Simulated Basic Safety Message: Concept & Application

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***Abstract*—In this paper, we introduce a concept called Simulated - BSM that leverages the combination of rich vehicular sensor feed (speed, object proximity, SLAM maps etc.), and emerging guaranteed low-latency communication protocols (DSRC, 5G) to enhance efficiency & safety of transport facilities. The main idea is that an ego-vehicle with local sensor feed capability creates a basic safety message for any identified rogue vehicles in its field of view, and broadcasts it to infrastructure for implementing efficient and safe control actions. System architecture details are discussed. The efficacy of S-BSM framework was successfully demonstrated in the context of enhancing safe & efficient operations at rural high-speed signalized intersection.**

I. Introduction

Societal activity is inherently dependent upon transportation systems and services, for moving people and goods. Efficient, and safe transport services are critical to societal productivity and well-being. The objective of Intelligent Transportation Systems(ITS) is to leverage real-time data and communications to make transportation safer, more efficient, and more environmentally sustainable. To achieve these objectives, both the automobile industry and the government agencies are proactively adopting new technologies at various levels (either at individual vehicle or at infrastructure level).

Automakers are constantly adding new features to their next generation vehicles to enhance the driving experience. Some of these features include parking assistance, blind-spot detection, night vision system, among others. These features, which are commonly known as advanced driver assistance systems (ADAS) are aimed to detect the environmental conditions and provide necessary feedback to enhance the situational awareness of the driver[1]. These systems are expected to be effective in situation of imminent collisions, assisting to avoid or mitigate them [2].

On the other hand, *government agencies* historically addressed the issues of transportation mobility & safety through strategic network instrumentation, and optimal system control. For the most part, fixed point sensors like video cameras, or loop detectors are used as infrastructure sensors. While this type of sensing is useful in understanding snap-shot characterization of average dynamic flows of the network, the information provided by these sensors isn't sufficient to reconstruct the individual trajectories of the vehicle. This might not be a major concern if the main objective is to enhance average efficiency of the system, but it might pose a major safety concerns in certain scenarios. For instance, in transport facilities like rural high-speed intersections, control systems do not know when a vehicle will be caught in a dilemma zone (the region where, at the onset of yellow on the major road, drivers are in a dilemma about whether to continue through the intersection or stop). As a consequence, these facilities, tend to have higher likelihoods of collisions. In fact, crash statistics suggest that more than half of all fatalities due to crashes occur in rural intersections [3].

To alleviate some of these safety concerns, in 1999, the USDOT mandated a low latency, wireless vehicular ad-hoc network protocol called dedicated short range communications (DSRC). The basic idea of this connected vehicle protocol is to alert the drivers to the presence of nearby vehicles (typically every vehicle broadcasts basic safety message (BSM) to make its presence known to other vehicles). Since its inception, a number of active safety applications have been developed [4], [5], [6]. In the recent years, there is an increasing interest in the transportation research community to leverage connected vehicle data to improve the efficiency of signal control. For instance, Guler et al. [7] proposed an algorithm that incorporates information from Connected Vehicles to determine the sequence of departures from an intersection. Dujardin et al. [8] proposed a multi-objective optimization interactive procedure for adaptive signal control. Feng et al. [9] proposed an algorithm to optimize the phase sequence and duration.

While all these efforts are very useful, none of them take into consideration, the shear complexity of the real-time data processing to derive useful (or relevant) information; instead, almost all of them simply assume that the information is just there. Furthermore, almost all of them assume high penetration of autonomous vehicles (AVs) as a requirement for developing any useful new algorithms. As noted earlier, irrespective of autonomous navigation capabilities, sensors in today's vehicles are capable of producing terabytes of useful information on car's environment, like speed, object proximity, SLAM maps etc. Furthermore, recent market studies indicate [10] that by the year 2029, 60% of all vehicles, or a cumulative 146 million cars, will have DSRC/V2X capabilities. This combination of rich vehicular sensor data, in conjunction with guaranteed low-latency communication protocol like DSRC, and the reality of 5G wireless systems in the near future, is making it possible to enhance safety of transport facilities without assuming the presence of any autonomous vehicles in the traffic stream.

To show the usefulness of these ideas, in this paper, we introduce a new concept called *simulated-BSM (S-BSM)*. The main idea is that the ego-vehicles local sensor capability can create a basic safety message for any identified "unsafe vehicle(s) (e.g. high speed)" in it's field of view, and broadcast that information to the infrastructure via a low-latency wireless ad-hoc networks (DSRC, 5G). The infrastructure in turn, will make use of this information and takes appropriate control decisions to ensure the overall safety of the system. We developed a new system architecture for this proposed system, and developed software infrastructure to realistically simulate these ideas. Finally, the concept of S-BSM is applied in the context of enhancing the safety of rural high-speed signalized intersections, and its effectiveness (number of vehicles caught in a dilemma zone) is tested in the simulation.

The rest of the paper is organized as follows: Section II introduces the concept of simulated-BSM in more detail, Section III presents details of simulation architecture, Section IV provides background information on safety issues pertaining to the rural high-speed intersections, and the ability of S-BSM in addressing of concerns, Section V presents details on simulation experiments, Section VI analysis of the results, and Section VII provides conclusions and points out future lines of work.

II. Simulated Basic Safety Message (S-BSM)

The concept of simulated-BSM is very simple. The main idea is that the ego-vehicles equipped with ADAS systems create a basic safety message for any identified "unsafe vehicle(s) (e.g. high speed)" in it's field of view, and broadcast that information to the infrastructure via a low-latency wireless ad-hoc networks (DSRC, 5G). Data feed from different onboard sensors can be used in generating S-BSM (e.g. LiDAR, cameras, and radars). However, in this framework, we assume that the surrounding vehicles are tracked using LiDAR sensor for the sole reason that the LiDAR data can be easily emulated within SUMO microscopic traffic simulator.

A. Localization, Segmentation, and Object Tracking

An ego-vehicle must first understand its current location, and the location of other vehicles in its field of view for the purpose of generating S-BSM. Typically, this is done by scanning different obstacles and landmarks within the local sensor's (LiDAR) field of view [11], [12], [13]. In the proposed methodology, the LiDAR is emulated by encapsulating the distance matrix as a LiDAR data frame, wherein each element of the matrix is the distance of an object (if it exists) from the ego-vehicle. To emulate the real-world sensor noise, each data frame is passed through a sensor noise model to introduce noise into the data [14]. This data, in turn, is passed through a fully convoluted neural network (FCNN) [15] to estimate approximate location, and heading of each vehicle with respect to the ego-vehicle. As per the results presented in recent research work [15], the FCNN framework shows lot of promise from the standpoint of accuracy and its usefulness in real-time 3D object tracking.

A Kalman filter in employed to track, estimate the speed, and the location of specific vehicles across multiple frames. Lastly, since SUMO microscopic simulator represents traffic networks in two dimensional XY-plane, there are no elevations or depressions in the road network and the height of each vehicle is the same. These limitations resolve into modulating the LiDAR sensor model with one beam for building 2D obstacle maps. This is done by passing each LiDAR data frame through a simple point-to-point segmenter that can estimate the approximate location of each vehicle.

Whenever an ego-vehicle identifies a vehicle(s) with aggressive driving behavior (referred to as rogue vehicle), it generates a S-BSM message using location, speed, and heading information of the rogue vehicle. The S-BSM, in turn, is encoded into a DSRC SAE J2735 message format (which is the message standard for a standard BSM), and sent over to the infrastructure agent via DSRC and cellular communication channels. The purpose of sending the same message over two communication protocols is to ensure the minimum operational latancies (For example, a message sent over cellular network might have a lower latency than a message requiring multiple DSRC hops to reach its destination). However, to avoid the redundant processing, both encoded messages have same ID, and the infrastructure agent processes the message that arrives earliest.

III. Simulation Architecture

The design framework for microscopic simulation of S-BSM raises three broad requirements. First, the simulator should be able to implement microscopic traffic flow characteristics of individual vehicles (e.g., position, velocity, car-following, and lane changing behavior). Second, the simulator should be able to simulate the latencies in DSRC and cellular communication protocol. Third, simulator should be able to simulate the behavior of ego-vehicles, which includes generating LiDAR scans, LiDAR data segmentation with respect to other vehicles, tracking and estimating an individual vehicle's location & speed, identify rogue vehicles in the environment, and finally generating S-BSM and send it to nearest infrastructure agent via DSRC and cellular communication protocols for appropriate control action.

While none of the existing microscopic traffic simulators satisfies all three requirements, it is easy to integrate open source traffic simulator SUMO with external packages or modules. The software architecture is detailed in Figure 1. As can be seen, SUMO can generate a traffic networks, implement traffic rules, and manage and maintain microscopic traffic flow characteristics. The behavior of traffic objects inside SUMO can be accessed and manipulated through the

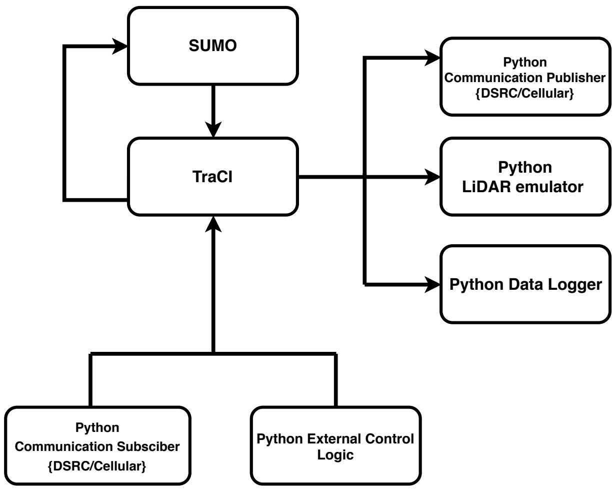

Fig. 1: Simulation Architecture

TraCI API. Two communication modules (one publisher, and the other subscriber) are developed to mimic DSRC & cellular communication networks. Interactions between ego-vehicles and LiDAR emulator are handled by publisher module, whereas interactions between ego-vehicles and the infrastructure are handled by subscriber module. Both publisher and subscriber modules model communication latencies using uniform distribution. Latency bounds for DSRC are set to [10ms, 100ms], whereas they are set to [300ms, 600ms] in the case of cellular. Book keeping for object tracking across multiple LiDAR frames is handled by data logger module. Lastly, the logic for generating actionable control decisions to ensure safe operations is handled by external control logic module.

Algorithm 1: Simulator Process Flow

```
δ_t = 100 millisecond (initialize time step);
t = 0 (initiate simulation time);
E_t = set of all ego-vehicles in the system during time t;
e_i = ego vehicle 'i';
N_(i,j) = set of vehicles within the field of view e_i;
n_(i,j) = vehicle within the field of view e_i;
r_(i,j) = identified rogue vehicle by e_i;
p_(i,j) = probability of e_i tracking n_j;
p_l = threshold probability for accepting sensor feed;
T = time when all the vehicles exit the simulation;
Q_t = set of S-BSM messages to be processed at t;
while t ≤ T do
    t += δ_t;
    if len(Q_t) != 0 then
        process S-BSM messages;
        take appropriate control actions;
    end
    for e_i ∈ E_t do
        e_i sends local sensor feed to LiDAR module;
        data passed through sensor noise model;
        builds obstacle maps;
        add obstacle map to the data logger;
        if p_(i,j) ≥ p_l then
            check if n_j qualifies as a rogue vehicle;
            assign n_j = r_(i,j);
            create S-BSM for r_(i,j);
            send S-BSM from all e_i ∈ E_t;
        end
    end
end
```

A. Simulation Flow

Algorithm 1 describes the simulation flow. As can be seen, SUMO sets up the traffic and vehicular environment and updates vehicle motion models at each simulation step. A set of vehicles with aggressive driving behavior is considered for the purposes of simulating scenarios requiring the generation of S-BSM. Similarly, a set of vehicles with advanced driver assistance systems is considered to simulate the ego-vehicles. The arrival sequence of both rogue vehicles and ego-vehicle is randomized using uniform distribution. Upon ego-vehicle generation, two persistent socket connections (one with publisher, and the other with subscriber) are established for the purpose of information exchange. For each ego-vehicle, TraCI simulates a 2D LiDAR view to generates data frames at 10 Hz. To emulate the real-world sensor noise, each data frame is passed through a sensor noise model. This data, in turn, is passed through a simple point segmenter to estimate approximate location, and heading of each vehicle with respect to the ego-vehicle. Book keeping for tracking vehicles across multiple frames is handled by a data logger module. A Kalman filter in employed to track, estimate the speed, and the location of specific vehicles across multiple frames. If ego-vehicle's object tracking algorithm suggests the presence of a rogue vehicle, it generates a S-BSM for the rogue vehicle. The S-BSM message is encoded into a standard BSM message type, and sent to infrastructure via subscriber socket connection. Infrastructure agent, processes the S-BSM messages in its queue, and assesses operational safety via external control logic, and communicates actionable control decisions to SUMO through TraCI.

IV. Application Context

High-speed, rural intersections are challenging transport facilities to instrument and control. These facilities tend to have higher likelihoods of collisions. In fact, crash statistics suggest that more than half of all fatalities due to crashes occur in rural intersections. Hence, they often demand special attention to ensure safe operation as control systems do not know when a vehicle will be caught in a dilemma zone. In principle, dilemma zone is the region where, at the onset of yellow on the major road, drivers are in a dilemma about whether to continue through the intersection or stop. Previous research efforts concluded that the dilemma zone boundaries are most precisely defined if travel time from the stop line (as opposed to distance) is used, and those boundaries extend from about 6 down to 2 seconds away from the stop bar.

Traditionally, agencies install lane-specific speed traps (pair of magnetic loops separated by a short distance) about 1,000 feet upstream of the stop line. Control logic monitors both speeds and lengths of the oncoming vehicles, and sends a user defined fixed long hold (typically about 10 - 12 seconds) on the main street green, whenever it identifies a vehicle traversing at speed above preset threshold value. This control strategy proved to improve safety, but at the cost of significant increased side street delays.

Moreover, ego-vehicles sensor information gives a richer information on rogue vehicle trajectories than that was given by fixed-point sensors. Also, there is no need to enforce a fixed long hold every time a rogue vehicle is detected. For instance, assume two rogue vehicle v_1, v_2 require t_1, t_2 seconds respective to pass through the intersection. Suppose their is a 't' second overlap in their trajectories, the total time needed for both vehicles to pass through the intersection is $t_1 + t_2 - t$ seconds. Our algorithm employs this logic for computing green time extension when there's more than one vehicle in the dilemma zone. So, whenever an ego-vehicle generates S-BSM for a rogue vehicle, our control algorithm forecasts trajectory for the rogue vehicle, if it perceives that the vehicle will be in a dilemma zone at the onset of yellow, it will extend the green time by an amount equivalent to it's expected time form the stop-bar.

V. Simulation Experiments

To analyze the efficacy of S-BSM in the context of improving safety of high-speed rural intersection, a number of experiments were performed with the proposed simulation framework. Specifically, we considered two intersections on US-70 (first intersection is at Swiftcreek road, and the other at Strickland road), which is about 10 miles east of Raleigh, NC. The volume and signal timing data are obtained from NCDOT. Proportion of rogue, and ego vehicles in the mixed traffic stream directly impacts the effectiveness of the proposed framework. To vary the proportion of rogue vehicles, We considered the following four basic scenarios:

1) Scenario 1: % rogue vehicles = 5, % EV = [0, 50]
2) Scenario 2: % rogue vehicles = 10, % EV = [0, 50]
3) Scenario 3: % rogue vehicles = 15, % EV = [0, 50]
4) Scenario 4: % rogue vehicles = 20, % EV = [0, 50]

For each of the four scenarios, the percentage of ego-vehicles on the main drag was varied between [0, 50] in increments of 10% from one case to the next, while keeping everything else constant. Therefore, for a given % of rogue vehicles, there are a total of 6 cases with varying % of ego-vehicles on the main drag. Through movements of the main drag have an average flow rate of 500 vehicles per hour across all scenarios.

For each scenario and % ego-vehicles, To randomize the arrival patterns of rogue, and ego-vehicles in the mixed traffic stream, 10 Monte Carlo simulations from different random seeds were considered. Please notice that S-BSM cannot be generated in the case with 0% ego-vehicles, and hence it is considered as the base case. Network instrumentation (speed traps), and control logic (whenever a rogue vehicle is detected, hold green for 10-seconds) for the base case are consistent with details presented in section IV. Simulation experiments for rest of the cases are conducted using the S-BSM simulation software package described in section III.

VI. Analysis of Results

Two performance metrics (one for safety, and the other for efficiency) are considered for evaluating the simulation results: 1) % of instances the system successfully resolves dilemma zone issues; 2) average green duration on main drag. Simulation output data for a given scenario and case was further processed to compute the statistics of these performance metrics. Lastly, S-BSM results are benchmarked against those obtained in the base case.

A. Dilemma Zone Metric

To evaluate safety, we computed the number of instances in which the system successfully forecasts a vehicle's trajectory, and takes appropriate control decisions to minimize the likelihood that the subject vehicle is caught in the dilemma zone. Figure 2 summarizes the descriptive statistics of % success for the base case. This figure presents standard box plot for the % success for each scenario; red circles in the plot represent median % success values, whereas the values within the box represent the data within the inter-quartile range.

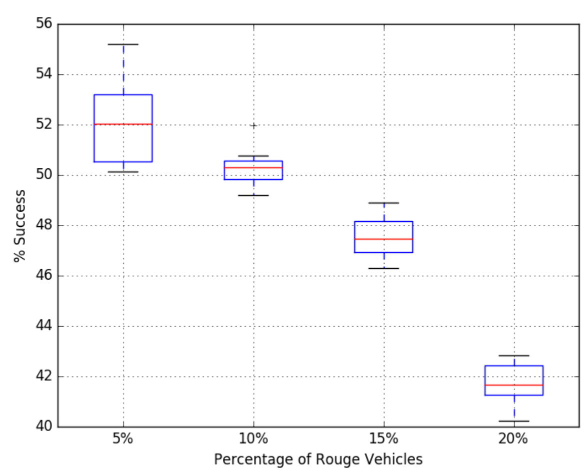

Fig. 2: Overall % success in resolving dilemma zone (base-case)

Figure 3 summarizes similar descriptive statistics S-BSM framework. It contains four subplots (one per scenario): each subplot presents standard box plot for the % success for a given % of ego-vehicles in the system. Please note that these results are generated using a subset of data, in which, the number of instances a dilemma zone scenario was resolved in which at least one ego-vehicle was present in the environment. This analysis directly evaluates ego-vehicle's ability to track a rogue vehicle and send pertinent information to the infrastructure for implementing efficient and safe control actions. In that sense, this analysis directly assesses effectiveness of S-BSM framework. While this information is very useful, it is also important to understand the impact of ego vehicle penetration in the overall traffic. To answer this question, we generated similar subplots but based on the total number of instances a rogue vehicle is caught in the dilemma zone irrespective of whether an ego-vehicle was present in the vicinity or not. These results are summarized in Figure 4.

Based on the information presented in the three figures, following inferences can be drawn:

- S-BSM framework outperformed the base-case in all four scenarios and for various ego-vehicle penetration levels.
- Whenever an ego-vehicle is present in the vicinity of a rogue vehicle, the likelihood that dilemma zone issues will be resolved is between 96 - 98% (see Figure 3).
- As the ego-vehicle penetration increases, the variance in % success is reduced (see Figure 4). A more interesting observation is that beginning at 20% ego vehicle penetration level, the increased percent of rogue vehicles in the mixed traffic stream seems to have no significant impact on the framework's ability to successfully handle dilemma zone scenarios.

B. Average Green Duration

Reduction in average green duration is viewed as an indication that the signal's performance had improved from the efficiency standpoint. This in turn, suggests an enhanced responsiveness to minor street needs. Average green duration values for both base-case and S-BSM framework are summarized in Table I. As can be seen, S-BSM framework produces significantly lower average green durations than those produced by the base-case suggesting S-BSM framework can be extremely useful in improving safety of rural transport facilities without compromising for efficiency.

VII. Conclusions and Future Work

Vehicular sensors in today's vehicles are capable of producing terabytes of useful information on car's environment, like speed, object proximity, SLAM maps etc. Moreover, market recent market studies suggest that by the year 2029, 60% of all vehicles, will have DSRC/V2X communication capabilities. To leverage the combination of this rich vehicular sensor data, and guaranteed low-latency communication protocol, we proposed simulated-BSM concept to enhance safety of transport facilities. The main idea is that an ego-vehicle with local sensor feed capability creates a basic safety message for any identified rogue vehicles in its field of view, and broadcasts it to infrastructure for implementing efficient and safe control actions. We discussed details of the system architecture. Finally, the concept of S-BSM was applied in the context of enhancing safe & efficient operations of rural high-speed signalized intersections. Simulation experiments were conducted to evaluate the efficacy of the system, and the results are benchmarked against a conventional control system. The results conclusively suggest that the S-BSM framework can be extremely useful in improving safety of rural transport facilities without compromising for efficiency.

In future, we plan to evaluate the efficacy of S-BSM system architecture using KITTI dataset [16].

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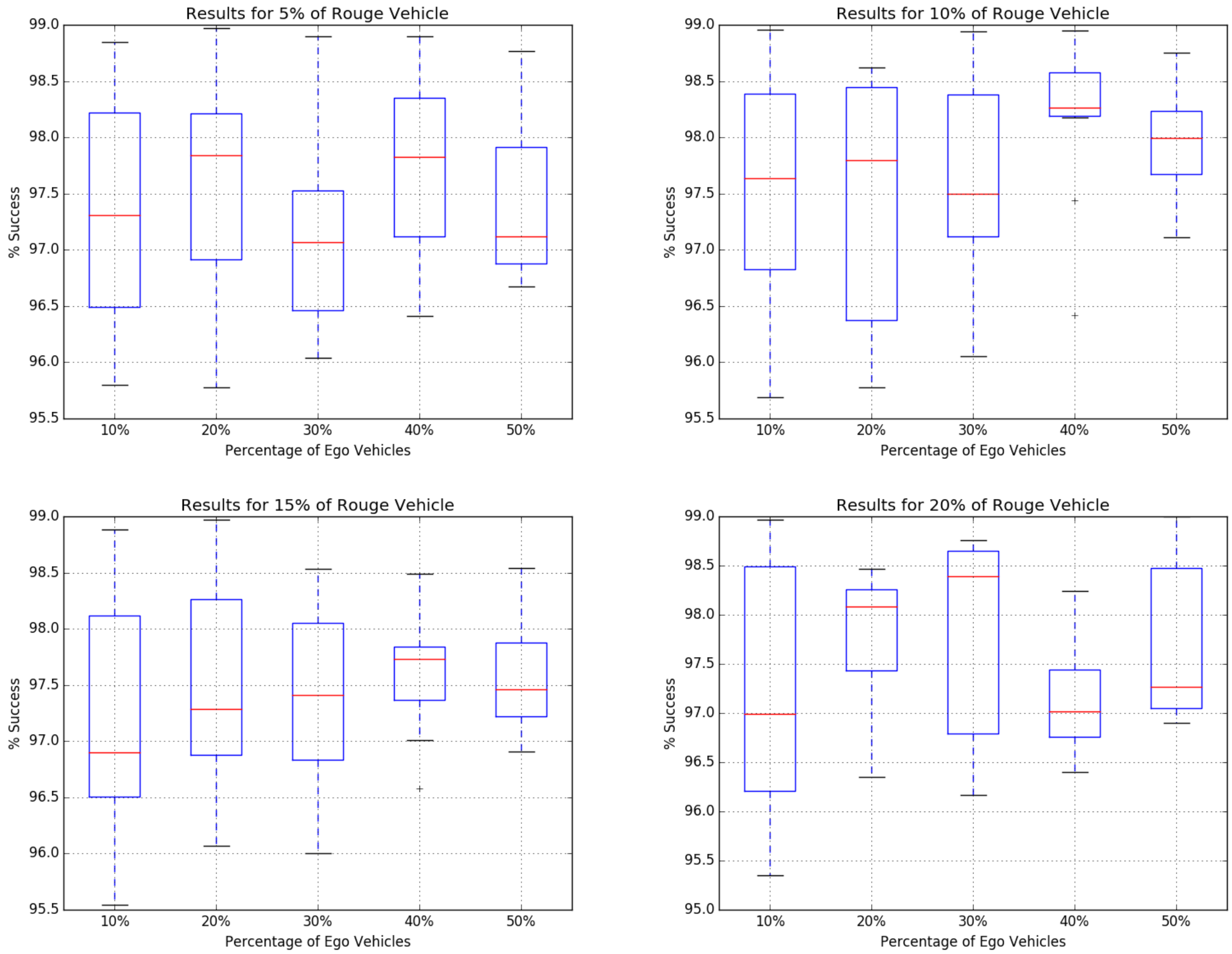

Fig. 3: % success in resolving dilemma zone when ego-vehicle is present

Average Main Street Green Duration (in seconds)								
% Ego Vehicles	**Scenario - 1**		**Scenario - 2**		**Scenario - 3**		**Scenario - 4**	
	Base Case	**S-BSM Case**	**Base Case**	**S-BSM Case**	**Base Case**	**S-BSM Case**	**Base Case**	**S-BSM Case**
10	**57.71**	**45.0**	**86.28**	**47.71**	**100.57**	**66.57**	**110.0**	**84.28**
20	**57.71**	**45.57**	**86.28**	**56.42**	**100.57**	**74.0**	**110.0**	**88.86**
30	**57.71**	**43.87**	**86.28**	**62.71**	**100.57**	**73.14**	**110.0**	**92.43**
40	**57.71**	**44.34**	**86.28**	**64.0**	**100.57**	**75.34**	**110.0**	**92.71**

TABLE I: Average green duration comparison (sec)

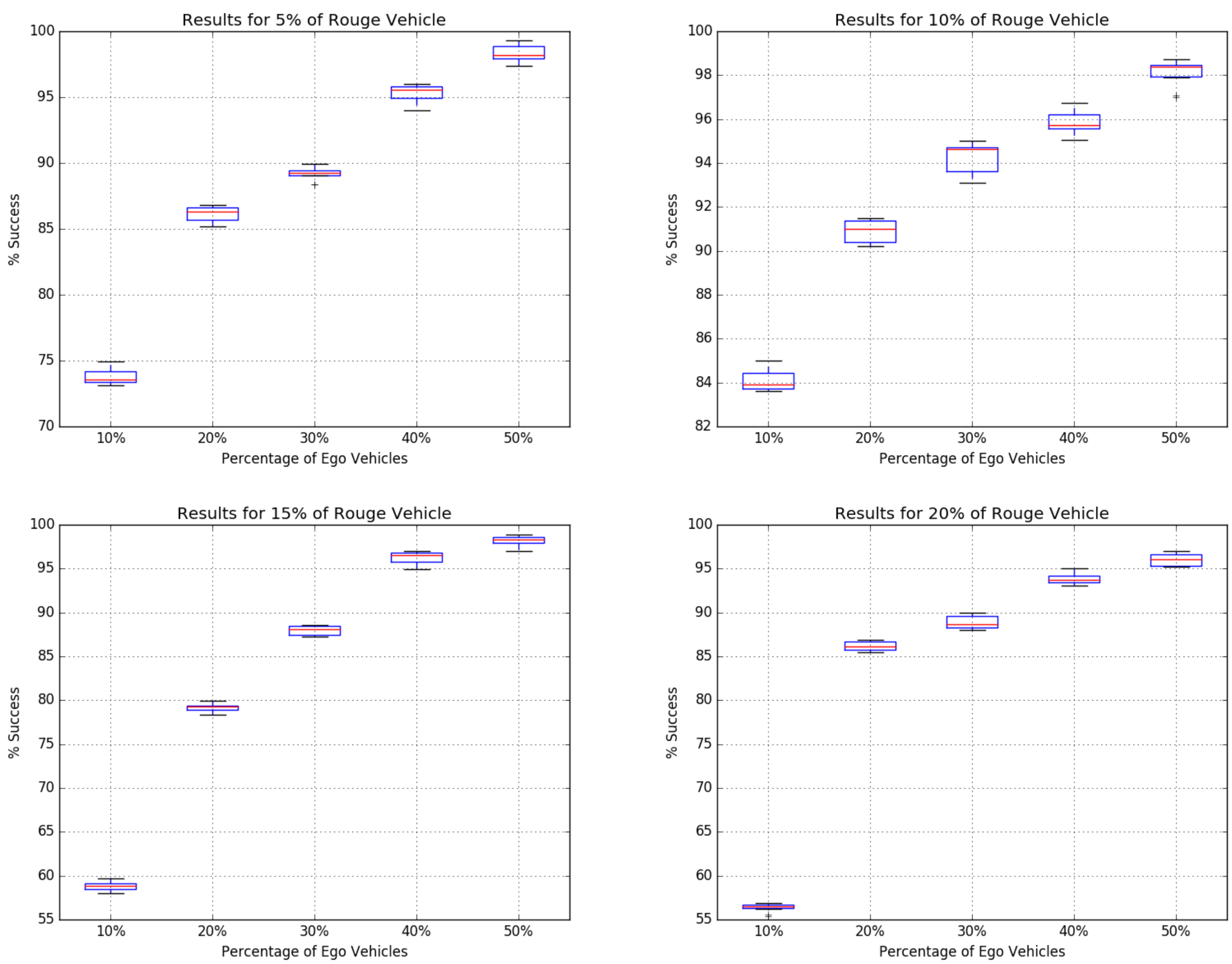

Fig. 4: Overall % success in resolving dilemma zone (S-BSM) (whether an ego vehicle present or not)