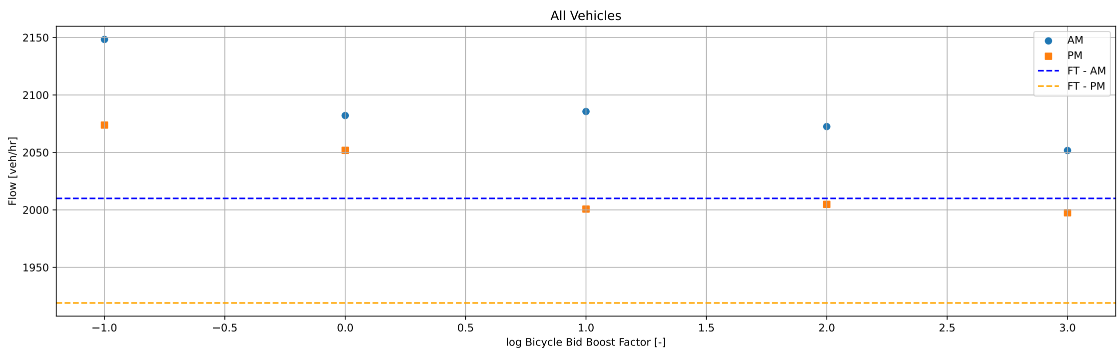


(c) Mean realised auction payment per vehicle [EUR], per individual mode and all together.

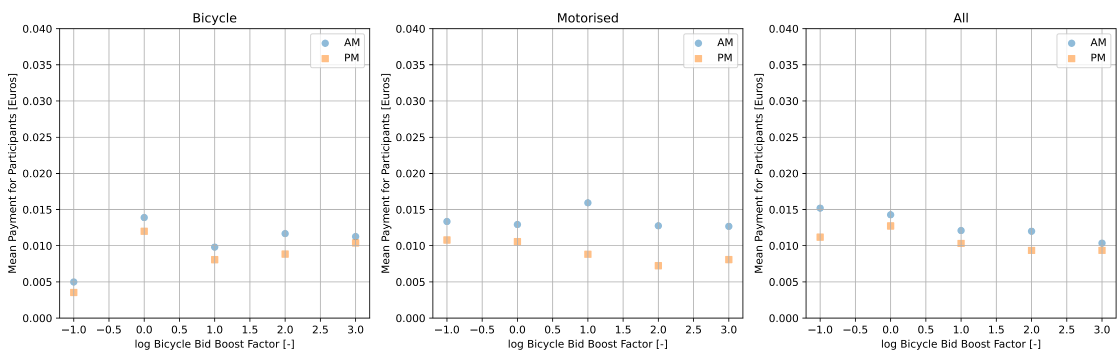
FIGURE 3: Auction-based mechanism with mode-dependent adaptive Lane Bidding Distance priority allocation simulation metrics.



(a) Mean vehicle delay [sec/km] per individual mode and all together, FT is the result for Fixed Time controller.



(b) Vehicle flow [veh/h] per individual mode and all together, FT is the result for Fixed Time controller.



(c) Mean realised auction payment per vehicle [EUR], per individual mode and all together.

FIGURE 4: Auction-based mechanism with mode-dependent Bid Boost priority allocation simulation metrics.

motor vehicles. From 5m to 50m there is a trend of both motor vehicles and bicycles experiencing decreasing delays as the default bid distance gets larger for the cycle lanes. Apart from bicycles with default bid distance of 2m, all the bid distance results indicate an improvement in both AM and PM periods for all vehicle types compared to the Fixed Time controller. Fig. 3b also shows that apart from for the 2m bid distance, when the auction process is not effectively functional for the bicycles, there is an improvement in flows through the junction for all vehicles in the AM and PM periods compared to the Fixed Time controller.

The results show an increase in bid payments with the increase in the bid distance (Fig. 3c). This is due to the bid for each vehicle depending on its position in the queue (on a red light) or its distance to the junction (on a green light). Having some of the phases with larger distances induces larger bids also from the other phases, in order for these to be competitive within the auctioning scheme, so average bids are increased. From 5m to 50m default bid distance, there is almost trebles from approximately 0.01 - 0.03 euros. However, this results in mean delays for all vehicles experiencing a considerable reduction from around 150 sec/km to around just below 100 sec/km. This indicates the promising potential of the technique, however, further research is warranted in evaluating the impact of the trade-off in terms of acceptability.

For Bid Boost, in Fig. 4a it can be seen that there is clear reduction in mean delay for bicycles as their bids are boosted with larger weighting factors. This comes at the expense of the motorised vehicles that experience an increase in mean delays with increasing bicycle bid boost factors. As there are more motorised vehicles than bicycles, the overall trend for all vehicles is an increase in mean delay for greater bid boosting of bicycles. For all amounts of bid boosting, apart from when the boost factor is 0.1 (i.e. -1 on the log scale) and the bicycle mode is effectively ranked lower than car, the mean delays are lower for motorised and bicycle traffic than under the Fixed Time controller (AM and PM). When the bid boost factor is 0.1, the deprioritised bicycles have a higher mean delay than the Fixed Time controller in the PM period but lower in the AM period. Furthermore, overall traffic has the largest improvement in delay compared to fixed time control with this boost factor. There appears to be a levelling off trend to the delays as the boost factor increases. This implies that, past a certain value of weighting for bicycles, they are fully prioritised over the motor vehicles and further increases will not lead to large changes in delay. This applies for the test case demand profiles, second-order effects such as induced demand would require additional investigation. Fig. 4b shows a slight decrease in overall flows for all vehicle types as the bicycle bid boost factor is increased, fitting with the increasing trend in overall delays for all vehicles. Even so, for both AM and PM the flows are higher than for the Fixed Time controller, indicating an improvement regardless of the boost factor.

The results for Bid Boost show smaller changes in mean bid payments compared to changing the default bid distance. In Fig. 4c, it can be seen that there is slight increase for bicycles' mean bid payments as the boost factor is increased, coinciding with a slight decrease for motor vehicles. Overall, for all vehicles, the mean bid payment only varies by a range of 0.010 - 0.015 euros as the boost factor varies. This implies the bid amounts overall are not heavily affected by providing different levels of priority to the bicycles, while yielding considerable changes to the mean delays of the different modes.

CONCLUSION

In this paper, we developed methods for dynamic priority allocation within local intersection traffic control using incentive-based mechanisms. Our approach provides an alternative to current state-of-the-art methods for vehicle class prioritization in traffic signal control, which typically focus on public transport and emergency vehicles, by leveraging connected vehicle technologies. Few works have explored incentive-compatible, market-inspired approaches, which tackle challenges in intersection management by distributing capacity through auctioning frameworks. These frameworks typically aim to maximize intersection performance for all traffic participants, regardless of transport mode. Considering the need for congestion mitigation and emissions reduction, developing fast, scalable techniques that translate modal policy criteria into operational control strategies is essential.

To bridge this research gap, we presented an extended SPSB auction mechanism where dynamically collected bids are adjusted by the auctioneer to express differential prioritization for multiple vehicle classes. A simulation based on a real-life intersection in Bordeaux, France, validated our approach. We conducted performance analysis of the proposed algorithms, focusing on the effect of key parameters and comparing transportation performance metrics against the fixed-time controller currently deployed.

Our results demonstrate that the proposed auction-based approach effectively allocates capacity while incorporating priority considerations, extending the state of the art for auction-based intersection control that has been previously limited to single mode traffic (*24*). Increasing the default bid distance for bicycle lanes reduced delays and improved flows for both bicycles and motorized traffic, though it resulted in higher bid payments, which could impact user acceptance in the long term. Conversely, increasing the weighting of bicycle bids reduced bicycle delays but increased delays for motorized traffic, lowering overall flow. Importantly, this redistribution of delays was achieved without significantly altering bid payments, potentially supporting user acceptance.

Both the Bid Boost and Lane Bidding Distance approaches yielded promising outcomes, often achieving lower delays and higher flows compared to the Fixed Time controller. These findings align with those of Iliopoulou et al., who observed similar improvements over Fixed Time controllers for single-mode traffic at simplified intersections (*24*). Among the approaches, Lane Bidding Distance with a larger default distance for bicycle lanes showed the greatest potential for reducing delays and increasing flows across all traffic types, despite resulting in higher mean payments.

Future studies could address some of the limitations of this work, providing deeper insights and broader applicability of the proposed approaches. The two priority implementation methods have so far been tested separately. Future research could investigate combining Bid Boost with Lane Bidding Distance to optimize key performance metrics and enhance the effectiveness of mode priority policies. Additionally, the trade-offs and impacts of prioritization on fairness and incentive compatibility require further examination in real-world settings. While Lane Bidding Distance led to a slight increase in payments, future studies should assess whether the modest rise in absolute costs (approximately €0.02) would influence user acceptance. Adjusting bid amounts to ensure payments are both meaningful and acceptable to travellers could offer a practical solution.

Moreover, while our approach performed well in a realistic scenario, further exploration of market-inspired schemes across multiple modes and complex, time-dependent hierarchies would be valuable. Investigating the integration of bids and payments into tradable credit systems also offers a promising direction for future research.

In summary, this work is a step towards providing traffic authorities with greater control over intersection vehicle flows, helping to enable sustainable and efficient mode-aware policies that meet the challenges of modern road infrastructure.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Alexander Roocroft & Marco Rinaldi; Model formulation and implementation: Alexander Roocroft & Marco Rinaldi; analysis and interpretation of results: Alexander Roocroft & Marco Rinaldi; draft manuscript preparation: Alexander Roocroft & Marco Rinaldi. All authors have reviewed the results and approved the final version of the manuscript.

CONFLICT OF INTEREST STATEMENT

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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