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Concepts of Signal Control Preemption for Emergency Vehicles in Connected Vehicle Environments

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ABSTRACT

Connected Vehicles (CV) share information among themselves and with the infrastructure, which contains parameters such as location, speed, acceleration, heading, and the status of majority of vehicle systems. This paper assesses an algorithm for emergency vehicles preemption, which aims to prioritize emergency vehicles through signalized intersections, while minimizing negative impacts on other vehicular traffic. The algorithm is based on the constant exchange of information, such as the expected arrival time based on accurate coordinates and speed of emergency vehicles, and the current signal status at the downstream intersection. The algorithms are created and tested in VISSIM microsimulation on a test-case network consisting of ten signalized intersections along State Street in Salt Lake City, Utah. The proposed algorithm can reduce delays of emergency vehicles at signalized intersections by up to 36 % and increase their speeds in excess of 50% along busy urban corridors, with minimal impacts on other vehicular traffic.

1. Introduction

Connected vehicle (CV) technologies enable vehicles to exchange information with each other (vehicle-to-vehicle [V2V]), with the roadside infrastructure (vehicle-to-infrastructure [V2I]), and with other equipped transportation systems users in real-time, using wireless-based communication technologies (ITSJPO 2018a, 2018b, 2018c). The CV systems combine different technologies, such as wireless communications, advanced vehicle sensors, advanced roadside infrastructure, and onboard computers/processing. Traffic control signals assign the intersection right-of-way to various traffic movements and transportation modes, temporally separating the conflicting ones. Actuated traffic signal control applies vehicle detection and preset signal timing parameters to adjust the operation to varying traffic demands. Traffic signal controllers also have built-in functions to introduce special operations for emergency, transit, and freight vehicles, such as preemption and priority.

The CV technology offers new tools for detection, communication, and decision algorithms based on the wide array of information being shared among vehicles, infrastructure, and control devices. CV technologies are gaining momentum in research and practice. They can be used to implement various advanced traffic control programs aimed at improving mobility and safety at signalized intersections.

The goal of this study is to develop and analyze CV-based Emergency Vehicle Preemption (PREEMPT) algorithm. PREEMPT is a special signal control mode that immediately alters traffic signal operation for the purpose of serving the approaching emergency vehicle (Urbanik et al., 2015). PREEMPT terminates the normal signal operation in order to perform this task. Preemption can also be used for other purposes, such as railroad crossings, or serving public transit vehicles. This study focuses only on emergency vehicles (EV), but the developed concept can also be applied in other cases. On-time detection and service request is critical in implementing preemption.

Traditionally, radar or infrared communication has been used to establish a connection between the approaching EV and the traffic signal, and request preemption. With the implementation of CV technologies, preemption can be improved by utilizing the information sent by the EV.

The algorithms were tested in VISSIM microsimulation, while the communication between vehicles and controllers was coded in Python using VISSIM's Component Object Model (COM) functions. Signal preemption logic was programmed directly in Econolite ASC/3 Software in the Loop (SIL) controllers embedded in VISSIM, using built-in preemption operation, and logic processor. The test-case network used in this research is a corridor consisting of ten signalized intersections along State Street in Salt Lake City, UT.
The next section summarizes the state-of-the-art studies on CV technologies and preemption signal operations. It is followed by the section describing the modeling methodology applied in this research, and the results and findings from the experiments. The conclusions are provided in the last section.

2. Literature Review

Emergency Vehicle Preemption (PREEMPT) is a special signal control mode that immediately alters traffic signal operation for the purpose of serving the approaching emergency vehicle (Urbanik et al., 2015). PREEMPT terminates the normal signal operation in order to perform this task. Preemption can also be used for other purposes, such as railroad crossings, or serving public transit vehicles. Preemption systems are designed to give emergency response vehicles a green light on their approach to a signalized intersection while providing a red light to conflicting approaches. The most commonly reported benefits of using preemption are improved response time, improved safety, and cost savings (FHWA, n.d.). Preemption can improve EV response times by reducing the probability that responding EVs will arrive at intersections during the red signal phase and encounter vehicle queues. An early green discharges the queue before the EV arrival, allowing the EV to maintain higher average speeds.

Malabanan et al. (2022) used VISSIM microsimulation to evaluate the delay reduction for emergency vehicles through signalized corridors, using a test bed in Bangkok, Thailand, by applying different preferential treatments. They found that the preemption implementation has the potential to reduce emergency vehicle delays by between 70% and 80%. Xie et al. (2017) used SMARTS traffic simulation software to assess the effectiveness of emergency vehicle preemption using three test beds in Melbourne, Manhattan, and London. The study results showed that preemption can result in EV travel time reduction of close to 63%.

CV technologies have the potential to improve priority operation through the utilization of the information shared between the EVs and the traffic signals. Das et al. (2022) MMITSS priority based on CV technologies. They developed a mixed integer programming model to consider the priority requests from multiple emergency vehicles and dilemma zone requests from freight vehicles. The study results show that the implemented algorithm has the potential to provide a smooth progression of the emergency vehicles, without significant negative impacts on general-purpose traffic. When compared to the traditional preemption, the MMITSS priority resulted in EV-intersection delay reduction of between 10 and 29 %. Noori et al. (2016) developed a method that uses V2V and V2I communication to determine the number of vehicles in the queue ahead of the approaching EV and provide early green to discharge the queue and clear out the route for the EV. The algorithm can look at all signals along the EV route and prepare a timely response. The method was tested in SUMO simulation using a real-world network in Toronto, Canada. The results showed a significant reduction in EV response times, ranging from 43 to 51 % depending on the area density when compared to no preemption. Shaaban et al. (2019) developed and tested a joint strategy for optimal path selection and EV preemption using CV communication and tested it in VISSIM microsimulation. The developed method first finds the optimal route for EVs through the network and prepares the intersection for preemption. One of the objectives of the research was to minimize negative impacts on other traffic. The results showed a decrease in the EV travel times ranging between 16 and 49 %, compared to no preemption. The vehicular traffic along the EV route also experienced a reduction in delays attributed to the EV preemption, while the increase in delays for the cross streets was not found to be significant. Obrusnik et al. (2020) developed a method for dynamic queue discharge in front of an oncoming EV, with the goal of providing preemption as short as possible to minimize negative impacts on other traffic. The method utilizes CV communication to determine the optimal preemption activation moment. It was tested in SUMO simulation and experimentally verified in the field. The results showed significant improvements in EV operations for low and medium congestion and queues, however, more improvements are needed for heavy congestion/long queues traffic states.

These examples show benefits that could be accomplished with the introduction of CV technologies. Considering the early stage of the development of signal control strategies based on CV, this paper aims to propose a simple and installation-ready algorithm that could be implemented in the field without additional adjustments. The algorithm proposes preemption for emergency vehicles that are in the detection range defined within 600 ft from the intersections.

Each intersection will adjust signal phasing based on information that receives from the EVs, considering the EV's arrival time and current signal timing in order to minimize negative impacts on other vehicular traffic while providing safe and immediate traverse for emergency vehicles. Moreover, simulation models are developed on real word coordinates in order to provide high fidelity of the models. Preemption settings are performed directly in the ASC/3 controller and are ready to be copied into field controllers.

3. Test-Case Corridor and Data Preparation

The test-case network for this study consists of a 10-intersection corridor along State Street in Salt Lake City, UT, as shown in Figure 1. This is a multi-modal corridor that carries a significant amount of traffic, with AADT of 37,000 vehicles per day along the busiest sections, according to the Utah Department of Transportation (UDOT). The busiest intersection in the test-case corridor is 2100 S, used by more than 9,500 vehicles during the PM peak period (4:00 – 6:00 PM), which is the interval used in this study. 700 S, Kensington Avenue, and 1910 S are minor streets/signalized driveways with insignificant traffic, therefore they were not included in the analysis. State Street also carries significant transit ridership. The major bus route along the corridor is Route 200, which is one of the Utah Transit Authority (UTA's) routes with the highest ridership. State Street has approximately 7% of truck traffic in the traffic flow. Bicycle traffic is high, because of the flat topography and the vicinity of the downtown area. Significant pedestrian traffic also exists in the area.

The data collection was performed in 2019 for the purpose of previous studies conducted along this corridor. The data were obtained through field data collection, UDOT, and UTA's databases, and included traffic volumes/intersection turning movements, travel times, signalized intersection control parameters, and transit operation characteristics. These data are used to develop, calibrate and validate the base microsimulation model.

The first dataset consisted of intersection turning movement counts, which included vehicular traffic, pedestrians, and bicyclists. These data were collected in the field for seven signalized intersections within the analysis networks (excluding 700 S, Kensington Avenue, and 1910 S), for the PM peak period (4:00 PM – 6:00 PM). UDOT's Automated Traffic Signal Performance Measures (ATSPM) system was also used for checking the turning movement counts, approach volumes, and signal timing data.

The second dataset consisted of travel time runs, which were performed using the floating car technique. Additional travel time data were obtained through online services, such as INRIX travel times, WAZE, and Google Maps. The third dataset consisted of signal timing data, which were obtained from the UDOT Traffic Operations Center (TOC), in the form of pdf files for all ten signalized intersections in the analyzed network. The fourth dataset consisted of transit data, including ridership, GPS, transit schedules, and vehicle capacities.

Figure 1. Test-Case Network on State Street, Utah

4. Development of Microsimulation Models

The CV-based emergency vehicle PREEMPT algorithm was developed and tested in VISSIM microsimulation. The algorithm uses the communication between the emergency vehicles and the traffic signals, to broadcast the information on location and the speed of the approaching vehicle. The communication, BSM information, and traffic signal operations were programmed through the VISSIM COM interface using Python. The main information contained in the BSM that was used for communication with traffic signals through RSU was the emergency vehicles' position (lat/long) coordinates, their speeds, and the request for preemption.

When the EV appears within 600 ft of the intersection, it starts transmitting the information to the traffic signal controller. The controller receives the information on the EV's location, speed, and route. It then enters a special preemption phase, dwelling in the green phase if it was green when the request was received, or ending green for conflicting approaches, and switching to green for the EV signal phase. This ensures that the approach is clear of vehicles, so the EV can cross the intersection without delays. The preemption was programmed directly in the ASC/3 signal controller software, using the built-in function for preemption and the logic processor. As this is EV preemption, the highest level of preemption is activated through this algorithm. The activation was achieved through a series of logical commands, programmed directly in the controller through its logic processor.

EVs would appear randomly and travel through the network. The majority of them would be using State Street, although some of them traverse the cross streets. Four simulation scenarios were developed and used for this purpose:

1. Base 2019 model. This is the base model developed, calibrated, and validated for 2019 traffic data, The model also introduces random EVs traveling through the network, but no preemption is enabled.
2. 2019 CV-EVP model. This is a continuation of the previous model, where the traffic demand and operations are the same as in the Base model, but preemption is activated for CV-equipped EVs. When the EVs enter the communication range, they transmit BSM to the signal controller and send a preemption request. The controller assesses current signal phases and assigns preemption accordingly. It is assumed that all EVs are equipped with connected vehicle technologies.
3. 2029 Base model. This model uses the same geometry as the base 2019 model, but the traffic demand is increased by 2.4% annual traffic growth rate, and the signal timings are updated accordingly through Synchro. No geometry updates are introduced. EVs appear randomly in the network but are not granted preemption.
4. 2029 CV-EVP model. This model combines preemption introduced in the 2019 CV-EVP model, and traffic demand and signal timings from the 2029 Base model. All EVs are assumed to be equipped and request preemption.

All models are run for 10 randomly seeded simulation runs, and the outputs are averaged, to incorporate any variations and stochasticity. The PM peak period (4:00 – 6:00 pm) was used for the analysis, with a 15-minute warm-up period.

5. Calibration and Validation of the Base Model

The Base model was developed, calibrated, and validated for 2019 existing traffic conditions along the State Street corridor. VISSIM version 21, coupled with Econolite ASC/3 SIL traffic controller software, was used for modeling. The data used in modeling include actual roadway and intersection geometries, traffic counts for vehicles, pedestrians, and bicyclists, corridor travel times, transit route and other ridership data, and signal timing data. The outputs were averaged from ten simulation runs with different random seeds. The Base model was calibrated for intersection turning movements and validated for corridor travel times. The calibration was performed for five major signalized intersections: 500 S, 600 S, 800 S, 1300 S, and 2100 S. For this purpose, the two-hour PM peak (4:00 – 6:00 PM) intersection turning movement counts were used. The comparison was performed for each approach and each movement separately. Figure 2. shows compiled calibration results for the five intersections and each movement, where the field counts were compared to the results obtained from the simulation. The coefficient of determination (R^2) for calibration was close to 1.0 for the entire network, showing satisfactory calibration results. For validation purposes, the corridor was split into seven segments in each direction, where one segment was between a pair of major signalized intersections. Travel times collected in the field were used to validate the model. The field travel times were averaged from five travel time runs in each direction during the PM peak period, using the floating car technique. Model validation is shown in Figure 3. It represents a comparison between the average field travel times and the travel times obtained from the simulation, including the standard deviation. The combined R^2 value for validation in both direction was 0.98. The calibration and validation results show a good fidelity of the Base model.

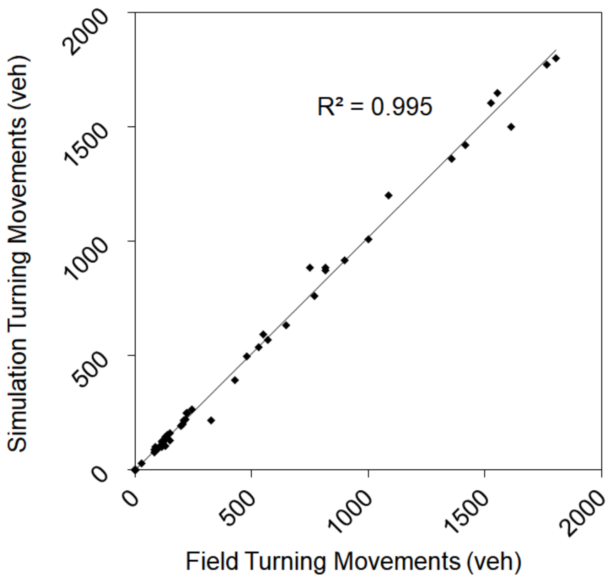

Figure 2. Base Model Calibration

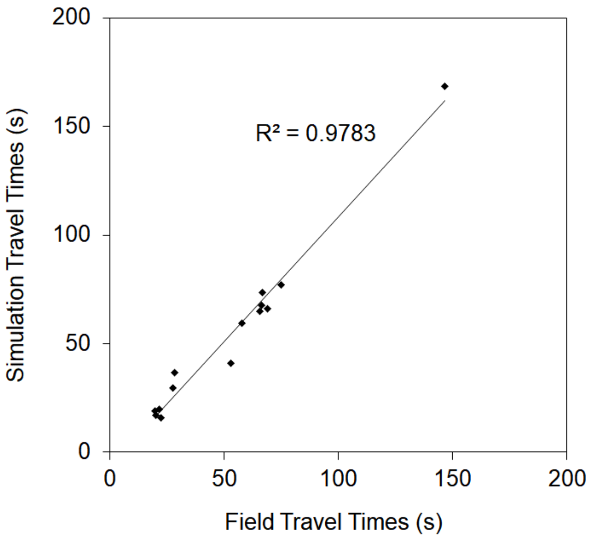

Figure 3. Base Model Validation

6. Results and Discussion

The main operational results included in the analysis contain the intersection performance measures, vehicular travel speeds, and network-wide performance measures. The results are analyzed for cars, transit buses, and EVs separately. Where applicable, the paired two-tailed t-test with a 95% confidence level was used to assess the statistically significant difference in obtained results.

6.1. Intersection Performance Measures

The intersection performance was assessed through the total vehicular delays (in veh-min) for each of the seven major intersections along the corridor. The comparison among the four models is provided in Table 1.

The implementation of the CV-based PREEMPT algorithm can reduce EV delays for all intersections along the corridor in both analyzed years. For the year 2019, the EV delay reduction ranges between 8% and 59%, with an average reduction of 36%. This difference is statistically significant. Only the intersection of State Street and 800 S resulted in higher delays for EVs with the preemption. For the year 2029, the EV delay reduction ranges between 2% and 34%, with an average reduction of 16%. Again, the reduction in EV delays is statistically significant.
The changes in total intersection delays for cars and buses along the corridor are not statistically significant. Depending on the intersection, it either slightly increases or reduces for both years, but overall, the changes are relatively small. The delay increase for cars and buses mainly comes from the movements that conflict with the EV signal phase.

Table 1. PREEMP Intersection Performance Results – Total Vehicle Delays (veh-min)

Intersection	Mode	2019 Base	2019 CV-EVP	*vs. 2019 Base*	2029 Base	2029 CV-EVP	*vs. 2029 Base*
500 S	Car	5800.8	5740.4	*-1.0%*	15833.1	15866.2	*0.2%*
	Bus	13.5	13.2	*-1.6%*	27.6	28.4	*2.9%*
	EV	12.7	5.3	*-58.7%*	21.4	20.8	*-2.8%*
600 S	Car	5743.8	5568.3	*-3.1%*	9976.2	10074.7	*1.0%*
	Bus	5.5	6.5	*19.7%*	13.2	13.2	*0.0%*
	EV	9.3	6.5	*-30.2%*	10.3	8.6	*-15.8%*
800 S	Car	5178.0	5335.5	*3.0%*	8660.1	8692.4	*0.4%*
	Bus	11.3	11.5	*0.9%*	13.3	13.0	*-2.4%*
	EV	2.7	2.9	*6.2%*	5.8	5.0	*-14.0%*
900 S	Car	1675.4	1840.2	*9.8%*	2757.8	2757.0	*0.0%*
	Bus	4.8	4.5	*-6.1%*	3.8	3.7	*-4.5%*
	EV	2.1	1.5	*-31.0%*	1.2	1.1	*-8.5%*
1300 S	Car	4799.9	4762.4	*-0.8%*	6380.2	6452.6	*1.1%*
	Bus	6.5	6.4	*-2.6%*	7.6	7.6	*-0.7%*
	EV	6.4	5.5	*-13.9%*	8.9	5.9	*-34.0%*
1700 S	Car	1879.0	2015.1	*7.2%*	4250.7	4193.8	*-1.3%*
	Bus	3.7	3.4	*-8.0%*	5.8	5.6	*-2.7%*
	EV	2.3	2.1	*-8.0%*	6.4	6.6	*2.5%*
2100 S	Car	6848.4	7105.0	*3.7%*	14206.4	13757.6	*-3.2%*
	Bus	9.5	8.6	*-10.0%*	8.5	9.4	*11.1%*
	EV	16.9	9.9	*-41.5%*	25.7	19.4	*-24.6%*
Average	**Car**	**31925.2**	**32366.9**	***1.4%***	**62064.7**	**61794.3**	***-0.4%***
	Bus	**54.8**	**54.1**	***-1.4%***	**79.9**	**80.9**	***1.3%***
	EV	**52.5**	**33.6**	***-35.9%***	**79.6**	**67.3**	***-15.5%***

6.2. Travel Speeds

The travel speed results were compiled for the entire corridor (between 500 S and 2100 S) for cars and buses, while for EVs they were recorded for the State Street corridor, as well as along 2100 S, 1300 S, and 600 S where EVs also appear. The speed results are provided in Table 2.

The implementation of the PREEMPT algorithm does not result in statistically significant speed changes for cars and buses. Along the main corridor, cars and buses actually benefit from the preemption. As far as the EVs, in the 2019 models, the speed increase is statistically significant for all corridors, and it ranges between 6% and 56%. Overall, for 2019, the EV speed increased by 32% on average when the CV-based PREEMPT is active. For the 2029 analysis years, the EV speed results are somewhat mixed, with some sections/directions experiencing a slight reduction in travel speeds, although they are not statistically significant. Overall, the EV speeds in 2029 increased 8% on average with the CV PREEMPT algorithm. This means that the algorithm is less effective in congested networks, which is to be expected.

Table 2. PREEMP Travel Speed Results (km/h)

Average Car Travel Speeds (km/h)						
Direction	**2019 Base**	**2019 CV-EVP**	***vs. 2019 Base***	**2029 Base**	**2029 CV-EVP**	***vs. 2029 Base***
SB	42.2	39.9	*-5.3%*	31.2	31.1	*-0.5%*
NB	35.2	35.2	*0.0%*	35.1	35.1	*0.0%*

Average Bus Travel Speeds (km/h)						
Direction	**2019 Base**	**2019 CV-EVP**	***vs. 2019 Base***	**2029 Base**	**2029 CV-EVP**	***vs. 2029 Base***
SB	22.2	22.0	*-0.7%*	18.5	18.3	*-0.9%*
NB	20.1	20.0	*-0.8%*	19.1	19.1	*0.0%*

Average EV Travel Speeds (km/h)						
Direction	**2019 Base**	**2019 CV-EVP**	***vs. 2019 Base***	**2029 Base**	**2029 CV-EVP**	***vs. 2029 Base***
State SB	38.9	41.2	*5.8%*	24.1	23.5	*-2.7%*
State NB	38.3	46.8	*22.3%*	36.2	35.7	*-1.3%*
2100 S EB	20.9	27.7	*32.3%*	11.1	16.1	*44.9%*
2100 S WB	19.1	29.9	*56.3%*	12.7	14.6	*15.2%*
1300 S EB	22.5	32.0	*42.1%*	20.0	20.0	*0.0%*
1300 S WB	27.0	38.0	*40.5%*	27.4	27.7	*1.2%*
600 S EB	27.2	34.3	*26.0%*	21.6	20.4	*-5.2%*

6.3. Network Performance

On the network-wide level, the analysis was performed for the average vehicle delays (s/veh), the average number of stops per vehicle, and the average network travel speed (km/h) for cars, buses, and EVs. The comparison of the network level results is given in Table 3.

The effectiveness of the implemented CV-based PREEMPT algorithm can be best seen on the network-wide level. For the year 2019, the average EV delay and the number of stops reduce significantly (49% and 70%, respectively), while the EV speed significantly increases (27%). Cars and buses do not experience any significant impacts of the PREEMPT strategies on the network-wide level. For the year 2029, the EV network performance is not as impressive as for 2019, but the results are still statistically significant. The average EV delays and the number of stops reduce by 37% and 44% respectively, while their speeds increase by 38%. No statistically significant impacts are observed for cars and buses on the network level. These results show that the CV-based PREEMPT is very effective in improving the operations of EVs, including their response times, which is of the utmost importance in the real world.

Table 3. PREEMP Network-Level Results

	Mode	**2019 Base**	**2019 CV-EVP**	***vs. 2019 Base***	**2029 Base**	**2029 CV-EVP**	***vs. 2029 Base***
Average Vehicle Delay (s/veh)	**Car**	68.6	69.6	*1.5%*	117.6	116.6	*-0.9%*
	Bus	256.1	254.9	*-0.5%*	361.1	366.2	*1.4%*
	EV	151.8	77.6	*-48.9%*	216.5	135.5	*-37.4%*
Average Number of Stops per Vehicle	**Car**	2.1	2.1	*1.6%*	3.3	3.3	*-0.4%*
	Bus	3.4	3.4	*0.8%*	5.3	5.4	*1.3%*
	EV	1.9	0.6	*-69.5%*	3.8	2.1	*-43.9%*
Average Vehicle Speed (km/h)	**Car**	21.8	21.9	*0.4%*	18.5	18.4	*-0.7%*
	Bus	21.8	21.9	*0.4%*	18.5	18.4	*-0.7%*
	EV	34.4	43.6	*26.7%*	21.4	29.6	*38.4%*

7. Conclusions

The development of new technologies, such as connected vehicles, creates opportunities to develop traffic signal control strategies that have the potential to improve the operations and safety of signalized intersections. This paper aims to develop, test, and evaluate the effectiveness of an algorithm that provides preemption for EVs. The algorithm was developed and tested in VISSIM microsimulation, where the communication between vehicles and controllers was coded in Python programing language using VISSIM COM functionality. The priority logic was programmed directly in Econolite ASC/3 SIL controllers embedded in VISSIM. The test-case network used in the analysis is a corridor along State Street in Salt Lake City, UT, consisting of ten signalized intersections.

The study developed an approach that used the latitude and longitude (lat/long) coordinates of the CV-equipped emergency vehicles and signalized intersections to establish communication, define the detection zone, and update the position and speed of the vehicles, as well as the status of the current signal phase in each time step, taken as 0.1 seconds. The study used the current vehicle routing, which can be communicated through the use of turn signals, to separate individual turning movements at intersections. EVs share location and speed to activate preemption strategies on intersection approaches for safe traversing without delays for the traffic signals.

The results showed that the implementation of CV-based PREEMPT strategies has the potential to reduce EV signalized intersection delays by up to 36% and increase their speeds in excess of 50% along busy urban corridors, without impacting other vehicular traffic.

Importance of smooth traverse of EVs through the urban network request constant improvements in traffic signal strategies. The introduction of CV technologies has the potential to change the way how traffic signals operate and how EVs are treated. This study proves the benefits of CV-based preemption while providing a simple algorithm that could be upgraded to result in fully adaptive traffic signal strategies.

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