Multimodal Signal-Vehicle Coupled Control (SVCC)

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Abstract:

This study advances the Signal-Vehicle Coupled Control (SVCC) model to optimize traffic signals at intersections for various transportation modes, including pedestrians, taking account of the needs of individuals with disabilities. Originally developed for Connected and Automated Vehicles (CAVs), the SVCC model was centered on optimizing signal timing and vehicle trajectories. However, most existing models overlook the safety and efficiency of non-vehicular road users, leading to increased delays and potential risks. The multimodal SVCC model incorporates active transportation and multimodal considerations, aiming to enhance both safety and efficiency for all users. By integrating pedestrians, including those with disabilities, into the optimization process, the multimodal SVCC outperforms traditional systems like actuated signal timing in reducing delays and conflicts. Additionally, it introduces adjustments to signal phase designs to ensure equitable access and safety at intersections. While the results demonstrate improvements in safety by reducing conflicts, further research is needed to explore infrastructure modifications that can minimize overall delays for all users.

Introduction:

New advancements enabled by the connected and automated vehicles (CAV) have attracted significant attention in the field of Intelligent Transportation Systems (ITS) (Guo et al., 2019; Shladover, 2018). Through their interaction with the surrounding environment, these vehicles provide abundant data that is offered along with their higher control flexibility, leading to a more enhanced urban traffic control (UTC). A key application of CAVs is the optimization of traffic flow at signalized intersections. This is made possible by technologies such as vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-everything (V2X) communications, which significantly contribute to the intersection optimization process, leading to improved safety, mobility, and sustainability (Liang et al., 2018; Niroumand et al., 2020).

Research has explored numerous approaches for optimizing CAV operations at signalized intersections. One such method, the multiscale Signal-Vehicle Coupled Control (SVCC), simultaneously optimizes vehicle trajectories and signal timings to improve intersection safety and efficiency. For a comprehensive review of CAV applications in urban traffic signal planning and control, one can refer to Guo et al. (2019). Although studies on signal planning control and optimization in the CAV environment are abundant, they are primarily focused on vehicular traffic and neglect other road users and their safety considerations. To be implemented effectively in real-world scenarios, these models need to account for multimodal transportation, including pedestrians, cyclists, and especially elderly and disabled populations.

Ensuring the safety and mobility of non-vehicular users, especially pedestrians with disabilities, is critical in creating inclusive, equitable, and efficient urban transportation systems.

Prioritizing only vehicular traffic can result in longer delays for pedestrians and cyclists, compromising their safety and discouraging active transportation modes. Moreover, individuals with disabilities face unique challenges at intersections, such as slower walking speeds, which necessitate additional time for safe crossing.

To date, few studies have integrated non-vehicular road users into CAV intersection optimization. Niels et al. (2020) proposed incorporating demand-responsive (i.e., actuated) signals for pedestrians (Niels et al., 2020b) and bicyclists into a signal free intersection with CAVs, while later work integrated pedestrian signal timing into CAV trajectory optimization (Niels et al., 2024). Other studies explored automated pedestrian shuttles to address pedestrian mobility in CAV-dominated intersections (Jiang et al., 2024; Wu et al., 2022).

This study aims to extend the SVCC model to accommodate a wider range of transportation modes, including pedestrians and cyclists, with particular attention to individuals with disabilities. By employing both model-based and learning-based approaches, we seek to optimize performance and safety for different road users, comparing the extended SVCC model against conventional signal timing systems.

Methodology:

The proposed multiscale SVCC model, initially designed for scenarios involving only cars, aims to optimize both traffic signal timing and vehicle trajectories—considering speed, acceleration, and position—at the same time (Guo & Ban, 2023). This model tackles the challenge of managing traffic across different spatial and temporal scales in urban environments. For example, traffic signal control at intersections focuses on minimizing delays and maximizing throughput, while vehicle-level control prioritizes reducing fuel consumption and travel time. The SVCC model optimizes both levels of control simultaneously, balancing the objectives of each scale. The SVCC model has been applied to a single intersection, representative of one in Downtown Seattle, Washington (Figure 1).

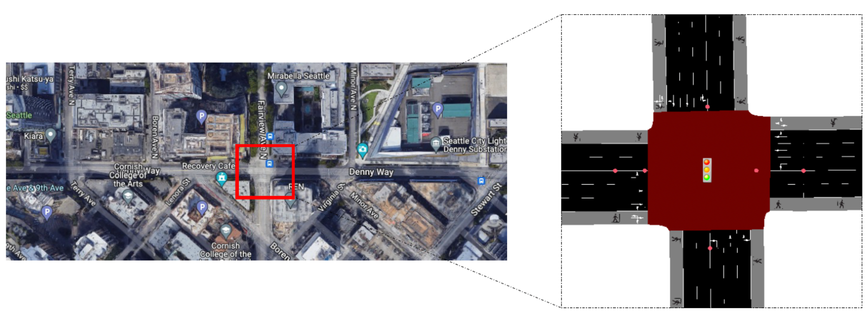

Figure 1. The Fairview Avenue and Denny Way intersection, Seattle, Washington (Guo & Ban, 2023)

Model-based approach:

The model-based approach decomposes the signal control problem into two scales: a slower-scale optimization for traffic signal timing and a faster-scale optimization for vehicle trajectories. Using a Model Predictive Control (MPC) scheme, the model minimizes total intersection delay and vehicle fuel consumption by iteratively adjusting the system over a prediction horizon. The slower-scale problem is formulated as a mixed-integer nonlinear program (MINLP), focusing on optimizing signal phases and vehicle trajectories over larger time intervals. It considers constraints such as vehicle dynamics, car-following behavior, and signal phase regulations, generating optimized signal phase timings and trajectories for vehicles approaching the intersection. The faster-scale optimization, modeled as a nonlinear program (NLP), focuses on refining vehicle trajectories at shorter time intervals to reduce fuel consumption while maintaining consistency with the slower-scale signal control problem.

The algorithm is implemented in Python and interfaces with the simulation software SUMO via the TraCI package. The steps of the model-based algorithm can be found in Figure 2. As can be seen, the model iteratively computes optimal signal phase timings and vehicle speed commands for the upcoming time step based on the results of the two optimization scales. For further details on the model formulation, refer to Guo & Ban (2023). The results from the model-based approach ultimately provide optimized signal phase timings and vehicle speed commands for the following time steps.

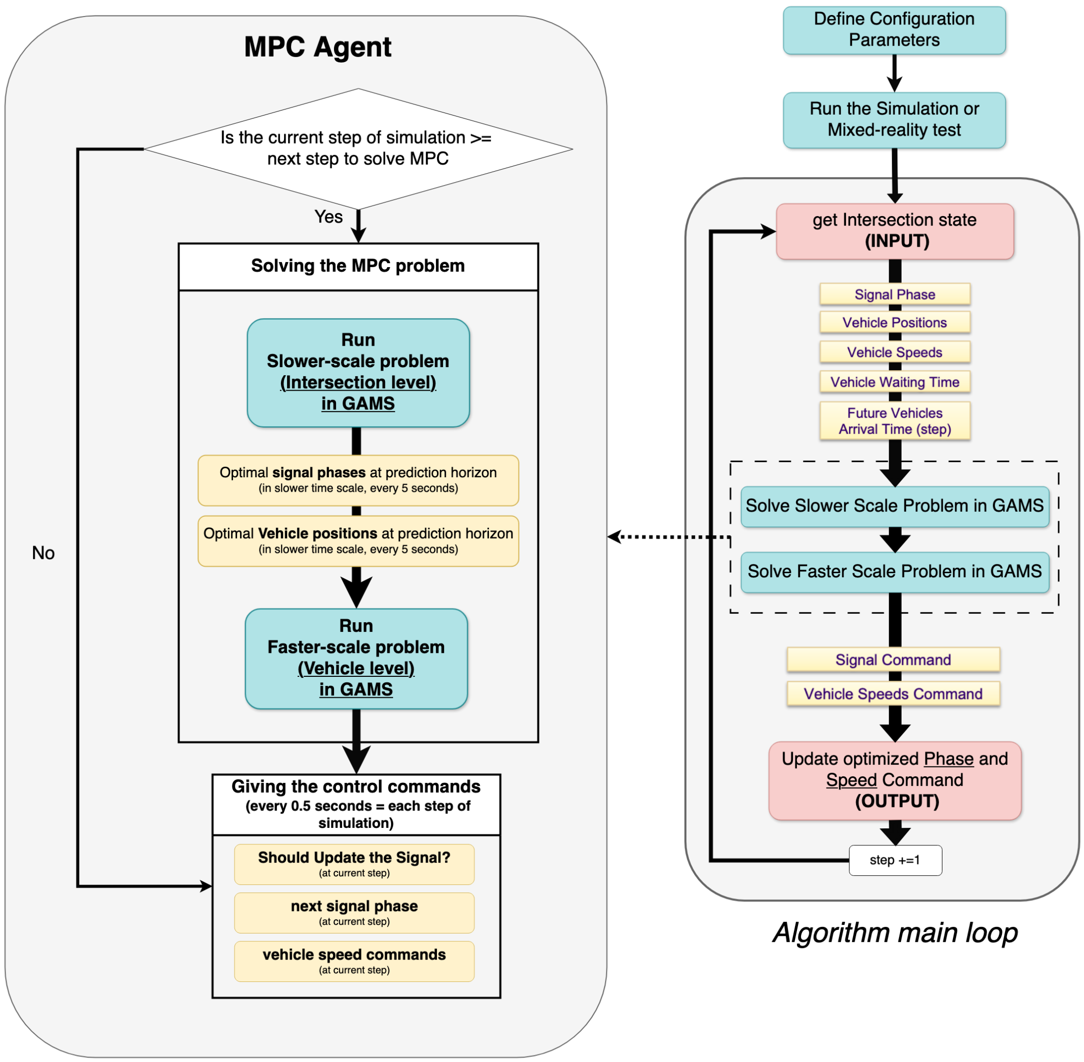

Figure 2. Model-base SVCC algorithm

Learning-based approach:

While the proposed MPC framework significantly improves the efficiency of the SVCC model, its scalability becomes a challenge as the system expands from a single intersection to a network of traffic signals, or when additional transportation modes are incorporated. As the problem grows in size and complexity, computational demands can substantially increase, leading to slower performance. To address this, we also explore various learning-based methods to reduce the computational burden of the optimization process.

One learning-based model we explore here is the Imitation Learning (IL) approach. This method relies on "expert" data, which in our case, is generated from the model-based approach discussed earlier. The learning approach uses deep neural networks, specifically ResNet, to determine optimal signal timings based on traffic states (Figure 3). Each incoming lane at an intersection is discretized into cells, and vehicle data such as position, speed, and waiting time are aggregated into matrices, which serve as input to the network. The policy output generates signal timings for the next two time steps. Although the method simplifies vehicle control by decoupling signal control from vehicle trajectory prediction, it uses a rule-based algorithm for CAV movement, factoring in right of way, speed limits, and deceleration strategies. This approach balances computational efficiency and practicality by focusing on signal control while applying preset acceleration and deceleration rules for vehicles, ensuring safety and fuel efficiency in urban intersections.

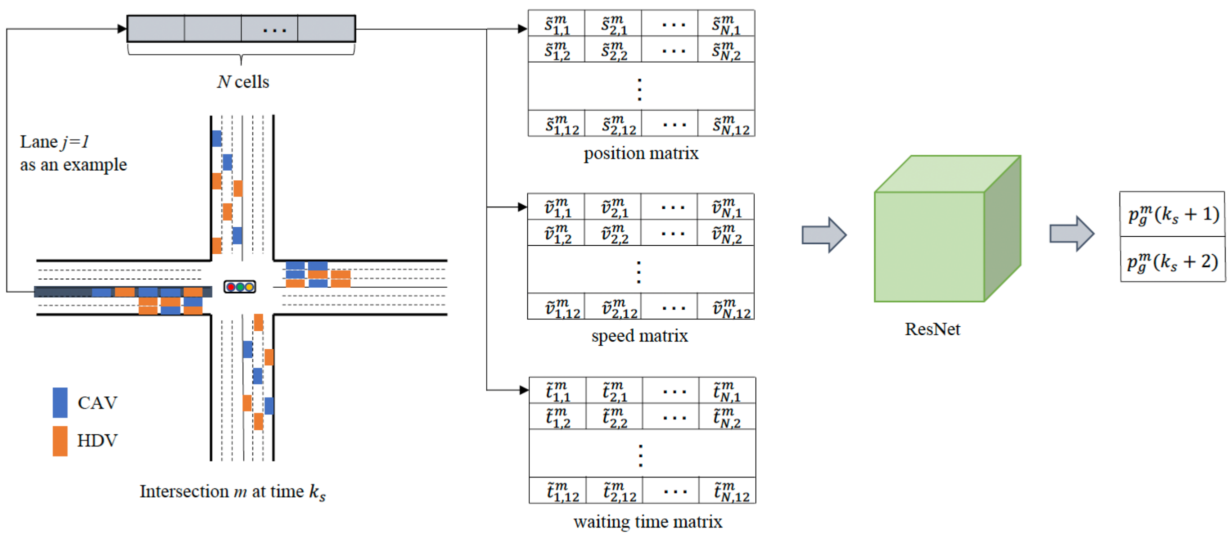

Figure 3. The ResNet based learning framework (Guo and Ban, 2023)

This project aims to extend the current model-based and learning-based SVCC frameworks to accommodate multimodal transportation by integrating pedestrians, including those with disabilities, into the optimization model. The model-based approach was modified to ensure a balanced optimization of delays for both pedestrians and CAVs. Key changes include a weighted sum of pedestrian and vehicle delays in the objective function, consistency between pedestrian phases and corresponding vehicle phases, and the introduction of a minimum pedestrian green time constraint. The pedestrian green time is calculated based on the following equation (FHWA, 2021):

$$G_p = 3.2 + \frac{L}{S_p} + 2.7 * \frac{N_p}{W}$$

Where L is the length of the crossing, S_p is the average pedestrian speed, N_p is the number of pedestrians crossing at the corresponding phase, and W is the width of the crossing.

It is important to note that when disability considerations are included, the average pedestrian speed decreases from 3.5 ft/s to 2.5 ft/s, necessitating an extended green phase (FHWA, 2006). Additionally, the clearance time must be extended to account for the slower speed of disabled pedestrians. The results of applying these changes are presented in the next section.

Results:

The model-based and learning based approaches have already shown to significantly improve the vehicle performance at signalized intersection (Guo, 2022) (Figure 4 and Figure 5). The comparison metrics include:

1. Average Fuel Consumption (mg/veh/m): This metric represents the total fuel consumption in milligrams by all vehicles approaching the intersection, divided by the number of vehicles and the average length of the incoming lanes (≈200m).
2. Average Waiting Time (s/veh): The total time in which the approaching vehicles' speed was below or equal 0.1 m/s divided by the number of vehicles.
3. Average Time Loss (s/veh): The total time lost due to driving below the ideal speed summed over all the approaching vehicles divided by the number of vehicles.
4. Average Queue Length (m): This metric indicates the average length of the queue from the intersection to the final vehicle in the line.

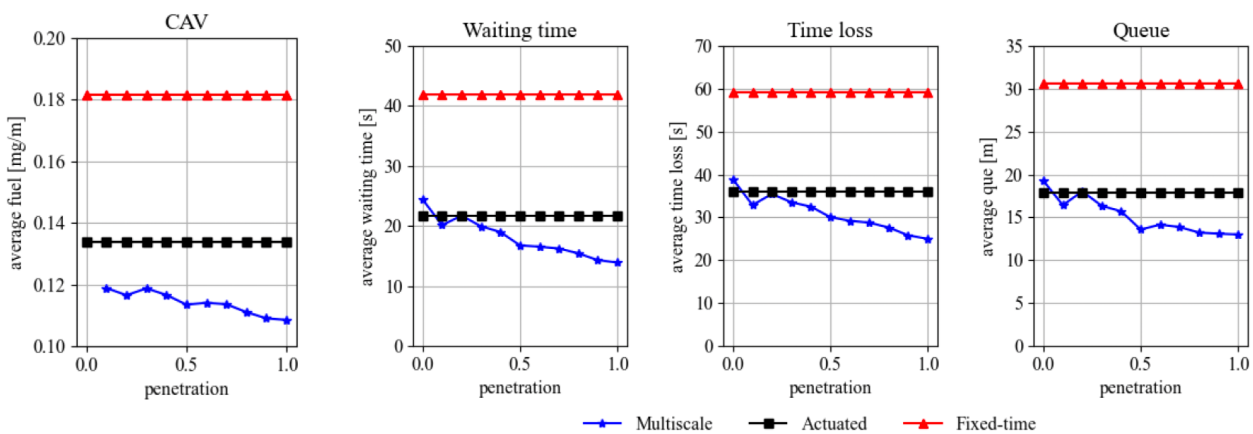

Figure 4. Performance results of model-based SVCC (blue) compared with fixed-time (red) and actuated (black) scenarios (Guo, 2022)

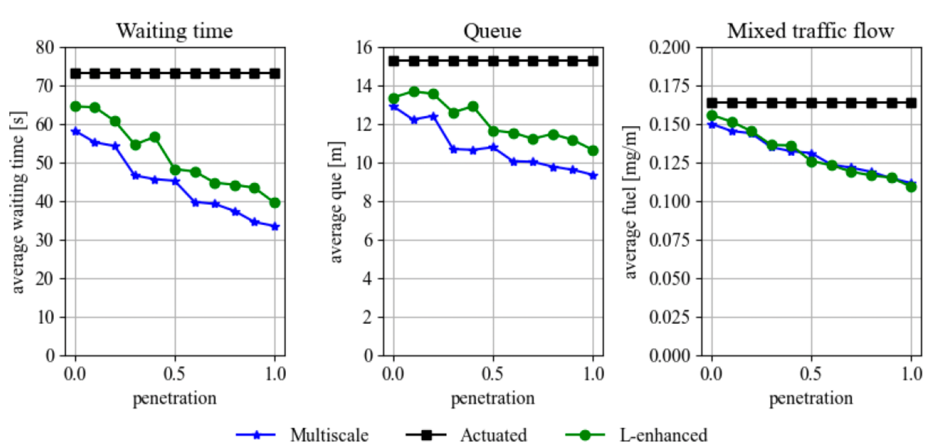

Figure 5. Performance results of Learning-based SVCC (green) model compared with model based (blue) and actuated signal timing (black) (Guo, 2022)

For the multimodal SVCC, pedestrians with and without disability were integrated into the single-intersection optimization shown in Figure 1. The following additional metrics were used to evaluate performance for pedestrians:

5. Average Pedestrian Time Loss (s/ped): The total time pedestrians spent walking or riding below their ideal speed, divided by their respective totals.
6. Number of Conflicts between Pedestrians and CAVs: The number of instances where pedestrians and CAVs were within 2 meters of each other (e.g., due to insufficient clearance time for pedestrians).

The results of the pedestrian integration into the model-based SVCC are presented in Tables 1-2 and Figures 6-7. The model was tested across different pedestrian demand scenarios (Low, Medium, and High Demand) and levels of symmetry (Asymmetric and Symmetric pedestrian demand). Scenarios were also analyzed using various weighting factors for pedestrians and vehicles, allowing for flexibility in prioritizing different modes. The results indicate that the multimodal SVCC with pedestrians outperformed actuated signal control in nearly all tested scenarios.

Table 1. Performance results for Symmetric Low, Medium and High pedestrian demand

Symmetric pedestrian demand								
	Metrics	Actuated	Model-based SVCC (vehicle/ped weighting factor)					
			(50/50)	% Decrease	(70/30)	% Decrease	(30/70)	% Decrease
Low Ped Demand	Fuel Consumption	85.06	52.06	-38.80	52.74	-38.00	52.13	-38.71
	Vehicle Waiting Time	19.37	10.1	-47.86	11.13	-42.54	11.03	-43.06
	Vehicle Time Loss	32.9	21.93	-33.34	22.97	-30.18	22.77	-30.79
	vehicle queue Length	15.25	9.83	-35.54	10.15	-33.44	9.45	-38.03
	Pedestrian Time Loss	26.33	19.4	-26.32	20.61	-21.72	21	-20.24
Medium Ped Demand	Fuel Consumption	85.94	57.12	-33.54	58.06	-32.44	56.53	-34.22
	Vehicle Waiting Time	21.31	16.98	-20.32	17.66	-17.13	16.65	-21.87
	Vehicle Time Loss	34.9	30.58	-12.38	31.52	-9.68	30.08	-13.81
	vehicle queue Length	16.87	12.49	-25.96	13.31	-21.10	12.28	-27.21
	Pedestrian Time Loss	30.55	22.49	-26.38	26.7	-12.60	20.18	-33.94
High Ped Demand	Fuel Consumption	84.95	58.28	-31.39	58.65	-30.96	59.3	-30.19
	Vehicle Waiting Time	19.88	18.3	-7.95	19.31	-2.87	20.85	4.88
	Vehicle Time Loss	33.74	32.05	-5.01	33.45	-0.86	35.56	5.39
	vehicle queue Length	15.25	13	-14.75	13.13	-13.90	14.39	-5.64
	Pedestrian Time Loss	39.85	27.45	-31.12	32.51	-18.42	24.25	-39.15

Table 2.Performance results for Asymmetric Low, Medium and High pedestrian demand

Asymmetric pedestrian								
	Metrics	**Actuated**	**Model-based SVCC (vehicle/ped weighting factor)**					
			0.5/0.5	**% Decrease**	**0.7/0.3**	**% Decrease**	**0.3/0.7**	**% Decrease**
Low Ped Demand	Fuel Consumption	85.41	52.31	-38.75	52.61	-38.40	52.08	-39.024
	Vehicle Waiting Time	20.43	9.62	-52.91	10.12	-50.47	10.13	-50.416
	Vehicle Time Loss	33.98	21.6	-36.43	22.31	-34.34	21.86	-35.668
	vehicle queue Length	15.88	9.57	-39.74	9.47	-40.37	9.22	-41.940
	Pedestrian Time Loss	23	20.41	-11.26	17.22	-25.13	20.96	-8.870
Medium Ped Demand	Fuel Consumption	86.77	56.08	-35.37	55.97	-35.50	55.72	-35.784
	Vehicle Waiting Time	22.27	14.79	-33.59	14.61	-34.40	14.64	-34.261
	Vehicle Time Loss	36.09	28.36	-21.42	27.97	-22.50	28.4	-21.308
	vehicle queue Length	17.75	11.88	-33.07	11.89	-33.01	11.64	-34.423
	Pedestrian Time Loss	31.88	24.4	-23.46	25.41	-20.29	21.71	-31.901
High Ped Demand	Fuel Consumption	85.39	57.21	-33.00	56.94	-33.32	59.46	-30.367
	Vehicle Waiting Time	20.62	17.03	-17.41	16.45	-20.22	19.76	-4.171
	Vehicle Time Loss	34.8	32.19	-7.50	30.33	-12.84	34.32	-1.379
	vehicle queue Length	15.8	12.1	-23.42	12.96	-17.97	13.91	-11.962
	Pedestrian Time Loss	39.68	26.07	-34.30	32.63	-17.77	25.21	-36.467

It is also evident from the results that as pedestrian demand increased, the multimodal SVCC model delivered greater benefits for pedestrian performance compared to the actuated signal scenario, though the benefits for vehicles decreased in higher pedestrian demand settings (Figures 6 and 7).

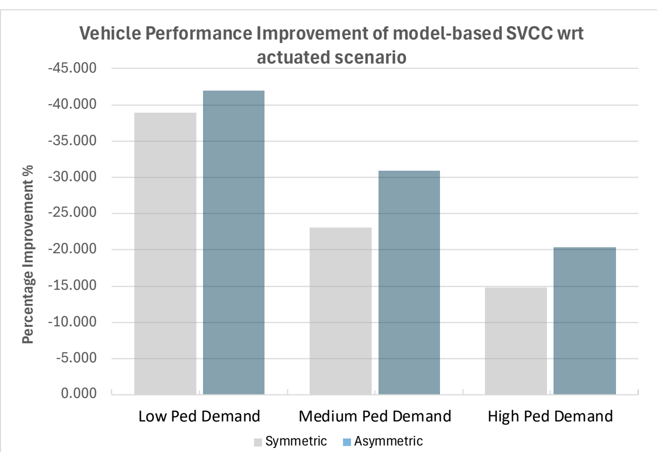

Figure 6. Percentage of improvement of vehicle performance

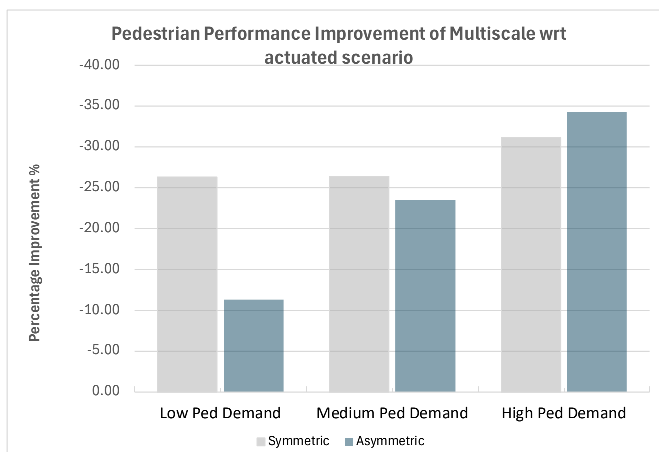

Figure 7. Percentage of improvement of pedestrian performance

Lastly, Table 3 presents the results of incorporating pedestrians with disabilities into the multimodal SVCC. The model was tested with various disability rates (i.e., 30%, 50%, and 70% of pedestrians with disabilities) to assess how performance differs compared to scenarios where no pedestrians are disabled. As expected, since pedestrians with disabilities have lower crossing speeds, the overall performance of all road users was negatively impacted.

Table 3. Comparison of results for pedestrians with disabilities

Asymmetric pedestrian demand										
	Metrics	Actuated	MultiScale SVCC	Disability rate						
				0.3	% increase	0.5	% increase	0.7	% increase
Medium Pedestrian Demand	Fuel Consumption	94.58	65.67	68.88	-27.173	68.52	-27.553	74.49	-21.241
	Vehicle Waiting Time	32.37	28.04	32.59	0.680	32.77	1.236	38.17	17.918
	Vehicle Time Loss	48.85	45.92	51.5	5.425	51.44	5.302	63.41	29.806
	vehicle queue Length	19.26	17.1	18.76	-2.596	18.87	-2.025	18.25	-5.244
	Pedestrian Time Loss	51.9	33.55	34.84	-32.871	37.85	-27.071	38.83	-25.183
	right-turn conflicts	156	125	157	0.641	162	3.846	192	23.077

Additionally, as the disability rate increases, the overall performance degrades for both cars and pedestrians. The average pedestrian delay rises, and the number of conflicts between vehicles and pedestrians also increases. This is because pedestrians with disabilities require more green time and clearance time to safely cross the intersection. These findings highlight the need for infrastructure adjustments—specifically, modifying signal green time, as well as yellow and all-red phases, to account for disability considerations. After applying these adjustments, the results are as follows:

Table 4. Results after signal phase adjustment to accommodate pedestrian green phase for pedestrians with disabilities

Asymmetric pedestrian demand (Disability rate=0.5)				
	Metrics	Previous signal phasing	adjusted signal phasing	% increase
Medium Pedestrian Demand	Fuel Consumption	68.52	69.49	1.416
	Vehicle Waiting Time	32.77	33.79	3.113
	Vehicle Time Loss	51.44	53.98	4.938
	vehicle queue Length	18.87	18.81	-0.318
	Pedestrian Time Loss	37.85	38.05	0.528
	right-turn conflicts	162	153	-5.556

The results in Table 4 indicate that adjusting traffic signals to accommodate the lower speeds of pedestrians with disabilities can effectively reduce the number of conflicts between pedestrians and CAVs, while mobility and sustainability goals are slightly impacted negatively. Further investigation is needed to identify necessary changes in infrastructure that can enhance other performance outcomes as well.

Conclusion:

This study demonstrates the effectiveness of extending the Signal-Vehicle Coupled Control (SVCC) model to accommodate pedestrians, including those with disabilities, into the optimization process. The integration of multimodal considerations, such as extended green and clearance times for disabled pedestrians can improve safety and accessibility at signalized intersections. While the model shows enhanced performance in reducing delays and conflicts for pedestrians compared to traditional signal control methods, further infrastructure adjustments may be necessary to fully optimize traffic flow for users with disabilities.

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