Proceedings of the 2021 IISE Annual Conference
A. Ghate, K. Krishnaiyer, K. Paynabar, eds.

Evaluation of 'Crowd-informing' on Parking Performance and Environmental Emissions: An Agent-Based Simulation of an Urban University Campus

Md Mamunur Rahman [1], Mateo Anthony Galvez [2], Yuan Zhou [1]
[1] Department of Industrial, Manufacturing and Systems Engineering
[2] Department of Civil Engineering
The University of Texas at Arlington
TX 76019, USA

Abstract

In urbanized regions, searching for a parking spot not only demands a substantial amount of valuable time but also burns additional fuel and emits a wide range of harmful pollutants. Vehicular emissions are one of the prime contributors to global warming and a leading cause of many health problems. In this study, we primarily focused to study the environmental impact due to vehicular activity during the parking space search process. As a case study, a high-fidelity microscopic traffic simulation model was developed for an urban university campus with 22 student parking lots to represent the parking behavior using agent-based modeling. To study the environmental impact, a high-resolution emission model was integrated into the simulation model. The necessary data required for this study was collected from field surveys and the university parking and transportation department. The amounts of different harmful pollutants were estimated for the current practice where the students searched for parking spots randomly without any information on the availability of the parking spaces in different parking lots. A what-if scenario was developed where the students were provided real-time information on space availability of the parking lots via 'crowd-informing'. Our simulation results revealed that for the what-if scenario, on average, the vehicles emitted 21.49% less carbon dioxide, took 55.63% less time to park, and burnt 18.65% less gasoline. The promising findings of this study will help the authority to adopt better parking policies which could potentially improve the air quality of the university campuses significantly.

Keywords: Smart Parking; Crowd-informing; Agent-based Modeling; Traffic Simulation; Emission.

1. Introduction

With an overall growth of universities' enrollment, the demand for parking spaces on or close to campus has increased across many campuses. This problem, not unique to university campuses, occurs across many densely urbanized regions across the world. This causes an increasing amount of time to search for a parking spot [1] which, in turn, leads to many problems in the future such as extended car miles, environmental impact, and more expenses on gasoline, not to mention the time wasted in the search for these parking spots and the resulting traffic congestion [2].

Smart parking system (SPS) and informing the users regarding parking availability of the parking lots or 'crowd-informing' using mobile applications are becoming popular day by day. In literature, several studies are found on the effectiveness of crowd-informing on parking performances like search time, parking fee, parking revenue, and walking distance from the parking spot to the destination as performance measures [3]–[5]. However, the number of studies addressing the environmental impacts of 'crowd-informing' or SPS is very limited. A study by Surpris et al. [6] is found in literature in this context where the authors studied a university parking lot to investigate the benefits of SPS on carbon dioxide (CO_2) emission. Their discrete event simulation results showed that smart parking could save on average 11 seconds per vehicle which could reduce 64.3 kg of CO_2 emission during a 19-week academic semester. There are several limitations to this study. First, the authors simulated only one parking lot which is not sufficient to represent the actual total parking system of a university. Second, to estimate CO_2 emission, the authors assumed a constant emission factor, 423 grams/mile, in their simulation model. Practically, CO_2 emission can vary significantly over a travel distance and it is a complex function of vehicle speed, acceleration, mass, aerodynamic drag, and several other factors. Lastly, the authors did not consider other harmful pollutants, e.g., carbon monoxide (CO), nitrogen oxides (NOx), and hydrocarbons (HC), in their model.

In this study, we addressed the aforementioned limitations and investigated the environmental impacts along with parking performances of the SPS using the agent-based modeling (ABM) approach. We integrated a high-resolution emission model into our microscopic traffic simulation. Consequently, the developed model provides a unique capability to evaluate the energy and environmental impact of different parking strategies with high accuracy.

2. Methodology

2.1 Estimation of Vehicular Emissions

Vehicular emissions can be estimated by the average speed emission model or instantaneous emission model. The average speed emission model requires a minimum amount of data and is computationally inexpensive, which makes it suitable for macro-level emission modeling. On the other hand, the instantaneous emission model is computationally expensive but capable of capturing emissions at the project level with great accuracy. In this study, we utilized one of the instantaneous emission models, the vehicle specific power (VSP) demand model which is recommended by the United States Environmental Protection Agency (US EPA) for project-level emission modeling [7]. VSP can be described as the instantaneous power demand per unit mass considering the loads resulting from acceleration, aerodynamic drag, hill climbing, and rolling resistance. It can be calculated utilizing Equation 1 [8].

$$VSP = v(a + g\,sin\theta + \mu_{rr} g\,cos\theta + C_f a) + \frac{1}{2m}\rho_a C_d A_f v^3 \quad (1)$$

where v is the vehicle speed (m/s), a is the acceleration or deceleration (m/s^2), g is the gravitational acceleration (typical value 9.81 m/s^2), θ is the road grade (we assumed 0 $radian$), μ_{rr} is the coefficient of rolling resistance (typical value 0.01), C_f is the mass correction factor (typical value 0.05), m is the vehicle mass (kg), ρ_a is the air density (typical value 1.225 kg/m^3), C_d is the coefficient of aerodynamic drag (typical value 0.32), and A_f is the vehicle frontal surface area (m^2). Once we have second by second VSP values of a vehicle, the corresponding environmental emissions can be estimated from Table 1.

Table 1: VSP bins and corresponding emissions. Source: [8].

VSP	Bin	CO_2 (g/s)	CO (g/s)	NOx (g/s)	HC (g/s)
vsp < -2	1	1.671	0.0078	0.0009	0.0005
-2 ≤ vsp < 0	2	1.458	0.0039	0.0006	0.0003
0 ≤ vsp < 1	3	1.135	0.0033	0.0003	0.0004
1 ≤ vsp < 4	4	2.233	0.0083	0.0012	0.0004
4 ≤ vsp < 7	5	2.920	0.0110	0.0017	0.0005
7 ≤ vsp < 10	6	3.525	0.0170	0.0024	0.0007
10 ≤ vsp < 13	7	4.107	0.0200	0.0031	0.0008
13 ≤ vsp < 16	8	4.635	0.0292	0.0042	0.0010
16 ≤ vsp < 19	9	5.161	0.0355	0.0051	0.0011
19 ≤ vsp < 23	10	5.633	0.0551	0.0059	0.0014
23 ≤ vsp < 28	11	6.535	0.1138	0.0076	0.0021
28 ≤ vsp < 33	12	7.585	0.2076	0.0121	0.0034
33 ≤ vsp < 39	13	9.024	0.4418	0.0155	0.0049
vsp ≥ 39	14	10.088	0.8823	0.0179	0.0109

2.2 Estimation of Fuel Consumption

The amount of fuel consumption at any time can be calculated using Equation 2 [9].

$$FR = \frac{\phi}{\psi\rho}\left(kNV + \frac{P_{engine}/\eta}{1000}\right) \quad (2)$$

where ϕ is the fuel to air mass ratio (typical value 14.7), ψ is the fuel calorific value (45.8 KJ/g for gasoline), ρ is the fuel density (0.7489 g/ml for gasoline), k is the engine friction factor (typical value 0.2), N is the engine speed (rev/min), V is the engine volume (L), P_{engine} is the engine output power (W), and η is the engine thermal efficiency (typical value 0.3). Engine speed N can be calculated using Equation 3.

$$N = 336.13\left(\frac{\alpha_{axle}\alpha_{tr}v_{mph}}{d_{tyr}}\right) \quad (3)$$

where α_{axle} is the axle gear ratio, α_{tr} is the transmission gear ratio, v_{mph} is the vehicle speed ($mile/hour$), and d_{tyr} is the tire diameter ($inch$). Engine output power P_{engine} can be computed using Equation 4.

$$P_{engine} = P_{tract}/\eta_{pt} \quad (4)$$

where P_{tract} is the tractive power required at wheels (W), and η_{pt} is the power train efficiency (typical value 0.85). Tractive power P_{tract} can be calculated utilizing Equation 5.

$$P_{tract} = VSP \times m \tag{5}$$

where VSP is the vehicle-specific power described in Equation 1, and m is the vehicle mass (kg).

3. Simulation Modeling

3.1 Agent-based Modeling

Agent-based modeling (ABM) is a bottom-up robust modeling technique where agents are the constituent units of the system. The macro-level behavior of the system is driven by the agent-agent and agent-environment interactions at a micro-level. ABM is capable of capturing the system behavior at a high level of granularity and this property has made it an excellent choice for modeling complex adaptive systems like microscopic traffic simulation. In this study, we modeled a university parking system using the ABM approach in AnyLogic (University edition 8.5.1), a powerful multimethod simulation modeling software that has been used in complex transportation problems successfully [10], [11]. Figure 1 exhibits the traffic simulation framework where vehicle volume data, vehicle arrival schedule, vehicle attributes, traffic signal, and road network geometry are the primary inputs of the simulation model. Necessary statistics, e.g., time, vehicle index, vehicle type, speed, acceleration, engine speed, and road grade data are collected every second for all the vehicles searching for parking spaces. The collected data are then plugged into the emission model to estimate the amount of CO_2, CO, NOx, and HC emissions.

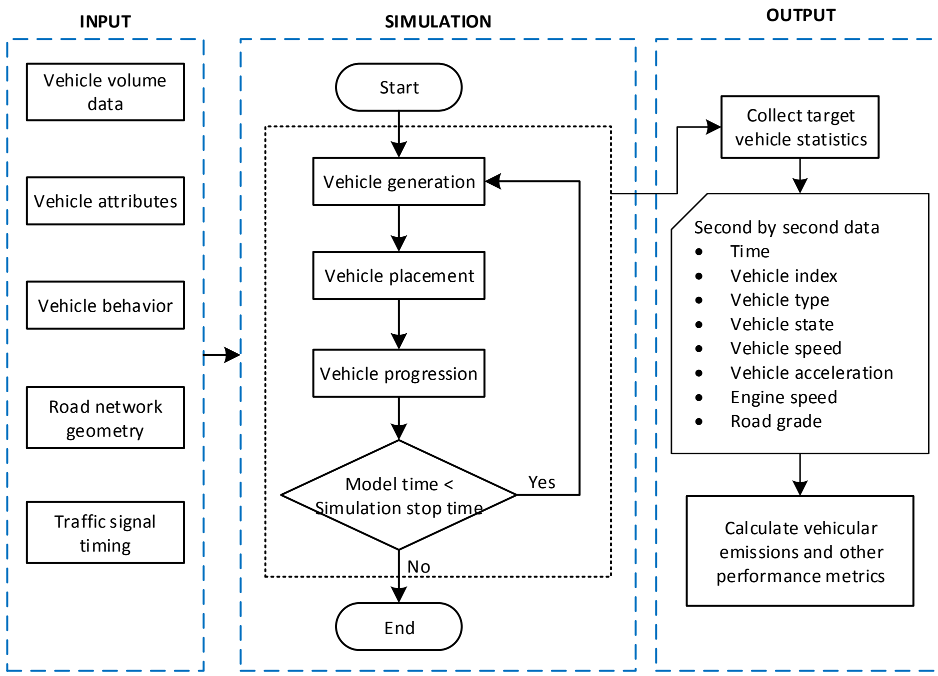

Figure 1: Traffic simulation framework followed in this study

3.2 Case Descriptions and Data collection

In this paper, the University of Texas at Arlington (UTA) campus has been selected as our case study. UTA is located in Arlington, Texas, one of the fastest-growing communities and the 48th most populous city in the United States [12]. The campus is categorized as an urban-type with an area of approximately 420 acres and a student body comprising of 43,939 graduate and undergraduate students. Driving is the predominant mode of transportation to reach the campus and the university has got 21 student general parking lots with an approximate capacity of 9,500 spaces [13]. Figure 2 illustrates the road network and location of the student parking lots in the AnyLogic simulation environment. The data required for this study are collected from the UTA Parking and Transportation Services, UTA Office of Records and Registrations, field survey, and the City of Arlington. These data include the capacity of the parking lots, students' arrival rate, parking demand, class schedules of the students, enrollment of the students, GIS map of the university area, traffic signal timings at road intersections, and street traffic volumes. The primary source of parking demand comes from the students who drive their vehicles to the campus for attending classes. Therefore, students' arrival, destination buildings, and parking demand data of the parking lots have been derived from the class schedule and enrollment data.

3.3 Agents

In the simulation model, two types of vehicles, sedan and SUV, are modeled as two classes of agents with a distribution of 79%, and 21%, respectively. The distribution is obtained from the field survey. Additionally, another class of vehicle agent is considered in the model, which is just a part of the traffic volume on the road network, not intended to park in the university student parking lots. By adding this third vehicle agent class, the on-campus and off-campus traffic flows, which interplay with each other constantly, can be represented in a more realistic manner. The parameters defined for the agents include- vehicle mass, engine volume, engine thermal efficiency, transmission gear ratio, axle gear ratio, power train efficiency, tire diameter, frontal surface area, destination building, parking lot preference order, search start time, search stop time, and parking duration.

3.4 Model Assumptions

Several assumptions are made for the simulation, which include – (a) All working days have the same demand pattern for parking. (b) An additional 10% arrival rate is added with the hourly arrival rate because some students come to campus with their vehicles for different reasons other than attending classes. (c) Only student parking is considered in this study; faculty, staff, and visitors are excluded. (d) Car-pooling is not considered. (e) No unauthorized vehicles park in the student parking lots.

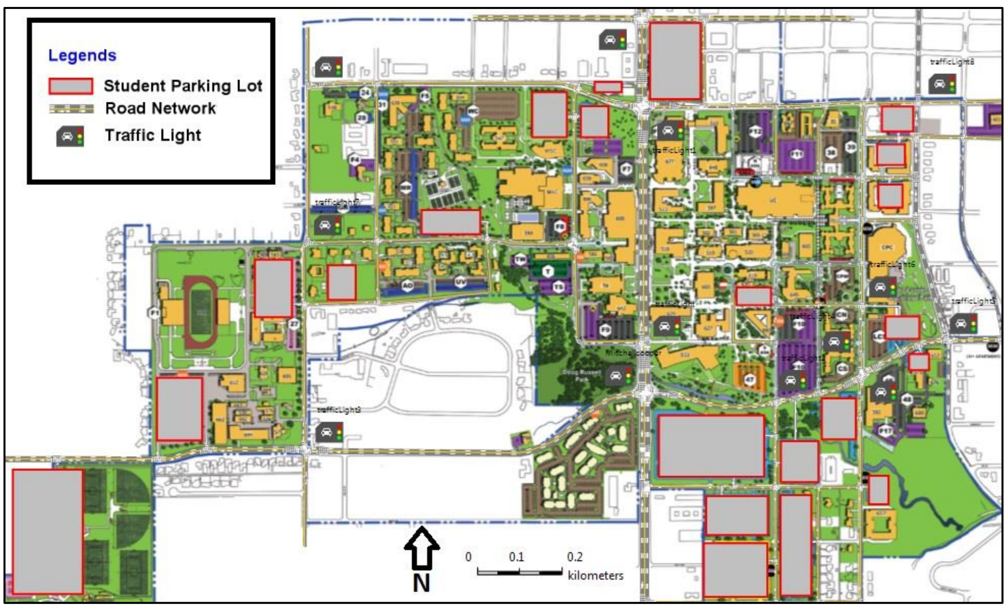

Figure 2: UTA road network and location of student parking lots in the AnyLogic® simulation environment. Base map source: [13]

3.5 Experimental Design

3.5.1 Baseline Scenario

This is the present case of the UTA parking system where the users do not have any sort of information regarding the parking lots' availability. After entering the university area, based on the destination building, a user drives towards his/her preferred parking lot directly. If no spot is available in the parking lot, the driver cruises to the next preferred parking lot, and this loop goes on until s/he could manage an empty parking spot. After parking there for a duration of T, the user exits from the parking lot and finally exits from the system. We assume that the parameter T follows a triangular distribution with a minimum value as 1 hour, maximum value as 10 hours, and mode value as 4 hours.

3.5.2 'Crowd-informing' Scenario

In this case, the users have access to parking lots' space availability information through 'crowd-informing' which can be described as the dissemination of collected and processed data to the target 'crowd' and it can be done through a mobile app or a website. To better understand the impact of 'crowd-informing' on parking efficiency, we presume that a mobile app that enables information dissemination is available. A central database is updated every time a vehicle is parked or exit from a parking lot. Users can get real-time information about the parking lots and choose one for the destination from his/her preference list.

4. Results and discussions

One of the advantages of ABM is that the activity of every agent can be traced distinctly. From our simulation, we collected statistics from every vehicle agent related to parking performance metrics including parking search time, distance driven, the number of lots searched, and fuel burnt during the search process for an empty parking spot. We also collected the related environmental emissions (i.e., CO_2, CO, NOx, and HC) from vehicular parking search activity. The simulation was run for the morning hours (7:00 am to 11:59 am) when the parking lots experience the peak demand for parking.

Figure 3 shows the sample distributions of the related performance metrics for baseline and ‘crowd-informing’ scenarios for a random simulation iteration. As per the plots, baseline distributions are skewed and have longer right tails; this means that the worst situations are more like to happen in the case of baseline scenario compared to the ‘crowd-informing’ scenario. The extreme values of parking search time, visited parking lots, traveled distance, burnt gasoline, and emitted CO_2 are 1,614 seconds (or 27 minutes), 4 lots, 4.7 miles, 1,067 ml, and 3,164 grams CO_2, respectively. On the other hand, as shown in the ‘crowd-informing’ scenario plots, access to real-time parking information not only improves the mean values of the performance metrics but also reduces the extreme cases (relatively shorter right tails of the distributions). For example, the extreme values of parking search time, visited parking lots, traveled distance, burnt gasoline, and emitted CO_2 are 446 seconds (or 7.4 minutes), 2 lots, 2.5 miles, 741 ml, and 1,976 grams CO_2, respectively.

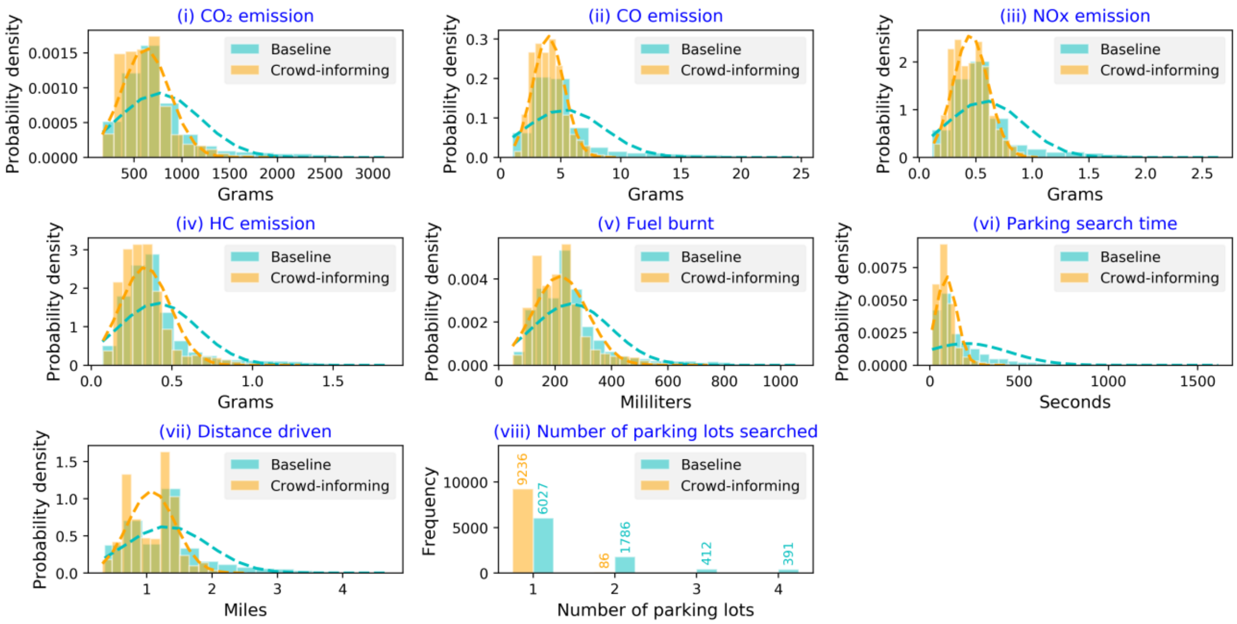

Figure 3: Sample distribution of different performance metrics for different parking strategies

Table 2 depicts the values of mean, standard deviation (SD), and confidence interval (CI) of the performance metrics for both baseline and ‘crowd-informing’ scenarios, and also compares the metrics in between these two. According to the table, if drivers are provided with real-time parking information, on average the search time will decrease by 55.63%, traveled distance will decrease by 18.94%, the number of searched lots will decrease by 43.58%, fuel consumption will decrease by 18.65%. Moreover, 21.49% less CO_2, 27.73% less CO, 23.73% less NOx, and 23.26% less HC will be emitted due to the parking search process. The 99% confidence intervals of the performance metrics for baseline and ‘crowd-informing’ scenarios do not overlap with each other. Therefore, we can say that the mean values of performance metrics for the ‘crowd-informing’ scenario are statistically different from the baseline scenario. Hence, the performance improvements obtained from the ‘crowd-informing’ scenario are statistically significant at the 0.01 level.

There are some limitations of this study. This study did not address the potential safety issue of using the mobile application during driving. Moreover, instead of going to the most preferred parking lot, drivers would utilize their previous experience and drive to the parking lots with a better chance of having empty spots. This aspect of human behavior has not been investigated in our simulation model. Future studies can address these aforementioned limitations.

Table 2: Summary results of the simulation experiments for 50 iterations

Performance metrics	Scenarios	Mean	SD	99% CI	Improvement
Search time (seconds)	Baseline	209.608	10.934	(205.464 - 213.752)	55.63%
	Crowd-informing	92.999	0.936	(92.733 - 93.265)	
Distance travelled (miles)	Baseline	1.320	0.016	(1.314 - 1.326)	18.94%
	Crowd-informing	1.071	0.007	(1.069 - 1.073)	
Number of lots searched	Baseline	1.788	0.030	(1.777 - 1.8)	43.58%
	Crowd-informing	1.005	0.003	(1.004 - 1.006)	
Fuel burnt (ml)	Baseline	264.967	10.822	(260.866 - 269.069)	18.65%
	Crowd-informing	215.559	7.460	(213.439 - 217.679)	
CO_2 emission (grams)	Baseline	780.053	28.386	(769.295 - 790.811)	21.49%
	Crowd-informing	612.448	18.671	(607.142 - 617.754)	
CO emission (grams)	Baseline	5.425	0.134	(5.375 - 5.476)	27.26%
	Crowd-informing	3.953	0.078	(3.931 - 3.976)	
NOx emission (grams)	Baseline	0.591	0.012	(0.587 - 0.596)	23.73%
	Crowd-informing	0.452	0.007	(0.45 - 0.454)	
HC emission (grams)	Baseline	0.426	0.021	(0.418 - 0.434)	23.26%
	Crowd-informing	0.330	0.014	(0.326 - 0.334)	

5. Conclusion

In this study, we used ABM to simulate the complex nature of the parking system of an urban university campus. A high-resolution emission model was integrated into our microscopic traffic simulation to evaluate environmental impacts due to different parking behavior. The developed simulation model can afford a high level of fidelity and sensitivity making it capable of evaluating different intervention strategies to improve the parking process taking into consideration environmental impacts in addition to other parking metrics. In the case study, we measured how the performance metrics changed if real-time parking information became available to the users through ‘crowd-informing’. The simulation results show that both environmental emissions and parking performance metrics improve significantly when users choose parking lots based on real-time parking spot availability information. We expect that the findings of this study will help the policymakers to develop and adopt more effective and environmentally sustainable parking strategies which could potentially improve the air quality of the university campuses.

References

[1] S. D. Boyles, S. Tang, and A. Unnikrishnan, “Parking search equilibrium on a network,” *Transp. Res. Part B Methodol.*, vol. 81, pp. 390–409, Nov. 2015.

[2] W. Liu and N. Geroliminis, “Modeling the morning commute for urban networks with cruising-for-parking: An MFD approach,” *Transp. Res. Part B Methodol.*, vol. 93, pp. 470–494, Nov. 2016.

[3] I. Benenson, K. Martens, and S. Birfir, “PARKAGENT: An agent-based model of parking in the city,” *Comput. Environ. Urban Syst.*, vol. 32, no. 6, pp. 431–439, Nov. 2008.

[4] K. Martens and I. Benenson, “Evaluating urban parking policies with agent-based model of driver parking behavior,” *Transp. Res. Rec.*, vol. 2046, no. 1, pp. 37–44, 2008.

[5] X.-Y. Ni and D. J. Sun, “Agent-based modelling and simulation to assess the impact of parking reservation system,” *J. Adv. Transp.*, vol. 2017, 2017.

[6] G. Surpris, D. Liu, and D. Vincenzi, “How much can a smart parking system save you?,” *Ergon. Des.*, vol. 22, no. 4, pp. 15–20, 2014.

[7] US EPA, “MOVES (Motor Vehicle Emission Simulator) model,” 2014. [Online]. Available: https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=72538&Lab=OTAQ. [Accessed: 24-Apr-2020].

[8] H. C. Frey, A. Unal, J. Chen, S. Li, and C. Xuan, “Methodology for developing modal emission rates for EPA’s multi-scale motor vehicle & equipment emission system,” *Ann Arbor, Michigan US Environ. Prot. Agency*, 2002.

[9] M. Ross and F. An, “The Use of Fuel by Spark Ignition Engines,” *SAE Transactions*, vol. 102. SAE International, pp. 478–487, 1993.

[10] M. M. Rahman, Y. Zhou, and J. Rogers, “Performance Evaluation of Median U-Turn Intersection for Alleviating Traffic Congestion: An Agent-Based Simulation Study,” in *IISE Annual Conference*, 2019.

[11] E. Karaaslan, M. Noori, J. Lee, L. Wang, O. Tatari, and M. Abdel-Aty, “Modeling the effect of electric vehicle adoption on pedestrian traffic safety: An agent-based approach,” *Transp. Res. Part C Emerg. Technol.*, vol. 93, pp. 198–210, 2018.

[12] US Census Bureau, “City and Town Population Totals: 2010-2018,” 2018. [Online]. Available: https://www.census.gov/data/tables/time-series/demo/popest/2010s-total-cities-and-towns.html. [Accessed: 23-Apr-2020].

[13] UTA, “Parking and Transportation Services – The University of Texas at Arlington,” 2020. [Online]. Available: https://www.uta.edu/pats/maps/general-parking-map.php. [Accessed: 21-Apr-2020].