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SPATIAL AGENT-BASED SIMULATION OF CONNECTED AND AUTONOMOUS VEHICLES TO ASSESS IMPACTS ON TRAFFIC CONDITIONS

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ABSTRACT

Traffic congestion and its effect on aging transportation infrastructures have been a significant issue in many cities. Various policies such as fast-track lanes have been applied to optimize traffic on roadways. However, the increasing adoption of Connected and Autonomous Vehicles (CAVs) motivates the question of whether they can reduce traffic congestion. This study aims to evaluate the integration of CAVs into existing transportation networks, comprising of both highway and urban roads. To quantify their impact, we develop and validate agent-based simulation models. Two study sites in the State of Oklahoma were identified. We then implemented connected cruise control, green light optimized speed advisory, dynamic route selection, and pedestrians' detection as behaviors for CAVs in the simulation. The results indicated that introducing CAVs to the selected road networks improved the traffic flow by more than 30% and 20% of the average travel time for the urban and highway study sites, respectively.

1 INTRODUCTION

Connected and Autonomous Vehicles (CAVs) are a radical evolution of the regular vehicles which are driven by humans. Reduction in manufacturing cost, growing willingness to pay amongst Americans and more welcoming changes in governmental policies towards CAVs adoption will result in a higher market share of CAVs in the near future (Bansal and Kockelman 2017). Their capabilities such as Connected Cruise Control (CCC), Green Light Optimized Speed Advisory (GLOSA), dynamic route selection, and pedestrian detection optimize travel time, assist drivers with disabilities, ease tiring long-distance travel and improve safety (Piao et al. 2016). CAVs have the ability to communicate with their environment through wireless networks where the environment can include other cars, pedestrians, and other infrastructure elements such as traffic lights. The three primary types of communications, including V2V (Vehicle-to-Vehicle), V2I (Vehicle-to-Infrastructure), and V2P (Vehicle-to-Pedestrian) use Dedicated Short Range Communication (DSRC) (U.S. Department of Transportation. 2015).

Recently, CAVs technology has begun to gather steam and has positioned itself to be a disruption in the transportation realm. Almost every vehicle being offered by manufacturers these days has at least some functionality built into them such as automatic breaking, and lane keep assist which is considered to be SAE level 2 automation, see Society of Automotive Engineers International. (2018). There are many research works that have theorized multiple benefits of such vehicles including highway safety, better flow and stability of traffic and improvement in environmental pollution (see Jadaan et al. (2017), Li et al. (2015), Zhou et al. (2017), Lioris et al. (2017), Monteil et al. (2013)). Of all transportation related challenges, traffic congestion causes tremendous loss to human productivity every year. For instance, in the US, Americans lose $87 billion annually in time, an average of $1,348 per driver by losing 97 hours

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in congestion (INRIX 2019; U.S. Department of Transportation. 2005). On a global scale, traffic jams slow down drivers and consequently affect the global economy by $1.4 trillion annually (Gwilliam, K. M. 2002). Therefore, studying and quantifying the impact of CAVs on traffic congestion is critical.

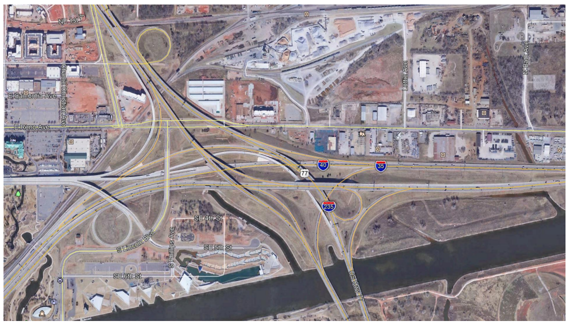
The promising impacts of CAVs in road networks, comprising of both CAVs and regular vehicles, are investigated in the literature. Among others, Lioris et al. (2017) showed that when vehicles that are connected through wireless networks, the adaptive cruise control feature increases the traffic throughput.Ye and Yamamoto (2018) utilized a modeling and simulation framework and evaluated the positive impacts of road capacity when CAVs penetration was increased in a road network, comprising both CAVs and regular vehicles (mixed traffic flow). Zhang and Cassandras (2019) also found that even with a 10% CAVs penetration in the conventional traffic, energy consumption performance was drastically better than their controlled experiment with no CAVs. Bandeira et al. (2021) recently assessed the environmental impacts and emission effects of CAVs in both mixed traffic flow and different road types including motorway, rural, and urban in a European city. The study also emphasized on the importance of studying the impacts of CAVs in multiple road types to enable government and policy-makers decide better on governing laws. Mahdinia et al. (2021) also performed an experiment to analyze the human-driven vehicular behavior when the automated vehicles are introduced to the transportation network. Their results demonstrated that the fuel efficiency and safety of the human-driven vehicle were improved while reducing the driving volatility.

The challenges involved in the evaluation of CAVs integration and impacts on transportation networks are mainly related to the difficulty in experimentation on roads and real-time evaluation, which leads to the increased cost of such experiments, disturbance to citizens and constraints in using huge number of vehicles. Therefore, simulation is an effective tool that can help scientists and engineers to implement the integration and analyze the impacts on transportation networks. Spatial agent-based modeling is a type of simulation which allows for modeling individual CAVs as agents, capturing their interactions with the geographical environment, and manipulating their behavior to understand how different scenarios impact the overall response of the system.

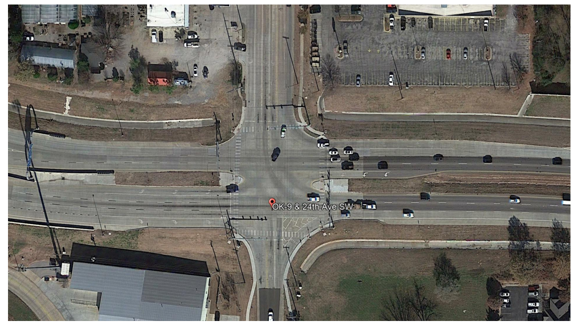
Numerous studies have utilized simulation models to understand the impacts of CAVs on the road network. For instance, Harper et al. (2018) studied the varying levels of CAV penetration in downtown Seattle to estimate the impacts of parking choices, additional miles travelled by the CAVs, and emissions under different scenarios using agent based simulation. Similarly, Kitajima et al. (2019) explored the idea of whether varying the levels of automation of CAVs impacted the number of crashes using traffic simulation-based approach in the city of Tsukuba, Japan. Their results indicated that the number of crashes decreased from 856 to 198 by increasing the level from manual to the highest level of automation. Luo et al. (2019) also performed scenario analyses using an agent-based simulation model to see if changing the levels of shared and private autonomous vehicles has an impact on accessibility in the regional parts of Japan. Their results indicated that with a substantial market share of autonomous vehicles, a considerable increase in accessibility can be observed.

Reviewing the literature reveals that it is critical to evaluate the collective performance of CAVs and regular vehicles in different road types, and study different communication capabilities among CAVs to quantify their impact on traffic congestion. To the best of our knowledge, not many studies have been carried out to quantify the impacts of CAVs at the network level (several intersections, traffic lights, interchanges, two- and three-lane traffic flows) for both highways and urban sites. Therefore, we intend to: (a) close this gap by developing a validated agent-based simulation model for two sites in the State of Oklahoma, (b) run different what-if scenarios for decision-makers, and (c) quantify and visualize the impacts in terms of average travel times in the mixed road settings. Specifically, the impact of CAVs communication capabilities in this mixed environment needs to be evaluated to understand how specific features impact traffic flows differently. To this end, two sites were identified: (a) the interchange system of I-235, and I-40, and (b) the intersection of OK-9 and 24th Ave (see Figure 1). The interchange system of I-235 and I-40 has been found to be frequently congested especially during the morning and evening rush hours. The intersection of OK-9 and 24th Avenue was selected as it is in an urban setting and has high traffic flows.

In the next section, we present our approach for developing the agent-based simulation model and CAVs communication protocols. The rest of the paper is organized as follows. Section 2 contains the detailed overview of the simulation methodologies, communication interface, data utilized in the study, and the study sites. Section 3 presents the results and simulation analyses. Finally, Section 4 concludes the study with a discussion on the impact of CAVs on traffic reduction, hardware requirements and costs for implementations.



(a) Highway interchange system for I-235 and I-40.



(b) Intersection of OK-9 and 24th Ave.

Figure 1: Study Sites.

2 DATA AND METHODS

CAVs can individually be assigned specific behaviors such as communication capabilities, and ability to change the physical characteristics of the vehicle including velocity, acceleration, and deceleration. To study how a population of such CAVs and regular vehicles would behave when they interact with each other, we implemented agent-based models using an object-oriented platform (AnyLogic).

Agents are managed through a three-layer architecture: (a) physical, (b) communication, and (c) trust. The physical layer entails the physical world as described by the roads, the number of lanes, intersections, the dimensions of the car traveling on the road, and etc. The communication layer includes the information exchanged between communicating vehicles in the network. The dynamics of the vehicles are established in this layer. The trust layer is mainly concerned with the trust a vehicle places in the information that it receives from its surrounding.

2.1 Road Networks

We first replicated the road network for the identified study sites using the Road Traffic Library. This was achieved by using Google Maps, taking snapshots of the satellite imagery, and then using it as the stencil on which the roads were drawn. The road networks were created carefully, and as close to the real network as possible including the grades on the roads and curves for road segments such as highway exits and merges.

We then obtained the travel demand data, including shapefiles that represented the road network in the form of road segments with each segment containing a multitude of features. We also imported the shapefiles into AnyLogic environment.

2.2 Traffic Data

The data for the baseline scenario (as-is road network) include the volume of traffic on each segment and time taken to travel the said segment, which is also known as the route assignment step in the traditional four-step transportation forecasting model (see McNally (2007)). The software packages used to generate the data are Cube and ArcView.

The complete dataset contained a total of 41415 rows and 120 features and covered 13060.8 miles of roads in Oklahoma. The data set was generated in February of 2019 and contained the expected traffic statistics and volume in the year 2040 based on current trends of traffic increase. Since the data contained the Annual Average Daily Traffic (AADT), we had the data for different traffic features of each road segment for each 24 hour period. Each day was divided into four time periods - Morning/AM (7am - 9am), Mid-day/MD (9am - 2:30pm), Evening/PM (2:30pm - 6:30pm) and Night/NT (6:30pm - 7am). Each road segment in the data was associated with the length of the segment in miles. The data also provided five different values for the time it would take for a vehicle to travel any road segment. The five different times corresponded to: free flow time, time taken to travel the road segment in the morning period, time taken in mid-day period, time taken in evening period and time taken in night period. The data set contained the volume of cars on each road segment for each time period of the day though it didn't differentiate between the different types of vehicles such as cars and trucks. The data also includes information about the signaling details including the signal cycle and green time per cycle ratio.

2.3 CAVs Agent

To implement the CAVs functionalities in the simulator, we first reviewed the literature comprehensively to identify different CAVs behaviors in physical (e.g., connected cruise control, lane change behavior, etc.), communication (e.g., digital short range communication), and trust layers. We then introduced and defined a new population of agents and implemented multiple algorithms to provide the agents with the identified behaviors and functionalities. The agent as implemented in the system has the following properties: road on which it is traveling, the direction of heading, its velocity, acceleration/deceleration, maximum acceleration and maximum deceleration. Each agent also keeps a list of vehicles that it finds in its proximity and can exchange BSM (Basic Safety Messages) with. It also has the property of whether that vehicle is in a congested condition or not. Whether the vehicle is in a congested state or not depends on two factors: (a) if the vehicle is traveling at a speed that is less than the specified parameter in the simulation, and (b) if it has been in that speed continuously for an amount of time, that would signal that the road is congested. For example, if there is a minor perturbation on the road and the concerned vehicle starts traveling at a speed below the congestion speed only for a very small time, it will not consider itself to be congested.

2.4 CAVs Communication

The most important behavior in CAV agents is the ability to communicate (see Algo. 1). Since the communication range is provided as a simulation parameter, the actual communication range of CAVs can be modified. The default value of the communication was set as 300 meters (U.S. Department of Transportation. 2015). The data shared through the BSM consists of the location, velocity, acceleration, and lane of the road. Furthermore, a vehicle also keeps track of the amount of time it spends traveling in speeds that are very low (for example, a vehicle traveling at 20mph on a highway where the maximum speed is 70mph is not ideal). If the vehicle stays in the low speed for an extended duration of time, the vehicle determines that the road and lane in which it is traveling is congested and adds this data to the BSM. The agents can poll the nearby vehicles (300 meters) and request BSM from them. The polling can be performed at a rate of 10Hz (Qin et al. 2017).

`requestBSM(i,j)` initiates a request of data from vehicle j to vehicle i. The BSM contains information about the vehicle sending the message including the road segment which they are on, the direction in which it is heading, its current location, speed and acceleration/deceleration.

In the simulation model, we parameterized both the range of communication (default 300 meters) and polling rate (default 10Hz). This is useful in case certain situations need to be simulated such as inclement weather conditions where the communication range might be adversely affected.

Algorithm 1 V2V Communication.

for all vehicles i **do**
  for all vehicles j **do**
    if $distance(i, j) < 300$ *meters* **then**
      requestBSM(i,j)
    end if
  end for
end for

2.5 Highway Study Site

The interchange system of I235 and I40 consists of more than 9 miles of road segments (75 segments) and has 29 nodes (including all exits and merges). The volume of traffic during different times of the day per road segment is graphically depicted in Figure 2.

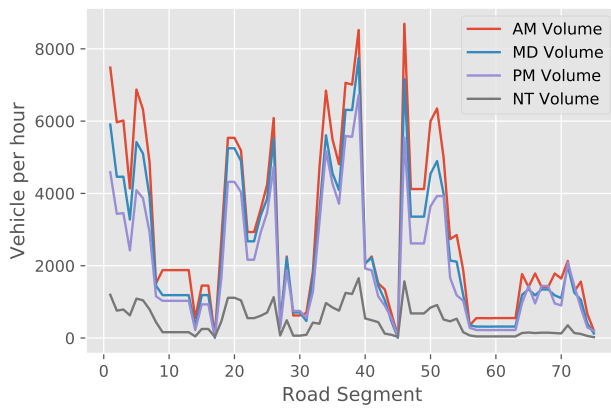


Figure 2: Volume of vehicles for each road segment in the interchange system of I235 and I40 during different times of the day (AM = 7am-9am, MD = 9am-2:30pm, PM = 2:30pm-6:30pm, NT = 6:30pm-7am.

To study the effects of CAVs on highway interchange system, we implemented the Connected Cruise Control (CCC) (Ge et al. 2018; Mersky and Samaras 2016). In a CCC system, every connected vehicle identifies a leading vehicle which travels on the same road, same direction and the same lane as vehicle itself and is traveling ahead of the vehicle in question. Once the leader vehicle is identified for any vehicle, it starts monitoring the BSM sent by the leader vehicle with the frequency that the vehicle can make decision (usually 10Hz, but it could be different). Depending on the location of the leader vehicle, speed and headway present between the leader vehicle and vehicle under consideration, the acceleration of the current vehicle is set. This process is described in Algorithm 2.

In certain situations such as when the connected vehicle identifies the road as congested, it can try to change its route if an alternate route can be identified. If the CAV, through BSM communication, can identify early enough that a road that it is going to travel on becomes congested in the near future, it can preemptively re-calculate an alternate route to avoid the congestion (see Algorithm 3). This routing algorithm is based on the shortest path between the origin-destination pair, and is invoked at every decision making instance for the CAV.

Algorithm 2 Connected Cruise Control.

$a_{curr} = a_{max}$
if $v_{self} = 0$ *and* $v_{lead} = 0$ $dist < 10$ **then**
  $a_{new} = 0$
end if
if $a_{curr} < a_{min}$ **then**
  break
end if
$v_{curr} = v_{self} + a_{curr} * decision\_freq$
$pos_{curr} = pos_{self} + v_{curr} * decision\_freq$
$dist_{curr} = p_{lead} - p_{curr}$
$headway = dist_{curr}/v_{curr}$
if $headway < headway_{min}$ **then**
  $a_{curr} = a_{curr} - 0.1$
end if
$a_{new} = a_{curr}$

Algorithm 3 Dynamic Route Selection.

$routes = array\ of\ routes$
$congested\_road = null$
$new\_route = null$
if $next\_road \in list\_congested\_roads \mid next\_road + 1 \in list\_congested\_roads$ **then**
  $routes = get\_routes(destination)$
  $congested\_road = next\_road$
end if
for $route \in routes$ **do**
  if $congested\_road \in route$ **then**
    continue
  end if
  $new\_route = route$
end for

2.6 Urban Study Site

The road network for OK-9 and 24th Avenue was created and the volume of traffic during different times of the day per road segment is graphically depicted in Figure 3.

The intersection was signalized based on the the obtained data, and we implemented signal phasing and timing (SPaT) protocol to communicate with the CAV approaching the intersection (see (National Operations Center of Excellence. 2019). A SPaT message can describe the current phase at the signalized intersection along with an estimate of the remaining time of that phase. This is utilized by the CAVs to calculate the optimum speed to approach the intersection with. To identify the optimum approach, we utilized the Green Light Optimized Speed Advisory (GLOSA) algorithm (see (Kundu et al. 2013; Bodenheimer et al. 2015; Djahel et al. 2015)) and let the CAV agents in the system alter their speeds based on the SPaT messages they received from the intersection infrastructure. Pseudo codes for the GLOSA is shown in Algorithm 4. If the vehicle is beyond the DSRC communication range from the intersection and cannot receive SPaT messages, it uses CCC Algorithm 2 to drive. This algorithm is employed by the leader of the connected cruise control vehicle string at every decision making instance. The details of the signalized intersection in the dataset are as follows. For the 24th Avenue, the signal cycle is 90 seconds

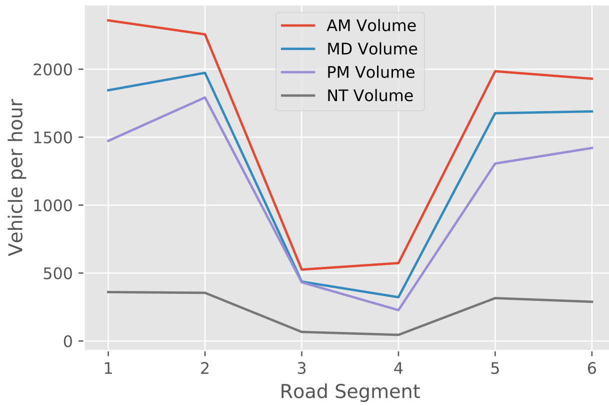


Figure 3: Volume of vehicles for each road segment at the intersection of OK-9 and 24th Avenue during different times of the day (AM = 7am-9am, MD = 9am-2:30pm, PM = 2:30pm-6:30pm, NT = 6:30pm-7am.

and green time per cycle is 50%. For the signals on OK-9, the signal cycle is 70 seconds and the green time per cycle is 50%.

Algorithm 4 Green Light Optimized Speed Advisory.

if $current\_phase == green$ & $(x/v_{curr}) > time\_to\_phase\_change$ **then**
  $decelerate, a_{curr} = a_{curr} - 0.1$
end if
if $current\_phase == red$ & $(x/v_{curr}) > time\_to\_phase\_change$ **then**
  $a_{curr} = (v_{signal} - v_{curr})/time\_to\_phase\_change$
end if
if $current\_phase == yellow$ & $(x/v_{curr}) < time\_to\_phase\_change$ **then**
  break
end if
if $a_{curr} < a_{min}$ **then**
  break
end if

3 RESULTS AND ANALYSES

3.1 Highway Study Site

Baseline scenario validation was performed by comparing the real traffic data to the one produced by the simulator. To simulate the population of regular vehicles, we first calculated the number of vehicles traveling along the road segment by dividing the volume by the number of hours in that time period. Vehicles were then generated on the source nodes of the road network at the equivalent rate. In case of intersections, since we were provided with the data of how many vehicles would be on any road segment, we calculated the probability of a vehicle going to any road at an intersection from any particular road.

After this step, we calculated the average time it took for vehicles in the simulation to travel various road segments and compared it to the average travel time in the dataset. We performed the t-Test analysis and observed that there was no statistical difference between the real data and that of generated by the simulator (see Table 1).

Table 1: Comparison of simulated and real traffic data for the highway interchange system of I235 and I40.

Time Period	**Real Data**		**Simulated Data**		**df**	**t-Stat**	**p-value**
	Mean	*Variance*	*Mean*	*Variance*			
7am-9am	0.2738	0.0670	0.2756	0.0718	148	-0.0431	0.4828
9am-2:30pm	0.2388	0.0463	0.2344	0.0441	148	0.1278	0.4493
2:30pm-6:30pm	0.2504	0.0541	0.2562	0.0583	148	-0.1498	0.4406
6:30pm-7am	0.1729	0.0136	0.1749	0.0150	148	-0.1031	0.4590

We then implemented the CAVs agents and added CCC behaviors and the ability to look for alternate routes depending on congestion. We ran the simulation for a 7-day period with 100 replications and collected the data generated. The average time taken to travel each road segment was collected during the four time periods per day.

For the first experiment, we assumed that all vehicles on the road were CAVs with the aforementioned functionalities. Results are given in the Table 2.

Table 2: CAVs performance at the interchange system of I235 and I40.

Time Period	**Non-CAV**		**CAV**		**Improvement**
	Mean	*Variance*	*Mean*	*Variance*	
7am-9am	0.2756	0.0718	0.1820	0.0109	33.95%
9am-2:30pm	0.2344	0.0441	0.1831	0.0111	21%
2:30pm-6:30pm	0.2562	0.0583	0.1831	0.0114	28%
6:30pm-7am	0.1749	0.0150	0.1724	0.0113	1.4%

We found that CAVs had a significant effect on the traffic performance. In the morning traffic, the overall time taken by vehicles to travel in the network improved by 34%, mid-day performance was improved by 21% and evening performance was improved by 28%. We did not find a significant improvement during night. The results are also depicted in Figure 4.

For the second experiment, we considered different penetration rates and measured the traffic performance with CAVs at 10%, 20%, 30%, ..., 100% during morning rush hours. The results are summarized in Table 3. As expected, the overall time required to traverse the road network decreases as the penetration rate of CAVs increases.

Table 3: Percentage of improvements in terms of average travel time for different CAVs penetration rates.

CAV %	**Mean**	**Variance**	**Percentage of Improvement**
10	0.2525	0.0226	8.39
20	0.2352	0.0542	14.65
30	0.2389	0.0239	13.34
40	0.2318	0.0206	15.90
50	0.2428	0.0196	11.90
60	0.2336	0.0180	15.26
70	0.2126	0.0162	22.86
80	0.2136	0.0153	22.51
90	0.1966	0.0130	28.68
100	0.1820	0.0109	33.95

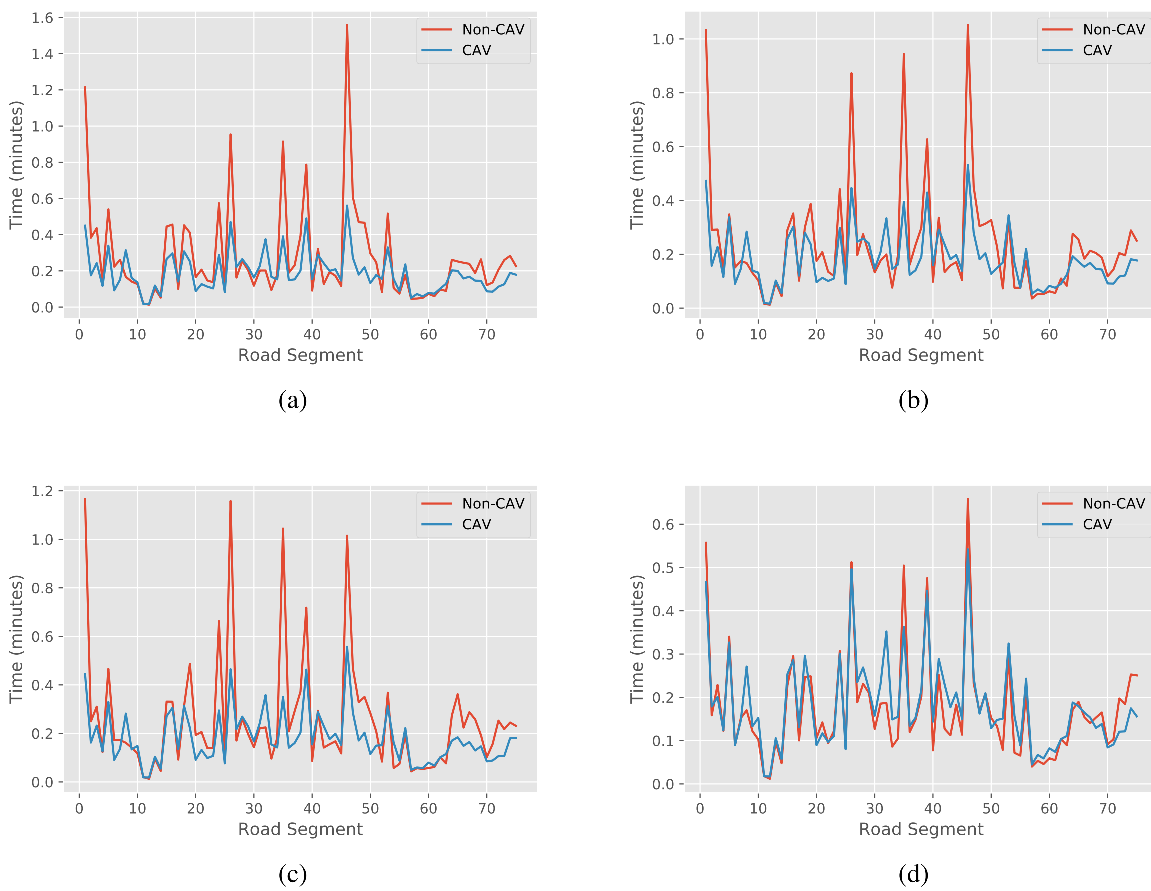


Figure 4: CAVs vs Non-CAV performance in terms of travel time per road segments for the highway study site. (a) during 7-9am. (b) during the hours 9am-2:30pm. (C) during the hours 2:30pm-6:30pm. (d) during 6:30pm to 7am.

3.2 Urban Study Site

The validation of baseline scenario was similar to the previous case study. We calculated the average time it took for vehicles in the simulation to travel various road segments and compared it to the average travel time in the dataset. We performed the t-Test analysis and observed that there was no statistical difference between the real travel times and that of generated by the simulator (see Table 4).

Table 4: Comparison of simulated and real traffic data for the intersection study site.

Time Period	**Real Data**		**Simulated Data**		**df**	**t-Stat**	**p-value**
	Mean	*Variance*	*Mean*	*Variance*			
7am-9am	0.41	0.10	0.25	0.02	7	1.18	0.139
9am-2:30pm	0.35	0.05	0.24	0.01	7	1.15	0.144
2:30pm-6:30pm	0.38	0.08	0.21	0.01	7	1.36	0.108
6:30pm-7am	0.29	0.03	0.19	0.01	8	1.32	0.112

It is perceived that CAVs contribute to improving the safety of users/people in road networks. For intersections, pedestrian safety is paramount. Since CAVs can have pedestrian detection capabilities, we added pedestrian detection behavior to the CAVs agents in the simulation model. The vehicles were provided with a 25 meter range of visibility for identifying the pedestrians (see Figure 5). If the CAVs agents identify a pedestrian in their visible range, they can come to a stop, thus avoiding pedestrian accidents. To model pedestrians behavior, we utilized the pedestrian library in AnyLogic and generated random arrival rates during different times of the day. Pedestrians move according to the simulated physical rules (e.g., crossing the intersection).

Figure 5: Pedestrian Detection. (a) State chart representing the logic for pedestrian detection, (b) CAV agent with front sensors to detect pedestrians.

We then implemented CAVs agents, traffic lights with the signaling phases available in the dataset, and allocated appropriate behaviors including CCC, GLOSA, and pedestrian detection. Using the vehicle volumes available for different time periods per day, we generated vehicles and ran the simulation for 7 days with 100 replications. The results are summarized in Table 5.

Table 5: CAVs performance at the intersection of OK-9 and 24th Avenue.

Time Period	**Non-CAV**		**CAV**		**Improvement**
	Mean	*Variance*	*Mean*	*Variance*	
7am-9am	0.25	0.02	0.15	0.03	39.96%
9am-2:30pm	0.24	0.01	0.16	0.01	33.33%
2:30pm-6:30pm	0.21	0.01	0.12	0.02	42.85%
6:30pm-7am	0.19	0.01	0.13	0.04	36.84%

It can be observed that CAVs contributed to more than 30% improvements in the traffic flow pattern by reducing the average travel time in the network.

4 CONCLUSIONS

We developed spatial agent-based simulation models to evaluate the collective performance of CAVs and regular vehicles on road networks. We defined certain behavioral characteristics (functionalities) for the CAVs agents in the simulation including Connected Cruise Control (CCC), Green Light Optimized Speed Advisory (GLOSA), dynamic route selection, and pedestrian detection. Having analyzed the simulation results, we quantified the potential impacts of CAVs in both highway and urban settings. As for the highway study site (I235 and I40), we evaluated the network performance by introducing CAVs at different rates such as 10%, 20%,..., 100%.

We also quantified the percentage of improvements in terms of average travel time for different time periods per day. As expected, we observed larger improvements in the morning (7am-9am) and evening (2:30pm-6:30pm) traffic. The second study site was the intersection of OK-9 and 24th Ave. We found that CAVs communication with the intersection infrastructure, using SPaT messages, was a major contributor to the CAVs performance. The results demonstrated that as the CAVs penetration in the vehicular volume on the road network increases, we can expect significant congestion relief in the road networks.

From implementation standpoint, adding communication capabilities to vehicles, such as CCC and GLOSA, would cost \$341 to \$350 (U.S. Department of Transportation Intelligent Transportation Systems. 2019). GLOSA capability also requires that intersections have the necessary hardware to communicate with vehicles. Upgrading intersections with SPaT technology would cost between \$15K to \$50K (National Operations Center of Excellence. 2019) with recent deployments suggesting a price as low as \$5K for an intersection. In addition, adding semi-autonomous capability to a vehicle might cost up to \$5k. Nonetheless, this should not deter the adoption of such technologies as new technologies cost considerably in the beginning, but the cost goes down as economies of scale come into the picture. While extensive impact analyses of CAVs technologies in terms of human-hours saved, reduction in fatalities, and gas/fuel saved are not covered in this study, we believe potential benefits in the aforementioned categories would offset the price of adopting this emerging technology.

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