Development of Emergency Vehicle Preemption Strategies on Smart Corridors in a Digital Twin Environment*

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ABSTRACT

Emergency Response Vehicles (ERVs), such as firetrucks, ambulances, etc. operate with the purpose of saving lives and mitigating property damage. As such, ERV travel-time reductions may result in significant benefits to the community. A common strategy to improve travel times is Emergency Vehicle Preemption (EVP). EVP seeks to reduce ERV delays by providing the right-of-way to ERVs as they approach an intersection. This study proposes a new Dynamic Preemption strategy that determines the need for preemption prior to the ERV reaching the vicinity of the intersection, utilizing real-time data streams. This paper evaluates the effectiveness of some existing and proposed preempt control strategies using a digital twin testbed consisting of a series of signalized intersections on an urban arterial in Georgia.

The best EVP strategy maximizes the improvement in ERV travel time while minimizing the adverse effect of preemption on the traffic in conflicting directions. Therefore, this study evaluates both the positive impact of EVP on the ERV as well as the adverse impact on the cross-street traffic. The study found that the potential exists for significant improvements in ERV travel time with the proposed Dynamic Preemption strategy, with minimal impact to the conflicting traffic. For the simulation corridor there was a 20% reduction in the ERV travel times with the implementation of the Dynamic Preemption strategy, compared to traditional EVP practices.

KEYWORDS

Traffic Signals, Emergency Response Vehicle, firetruck, Emergency Vehicle Preemption, dynamic preemption, digital twin

INTRODUCTION

With recent efforts towards pilot testing and deployment of Connected Vehicle (CV) and V2X technologies [1, 2] there is a significant surge in the quantity and variety of data that is becoming available for feedback into real-time operations of transportation management systems, especially signal systems. Among the wide array of applications proposed for CV technology, advancement of Emergency-response Vehicle Preemption (EVP) is one that is ripe for implementation [3-5] as it targets a specific set of vehicles and does not require a substantial penetration of On-Board Units in the general traffic. This paper explores the potential of using real time data made feasible by CV technology, for the development of advanced strategies and algorithms for EVP.

The reported benefits of EVP have been somewhat limited, especially in congested roadway conditions [4, 6, 7]. Most legacy systems are constrained by the line-of-sight requirement between the Emergency Response Vehicle (ERV) transmitter beacon and the preemption request receiver at the traffic signals. To address this constraint [8-11]CV technology provides a potentially seamless means to integrate live ERV vehicle position data, as well as the general traffic data and multiple intersections' signal status data-streams. Such data enables enhanced strategies to optimize EVP performance, with the possibility of creating ERV route specific free-flow paths through multiple signalized intersections. By anticipating the arrival of the ERV, based on its position as recorded by CV messages received at other roadside units (RSUs) in the system or through a centralized cellular system, vehicles on the approach of interest may be cleared before the ERV arrives. While anticipatory route clearance-based methodologies have been proposed before [4, 12], and have seen limited implementation using GPS and cellular-phone based technologies, there is not sufficient literature on clear before-after evaluations of a distributed predictive EVP implementation, as presented in this effort. Research on the parameters, thresholds, etc., that govern currently available EVP implementations are also scarce.

This paper provides a methodology for developing and studying a new Dynamic Preemption (DP) EVP strategy that utilizes the new data streams that could be made possible through the infusion of CV technologies into the traffic stream. In the presence of such high-quality real-time traffic data, efforts have sprung up all over the globe that have leveraged digital twins and CV data (e.g.

accurate vehicle trajectory, real-time signal information, etc.) to address traffic problems [13-16]. To mimic the capability of (1) a real-time traffic information extraction process, and (2) a feedback loop to implement changes in the traffic in real-time using the extracted traffic information, a digital twin is used in this paper. It is these characteristics that distinguish this approach from a traditional simulation. The digital twin acts as a surrogate for the field, enabling the implementation of different strategies on the network and evaluation of the key performance indices (KPIs) prior to field implementation. The real-time (i.e., wall clock time) data streams and feedback being drawn from the digital twin replicate a real-time field implementation. The paper illustrates the steps involved in the real-time data ingestion, development of the digital twin, and experimental design to evaluate the efficiency of the strategy under simulated field conditions. The study compares the proposed algorithm's performance to a traditional check-in check-out-based EVP strategy. Both the reduction in ERV travel-time as well as potential impacts on the non-ERV vehicles are considered in the evaluation. The general assumption with most EVP studies is that the EVP strategy that minimizes emergency vehicle travel time should be selected. However, consideration should be given to the possibility that strategies with similar ERV performance may have different impacts on the general traffic. This study demonstrates the impact of two different strategies for returning the signal operations to normal operation after an EVP actuation. The traffic flow recovery process post EVP actuation is evaluated by measuring the effect of EVP on the travel times of mainline and cross-streets vehicles.

BACKGROUND RESEARCH

This section provides a brief introduction to EVP and as well as a summary of previous studies relevant to this research. Per MUTCD [17], traffic signal preemption is defined as the change in operation of a traffic signal from normal mode to a special control mode. The primary objective is to provide green indications along the path of a certain vehicle class, allowing for hindrance-free passage. Preemptive control can be given to trains, boats, ERVs, and light rail transit [18]. EVP is preemptive operation intended for ERVs, such as firetrucks, ambulances, etc. EVP provides right-of-way to the ERV, minimizing the delay in reaching the incident location and ensuring a safe and clear pathway for the ERV [19], [20]. The preemption triggering message can be conveyed to the signal cabinet through a multitude of methods; the vehicle/driver could externally relay the message (by use of strobe, siren, pushing buttons, etc.) or the infrastructure could be equipped to sense ERVs through pavement loops, radio transmission, or other vehicle to infrastructure (V2I) technologies [18].

The preemption process involves two transition phases, one going into the preemption state, and the other coming out of preemption to restore normal signal operations. The Traffic Signal Timing Manual (STM) [18] states that, for both transitions, the yellow and all-red intervals shall not be shortened or omitted. While not covered in this background the STM includes additional transition guidance related to pedestrian timing constraints, returning to a red indication, allowable indication transitions, and accounting for multiple preemption requests.

Several studies evaluating EVP considered the delays experienced by non-ERVs on opposing approaches in addition to potential ERV travel time reductions. [21] focuses on investigating the effect of preemption calls on closely spaced intersections. This case study was performed in a simulated environment by linking a model built in TSIS/CORSIM to the signal controllers using Hardware in the Loop Simulation (HILS) technology. Four intersections along SR-26 in Lafayette, Indiana were simulated, incorporating seven potential preemption paths with one-to-three preemption calls on each path. At each intersection, preemption calls were made at a predetermined fixed distance of the ERV from the stop-bar. Three algorithms were considered for the phase transition: smooth (lengthen or shorten local cycle by up to a select maximum percentage), add (local cycle may be lengthened only), and dwell (controller rests in coordinated phase). It was found that the smooth transition algorithm worked best in most cases, with the level of slack time in the cycle also an important factor. While studying the effect of ERVs, the study found that for both arterials and side streets, having a single preemption call in the simulation period had little to no effect on the overall travel time and delay.

A study evaluating the disruption of coordinated signals, using microscopic simulation models based on multiple locations in New York City, observed that the EVP related disruption took a maximum of four signal cycles to recover [22]. Another study used MATLAB simulation to study the effectiveness of two different EVP control strategies. The study suggested the use of a predefined "notification time period," designing an algorithm to minimize the ERV travel time while also minimizing the adverse effect of preemption on the side streets [23]. There were several other studies [24, 25] that explored this tradeoff as well, highlighting that ideally a balance needs to be maintained to manage delays for movements that conflict with the ERV path. Among the more recent EVP research efforts, [26] demonstrated the use of fuzzy logic to select the preemption phase and extend the green time, based on demand and queue length in a V2V and V2I environment. Other studies approached this problem from the network path perspective, as a route planning problem [27-29], where the vehicle responds to the state of the system rather than the system responding to the needs of the vehicle. While the opportunity for optimization is limited in a network where the demands are fairly balanced, there are opportunities for magnifying the impacts of each approach by adopting a combination of EVP and route optimization.

The existing literature shows that it is imperative that a study of the impact of EVP account for non-ERV as well as ERV travel times. This paper demonstrates the evaluation of EVP strategies including the one developed in this study and other traditional strategies on a medium sized network (with 25 intersections) using preemption on 8 contiguous intersections specifically focusing on EVP in a coordinated system.

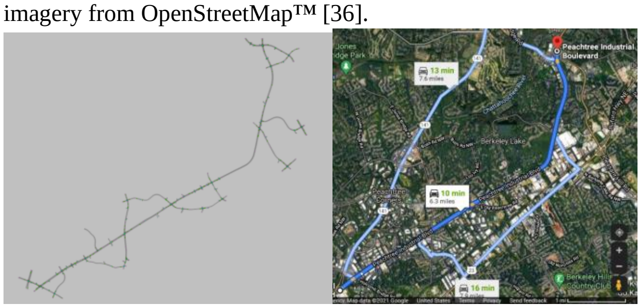
STUDY DESCRIPTION

This study proposes a new EVP strategy that dynamically adjusts the preemption trigger time to produce the maximum ERV delay reduction with the minimum disruption to other traffic. In the absence of real-world CV data in the study corridor, the study creates data streams in a simulated environment that replicate data streams that can be abstracted from CV data. Additionally, a simulation approach was chosen in favor of a before-after study given the advantages of rapid evaluation of multiple scenarios as facilitated by a simulation environment. The case study focuses on investigating preemption strategies during the PM peak hour, typically the most congested period for this corridor. This paper does not delve into the technicalities of CV implementation such as the range and accuracy of CV equipment, although additional information may be found in [30]. The following assumptions made in this study as it relates to CV infrastructure:

- A sufficient penetration of CVs exist that would yield a reasonably accurate estimate of the queue lengths. Existing studies have established that such estimation is feasible [31-34].
- The ERV has an OBU that provides its GPS location in real time.
- The path of the ERV is known.
- The states of the signals are available in real time, and it is possible to push out phase change requests to the signal controllers.

1 Study Site

The digital twin simulation models a 6.2 mile stretch along the Peachtree Industrial Boulevard (PIB) corridor from Holcomb Bridge Rd at the south-west end to Pleasant Hill Rd on the north-east end, in Norcross, Georgia. The model includes 25 intersections on and around PIB. The layout of the network in PTV VISSIM® [35], and the network extents in satellite view, are shown in Figure 1 (a) & (b), respectively. For consistency in naming convention, PIB direction of travel is deemed to be North / South throughout the length of the corridor for the rest of this paper. The cross-street approaches are defined as Eastbound (EB) and Westbound (WB). For this model, the system entities, consisting of the network geometry and the signal-heads, were built based on satellite imagery from OpenStreetMap™ [36].



(a) (b)

Figure 1: Case Study Network of Peachtree Industrial Boulevard: (a) VISSIM® Simulation Model, (b) Satellite View by Google Maps™ [37].

2 Data Sources

A pre-COVID pandemic time was chosen for the input data to ensure that the traffic and signal plans in the model represented typical traffic operations. Signal control data was based on a non-holiday weekday: Tuesday, October 01, 2019. Signal plan information was obtained directly from the field controllers, representing the active plans. The signals along the corridor are semi-actuated coordinated, with a 160 second cycle.

For simulation model calibration, a comprehensive volume study was not available for this corridor. Thus, for the major and minor road approach volumes, data was assimilated from multiple sources including short-term historical turn-volume count data, counts obtained from post-processing stop-bar presence detector activations, recent traffic studies on the corridor, available Automated Traffic Signal Performance Measures (ATSPM), etc. The signals on this corridor are also connected to a central server where the high-resolution signal phase and timing (SPaT) data, as well as detection data, is archived. The archived data had vehicle on-off pulse information corresponding to inductive loop detectors upstream of the stop-bar for the major road through lanes. The pulse data was post-processed to generate vehicle detection data for additional volume calibration. Finally, volume balancing and volume constraint computations based on signal cycle allowance and roadway geometry were used to generate estimates to fill volume gaps or inconsistencies in available data.

DIGITAL TWIN MODEL

The digital twin is constructed using PTV's VISSIM® version 2021 service pack 10 [35] microscopic simulation model. VISSIM®'s Ring Barrier Controller (RBC) add-on module was used to simulate the signal controllers and preemption strategies. The replicate runs are partially automated by using Python 3.7 [38] scripts to drive VISSIM® using its Component Object Model (COM) interface. For each simulation run the network is initially loaded with 50% of the target volume for the first 15 simulation minutes. Then the volume is raised to 100% for the next 75 simulation minutes. Effectively, out of the total 90-minute runtime, the first 30 minutes are utilized for model initialization, and only the last 60 minutes are used for collecting data to generate performance metrics corresponding to the PM peak hour (5 pm to 6 pm). In each simulation run, a single preemption event is modeled to ensure complete independence of the results related to each actuation.

3 ERV Behavior

Besides having a list of default vehicle types, VISSIM® enables the incorporation of external vehicle models that reflect operational characteristics unique to a given vehicle type. One such model was used to create an ERV vehicle class, with specific features resembling a firetruck. The 3D model and characteristics were obtained from the VISSIM® website [39], and the max-speed and acceleration characteristics of the vehicle were selected to mimic a typical Heavy Goods Vehicle (HGV) in VISSIM®, as it was observed that those mimic a standard firetruck the best. It must be mentioned that while that was a starting point for the choice of ERVs, this calibration process takes care of any possible future inconsistencies in driver behavior of the entire fleet, ERVs included. For this study, an ERV must pass through an intersection during a green, utilizing lanes in the correct direction of travel. That is, simulated ERV behavior does not allow for running a red or passing through the intersection in the lanes of the opposing traffic.

4 Model Calibration & Validation

Model calibration, i.e., adjusting model parameters to maximize the agreement of the model behavior to field observations [40], is an essential step to ensure that the model accurately represents the field. While fine-tuning the key parameters of the model to mimic real traffic in the network is necessary, it is not always possible to match the traffic vehicle-to-vehicle. Nor is such matching desirable as it may lead to overfitting the model, negatively affecting the robustness, translatability, and generalization of the results. In this study, the calibration effort ensured that the model sufficiently reflected the field conditions, considering both mid-block free flow speeds and saturation headways departing a signal. Validation tests with travel-time as the performance metric were performed to confirm the sufficiency of the calibration. Model calibration and validation processes are described in the following sections. A more in-depth discussion on each of these processes can be found in [30].

4.1 Model Calibration

As a first stage of calibration, speed collected from the GPS data for the corridor was used as the baseline and was compared to the speed distribution of the simulation corridor. To make the simulation speed comparable to the baseline, the distribution of "desired speed" parameter, which is an indicator of the free-flow speed of the network, was tweaked. This speed distribution was subjected to a deconvolution process to extract the data-points representing the free-flow speed in the network. A deconvolution process followed the methodology developed in a previous study [41] and allowed for the estimation of the free flow speed distribution, rather than a single free flow speed value. After the deconvolution process the corridor data points could be represented as a mixture of four Gaussian distributions. Of those distributions, the distribution with Mean: 52 mph, SD: 8 mph was chosen for the free flow speed distribution. This aligns well with the overall 85th percentile corridor speed of 51 mph.

Another parameter crucial for model calibration, pertinent to this analysis, is saturation headways [42]. The detector data on the major intersections were extracted from MaxView™ [43] system's database and that is used as the baseline. The headways in the simulation are controlled by modifying the multiplicative and additive factors in the Wiedemann 74 car-following model [44] for VISSIM®.

Four random seeds of VISSIM simulation results were compared to four weekdays of field detector data. For example, as shown in **Figure 2**, approximately 1175 data-points per VISSIM simulation were compared to approximately 1400 data-points of field detector data at the NB approach of the PIB and Medlock Bridge Road intersection. The average headways (as depicted by the dotted vertical lines) for the field and VISSIM® after calibration lie very close to each other, in the 2.3-2.4 s range. The Cumulative Distribution Function (CDF) lines, shown as the orange and blue monotonically increasing lines, are also similar. A two-sample Kolmogorov Smirnov (KS) test, a non-parametric statistical hypothesis test, performed on the two distributions concluded that the null hypothesis "the headway data sets come from the same distribution" cannot be rejected at a 90 percent confidence level. The calibrated VISSIM® model has additive and multiplicative parts of the safety distance as 2.5 and 5.5 respectively (whereas the software defaults are 2 and 3 respectively).

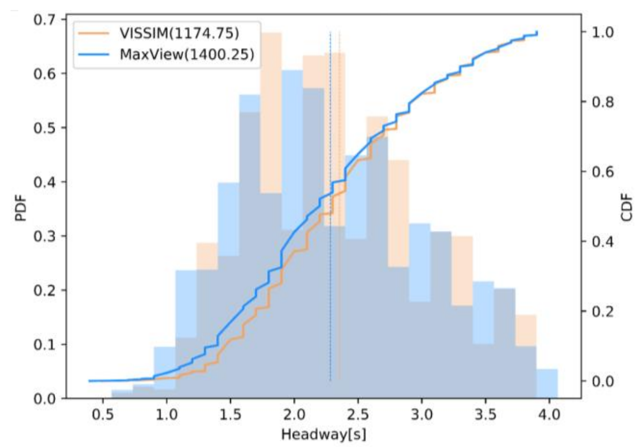


Figure 2: Calibration Results: Headway Distribution for Northbound (NB) Movement at PIB @ Medlock bridge Rd: MaxView vs VISSIM® [30]

As a final calibration step, minor changes were made to the signal timing splits and vehicle extension timers at several intersections to better serve the synthesized traffic volumes.

4.2 Model Validation

For model validation, travel-time is the primary reported performance metric, although volumes were also confirmed to match expected field conditions. The traffic on the PIB corridor is directional with the PM peak traffic direction being north; additionally, the EVP study will focus on the NB direction of travel. While this discussion on validation using travel time is presented for NB direction travel, a similar process was undertaken for the SB direction, finding acceptable travel time performance.

Checkpoints were placed at two intermediate points on the NB PIB route to divide the corridor such that sufficient complete vehicle traces could be captured for each segment. The average travel time at the checkpoints were summed to determine a total average travel time for the entire 6.2 mile stretch of the NB-through route along the PIB. As a benchmark, weekday travel time data from (a) the Regional Integrated Transportation Information System [45] and

(b) Google Maps™ [37] [recorded at 5-min intervals during the 5-6 PM period on July 16, 2021] were used. The average RITIS travel time was 960 seconds, while Google Maps travel time averaged 825 seconds. The average travel time derived from the model was 857 seconds. As per criteria set by Federal Highway Authority (FHWA)’s Traffic Analysis Toolbox [42], the simulated travel time should be within 15% of the field. The travel time in VISSIM lies within 15 percent of either of the data sources and satisfies the suggested validation criteria.

5 Experiment Design

Experiments were undertaken to study the impact of preemption on ERV and non-ERV (i.e., other vehicles in the network) performance. The experiments studied the impact of EVP during the PM peak, for an ERV with a NB route along the corridor. The EVP impact is evaluated with respect to the entry transition of the signal from normal to preemption operation. Two algorithms for entry transition into preemption are considered: 1) traditional check-in check-out (CI-CO) with a preempt trigger (i.e., ERV detector in the roadway) set a fixed distance from the intersection, and 2) a dynamic preemption call placement based on the required clearance time of the estimated number of vehicles between the ERV and the signal. Additionally, to ensure that the effect of the signal coordination, or rather the disruption thereof, is investigated in sufficient detail, the ERV route was chosen such that the ERV passed through multiple intersections along the coordination path. The field ERV GPS data collected as part of this effort was used to observe historical travel patterns and ensure that the path chosen was representative. The path chosen is shown in Figure 3 (a) and (b), as a series of historical GPS points, and as part of the model network in VISSIM®, respectively. It is worth mentioning that while this study is evidence to the effectiveness of discussed EVP algorithms, extending the experiments onto more diverse corridors would provide more robustness to the findings.

(a) **(b)**

Figure 3: The Mainline Route chosen for the Study (a) Field ERV GPS data along the mainline overlaid on OpenStreetMap™ [36], (b) Mainline ERV Route Static Routing Decision in VISSIM®

5.1 Experiment 1: ERV Entry Time

The time at which an ERV makes a preemption request, relative to the local cycle and coordination plan, is likely to affect the impact of preemption on the traffic. In first set of experiments presented this effect is explored by introducing an ERV into the network at different simulation times, such that preemption calls are placed at different points in the signal cycle of the first intersection (PIB at Medlock Bridge Road) of the ERV route.

5.2 Experiment 2: Entry Transition

In the second experiment presented two entry transitions are tested, a traditional check-in check-out (CI-CO) preemption strategy (i.e., the preemption call is placed a fixed distance from the intersection) and a customized dynamic preemption (DP) strategy for an identical experimental setup in terms of arrival of the ERV into the network. For the traditional CI-CO setup, a check-in detector is placed a fixed distance from the intersection. When the ERV reaches the detector, a preemption call is placed. The call remains active until the vehicle crosses a check-out detector (or times out), which is generally placed immediately downstream of the intersection. One drawback of this setup is experienced when an ERV enters the back of a queue that extends past the check-in detector. In this situation, the preemption call is not placed until the queue is sufficiently processed that the ERV reaches the detector. Additionally, this method is insensitive to the number of vehicles queued between the ERV and intersection, likely resulting in inefficient performance.

5.2.1 Dynamic Preemption

To improve the performance of CI-CO preemption, this study leverages the potential of real-time field detection and ERV CV data, developing a DP algorithm. [46, 47] In this algorithm, it is assumed the ERV has a CV OBU. However, other traffic is not assumed to be CV, allowing for earlier field implementation of the proposed method. In this algorithm, the queue-length on each approach of the ERV path is monitored. Based on the queue lengths, the time of the preemption trigger is set to ensure that the ERV traverses the intersection without (or with minimal) slow down. At each approach along the ERV route a sufficient time must be allocated to clear the vehicles in the queue, as well as those in between the end of the queue and the ERV, prior to the ERV arrival. Transition time must also be allocated for the signal controller to serve the current phase yellow, red-clearance, and any necessary in-progress pedestrian-walk phases. To account for field data limitations, a primary assumption for the algorithm is made that the number of vehicles in the approach queue is same as the number of moving vehicles between the back of the queue and the approaching ERV. While recognized as a rough approximation, this assumption accounts for current field data limitations to attain active counts of moving vehicles on the roadway. While it is possible within the simulation environment to determine the number of vehicles between the existing queue and the approaching ERV, utilizing this data would reduce the transferability of the method to the field. Current efforts are exploring improving this estimate using likely available field data. For instance, the queue length and the number of non-queued vehicles ahead of the ERV may be estimated based on real-time detector data from the current and upstream intersections, or from the location information in the

Basic Safety Message from CVs (with sufficient penetration of CVs). However, this estimation is a non-trivial problem and has been studied by other researchers [32, 33]. It is not discussed in this study for brevity. In the proposed DP algorithm, a preemption decision may be made as early as when the ERV begins to approach the upstream intersection for the subject approach. Thus, it is assumed that the ERV route is known at least two intersections in advance. The preempt call time is calculated as follows.

If "n" cars are present in the queue, assuming that the headway is 2 seconds and an additional reaction time (i.e., start-up lost time) of 4 seconds, the time taken to clear that queue would be (4+ 2*n) seconds. To clear the "n" vehicles between the end of the queue and the ERV, an additional 2*n seconds are taken. For the transition from current signal state to the preempt phase, an additional 5 seconds is added. This results in an overall total of (9+4n) seconds for the advance placement of the EVP call prior to the ERV reaching the intersection. Therefore, in a corridor with a free flow speed of "v" ft/sec, the preemption will be triggered by the ERV at (9+4n)*v feet from the intersection, when the intersection in question has a queue length of "n" cars. The algorithm can be summarized by the flowchart in Figure 4.

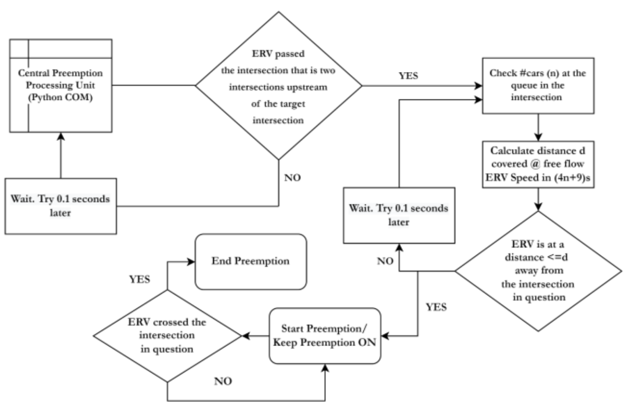


Figure 4: Dynamic Preemption (DP) Algorithm Implementation Flowchart

RESULTS

Experiment 1 - Impact of ERV arrival-time It is expected that the time at which an ERV makes a preemption request, relative to the local cycle and coordination plan, is likely to affect the entry into and exit from preemption and thereby affect the impact of preemption on general traffic. As stated, this effect is explored by introducing an ERV into the network at different simulation times, resulting in ERV arrival times throughout the signal cycle of the first intersection (PIB at Medlock Bridge Road) in the route given in Figure 3 (a, b). For reflecting a cross section of arrival times, 32 different scenarios are created, with successive five seconds increments in the time of introduction of the ERV into the network (fully covering the 160 second cycle). To account for stochastic variability, ten replicate runs per scenario are performed using ten random seeds. Thus, a total of 32*10=320 simulation runs were conducted in the study of ERV arrival time. For these runs, the DP algorithm is utilized.

Throughout the travel time comparisons in this study, a hybrid boxplot is used (refer **Figure 5**). In the hybrid boxplot, for the replicate trials of each scenario (ten per scenario in this experiment), the red square dots represent the mean, and the top and bottom of the solid box represent the 75th percentile and 25th percentile, respectively. The difference between the 25th and 75th percentiles is the inter-quartile range (IQR). IQR represents the spread for the middle 50 percent of data-points around the median [48]. The black line drawn on the solid box is the median; the whiskers around the box span within 1.5*IQR of the box boundaries and the points that lie beyond the whiskers are outliers [49]. Figure 5 shows the effect of the staggered entries on the travel-time (y-axis) of the ERV (traveling the length of the eight-intersection route) with each box and whisker plot showing the travel time variability across the ten replicate runs for an ERV entering at the given simulation time (x-axis). The time of the entrance into the network, and thus time of the preempt call, relative to the local cycle is shown to have an impact on the ERV travel time, with the mean travel time across scenarios ranging from 438s to 470s, while IQR ranges from 27s to 89s.

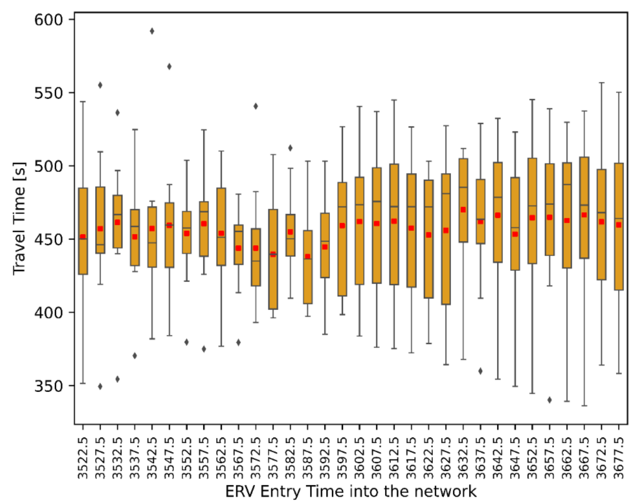
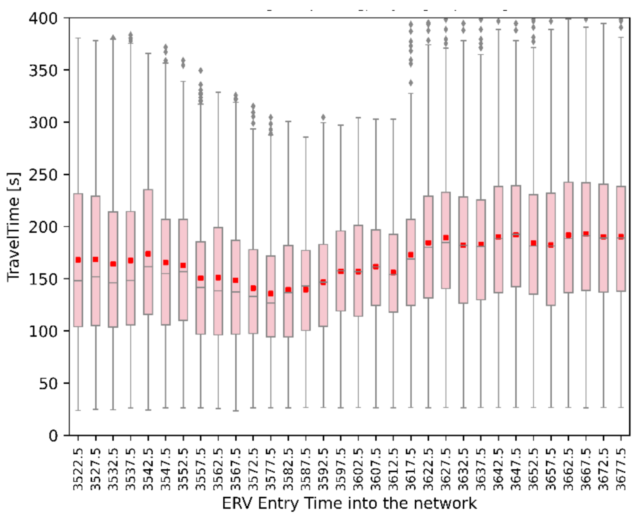
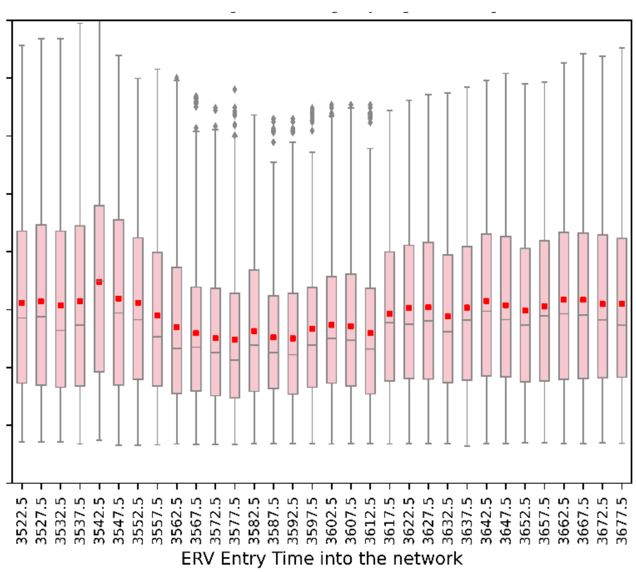


Figure 5: Impact of staggered ERV entry time on ERV Travel Time

Figure 6 (a) & (b) show similar effects on the side-street through movement travel times at the first preemption-activated intersection of PIB at the Medlock Bridge Road intersection. The impact is measured from the preemption event to two cycles after the end of preempt. Mean side-street travel time for through moving vehicles ranged from 136s to 193s and from 124s to 174s on the EB and WB through movements, respectively. In addition, the IQR for travel time ranged from 72s to 127s and from 80s to 144s on the EB and WB through movements, respectively. Given the range of variability seen for all movements in traffic (on both the main-line and the side-streets), all subsequent experiments include using a range of times for the infusion of the ERV into the network, uniformly covering the cycle length of the signals of the corridor (i.e., 160s).



(a)



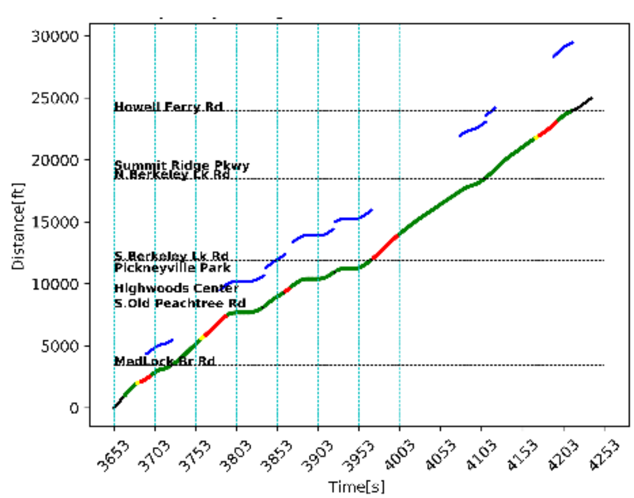
(b)

Figure 6: Variation in Travel Time for side-street through movement (PIB @ Medlock Bridge Road) for (a) EB Through and (b) WB Through with Different ERV Arrival Times.

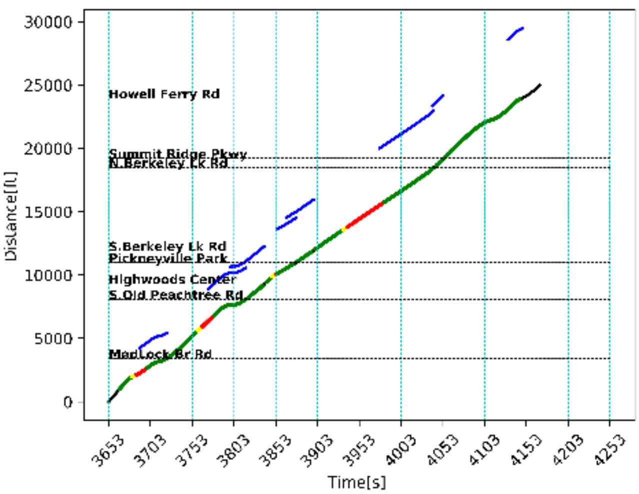
6 DP vs CI-CO

As shown in Figure 3, the ERV used in this experiment enters at the Southern part of the network, upstream of PIB @ Tech Parkway South and travels NB through eight intersections, from the Medlock Bridge Road intersection to the Howell Ferry Road intersection, where it takes a right turn and leaves the corridor. For a CI-CO setup, there are two significant potential drawbacks: 1) if the back of a queue extends past the check-in detector the ERV does not trigger the preemption call until it advances in the queue to the detector, and 2) the call is set at a fixed distance, without consideration of the real-time traffic conditions. Using the DP approach to determine when to place the call while the ERV is potentially further upstream avoids these issues, increasing the likelihood of a successful queue flush prior to the ERV arrival at the intersection box. As with the prior experiment, there are 32 runs of ERV network entry samples for each random seed, thus 320 runs over 10 random seeds.

The trajectory plots in Figure 7 provide a visualization of the difference between these methods. The color in the ERV trajectory represents the GREEN/AMBER/RED signal state of the next downstream intersection at the corresponding time. The blue line running in parallel to the trajectory represents the timespan of an active preemption call by the ERV while traveling along its trajectory. Figure 7 (a) and (b) present an example scenario, comparing an ERV entry into the network at the same simulated time, for CI-CO and DP, respectively. Figure 6 (a) has preemption enabled with a CI-CO implementation, where the detector is placed on an approach 1000 ft upstream of the intersection or, where 1000ft is not available, immediately after the upstream intersection. Figure 7 (b), with the same entry time as Figure 7 (a), depicts the ERV trajectory using DP to place preemption calls. Within this example the drawback of CI-CO is evident, particularly at closely spaced intersections. In the CI-CO strategy the ERV is unable to place the call sufficiently early to allow for the queue to clear, instead of being delayed in the queue while the downstream vehicles clear. The DP approach can clear the queue more consistently prior to the ERV arrival, resulting in a significant reduction in delay.



(a)

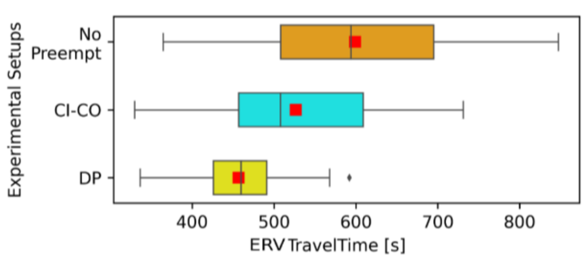


(b)

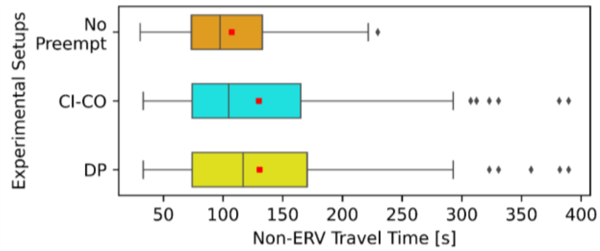
Figure 7: ERV Trajectory in the PIB VISSIM® network: preemption enabled: (a) CI-CO, (b) DP

The impact of this difference in preempt methods may also be seen in the impact to ERV and non-ERV travel times, Figure 7. For the ERV travel time, Figure 7(a), averaged across all arrival times, the CI-CO provides an approximately 73s advantage over no-preempt while DP provides a 142s advantage. The difference in the ERV travel time between Preempt disabled and CI-CO, as well as between CI-CO and DP, were found to be statistically significant, based on a non-parametric one-way ANOVA H-test, Kruskal Wallis (KW) [50] at 5% significance level. This comparison provides a strong demonstration of the advantages of an approach, such as DP, leveraging CV data.

When considering the impact on the side-streets as reflected by Figure 8 (b) within the first two signal cycle lengths after the preemption activity, it is seen that the effects on side street traffic was comparable, with the average travel time being 107s, 130s and 131s for "no preempt", CI-CO, and DP respectively. The difference between CI-CO and DP travel-times were found to be statistically insignificant using the KW-test. Similar trends are observed for other intersections as well. Hence the overall gain in ERV response time with negligible excess side-street traffic delay provides a strong argument for preempt in general, as well as seeking advanced CV based preempt methods.



(a)



(b)

Figure 8: Overall travel time under three entry-transition experimental setups: (1) Preempt Disabled, (2) Check-in Check-out, (3) Dynamic Preemption for (a) (top) ERV through the designated route; (b) Non-ERVs at PIB @ Highwoods Center WB-Through for 2 signal cycles after EVP activity.

7 Real-time Feasibility of the Runs

For in-field implementation of the developed algorithm, it must be ensured that the system may execute at a real-time pace. Hence, an experiment investigating the real-time feasibility of the system was performed. In this experiment the simulation timestamps are tracked alongside the wall clock time, during the time the DP algorithm is active in the run. The experiment is repeated with ten random seeds, and all the runs are made on a single machine the following specifications: Intel® Core ™ i7-7700 CPU @ 3.60GHz and 16GB of RAM. A fair experimental setup for testing the real-time usability of the system would be to implement a Software in the Loop Simulation (SILS) architecture. This enhances the understanding of how the simulated EVP strategies could be implemented on a real-field controller common in engineering practices all over the state of Georgia.

For this experiment, Intelight's MaxView® Advanced Traffic Management System (ATMS) software [51] was used. A subset of the signalized intersections is run externally using the MaxTime® signal software. This process runs individual signalized intersections each using independent processing units. Hence, this architecture takes significantly slower to run compared to the in-built VISSIM® controllers. Hence the SILS system keeping up with real time, despite having this barrier of computational load created by the multi-threading provides stronger evidence for successful implementation of the digital twin in the near future.

The SILS model runs at 5X and 4X real-time speed without and with the DP algorithm running in the background. This is clearly fast enough to maintain a system that needs to run on a second-by-second feedback system. Hence, the EVP digital twin model proves to be capable of real-time information flow under a multitude of computational loads.

CONCLUSION & FUTURE WORK

This study demonstrates the positive effects of EVP combined with CV and V2X technology by implementing a DP architecture in a microscopic simulation model, using travel time as the primary metric, under a digital twin framework. For the case studied, DP with either exit transition led to an approximate 23% (~140s) reduction in average travel time for the ERV. While not as significant, it was seen that traditional CI-CO also had the potential to improve ERV travel time, with approximately half the benefit seen in DP. When considering the side-street, it was observed there is a disruption in travel behavior on the side streets, leading to increased cross street travel time with preemption. However, both the DP and CI-CO had similar impacts.

It is recognized that the percentage improvements or degradation in travel time are not directly transferrable to other corridors, with each corridor, given its unique characteristics and demands, requiring its own analysis. However, this study, along with others in the literature, demonstrates the potential benefits of emergency vehicle preemption strategies and critically the potential for additional benefits that may be gained through a CV implementation. Several improvements could be made to the experiment design that could provide for a more robust study in future. First, rather than choosing a mainline ERV route, the route could be a mix of the main and side-streets. Second, scenarios with arrival of multiple ERVs at an intersection should be explored to understand the interaction of overlapping preemption request calls. Third, there have been several studies tackling path planning problems for EVP [27-29]. Since it was known a prior that the ERV will only be traveling on the mainline utilizing a designated route, this is not included in the current experimental architecture. Fourth, the comparative analysis of EVP could have been extended beyond just travel time to additional metrics such as average queue-length, cycle failures on the cross streets, etc. to provide more depth to the findings. Fifth, the interaction between multiple ERVs leading to concurrent EVP calls need to be studied for algorithm sensitivity and is being studied in a follow-up study. Sixth, while successful, the DP algorithm developed is a simple heuristic. Additional refinement of the algorithm is merited. For example, an EVP calling algorithm could be developed that uses available real-time traffic metrics combined with novel Machine Learning techniques. Efforts are being made in this direction. Seventh, the algorithm needs to be tested on real-world pilot projects to demonstrate the reliability of the underlying algorithms. Lastly, KPIs besides travel time such as emissions, fuel consumptions, etc. could be used for the effectiveness of EVP.

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