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Modeling the effect of electric vehicle adoption on pedestrian traffic safety: An agent-based approach

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ABSTRACT

When operated at low speeds, electric and hybrid vehicles have created pedestrian safety concerns in congested areas of various city centers, because these vehicles have relatively silent engines compared to those of internal combustion engine vehicles, resulting in safety issues for pedestrians and cyclists due to the lack of engine noise to warn them of an oncoming electric or hybrid vehicle. However, the driver behavior characteristics have also been considered in many studies, and the high end-prices of electric vehicles indicate that electric vehicle drivers tend to have a higher prosperity index and are more likely to receive a better education, making them more alert while driving and more likely to obey traffic rules. In this paper, the positive and negative factors associated with electric vehicle adoption and the subsequent effects on pedestrian traffic safety are investigated using an agent-based modeling approach, in which a traffic micro-simulation of a real intersection is simulated in 3D using AnyLogic software. First, the interacting agents and dynamic parameters are defined in the agent-based model. Next, a 3D intersection environment is created to integrate the agent-based model into a visual simulation, where the simulation records the number of near-crashes occurring in certain pedestrian crossings throughout the virtual time duration of a year. A sensitivity analysis is also carried out with 9000 subsequent simulations performed in a supercomputer to account for the variation in dynamic parameters (ambient sound level, vehicle sound level, and ambient illumination). According to the analysis, electric vehicles have a 30% higher pedestrian traffic safety risk than internal combustion engine vehicles under high ambient sound levels. At low ambient sound levels, however, electric vehicles have only a 10% higher safety risk for pedestrians. Low levels of ambient illumination also increase the number of pedestrians involved in near-crashes for both electric vehicles and combustion engine vehicles.

1. Introduction

The U.S. Department of Transportation has declared pedestrians to be the top-priority roadway agents in terms of traffic safety (NHTSA, 2010), as statistics have shown that traffic accidents involving pedestrians have become a major traffic safety concern. In 2014, there were 4884 pedestrian fatalities and 65,000 injuries from a total of 44,820 fatal traffic crashes. Pedestrians are even more likely to be involved in traffic crashes in urban areas (78% of total pedestrian fatalities) and under low-light conditions (72% of total

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pedestrian fatalities) (NHTSA, 2016). With the current increasing trend in hybrid/electric vehicle adoptions, regarding concerns have increased due to the silent engines and low sound levels of such vehicles, which non-motorists (pedestrians, bicyclists, skaters, etc.) cannot rely on as easily to warn of approaching vehicles in the urban areas. The National Highway Transportation Safety Agency (NHTSA) has therefore called these cars “quieter cars” in a 2009 report, which concluded that hybrid electric vehicles (HEVs) are two times more likely to be involved in a pedestrian crash than internal combustion engine vehicles (ICEVs) (Hanna, 2009). This report, however, was updated in 2011 with more extensive data by adding crash files reported to the state database in recent years. According to the report, accident rates are highly dependent on vehicle speed, maneuvering, and location, but the largest difference between the involvement rates of HEVs and ICEVs in pedestrian crashes (the former being 22% greater than the latter) is observed when the average vehicle speed is less than 35 mph, during low-speed maneuvers, and when pedestrians are on the roadway (Wu and Austin, 2010). The NHTSA has also performed another extensive study on quieter cars posing a safety risk for blind pedestrians. This second study included two phases of research. The first phase studied the determination of overall sound levels and general spectral content for a selection of hybrid-electric and internal combustion vehicles under different operating conditions, as well as the evaluation of detectability for low and high ambient sound levels (Garay-Vega et al., 2010). The second phase proposed potential specifications for vehicle sound levels to be used in HEVs, including adding a synthetic vehicle sound (Hastings et al., 2011). The solution of placing a synthetic sound source into silent vehicle has been extensively studied recently. For instance, in a technology research study, the Japanese electric vehicle manufacturer Nissan developed a synthetic sound system called VSP (Vehicle Sound for Pedestrians), which emits a synthetic sound to satisfy three key concerns: to provide detectability for pedestrians, to provide silence for drivers, and to maintain a quiet environment for the neighborhood as a whole (Tabata et al., 2010).

There are many factors affecting pedestrian traffic safety, including the relative illumination of the traffic environment, pedestrian and driver behaviors, vehicle technology, vehicle and ambient sound levels, vehicle traffic density, traffic flow speed, traffic signage, and other applicable factors. Some of these factors can be linked to the adopted vehicle type by making correlations with driver behavior as well as pedestrian perception. Since EV drivers are at a higher economic level and are therefore more likely to have received a better education, they demonstrate more careful traffic behavior (Shinar, 2007). Additionally, higher internal car noise increases drivers' risk-taking propensity (Horswill and Coster, 2002). On the other hand, the relative silence of the average EV's engine will make it less detectable by oncoming pedestrians and therefore more likely to be involved in collisions. Since EV adoption therefore has both positive and negative impacts on the pedestrian's traffic safety, the overall resultant effect can be investigated with an agent-based modeling approach. Agent-based modeling (ABM) is a new approach to computational modeling that simulates dynamic systems with various interacting agents. ABM has gained significant attention over the past 10 years, during which time the systems that have needed to be analyzed and modeled have become more complex in terms of the different interdependencies involved. ABM is particularly useful when there are interacting agents and factors that simultaneously affect each other, and is now being applied to topics such as market analysis, organizational decision-making, energy analysis, air traffic control, etc. For instance, Noori and Tatari (2016) used an agent-based model for regional market penetration projections of EVs, and discovered that government subsidies play a vital role in EV market adoption. Similarly, Shafiei et al. (2012) developed a multi-agent environment to predict the market share of EVs in Iceland. and concluded that successful EV market penetration occurs in scenarios with low gasoline prices, or with a combination of medium-level gasoline prices and constant EV price only when supporting policies such as tax exemptions are available. The ABM approach has been also recently used in transportation modeling, such as in a recent study that modeled the dynamic route choice behavior of individual drivers under the influence of real time traffic information (Dia, 2002). Using a similar approach, Waraich and Axhausen (2012) developed an agent-based parking choice model in their study to investigate the overall effects of parking capacity and pricing on parking-oriented transportation policies. Another study simulated electric vehicle driver behavior in road transport and electric power networks (Marmaras et al., 2017).

The traffic flow on pedestrianized streets was analytically studied by many researchers. Daganzo and Knoop (2016) provided analytical formulae predicting the capacity and macroscopic fundamental diagram (MFD) of pedestrianized streets. According to study, free-flow speed on the pedestrianized street declines proportionately with the pedestrian flow and capacity declines by an amount proportional to the square root of the pedestrian flow. In another study, Zeng et al. (2014). carried out pedestrian behavior analysis at signalized intersection through a microscopic simulation model that employs a social force theory. The study concludes that the microsimulation model enables visually representing the pedestrian crossing behavior in the real world Crociani and Vizzari (2014) modeled the interaction between vehicles and pedestrians in an area of a zebra crossing. By providing simple pedestrian crossing scenarios in an agent based environment, the study showed the mutual perception of pedestrian and vehicles cooperating to avoid accidents. Lobjois and Cavallo (2009) examined the road crossing decisions by the age and gender factors. According to study, the gender doesn't have obvious effect and age factor showed that the young group had a greater number of tight fits and missed fewer opportunities on the crossing task. Similarly Dommes et al. (2012) investigated age related differences for the street crossing behavior. Gorrini et al. (2016) conducted an empirical study to model the pedestrian-vehicle interaction on urban unsignalized intersections. Another pedestrian crossing behavior model was developed for Chinese cities where the pedestrians' road crossing behavior is different than the pedestrian behavior in European countries. Yang et al. (2006) classified pedestrians into two types: law-obeying ones and opportunistic ones. The model has shown the high rate of pedestrians' red light running characteristics in Chinese cities. This study also provides a vehicle pedestrian interaction in pedestrian crossings and measures the difference between conventional and electric vehicles. A traffic micro-simulation is carried out using a powerful multi-method 3D simulation environment called AnyLogic (AnyLogic: Multimethod Simulation Software, 2016). AnyLogic is a unique tool that combines the System Dynamics, Discrete Event, and Agent-Based modeling methods into one model development environment, allowing the AnyLogic software to provide a great deal of flexibility with its built-in Java capabilities, as all of the complex agent behavior in the simulation can therefore be modeled with Java coding. A model developed in AnyLogic is fully mapped into Java code and, having been linked with

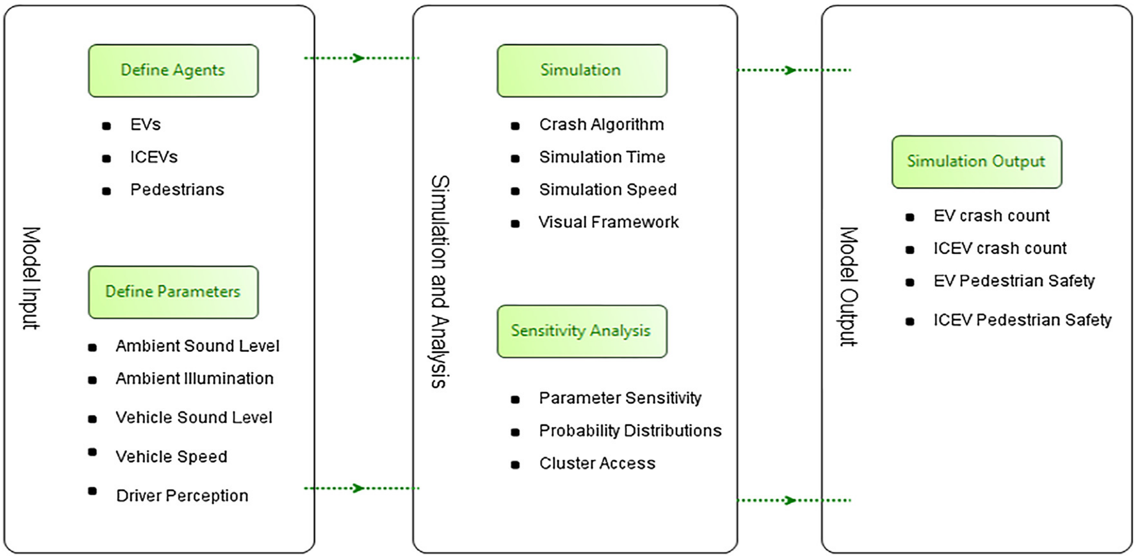

Fig. 1. The framework of the simulation methodology.

AnyLogic simulation engine (also written in Java), and, optionally, with a Java optimizer, becomes a completely independent standalone Java application. This makes AnyLogic models cross-platform: they can run on any Java-enabled environment.

2. Methodology

The methodology of this study starts with establishing and explaining the simulation environment and the analysis structure. Section 2.1 clearly illustrates the traffic simulation framework and explains how the various simulation agents and parameters are defined within this framework. Section 2.2 provides detailed information on near-crash events, which forms the primary output of the simulation. The near-crash logic and its associated programming algorithm are both explained in this section as well. The crash phenomenon occurs when two conditions are not met: failure of vehicle detectability and insufficient vehicle sight stopping distance. Section 2.3 illustrates the auditory vehicle detectability, which is controlled by the model parameters associated with ambient sound level, ambient illumination, vehicle sound level, and vehicle speed. Section 2.4, on the other hand, explains vehicle sight stopping distance and summarizes its associated dynamic calculations within the simulation. Fig. 1 summarizes the methodology framework.

2.1. Traffic simulation framework

The traffic simulation model in this study simulates a simple real-world signalized traffic intersection environment. The images and other visual entities used to represent this intersection are taken from the downtown area in Orlando, FL.[1] The signalized intersection connects 4-lane undivided urban roadways with a maximum speed limit of 30 mph, and there are four uncontrolled pedestrian crossings located near the potential pedestrian flows (a bus stop, a hospital, an office building entrance, etc.). There is also a nearby parking lot, which only diversifies lane selection behaviors. The traffic simulation environment is shown in Fig. 2. The stop lines of the traffic lights are shown as red lines, the pedestrian crossings are shown as dashed black lines connecting two sides of the road bordered with green lines. The green car objects represent the EVs whereas the brown car objects are ICEVs.

The agents defined in this model are pedestrians, EVs, and ICEVs. All three of these agents have initially empty populations, but are created within the environment by the readily available source blocks, with each source block creating agents at a previously defined rate. Vehicle objects are created at the road ends based on previously defined acceleration, velocity, and geometric properties. Pedestrians are likewise created at certain attraction points, and are moved to the designated pedestrian crossings using a previously defined Poisson Probability Distribution function (Gerlough and Schuhl, 1955). The agent based parameters defined in this model (ambient sound, ambient illumination, ICEV flow rate, and EV flow rate) are all key factors that will affect the simulation analysis results, and can be dynamically changed during the simulation in the simulation window as shown in Fig. 3.

The AnyLogic model allows its users to benefit from the object-oriented programming through the object relationship blocks available from the AnyLogic libraries. The Road Traffic Library was extensively used here to model, simulate and visualize vehicle traffic. The library supports detailed yet highly efficient physical level modeling of vehicle movement. It is suitable for modeling highway traffic, street traffic, on-site transportation at manufacturing sites, parking lots, or any other systems with vehicles, roads, and lanes. This library includes:

[1] Intersection of Church St. and Orange Ave. Orlando, FL, USA

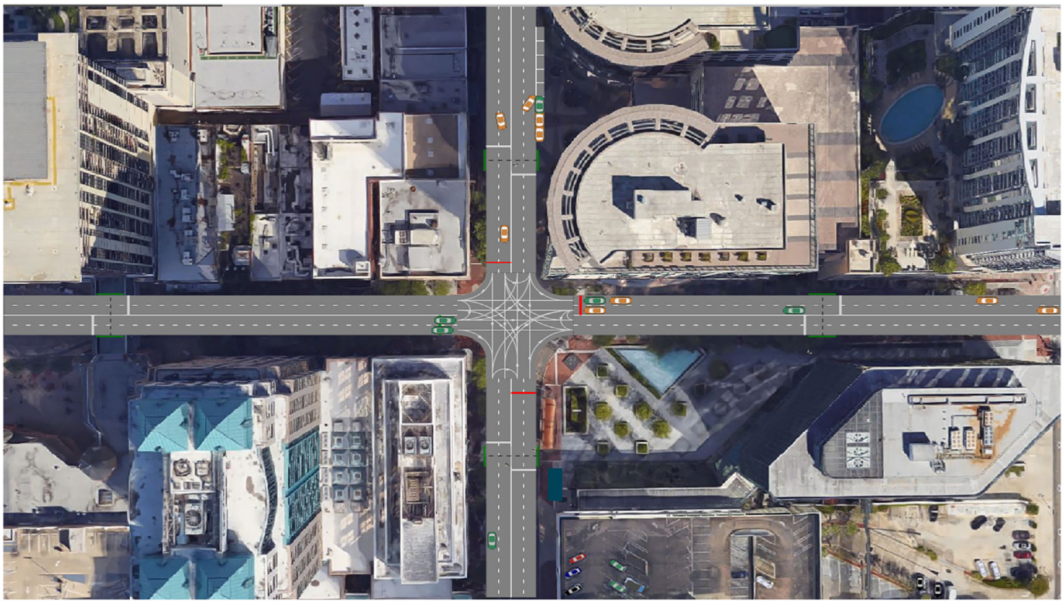

Fig. 2. The occupied intersection taken from the traffic simulation.

Fig. 3. 3D simulation window of the AnyLogic model.

- Visual space markup shapes (road, intersection, bus stop, parking lot, stop line) to draw road networks.
- Driver behavior: speed control, choosing less busy lane, giving way when lanes merge, avoiding and detecting collisions on crossroads.
- Support of user-defined car types with custom animation and attributes.

The car object blocks in The Road Traffic Library are used to control the car objects. The car object behavior and the corresponding relationships were thereby developed using these blocks as explained in Fig. 4. CarSource block generates cars and puts

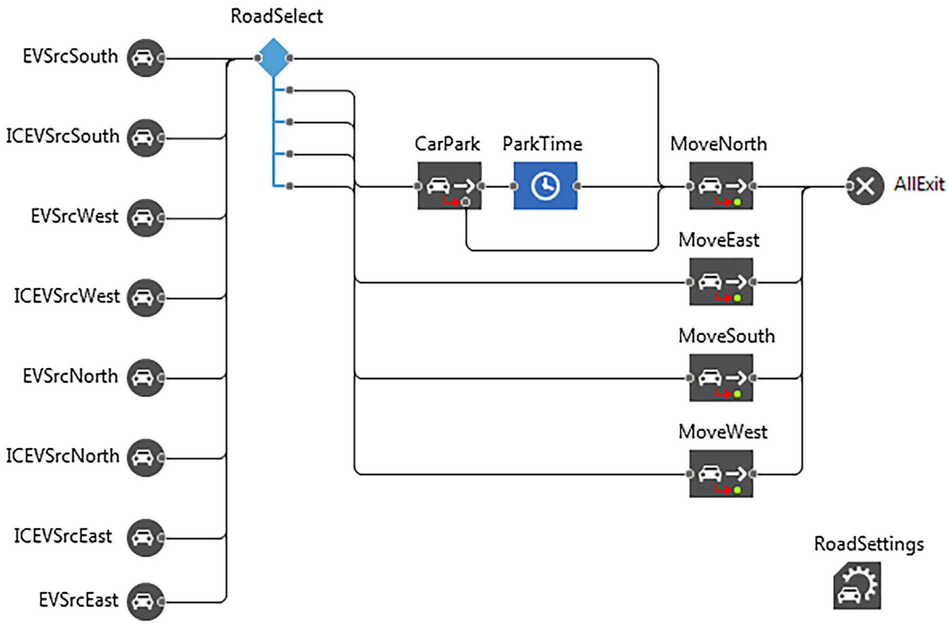

Fig. 4. The logic chart for car objects in AnyLogic.

them into the specified location inside a road network (on a road or in a parking lot). Arrivals of cars can be defined by inter-arrival times, arrival rate, rate schedule, arrival schedule, or inject function calls. CarDispose removes a car from the model and CarMoveTo block controls the car movement. A car can only move while inside a CarMoveTo block. When a car enters CarMoveTo, it calculates the way from its current location to the specified destination. The destination can be road, parking lot, bus stop or stop line. If the destination is a road, car will first move along the shortest way to the beginning of the road and then move along this road till exit. If there is no way from the car's current location to the specified destination, car exits the block. TrafficLight block simulates the traffic light through signaling device positioned at road intersections, pedestrian crossings, and other locations to control conflicting flows of traffic. RoadNetworkDescriptor block allows setting actions which will be executed for each car in the following cases: on entering network, on entering road, on changing the lane, etc. This block also enables road density map that displays the current state of traffic jams on roads of the network. In addition to Road Traffic Library blocks, Process Modeling Library blocks are used to in the logic model. The Select block determines their turning directions using the defined probability distribution, while the Delay block is used to keep parked vehicle objects in the parking lot for a given time interval. Finally, when all of the vehicle objects in the model complete their instructions, they exit the environment through the exit blocks.

The behavior of the pedestrian agents is similarly defined using the blocks available from AnyLogic's Pedestrian Library. This library is dedicated to simulate pedestrian flows in a physical environment. It allows creating models of pedestrian buildings (like subway stations, security checks, etc.) or streets. Models allow collecting statistics on pedestrian density in different areas, to assure acceptable performance of service points with hypothetic load, estimate lengths of stay in specific areas, detect potential problems with interior geometry, effect of adding obstacles and many other applications. In models created with Pedestrian Library, pedestrians move in continuous space, reacting on different kinds of obstacles (walls, different kinds of areas) and other pedestrians. Using the Pedestrian Library blocks, pedestrian crossings are placed at four different locations. The pedestrian flow control chart is created as in Fig. 5. Pedestrian models consist of two main parts: environment and behavior. Environment incorporates walls, different areas, services, queues, etc. Generally, environment object consists of its graphical definition, composed by specific space markup shapes. Resources (for instance, services) are also elements of the environment. Pedestrians are formed in the defined environment and moved according to simulated physical rules. On the other hand, pedestrian moves in flowchart just like other agents. Pedestrian flow rules are exactly the same as agent flow rules in Process Modeling Library. The difference is that pedestrians move according to physical rules in the simulated environment.

The simulation model includes four dynamic parameters that can be changed during the simulation using the slider bars: ICEV rate, EV rate, ambient sound level, and ambient illumination level. These parameters are all initially set to default values, and will all be changed dynamically in the sensitivity analysis to be performed in this study. In addition to dynamic parameters, two functions are also defined in the model: Detection Distance and Sight Distance. These functions employ the dynamic parameters and are recalculated at each event time step. Event is a simulation model block that is useful to schedule action in the model. The accident event checks all the pedestrian crossings 5 times per second to detect the accidents between pedestrians and car objects. Agents are main building blocks of AnyLogic model. Agent is a unit of model design that can have behavior, memory (history), timing, contacts, etc. Within an agent; variables, events, state charts, stock and flow diagrams can be defined.

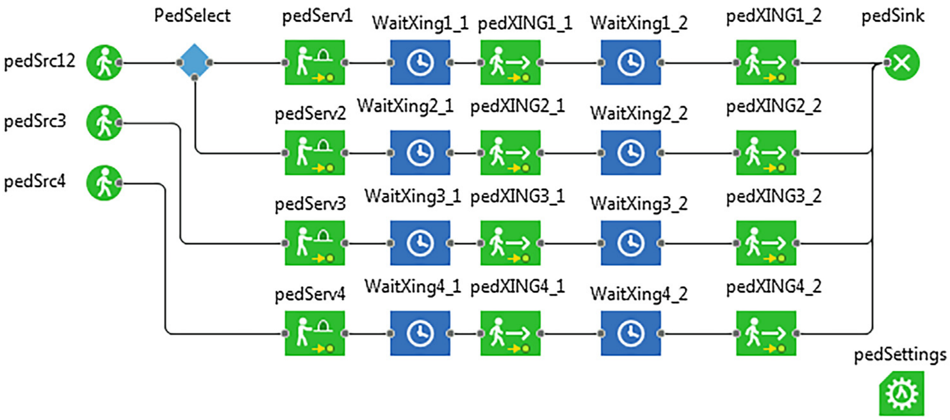

Fig. 5. The logic chart for pedestrian objects in AnyLogic.

2.2. Vehicle pedestrian interaction on crossings and Near-Crash definition

In many cases, such as crashes in which pedestrians are involved, the amount of available crash data is quite small, as such crashes mostly involve physical injuries and are typically reported to the state officials. However, near-crashes in which physical contact does not occur will carry the same risk as crashes do in terms of pedestrian safety. Therefore, the crash algorithm in this traffic safety simulation is extended to include a wider range of incidents by accounting for near-crashes. The National Highway Traffic Safety Administration (NHTSA) defines a near-crash as any circumstance that requires a rapid, evasive maneuver by the participant vehicle or by any other vehicle, pedestrian, cyclist, or animal to avoid a crash (Guo et al., 2010). According to the NHTSA, near-crashes can be used as crash surrogates when analyzing driving data if the causal mechanisms for near-crashes and crashes are the same or are similar. Therefore, near-crashes can also be considered as crashes for purposes of this study. In this study, near-crashes are manually coded within AnyLogic's Java action classes. Inside an event block, the code is executed 5 times per second to detect any near-crash event in the traffic environment, such that the near-crash algorithm basically scans through all of the vehicle objects in the simulation window and retrieves the locations of each near-crash event. If one or more of the vehicles are present inside a crosswalk while a pedestrian is crossing the road, then the event is reported as a crash for the corresponding vehicle type. Furthermore, the pedestrians who failed to see the approaching vehicle but detected it by hearing will stop if the vehicle has passed the auditory detectability distance, which is calculated dynamically using the auditory detectability function. Similarly, the vehicles will also detect pedestrians crossing the road and decelerate if the pedestrians are within the sight distance. For this purpose, imaginary traffic lights that are hidden in the pedestrian crossings are automatically turned on and a red signal is sent to the vehicles. If a vehicle does not stop in time while a pedestrian is crossing the road, a near-crash event will occur. A pseudo-code for the crash algorithm is provided below: The pseudo-code above only presents the primary algorithm logic. On the other hand, the real code is more complex and considers factors such as lane-sensitive crash detection, relative positioning of pixel locations, and so on.

```
int EVcrash; //number of EV crashes
int ICEVcrash; //number of ICEV crashes
for (j = 1;j < = get.roads;j + + ) //Loop through all the roads in the environment
  for (i < cars on road j) //Loop through cars on the selected road
    //When a car passes the detection distance…
    if (Car.location > XING.location - detectDistance(Car.speed))
      Pedestrian.wait(); //Send wait msg to the pedestrians near XING
    //When a car passes the sight distance…
    if (Car.location > XING.location - sightDistance(Car.speed))
      Car.stop(); //The stop message is sent through dummy traffic light
    //Detect a crash when a car is in the crossing
    if (Car.location = XING.location)
      //if there is pedestrian on the road
      if (Pedestrian.isOnXING = true)
        //Report the crash for EVs and ICEVs
        if (get.CarType = "EV")
          EVcrash + +;
      else if (get.CarType = "ICEV")
          ICEVcrash + +;
```

The vehicle and pedestrian behavior is modeled inside agent behavior blocks in Java code. The individual agent behavior is dependent on the interaction between other agents. Basically, a vehicle agent yields to the pedestrian agent and begins deceleration from a safe stopping distance. On the other hand, pedestrian agents perceive an incoming vehicle from an auditory perception distance when they fail to perceive by sight. Similar vehicle-pedestrian agent interaction models were used in the literature (Crociani and Vizzari, 2014). In Fig. 7, the logic chart represents the behavior of vehicle objects approaching to pedestrian crossings. When a vehicle is detected on a road, first its type (EV or ICEV) is registered into an array. Then, Sight Stopping Distance (SSD) is calculated for that vehicle. If there is a pedestrian inside the crossing, the vehicle's distance is checked whether it is smaller than SSD. If that condition is satisfied, a stop signal is sent to the vehicle agent. If a vehicle cannot stop before the yield line and if there is a pedestrian on the same lane, a near-crash condition is generated and stored in an array.

Fig. 8 similarly demonstrates the pedestrian behaviors on the crossing. After a vehicle agent is detected and its type is determined, Auditory Detection Distance (ADD) is calculated. If the vehicle's distance to the crossing is less than ADD, a wait signal is sent to the pedestrian agent. If the vehicle agent is outside of the detection distance, then the pedestrian agent enters the crossing.

2.3. Auditory vehicle detectability by pedestrians

The detection distance is the distance from the vehicle at which the vehicle is first detected, and this distance is estimated dynamically inside the simulation using a prediction equation developed by Emerson et al. (2013). In Emerson et al.'s study, a multivariate regression analysis is carried out based on a set forward and backward vehicle hearing detection under different ambient conditions and for different vehicle sound levels (internal combustion engine vehicles, hybrid vehicles operating in electric mode (EM), and the same hybrid vehicles operating in EM but with five different artificially generated sounds) to find the regression equation constants of the potential predictor variables. The original equation included the following factors in the prediction equation:

- Minimum ambient sound level in unweighted decibels.
- Average and peak wind speed in miles per hour,
- Score on hearing loss questionnaire,
- Hearing loss at 500, 1000, 2000, 4000, and 8000 Hz,
- Vehicle velocity at detection,
- Amplitude modulation depth difference (11 versus 5.5 dB and 11 versus 28 dB),
- Primary modulation frequency band
- Vehicle sound level in decibels, within the following 1:1 octave bands: 63, 125, 250, 500, 1000, 2000, 4000, and 8000 Hz.

The forward detection distance was defined as the distance from the approaching vehicle to the test participant at the time when the participant pulled their detection trigger. The crossing margin on the other hand is defined as the time (in seconds) calculated by subtracting 6.9 s from the time between an experiment participant pulling the trigger and the vehicle in question passing the participant. This 6.9 s represents the time required for a typical person to cross a two-lane street, assuming a crossing width of 24 ft and a walking speed of 3.5 ft/s. Although the simulated roads in this study are four-lane undivided highways, the crossing margins are still calculated for 24 ft instead of 48 ft; because the pedestrians have the tendency to stop in the middle and check for vehicles again. The test results used in parametrization of forward detection distance for subjects with no hearing impairment are summarized in Table 1. The table shows a correlation of the detection distances by the test subjects with different sound modulations including different internal combustion (IC) and electric modes (EM). The data is presented with mean and standard deviation values.

The resulting equation has been simplified in this study in order to include only the following variables:

- Ambient sound level (in dB)
- Vehicle velocity at detection (in mph)
- Vehicle sound level (in dB)

In this simplified equation, some of the variables from the original equation (wind speed, hearing loss, amplitude modulation

Table 1
The forward detection distance and crossing margin for no hearing impairment (Emerson et al., 2013).

Type of Sound	Detection Distance (ft.)		Crossing Margin (s)	
	M	SD	M	SD
Sound 1	560.7	77.8	31.7	4.6
Sound 2	351.0	36.4	16.1	2.3
Sound 3	607.9	63.6	33.4	4.7
Sound 4	464.9	141.1	26.3	0.9
Sound 5	657.2	62.7	41	4.8
Saturn (EM)	451.4	59.1	25.8	4.4
Saturn (IC)	379.3	263.5	18.8	1.9
Prius (EM)	216.5	64.0	8.3	4.3
Cobalt (IC)	346.1	52.8	16.8	3.6

Table 2
The regression coefficients of the simplified prediction equation.

Variables	B	SE B	Range for x (CI = 95%) Lower	Upper
Constant	57.24	8.00		
Ambient sound level (dB)	−0.54	0.15	30	60
Vehicle velocity at detection (mph)	−3.17	0.50	0	35
Vehicle sound level (dB)	0.53	0.15	40	90

difference, etc.) have been input as average values. The annual average for wind speed is taken as 8.5 mph for Orlando downtown area (Florida State University, n.d.), the average modulation of 11 dB is accepted as an input value, and no hearing impairment is assumed among the pedestrians. Furthermore, an average vehicle sound level is chosen for EV and ICEV separately. Hence, the finalized prediction equation becomes:

$$y = \alpha + x_1B_1 + x_2B_2 + x_3B_3 + \varepsilon \tag{1}$$

where y is a continuous dependent variable; α is the regression constant; B_1, B_2 and B_3 are multivariable regression coefficients; x_1, x_1 and x_3 are the predictors; and ε is the regression error. Table 2 summarizes the regression analysis through which the regression coefficient values are found.

From the statistical F-test results, the final prediction equation provides a good estimate for the crossing margin, The detection distance is then found by multiplying the crossing margin by the vehicle velocity at detection (Emerson et al., 2013). The final equation after becomes as in Eq. (2).

$$y = 57.24 - 0.54x_1 - 3.17x_2 + 0.53x_3 \tag{2}$$

where

x_1: Ambient sound level (dB)
x_2: Vehicle velocity at detection (mph)
x_3: Vehicle sound level (dB)

Vehicle sound levels are taken as average values for both EVs and ICEVs, but the sound level is also dependent on vehicle speed and maneuvering (accelerating, decelerating, or maintaining constant speed). Jasic (2009) has conducted a study on approach warning systems for hybrid vehicles, from which a relationship is provided for vehicle speed and equivalent vehicle sound pressure (L_{Aeq}) (JASIC, 2009). The graphical relationship is fitted into a simple linear equation, and thus the following two relationship equations are derived. For EVs,

$$L_{Aeq} = 28 + 1.6 \times V \tag{3}$$

For ICEVs,

$$L_{Aeq} = 48 + 0.9 \times V \tag{4}$$

where

L_{Aeq}: Equivalent sound level (in dB)
V: Vehicle speed (in mph)

AnyLogic dynamically calculates the derived equations 5 times per second for each of the function classes to further ensure simulation accuracy. The above formulation was derived to determine an empirical relationship between vehicle sound and vehicle's detectability. However, the study assumed pedestrians failing to maintain perception of an approaching vehicle by sight. The probability of such pedestrians is represented with a Poisson Probability Distribution function in which the parameter lambda (λ) is varied with ambient illumination level. The pedestrian objects are generated according to the defined probability distribution. The effect of light conditions (daylight, dark–street lights on, dark–no lights, etc.) on number of pedestrians failing perception by sight for approaching vehicles at slow speeds is estimated and the mean found to be 15.4% higher in dark condition when the street lights are on (Wu and Austin, 2010).

2.4. Vehicle stopping sight distance

EV and ICEV driver characteristics differ considerably from each other, primarily in terms of economic status, education levels, and target ages, all of which are prominent factors that define driving behaviors. Studies show that EV drivers are more educated on average, often with higher household incomes than the majority of ICEV drivers (87% of the survey participants who owned **EVs had earned a college degree with an average income of $150,000) (Electric Transportation Engineering Corporation, 2013). Consequently, EV drivers take fewer risks and are generally more likely to stay under the speed limit. This behavior gives EV drivers a better chance to stop on time by having less perception-reaction time, and therefore a shorter Stopping Sight Distance (SSD).

The SSD is defined as the minimum sight distance needed for drivers to see an object on the roadway ahead and safely bring vehicles to a stop before any possible collision can occur (Stein and Neuman, 2007). The SSD is calculated by summing the distances traveled during the perception-reaction time and braking time for the driver in question. Perception-reaction time is determined based on observed behavior on human characteristics such as alertness and visual acuity, as well as the type and condition of the highway. Braking time, on the other hand, is dependent on the vehicle's speed and deceleration capacity (AASHTO, 2001). Based on these factors, the SSD is estimated using the following equation:

$$SSD = 1.47Vt + 1.075\frac{V^2}{a} \tag{5}$$

where

V: Vehicle speed (mph)
t: Perception – reaction time (s)
a: Deceleration rate (ft/s^2)

A function class is created to dynamically calculate the SSD in AnyLogic using the real-time velocities of the simulated vehicles, with mean perception-reaction times of 2.5 s for ICEV drivers and 1.9 s for EV drivers from a normal probability distribution with standard deviations of 0.43 s for ICEV and 0.31 s for EV (Van Themsche, 2015). Since EV drivers tent to be more careful, a higher alertness level was chosen for EV drivers (JASIC, 2009). The effect of vehicle technology on vehicle deceleration capacity has been omitted.

3. Simulation results

3.1. Multi-node cluster simulation using a super-computer

It was intended to execute the developed traffic simulation in AnyLogic for a full simulation year. Therefore, a highly accelerated simulation was needed. For this purpose, the simulation speed was set to the highest rate in AnyLogic (with one model time unit of a second being equivalent to 500 real-time seconds), while CPU allocation was also adjusted to maintain a sufficient CPU power. Additionally, all graphic features were set to their lowest values. However, despite these measures, only one simulation was estimated to take approximately 3 days on a regular computer, so it was quite necessary to use a super computer support considering simulation needs to be run 9000 times for a reliable sensitivity analysis. UCF's Advanced Research Computing Center provided an access to their Newton Visualization Cluster (UCF Advanced Research Computing Center, 2014), which includes two nodes with dual NVIDIA GTX680 cards and one node with a NVIDIA Tesla GP-GPU unit. In order to run the simulation on the Newton cluster, a Linux version of the simulation was created. The simulation model runs over a complete Java platform. Therefore the multimode CPU power was not helpful enough, but the use of a cluster with high graphics performance benefited the analysis greatly. The computation speed of Newton cluster finished the sensitivity analysis in approximately two hours.

3.2. Sensitivity analysis

The traffic simulation in this study is carried out based on several assumptions. First, the traffic flow rates for EVs and ICEVs are assumed not to vary by month or season, latest annual average daily traffic (AADT) count values by Orange County Government of Florida belonging to the simulated intersection were used for the simulation (19,369 vehicles per day in NS direction and 16,859 vehicles per day in EW direction). The pedestrian flow rates are similarly retrieved from Orange County pedestrian counts (45, 52, 52 and 54 per day respectively on the four intersections) (Orange County Traffic Eng. Dpt., 2014). Furthermore, the model's flow rates are set as dynamic parameters that can be changed during the execution of the simulation. The pedestrians near the crossings are put into a queuing process as defined by a Poisson probability distribution function. Similarly, Road Select Blocks define vehicle turns inside the intersection through the use of constant probability distributions. The existence of many different probability distributions and the innate agent behaviors of the vehicle objects provide a visible sensitivity range for the total number of crashes after 9000 consecutive simulations. The sensitivity analysis is then carried out using the Newton cluster. The reason for simulation duration being set to one year is that the total numbers of crashes are very small (between 0 and 2) when it is run for one month, thus cannot produce reliable statistics. Fig. 6 shows number of near crashes per year for EVs and ICEVs under different ambient sound levels and illumination levels. Since the simulation accounts for near-crashes in specific intersection environments and in locations where crashes are more likely to occur, the number of near-crashes is expected to be higher than the amount of actual crashes. Therefore, the analysis output can only be verified by analyzing near-crash numbers relative to each other. The sensitivity analysis results are presented in Fig. 9.

According to the sensitivity analysis results, pedestrian safety comparisons have wide uncertainty ranges between EVs and ICEVs under different ambient sound/illumination conditions. The results show that EVs and ICEVs are both more likely to engage in crashes with pedestrians at night, when the illumination level parameter is set to low during the simulation. Although direct visual detectability is harder at night, auditory detectability increases due to lower ambient sound levels, as high ambient sound levels drastically increase the total number of near crashes for EVs by lowering the chance of their detectability. Although the number of

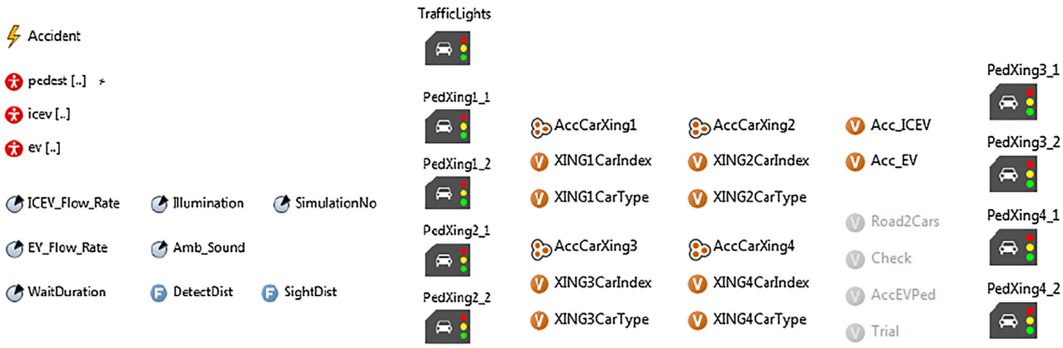

Fig. 6. AnyLogic simulation parameters, variables, functions and agent.

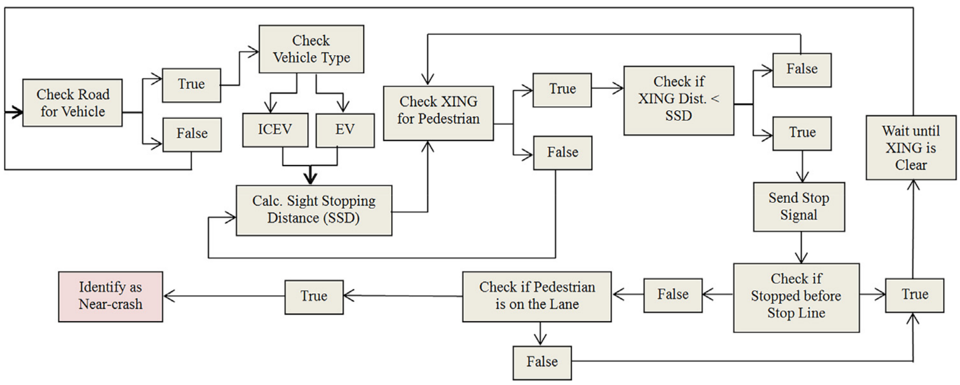

Fig. 7. The logic chart for vehicle behavior in the simulation model.

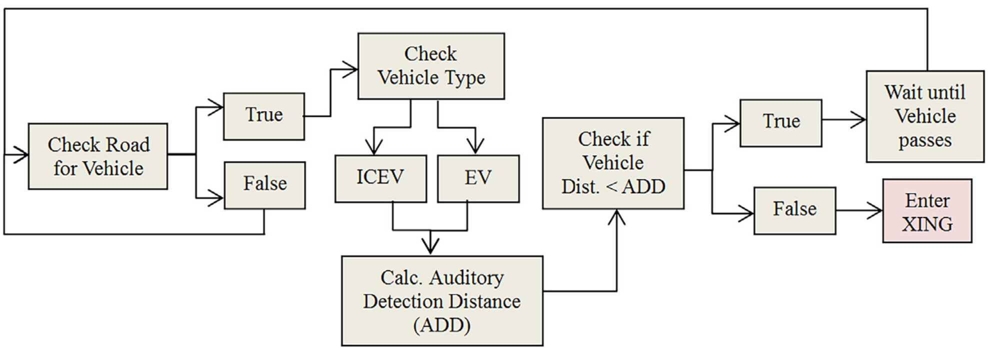

Fig. 8. The logic chart for pedestrian behavior in the simulation model.

near-crashes for ICEVs also increased considerably, a significant difference is seen between two vehicle types. In times with low ambient sound, the auditory detectability of EVs is not seriously low, and the improvements in Stopping Sight Distance (SSD) almost compensate for detectability problems. Overall, both EVs and ICEVs demonstrate a similar number of near-crashes. In all cases, EVs pose a higher traffic safety risk to pedestrians than ICEVs do, although the difference becomes especially critical for situations with higher ambient sound levels and lower illumination levels (nighttime).

3.3. Validation of results

The sensitivity analysis carried out in the simulation shows that EVs pose a greater safety risk than ICEVs (approximately 30% higher safety risk) during the day and when ambient sound levels are high, while the safety risk is relatively lower at night and when ambient sound levels are low. For validation purposes, the gathered results are compared with the relevant statistical data and analysis reports as published by various government institutions. In 2009, for example, the NHTSA released the report “Incidence of Pedestrian and Bicyclist Crashes by Hybrid Electric Passenger Vehicles”, which found that 77 out of the 8387 total EVs and hybrid vehicles (HEVs) that were involved in crash incidents with pedestrians, and that 3578 out of a total of 559,703 ICEVs were reportedly

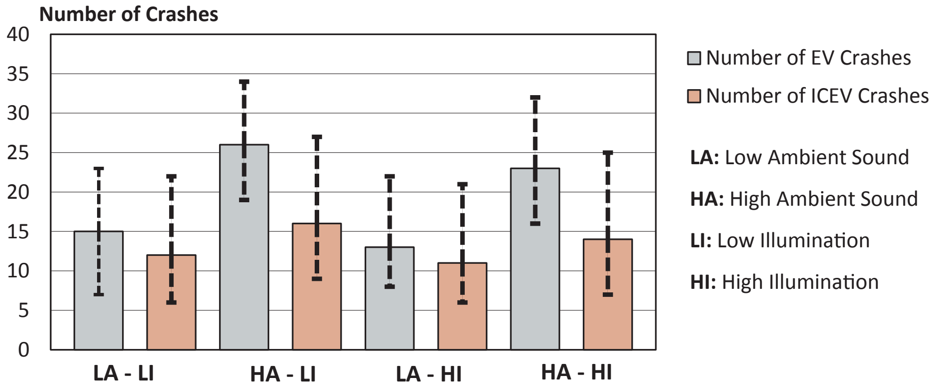

Fig. 9. Sensitivity analysis results of the traffic micro simulation in terms of number of near-crashes.

involved in similar pedestrian crashes (Hanna, 2009). According to the report, HEVs are 40% more likely than ICEVs to be involved in pedestrian crashes. In the updated NHTSA report published in 2010, the odds ratios were recalculated using more extensive crash data to separately evaluate the number of crashes involving pedestrians and/or bicyclists. According to this updated report, 186 out of the 24,297 HEVs and 5699 out of the 1,001,000 ICEVs that were involved in pedestrian crashes, producing a lower odds ratio for HEVs at 20% more crashes than ICEVs (Wu and Austin, 2010). In order to obtain more updated statistics in which more EVs are involved in incidents, a statistical review was carried out using one of the major online crash history databases: the Fatal Analysis Reporting System (FARS) archived by the National Highway Traffic Safety Administration. The recorded fatal crashes from 2010 to 2013 were analyzed to validate the simulation results (National Highway Traffic Safety Administration, 2014). According to the FARS data, hybrid and electric vehicles constitute less than 1% of the total number of fatalities, even though both of these vehicles have recently gained significant popularity in the US market. One of the reasons why these vehicles have very few reported incidents can be attributed to the fact that most of the crashes regarding EVs and hybrid vehicles cause no or little injury, since they mostly occur at very low speeds when the vehicles approach the pedestrians and bicyclists too silently to be detected in time (Chen et al., 2015). The summary provided in Table 3 below compares the number of collisions caused by ICEVs and by EVs/HEVs, with and without non-motorized modes.

The table above shows that EVs/HEVs are 2.7 times more likely to collide with non-motorized users than with other vehicles (non-motorized: 0.67% vs. vehicle: 0.25%) during the daytime, and the chi-square test confirms that this difference is statistically significant ($\chi2 = 6.130$, $p = 0.013$). Furthermore, at nighttime, it was shown that pedestrians and bicyclists are 4.9 times more likely to be involved in collisions with EVs and HEVs (non-motorized: 0.68% vs. vehicle: 0.14%), and this difference is also found to be statistically meaningful ($\chi2 = 27.303$, $p < 0.001$). The FARS data indicates that non-motorized road users are much more vulnerable to EVs and HEVs at nighttime, because vehicles are much less visible during nighttime, requiring pedestrians and bicyclists to rely primarily on sound to detect approaching cars. This strongly implies that EVs and HEVs are riskier because they have lower noise levels, and since the near-crash events in the simulation are not always fatal and EVs are more likely to be involved in non-fatal crashes at low speeds, a higher risk in this regard was indeed expected. Although the FARS data supports the results of the sensitivity analysis, it must be noted that there is very little reported data available for comparison, since most of the EV-involved crashes are not fatal and generally occur at very low vehicle speeds. However, the simulation in this study examines near-crash events, which also include fatal near-crashes.

4. Conclusion

The growing popularity of EVs and HEVs in the U.S. has raised questions about whether or not EVs or HEVs might pose a different crash risk compared to conventional vehicles. Many advocacy groups have asserted that the average EV's/HEV's silent engine is the primary risk factor for pedestrians and cyclists. On the other hand, many other groups claim that EV/HEV drivers tend to be more educated and therefore more likely to obey traffic rules, and that the risks caused by the aforementioned silent engines can be solved

Table 3
Fatal crash history data between 2010 and 2013 from FARS for Hybrids/EVs and ICEVs.

Time period	Collision type	ICEVs	EVs/HEVs	Sum
Daytime	Vehicle-to-vehicle	6051 (99.75%)	15 (0.25%)	6066
	Involving non-motorized users	1330 (99.33%)	9 (0.67%)	1339
	Sum	7381	24	7405
Nighttime	Vehicle-to-vehicle	9705 (99.86%)	14 (0.14%)	9719
	Involving non-motorized users	3926 (99.32%)	27 (0.68%)	3953
	Sum	13,631	41	13,672

using relatively simple methods such as using an artificial sound system, resulting in an almost insignificant effect on overall traffic safety for EVs and HEVs. All of these positive and negative factors were investigated through an agent-based modeling approach in terms of their effects on pedestrian traffic safety. The factors affecting pedestrian safety were split into two model parameters: *auditory vehicle detectability distance* and *vehicle sight stopping distance*. Through 9000 subsequent traffic micro simulations in AnyLogic, a sensitivity analysis was carried out to find the total number of near-crashes involving EVs and ICEVs throughout an entire year, after which the sensitivity results were then compared with real statistical crash data for validation purposes. Based on the simulation results, the following conclusions were drawn:

- Although EVs have lower auditory vehicle detectability distance by pedestrians than ICEVs do (due to their low engine sound levels), EVs have also slightly lower stopping sight distance (SSD), meaning that they are more likely to stop in time when the driver sees a pedestrian who is crossing the road. However, the advantage of EVs in terms of SSD is not strong enough to compensate for their high near-crash risk due to their lower degree of auditory detectability.
- Higher ambient sound levels drastically increase the number of near-crashes for EVs. In rural areas where ambient sound levels are low, EVs pose significantly less safety risk than in urban areas where ambient sound levels are high. ICEVs also pose slightly higher pedestrian safety risks at higher ambient sound levels.
- Ambient illumination is another prominent factor that must be taken into account for pedestrian traffic safety. Under low-light conditions, pedestrians become more dependent on hearing to detect oncoming vehicles, and therefore have a higher crash risk under such conditions.
- Overall, EVs pose a 25% higher risk to pedestrian traffic safety than ICEVs do. Although this safety risk is not as high as that observed in previous statistical reports, there is still a statistically significant difference between the near-crash risks of EVs and ICEVs. Therefore, certain solutions are advised to reduce the safety risk of EVs to pedestrians (artificial sound system, smart warning systems via mobile phones, etc.).

The agent based model developed in this paper indicates the necessity of modifications in the urban designs and highway systems. It is inevitable that EV adoption rate in the future will keep increasing exponentially and therefore will require specific highway design principles, codes and regulations. The incompatibility of EVs into current highway design practice has potential to cause traffic safety issues especially for pedestrians. The main limitation of this agent based model simulation is that it only simulates a specific type of traffic environment in which signalization and pedestrian crossings are present in a simple urban intersection. Another limitation is that the agent based model lacks an advanced pedestrian crossing decision model but rather employs a probabilistic approach for crossing behavior. Furthermore, some important model parameters such as effect of illumination, ambient sound and vehicle sound detectability are based on specific literature studies. With more experimental work and observations, the analytic description of agent relationships can be improved. A further study in the future will address these limitations and extend the scope with more model considerations.

This research can be extended in the future in various ways. First, the simulation environment can be improved significantly by adding cyclist agents, more vehicle types (buses, trucks, emergency vehicles, etc.) and different near-crash mechanisms into the environment. Even the environment itself can be extended to a complete urban city with the help of increased computing power. Secondly, the simulation parameters can be studied further by considering also the increased affordability of EVs in the future and by defining perception reaction time parameters more explicitly to include age and education factors in a clearer way; and these parameters can be supported with statistical data. Lastly, the simulation can also be improved in a way that it touches some of the sustainability solutions such as smart city concept which entails EV communication with pedestrian agents using certain digital warning systems through cell phones.

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