Optimization-Based Autonomous Intersection Management: A Real-World Simulation Study

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1 INTRODUCTION

In future scenarios where 100% of vehicles are connected and automated, traditional traffic signals might become obsolete. Instead, vehicles at intersections could be smoothly coordinated through communication between vehicles and infrastructure, ensuring seamless traffic flow. The so-called autonomous intersection management (AIM) was first proposed by Dresner & Stone (2004). In recent years, there has been a shift from simpler first come, first served approaches to more advanced optimization-based strategies in AIM (Zhong *et al.*, 2021). These optimization-based strategies have shown significant improvements in capacity and delay reduction compared to slot-based methods and conventional traffic signal control (TSC) (Yu *et al.*, 2019).

Although multimodality is central to urban transportation, pedestrians, cyclists, and public transport vehicles have rarely been integrated into AIM systems Namazi *et al.* (2019). The authors of this paper presented an optimization-based approach for AIM at an intersection with pedestrians in (Niels *et al.*, 2024). This study extends the existing research by extending the methodology developed in (Niels *et al.*, 2024) and applying it, for the first time, to realistic multimodal and heterogeneous traffic, including cars, trucks, buses, pedestrians, and cyclists, and simulating it at a real intersection. Surrounding intersections are also taken into account for cyclists. Firstly, this consideration leads to more realistic arrival patterns of cyclists at the intersection. Secondly, it allows for a green wave for cyclists who traverse multiple consecutive intersections and travel at a similar speed. The abstract briefly presents the optimization problem, the simulation study, and the results.

2 OPTIMIZATION-BASED MULTIMODAL AIM

An overview of the multimodal AIM is shown in Fig. 1. It is assumed that pedestrians and cyclists (jointly referred to as vulnerable road users (VRUs) in the following) do not directly communicate with the controller, but they are recognized by sensors, and the right of way is communicated to them via signals. Cyclists are detected at the upstream intersection. Their arrival time at the considered intersection is estimated based on average cycling speeds, but actual arrival times can differ due to their heterogeneous behavior.

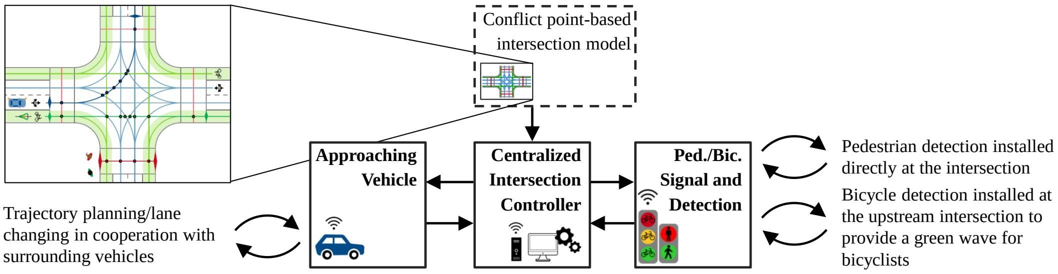


Figure 1 – *Control architecture of the proposed AIM scheme.*

The overall objective of the multimodal control is to minimize the total delay at the intersection while ensuring that all road users can cross safely. In the presented approach, road user delays can be weighted to prioritize certain movements. Following a rolling horizon approach, the problem is set up and solved in fixed time intervals ϕ. At time $t^k = \phi \cdot k$, the control takes all vehicles on the approach to and within the intersection (denoted by $\boldsymbol{V}^k$ and $\widehat{\boldsymbol{V}}^k$, respectively) and all requested and scheduled signal phases (denoted by $\boldsymbol{P}^k$ and $\widehat{\boldsymbol{P}}^k$, respectively) into account.

Objective function: The objective function aims at assigning vehicle arrival times (t_i) and start times of green phases (t_p) in such a way that the total delay is minimized:

$$\min \left(\sum_{i \in \boldsymbol{V}^k} \gamma_i \cdot \left(t_i - t_i^{min}\right) + \sum_{p \in \boldsymbol{P}^k} \gamma_p \cdot \left(t_p - t_p^{min}\right) \right) \tag{1}$$

where γ_i and γ_p are weighting factors, and t_i^{min} and t_p^{min} are the earliest possible assigned time for each vehicle v and signal phase p (which serve for calculating the delay).

Constraints: When the optimization problem is set up at time t^k, the constraints need to ensure physical limitations of vehicles approaching the intersection and resolve conflicts with already scheduled and requested vehicle arrival times and signal phases. Additionally, road user delays can be bounded for obtaining a balanced control scheme. First, a vehicle i cannot be scheduled earlier than its earliest possible arrival time $t_i^{LB}(t^k)$ considering its current position and speed. Similarly, a signal phase should not be scheduled to start before assigned VRUs are expected to arrive. Additionally, vehicles should not overtake on the approach to the intersection to avoid unnecessary lane changes. A minimum headway Δ^{min} needs to be respected between two adjacent vehicles. These assumptions lead us to the first set of linear constraints:

$$t_i \geq t_i^{LB}(t^k) \qquad \forall\ i \in \boldsymbol{V}^k \cup \boldsymbol{P}^k \tag{2a}$$

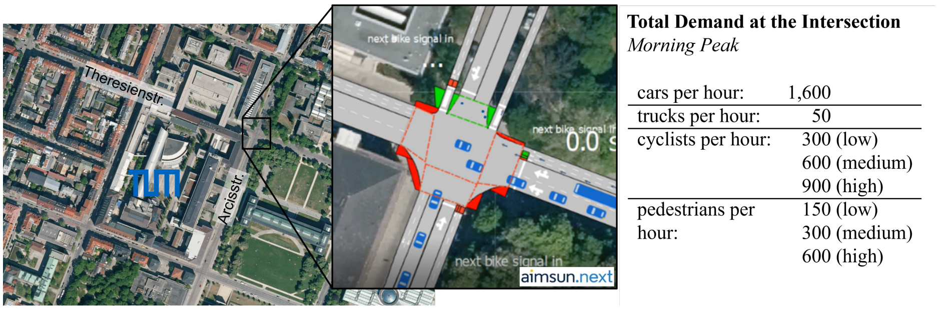
$$t_i \geq t_j + \Delta_{ji}^{min} \qquad \forall\ i \in \boldsymbol{V}^k, j \in \boldsymbol{V}^k \cup \widehat{\boldsymbol{V}}^k \mid o_i = o_j \ \&\ dist_i(t^k) > dist_j(t^k) \tag{2b}$$

where o_i and o_j denote the entrance lanes, and $dist_i(t^k)$ and $dist_j(t^k)$ denote the distances of vehicles i and j to the intersection at the time the problem is solved.

In order to resolve conflicts within the intersection, only one vehicle or a group of VRUs is allowed within any conflict region (given by the overlapping paths of road users) at a time. Let e_i and e_j be the points where vehicles i and j enter the intersection, and let c_{ij} be their common conflict point. Furthermore, let t_i and t_j be the times that they enter the intersection zone and v be their speed. Then vehicle i arrives at the conflict point at time $t_i + \frac{dist_{e_i,c_{ij}}}{v}$, where $dist_{e_i,c_{ij}}$ is the distance between e_i and c_{ij} following the vehicle path (analogous for vehicle j). Now, it needs to be ensured that

$$t_i + \frac{dist_{e_i,c_{ij}}}{v_i} \geq t_j + \frac{dist_{e_j,c_{ij}}}{v_j} + \Delta_{ji}^{min} \qquad \text{if } t_i + \frac{dist_{e_i,c_{ij}}}{v_i} \geq t_j + \frac{dist_{o_j,c_{ij}}}{v_j} \tag{3a}$$

$$t_j + \frac{dist_{e_j,c_{ij}}}{v_j} \geq t_i + \frac{dist_{e_i,c_{ij}}}{v_i} + \Delta_{ij}^{min} \qquad \text{if } t_j + \frac{dist_{e_j,c_{ij}}}{v_j} > t_i + \frac{dist_{e_i,c_{ij}}}{v_i} \tag{3b}$$



Total Demand at the Intersection
Morning Peak

cars per hour:	1,600
trucks per hour:	50
cyclists per hour:	300 (low) 600 (medium) 900 (high)
pedestrians per hour:	150 (low) 300 (medium) 600 (high)

Figure 2 – *Intersection modelled in the microscopic simulation Aimsun Next (Munich, Germany)*

for all vehicles i and j in $\boldsymbol{V}^k \cup \widehat{\boldsymbol{V}}^k$, depending on which vehicle passes the conflict point first. The same holds for conflicts with vehicles and VRUs, i.e., for vehicle i in $\boldsymbol{V}^k \cup \widehat{\boldsymbol{V}}^k$ and signal phase j in $\boldsymbol{P}^k \cup \widehat{\boldsymbol{P}}^k$. In this case, several VRUs assigned to the same signal phase are assumed to cross the intersection together; Δ^{min} incorporates the green phase duration and the necessary clearance times. The logical conditions in (3) cannot directly be included in the optimization problem. Therefore, the so-called Big-M method is applied (Williams, 2013).

Finally, delays of individual road users can be bounded by suitable upper bounds Θ:

$$t_i \leq t_i^{min} + \Theta_i \qquad\qquad \forall\ i \in \boldsymbol{V}^k \cup \boldsymbol{P}^k \tag{4}$$

3 SIMULATION STUDY AND RESULTS

The presented control scheme has been evaluated using a microscopic simulation of a realistic intersection in Munich with the measured multimodal demand, including cars, trucks, buses, pedestrians, and cyclists. The morning peak hour is simulated with a total demand as indicated in Fig. 2. Since no exact numbers on VRU activity were available, demand was estimated based on measurements at neighbouring intersections and manual short-period counts of 15 minutes. To account for estimation inaccuracies and to explore the effects of changing VRU demand, in addition to the estimated demand (“medium”), two scenarios with lower and higher demand are analyzed. A bus line runs on the main road (a one-way street with two lanes) every five minutes.

Results are compared to a replication of the fully actuated TSC featuring bus prioritization, which is implemented in reality. The TSC was modeled in Aimsun Next, which adheres to the standards of the American National Electrical Manufacturers Association (NEMA, 2003) with an initial cycle time of 90 seconds. In the AIM scenario, the presented mixed-integer linear problem is modeled and solved using Gurobi. Weighting factors γ are equal to one for all road users except for buses, which are prioritized via a weighting factor of 30. Pedestrian waiting times may not exceed 40 seconds, and cyclist waiting times may not exceed 10 seconds (based on their expected arrival times). VRU green phase durations are at least 5.4 seconds; bicycle green phase durations are extended depending on the number of cyclists approaching the signal.

3.1 Delays

An overview of the results is shown in Fig. 3. In the “medium” scenario, the AIM scheme leads to car/truck and bus delay reductions of more than 70% while at the same time keeping VRU delays on approximately the same level as with the TSC. The bus prioritization is effective in both control scenarios. In the AIM scenario, increasing VRU demand reduces VRU waiting times as their accumulated weight in the objective function increases. Furthermore, the extended green phases lead to more cyclists passing without stopping: from 64% in the scenario with low VRU demand to 75% in the scenario with high VRU demand (in comparison to approximately 49% in the TSC scenario). Hence, green phase durations and weighting factors need to be tuned for specific scenarios. Additionally, green light optimal speed advisory could reduce bicycle delays.

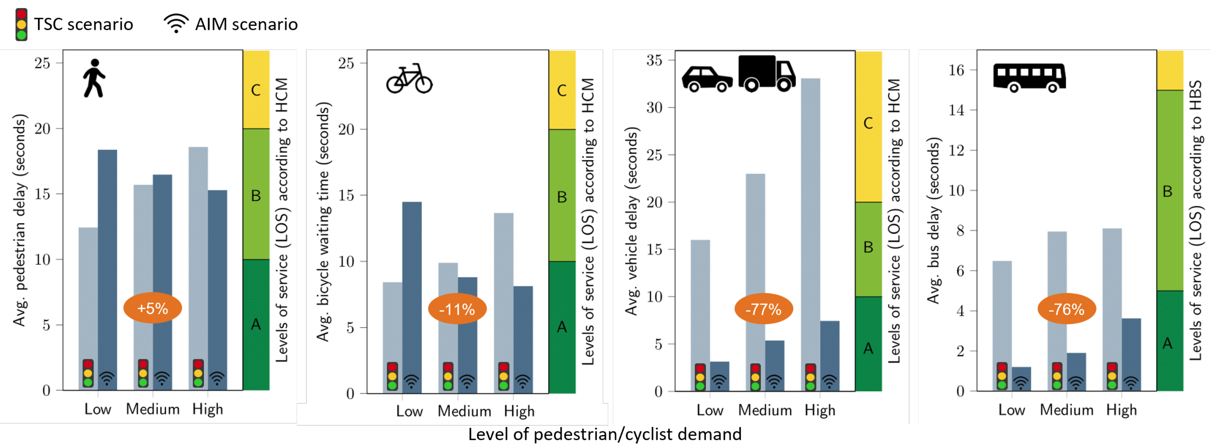


Figure 3 – *Average road user delay at the considered realistic intersection.*

3.2 Energy Consumption and Driving Discomfort

Energy consumption and driving discomfort can be reduced by optimizing vehicle trajectories on the approach to the intersection. For this purpose, the vehicle arrival times scheduled within the AIM framework were used for optimized trajectory planning, where the sum of squared accelerations was minimized. In summary, the energy consumption caused by the delays and accelerations occurring at the intersection can be reduced by up to 54% in the “medium” scenario. Furthermore, the maximum applied acceleration and deceleration values are significantly reduced (on average by 47% and 66%, respectively). To further increase driving comfort, jerk could be included in the objective function of the trajectory optimization problem.

4 DISCUSSION

The proposed setup allows for the integration of heterogeneous road users and is easily transferable to other intersection layouts. The results demonstrate the enormous potential for reducing the waiting times of road users and illustrate the effective prioritization of public transport vehicles. Given the promising simulation results, a more VRU-friendly setup is conceivable for future analyses. This can be realized by changing green phase durations, maximum waiting times, and weighting factors. Furthermore, the authors are working on the consideration of downstream congestion and the coordination of several intersections on a road stretch or even in a network.

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