

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

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

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18 Word Count: $4627 + 2 \text{ table(s)} \times 250 = 5127$ words

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1 ABSTRACT

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

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

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

20

21 *Keywords:* Multi-modal traffic control; Traffic priority; Traffic management; Traffic control; Auc-
22 tion

1 INTRODUCTION

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

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

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

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

31 The AIM-based auction approaches control the crossing sequence of individual autonomous
32 vehicles through the intersection (13). This can be done by vehicles bidding for access to discrete
33 tiles of intersection space (18) or individual predefined trajectories (19). The computation time of
34 the approaches are increased by the resolution of tiles and the evaluation of potential collisions be-
35 tween trajectories (16). With AIM-based approaches there is trade-off between the computational
36 requirements and the level of model detail, which can limit the complexity of vehicle movements
37 (13).

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

44 The auction types used in signalised auction-based control have mostly lacked considera-
45 tion of incentive compatibility (i.e. truthful bidding). Performance levels of auction-based schemes

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

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

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

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

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

43 The proposed auction-based control is evaluated using a test case intersection based on a
44 real-world road system in Bordeaux, France. It is compared against the current fixed-time signal
45 control used by the local traffic management authorities. Our tests focus on priority allocation for

1 bicycles, although our methodology is generic and can be applied to one or more modes, so long
2 as these can be ranked in a defined hierarchy of importance.

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

8 **METHODOLOGY**

9 **Conceptual framework**

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

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

26 **Policy-oriented bidding distance determination**

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

37 At each time step t , a new auction is triggered and an initial bidding distance factor is
38 determined based on the average waiting time for each lane l with a red light indication. Sub-
39 sequently, the proposed bidding distance per lane is calculated as the sum of a fixed component
40 of the lane type-specific default bidding distance $d^{l,u}$ and a variable component depending on the
41 current waiting time observed. In order to avoid strategic misreporting, the waiting time is not
42 reported directly by the users, but measured through connected vehicle capabilities and assumed
43 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

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

4 **Bidding scheme**

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

Algorithm 1 Bid Distance Calculation

```

1: for each phase  $s \in A^t$  do
2:   if  $e_s^t == 0$  then
3:     for each lane  $l$  in  $L_s$  do
4:       if  $q_l^t > 0$  then
5:          $z_l^t = \frac{\sum_{i \in K_l^t} w_i^t}{q_l^t}, \quad l \in L_s$ 
6:       else
7:          $z_l^t = 0, \quad l \in L_s$ 
8:       end if
9:     end for
10:   end if
11: end for
12: for each phase  $s \in A^t$  do
13:   if  $e_s^t > 0$  then
14:     for each lane  $l$  in  $L_s$  do
15:        $d_l^t = \hat{d}^{b,u}, \quad u \in U$ 
16:        $d_l^t \rightarrow D_s^t$ 
17:     end for
18:   else
19:     for each lane  $l$  in  $L_s$  do
20:        $d_l^t = (a + \frac{z_l^t}{\sum_{k \in L} z_k^t}) \hat{d}^{b,u}, \quad l \in L, u \in U$ 
21:        $d_l^t \rightarrow D_s^t$ 
22:     end for
23:   end if
24:   for each lane  $l$  in  $L_s$  do
25:      $d_l^t = \frac{\text{argmax}(D_s^t)}{|L_s|}, \quad l \in L$ 
26:   end for
27: end for

```

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

$$4 \quad P_i(w_i^t) = \min(P_i^{max}, 1 + \frac{1}{1 + e^{-\alpha_i^1 * (w_i^t - \alpha_i^2)}}), \quad (1)$$

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

13 *Bid calculation*

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

17

- 18 (i) For users who are currently in a queue at the red light, the time needed to cross
 19 through the intersection depends on their location at the queue n_i^t and the saturation
 20 headway ρ .
- 21 (ii) For users who have entered the lane-specific auction bidding distance and face a
 22 green light indication, the time needed to cross the intersection depends on their
 23 current speed v_i^t and distance x_i^t from the junction.

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

$$25 \quad b_i^t = \begin{cases} P_i(w_i^t) \cdot \rho \cdot n_i^t \cdot VOT_i, & \text{if } s_i^t = \text{red} \\ P_i(w_i^t) \cdot v_i^t \cdot x_i^t \cdot VOT_i, & \text{if } s_i^t = \text{green} \end{cases} \quad (2)$$

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

1 *Bid boosting*

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

$$4 \quad \bar{b}_i^t = h^j * b_i^t \quad (3)$$

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

Algorithm 2 Adaptive Traffic Signal Control

```

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

```

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

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

14 RESULTS

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

20 Case study: bicycle prioritization on Bordeaux intersection

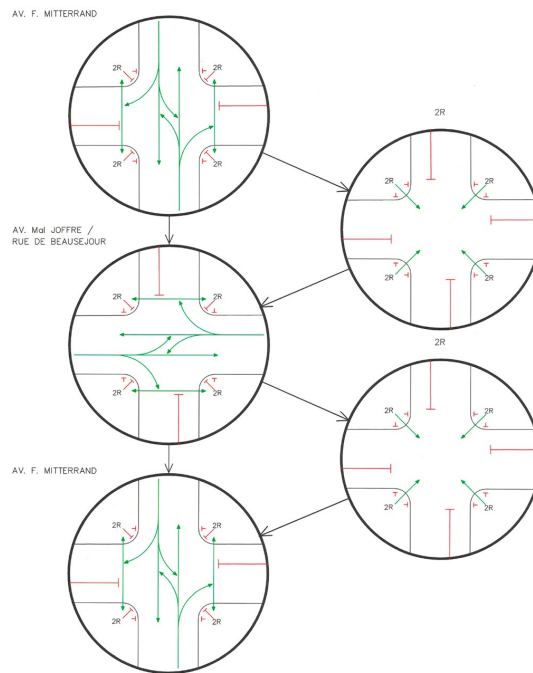
21 To set up a virtual pilot of the intersection control, we create it in AIMSUN simulation software.
22 The test intersection is replicated in as much detail as possible, including lane configuration and
23 measurements, movements, pedestrian crossings and dedicated / shared bicycle infrastructure.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

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

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

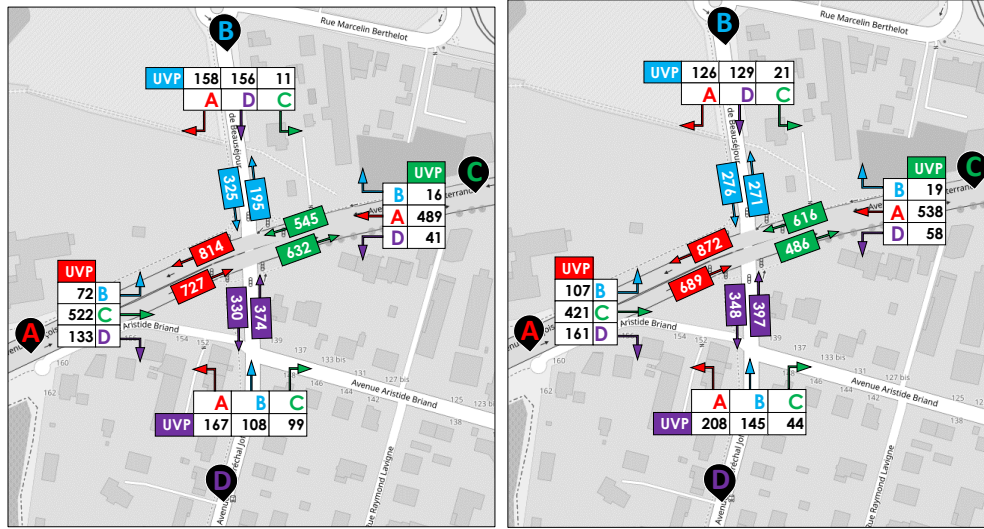


(a)



(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

1 controller.

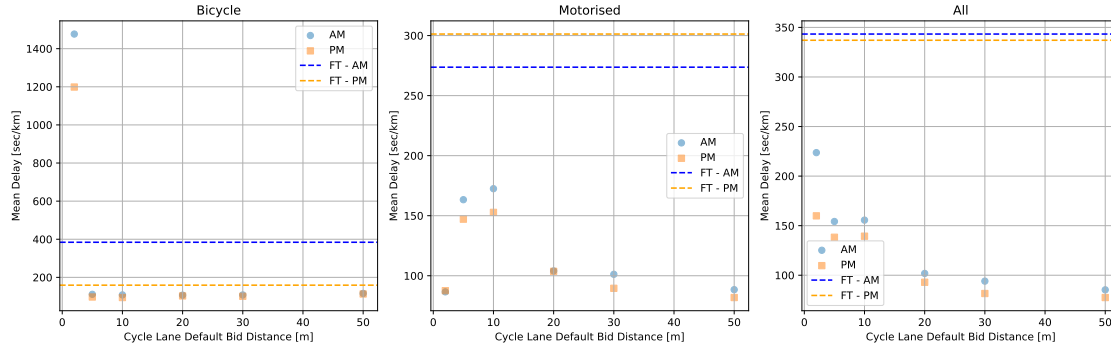
2 To simulate our proposed auction-based control approach, we employed AIMSUN's Python
3 interface, to make an externally controlled traffic light plan, which operates based on Alg. 1 and 2.

4 **Simulation results**

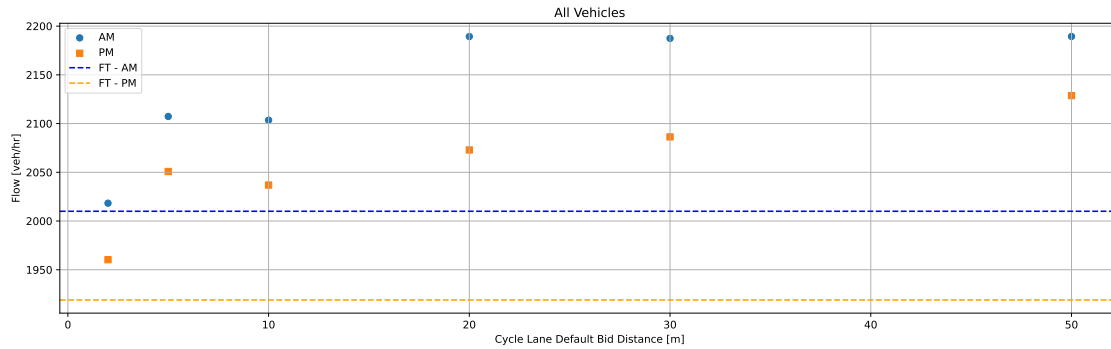
5 In this section we showcase results for the case study intersection using priority allocated by mode-
6 dependent adaptive Lane Bidding Distance adjustment (Fig. 3 (a-d)), and priority allocated by Bid
7 Boost (Fig. 4 (a-d)). These two approaches are compared to the performance of the current Fixed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

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

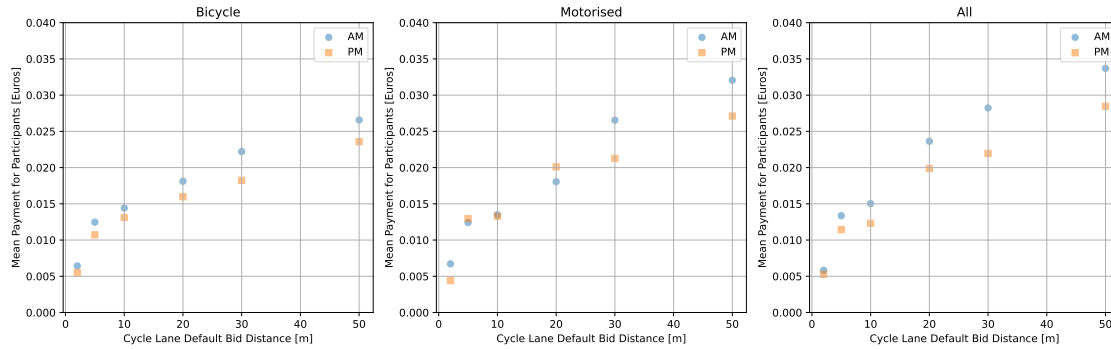
14 In Fig. 3a, it can be seen that when bicycle default bid distance is 2m, the bicycles are
15 effectively not able to compete in the auction and they experience much larger delays than the



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

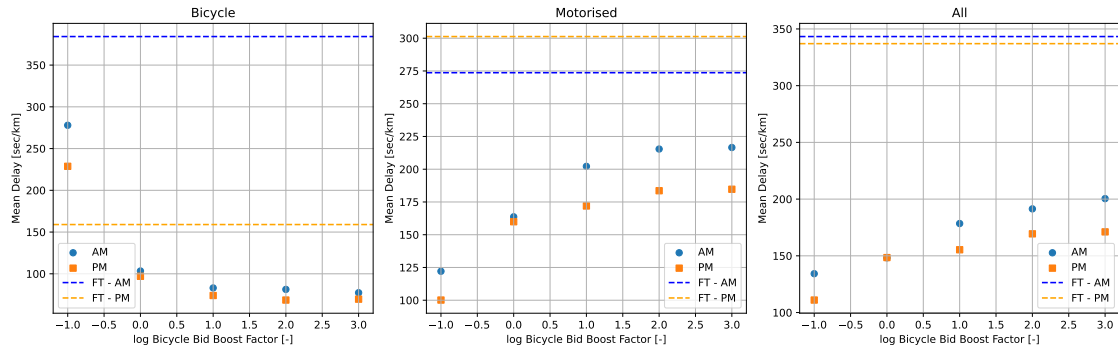


(b) Vehicle flow [veh/h] per individual mode and all together, FT is the result for Fixed Time controller.

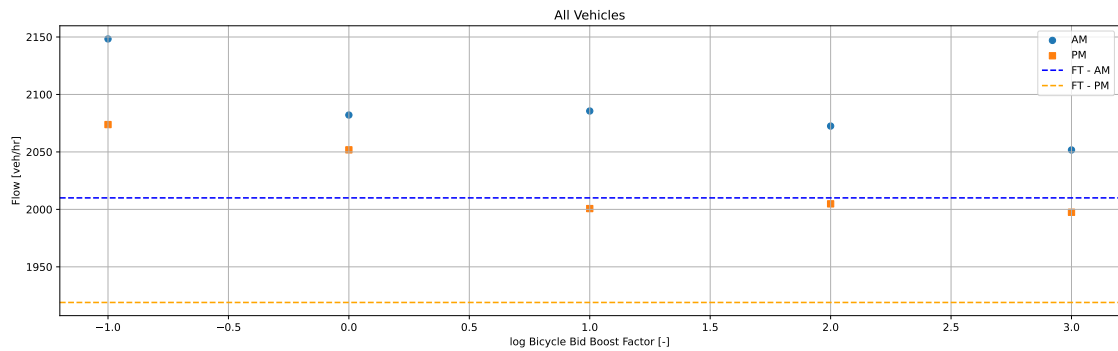


(c) Mean realised auction payment per vehicle [EUR], per individual mode and all together.

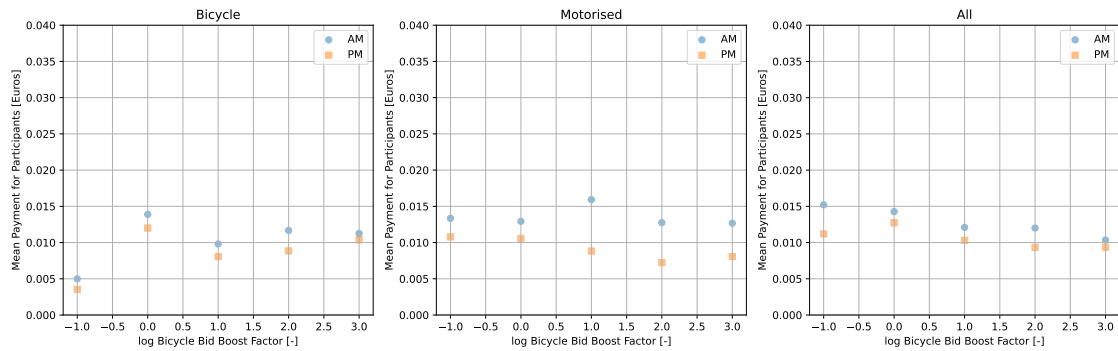
FIGURE 3: Auction-based mechanism with mode-dependent adaptive Lane Bidding Distance priority allocation simulation metrics.



(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.

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

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

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

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

35 CONCLUSION

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

1 is essential.

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

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

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

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

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

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

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

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8 The authors declared no potential conflicts of interest with respect to the research, authorship,
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