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A SYSTEMATIC COMPARISON FOR CONSISTENT SCENARIO DEVELOPMENT USING MICROSCOPIC SIMULATION SOFTWARE

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ABSTRACT

This study aims to explore a methodology that enables the development of consistent traffic microsimulation for emerging traffic and vehicle control technologies for improved mobility and energy efficiency across different modeling platforms. Researchers might study the same application on different platforms and have the need to benchmark across platforms. However, there lacks a systematic study on simulation software comparison, especially for emerging mobility and energy efficiency applications. For this, a systematic scenario development and evaluation approach is presented and demonstrated to compare scenarios generated in different traffic microsimulation platforms. Network-level and vehicle-level trip performance results of the traffic scenario are evaluated in three microscopic simulation platforms — VISSIM, AIMSUN, and SUMO. The results indicate that the network-level performance is consistent among the three software suites except when the demand is high, where the energy consumption performance varies.

1 INTRODUCTION

With the onset of advancements in vehicle and infrastructure sensing capabilities, the availability of high-quality traffic data increases rapidly. These data are frequently used to develop realistic traffic scenarios using microscopic simulation software platforms to assess operations and control strategies for improving mobility and reducing environmental impacts (Saroj et al. 2021; Mutasem Alzoubaidi and Farid 2023). In general, based on the level of detail, traffic simulation models are classified as microscopic, macroscopic, or mesoscopic simulations. In a microscopic simulation, each individual agent (vehicle, road user) reacts to their current environment, and the traffic state results from the individual decisions of the agents (Matthew, Tom V. 2023). That is, individual driver-driver and driver-road interactions are modeled within a traffic stream. In comparison, macroscopic models focus on the traffic flow (i.e., aggregated traffic volumes) without considering individual agents.(Matthew, Tom V. 2023).

Traffic microsimulation software, like AIMSUN, PTV VISSIM, Corsim, Transmodeler, Simulation of Urban Mobility (SUMO), and Paramics are commonly used for such studies. The software can differ from one another in several criteria (Ejercito et al. 2017), such as open source and free use, operating system portability, creating traffic networks and associated vehicle patterns, quality of the graphic user interface (GUI) and documentation, simulation output (data and files), ability to simulate very large traffic networks, ability to simulate macroscopic simulations and central processing unit (CPU) and memory performance. The same application might be studied on different platforms by different researchers, and a cross-platform benchmark is needed. With the rise in the use of machine learning, deep learning, reinforcement learning algorithm-based applications that are trained on simulation scenarios (Han et al. 2022; Naing et al. 2021; Eriksen et al. 2020; Vázquez et al. 2020; Gamarra et al. 2021), it becomes crucial to have a consistent scenario that allows the use of the already developed algorithms on one platform to be used on another platform to further improve the algorithms or provide comparisons with newly developed algorithms. In this paper, a consistent scenario is defined as a traffic simulation scenario that produces comparable performance measures for the application being studied across different simulation platforms when developed using the same key data input, such as traffic demand, control, network, etc. However, due to the underlying distinctions in the parameter values and distributions of different traffic simulation platforms used to simulate vehicles on the network, simulation-generated performance measures can differ even for the same traffic scenario.

This study presents a systematic approach to compare the closeness of traffic scenarios developed to study vehicle and traffic control strategies for improved mobility and energy consumption on different microsimulation software platforms. The closeness of the traffic scenario is evaluated based on the approach taken to develop the scenario in the three software platforms compared in the paper, and the performance measures attained for the traffic scenario developed with the same key inputs. In addition, this paper presents a case study comparing the network development efforts and evaluating the results of the same real-world traffic scenario (i.e., traffic network, volumes, turn ratios, intersection operations, and arterial speeds) in three widely used platforms – PTV VISSIM (VISSIM. 2022), AIMSUN (Aimsun. 2022), and SUMO (Lopez et al. 2018).

The presented systematic approach to compare scenarios will establish a foundation for conducting a comparative study of emerging applications in mobility and energy efficiency, such as connected and automated vehicles in everything-in-the-loop (XIL) co-simulation (Shao et al. 2023; Shao et al. 2022; Shao et al. 2023) that use the microsimulation environment with other hardware, software, and vehicle simulators (e.g. CARLA, IPG CarMaker). An example of XIL co-simulation approach is using co-simulation of IPG CarMaker and microsimulation software where IPG CarMaker is used to emulate the detailed dynamic vehicle model and 3D virtual environment, and microsimulation software provides the environment/scenario in which the performance of this vehicle model can be evaluated.

2 LITERATURE REVIEW

Although several comparative studies exist in the literature, further studies are needed as these modeling platforms and tools are constantly being updated. Existing work mostly focused on the network-level comparison of overall traffic characteristics, while vehicle-level evaluation is needed for emerging vehicle and traffic control applications. Furthermore, very few studies included a quantitative and systematic comparison of results from different microscopic simulation software. To our knowledge, no study has conducted a quantitative comparison of performance metrics for VISSIM, SUMO, and AIMSUN.

2.1 Comparative Studies on Traffic Simulation Software

In an earlier comparative study, Maciejewski et al. discussed issues with model construction, calibration, and result analysis for three software – TRANSIMS, SUMO, and VISSIM (Maciejewski 2010). A network in Poland with six signalized intersections was used for this study.

In the paper, the concurrent number of vehicles in the network during the length of the simulation period was compared for the three software – SUMO, TRANSIMS, and VISSIM, when the same traffic volume was given as input. The results indicated that during simulation, the number of vehicles concurrently traversing the network in SUMO was greater than in TRANSIMS and VISSIM by 20% - 25%. However, consistency was observed in increased traffic volume scenarios at congestion initiation and propagation locations.

In another study, VISSIM and CORSIM were compared to simulate a network (Sun, Zhang, and Chen 2013). The study conducted calibration of the simulation network with travel time as the control parameter in the two platforms, followed by a sensitivity analysis using four different traffic input volumes. The average control delay, average queue length, and cross-sectional volume from the two platforms were compared.

In an earlier work (Panwai and Dia 2005), microscopic car-following behavior for VISSIM, AIMSUN, and PARAMICS was compared based on the same input dataset and the same leader vehicle behavior. The car following behavior parameters from the developed scenario were compared to real-world data. The results showed lower error for the Gipps-based model in AIMSUN, while similar error values were observed for the psychophysical car-following model in VISSIM and PARAMICS. In another effort, Passos et al. compared seven microscopic traffic simulators – VISSIM, PARAMICS, AIMSUN, MITSIM, SUMO, MAS-T2er Lab, and ITSUMO (Passos, Rossetti, and Kokkinogenis 2011). The comparison criteria included qualitative discussions on extension capabilities, computational processing approach, entities simulated, agent orientation, simulation approach, and visualization capabilities of the simulation software.

In a comparative study, Ratrout et al. (Ratrout et al. 2009) conducted a review of several macroscopic and microscopic traffic simulation software considering their ability to model freeway operations, urban congested networks, project-level emission modeling, and variations in delay and capacity estimates. This study highlighted that AIMSUN, CORSIM, and VISSIM were suitable for modeling congested arterial roads and freeway networks. A similar effort was carried out by Pell et al. (Pell et al. 2017), where a qualitative comparative study to investigate the abilities of seventeen different microscopic traffic simulation software to perform real-time or online simulations was conducted. The study provided a qualitative comparison of the presence of different modeling criteria, such as model size restrictions, intelligent transportation systems functionalities, and modeled objects and phenomena in the software. In another effort, Saidallah et al. (Saidallah et al. 2016) provided a qualitative comparison of eleven different software including AIMSUN, CORSIM, and SUMO. The comparison included criteria such as the maximum area that can be simulated, map import-ability from Geographic Information Systems (GIS), and the complexity of road network development.

In a 2017 study, Ejercito et al. presented a comparison of MATSim, SUMO, AIMSUN, and PTV VISSIM based on criteria such as software ownership - open source or commercial, operating system portability, creating traffic networks and associated vehicle patterns, quality of GUI, and documentation (Ejercito et al. 2017). This study highlighted that the GUI of AIMSUN and SUMO was easier to use than the GUI of VISSIM. Further, the study also noted that VISSIM is a good platform for simulating large traffic networks. In a recent 2022 study (Martinez-Estupiñan et al. 2022), AIMSUN 8.2.0 and SUMO 1.3.1 are compared. The study compared network-level traffic characteristic values such as average speed, average density, and average travel time and found the values to be similar for both platforms.

2.2 Overview of PTV VISSIM, AIMSUN, and SUMO

VISSIM is a commercial, time step-oriented, behavior-based microscopic traffic simulation tool by the PTV Group, capable of modeling multi-modal traffic. It offers a VISSIM component object model (COM) interface that allows access to the network elements using object model hierarchy using programming languages like C, C++, Python, and VB.Net (VISSIM. 2022).

AIMSUN is a commercial traffic simulation software used in transportation planning and engineering, to model multi-modal and multi-scale mobility. It comes with a built-in toolkit that can be further enhanced and extended with Python scripts, APIs, and software development kits (SDKs) (Aimsun. 2022).

SUMO is a free, open-source microscopic, multi-modal traffic simulation platform implemented in C++. SUMO offers high interoperability through the use of Extensible Markup Language (XML) documents. SUMO has several applications, such as `netconvert`, `netgenerate`, and `duarouter`, etc., that assist with simulation scenario generation (Lopez et al. 2018).

2.3 Overview of this Paper

In the literature, most studies provided a qualitative comparison of the different microsimulation software based on their abilities. Further, in the few studies in the literature that compared microsimulation platform performances quantitatively, either network/system level performance or vehicle/agent level performance were compared. The closeness of models developed on different microsimulation software at both network and vehicle levels is critical for emerging traffic and vehicle control studies. A closer look at distributions of vehicle-level performances is needed than statistical averages. Therefore, this paper demonstrates a systematic approach presented in Figure 1 to develop a consistent scenario and compare it across three simulation platforms.

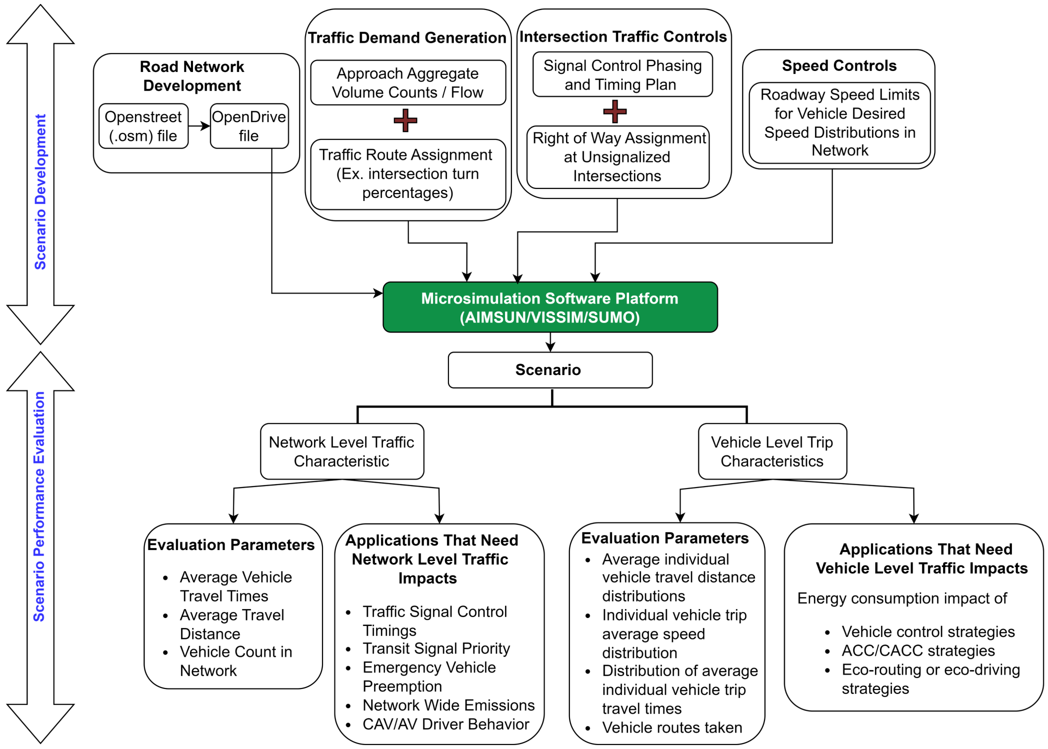


Figure 1: Systematic approach for scenario development and performance evaluation comparison across different microscopic simulation software based on application.

The first step – *Scenario Development* focuses on the development of roadway network geometry, followed by demand generation, route assignments, setting signalized and unsignalized intersection controls, and speed limits in the network. The second step – *Scenario Performance Evaluation* presents the network-level and vehicle-level traffic performance measures that need to be assessed considering the intended application of the scenario. For example, to evaluate different scenarios developed to study emerging vehicle and traffic control strategies for energy efficiency, a suitable comparison would include the distributions of vehicle-level characteristics in addition to simply comparing traffic-level statistics. In the next sections, this systematic approach was implemented using a case study.

3 COMPARISON OF TRAFFIC SCENARIO DEVELOPMENT USING A CASE STUDY

To perform a comparison of the network development process and performance measures from the three microsimulation platforms – VISSIM, SUMO, and AIMSUN, the same scenario was created in the three platforms. A portion of the Downtown Chattanooga network was selected for this case study, as a real-world data-calibrated SUMO network file has already been developed in a previous project by the research team (Park et al. 2022; Yin et al. 2023).

3.1 Network Development

Networks in OpenStreetMap (`.osm` file) can be converted to OpenDRIVE (`.xodr`) files using SUMOs' netconvert command line application (SUMO. nd). However, network development using OpenStreetMap and OpenDRIVE is still challenging. For example, OpenStreetMap does not provide accurate information about the number of lanes, speed limit, intersection geometry, etc. In addition, OpenStreetMap relies on its community of contributors to update and maintain the map data. This decentralized approach can lead to inconsistencies and delays in updating the map. These limitations often lead to a need for manual intervention to fix the mismatch between real-world road geometry and generated network.

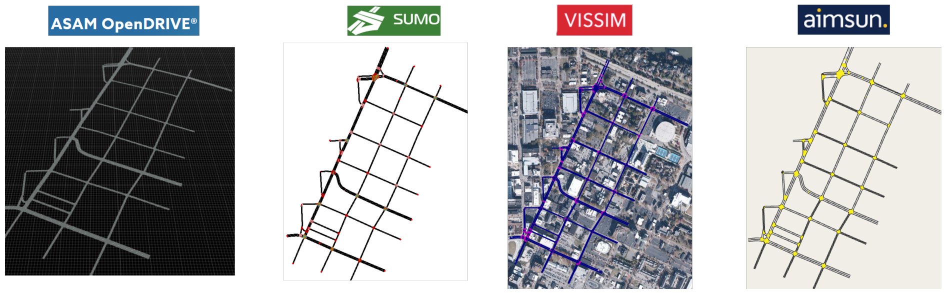


Figure 2: Chattanooga Downtown road network developed using OpenDRIVE (.xodr) file.

The pre-developed SUMO file with the Downtown Chattanooga network was converted to an OpenDRIVE file (`.xodr`) using the `netconvert` command line application of SUMO (SUMO. nd). The OpenDRIVE network files (`.xodr`) can be imported to VISSIM, SUMO, and AIMSUN. The SUMO converted OpenDRIVE Chattanooga Downtown network was imported to VISSIM and AIMSUN to create roadway geometry. Figure 2 shows the network files generated originally in SUMO and later in VISSIM and AIMSUN by importing the SUMO-converted OpenDRIVE file.

Network Import Differences: A network is defined using *Junctions* (intersections) and *Edges* in SUMO and Nodes (intersections) and Sections in AIMSUN; Whereas in VISSIM, the basic network format consists of Links and Connectors. In VISSIM, the intersection is defined using overlapping links/connectors between different approaches to the intersection, whereas in AIMSUN and SUMO, this geometry is an area with a fixed route from one approach to another. This increases the chances of potentially unrealistic network geometry in VISSIM when an OpenDRIVE file is imported. Some of the network geometry errors found in VISSIM for the Chattanooga Downtown network were related to link and connector overlaps, the presence of many unnecessary link and connector linkages, or the presence of open links (links that were not connected at all). This highlighted the need to automate the identification of the network geometry errors in the three software to expedite the accurate network development process.

3.2 Traffic Demand Generation

For this case study, real-world demand data from the previous study were used. The demand data consist of 10-minute volume aggregates at the boundary entry links of the network and 10-minute turn movement percentages at every junction approach. Ten-minute aggregate volume counts were obtained for the evening peak hours, i.e., 3 PM – 6 PM, starting at entry links of the network boundary.

VISSIM: network objects – ‘vehicle inputs’, ‘time intervals for vehicle inputs’, and ‘vehicle composition’ were used to assign 10-minute volume aggregates at the entry links of the network boundary in an automated way using VISSIM COM. ‘static route decisions’ were used to provide input for percentages for different turns from each approach. The assignment of turn percentage values was automated using VISSIM COM.

SUMO: XML files containing vehicle flow (10-minute aggregated volumes) and turn ratio information were used to generate vehicle routes in SUMO. SUMOs’ routing application `jtrrouter` was used to create vehicle routes by turn probabilities (`.rou`) file that is primarily used to run the scenario in SUMO.

AIMSUN: Traffic State in AIMSUN consists of input flows and turn percentage for each time slice (10-min interval). This was used to define the demand in this case study. In AIMSUN, at each intersection, each vehicle determines its movement (turning movement and lane choice) for the next three intersections or four sections (including the one it is currently on) based on the input of the traffic state. This decision of movement is dynamically updated every time the vehicle crosses an intersection.

3.3 Signalized Intersections

The network consisted of 11 signalized and 20 plus unsignalized intersections. Field signal phasing and timing plans collected from the real world were used in this case study. For simplicity, the historical signal timing was implemented as fixed signal timing plans. The same finalized signal plan for the 11 intersections was implemented in the three software platforms to ensure a uniform control scenario.

The signal control setup GUI and procedure to define phases and timing plan are different in each platform. In SUMO, signal timings could be defined per lane per turn movement while in VISSIM a signal phasing and timing plan is typically defined only at per lane level using the signal head and signal controller network object. In AIMSUN, signal timing is defined for each turning movement instead of each lane.

The signal timing configuration setup was performed manually on the three platforms. It is possible to automate the signal control setup process using VISSIM COM and New Ring-Barrier-Control module in VISSIM 22 that provides editable JSON files with signal controller parameters. However, complete automation of signal control generation is challenging, since it requires determining the location of the placement of the 'signal head' object on VISSIM links. In comparison, in SUMO, the `.net` XML file format can be used to automate the signal timing assignment process. A common challenge to automate the signal control setup in the three microsimulation platforms is the need to determine an accurate phase order configuration, along with signal timing and phasing plans. For this, to avoid an erroneous signal phase implementation if the signal phase layout plan is not available from the city, an actual field view of signal heads is needed. These reasons make configuring signal timing and phasing plans in the simulation a time-consuming process irrespective of the platform used in this study.

3.4 Unsignalized Intersection

The GUI and objects required to set up yield or stop control at the unsignalized intersections are different in the three platforms. Although this was done manually, it could be automated. However, like signalized intersection setup, unsignalized intersection setup also needs to include information from the field on the intersection configuration, making it complex to completely automate. In VISSIM, this involves setting priorities for movements in the conflict area. In SUMO, the control of each junction is defined by setting the type of junction, such as "all-way stop" and "priority stop". In AIMSUN, each turning movement is assigned with no control, stop control, yield (to a specific movement), and right turn on red during the defining of intersections. To create comparable scenarios, the same yield control configuration at all unsignalized intersections was applied in the network in the three software.

3.5 Roadway Speeds

Roadway speeds were defined in the three platforms manually. Often roadway speeds are obtained from field view thus, making it complex to completely automate. To ensure similar vehicle speed assignment across the network in all three software, the same link/edge speeds were assigned in the three software.

4 RESULTS OF CASE STUDY

In this case study, the network and traffic attributes, e.g., maximum acceleration distribution, and car following parameters, were not tuned at this stage in VISSIM, AIMSUN, and SUMO. As a first step, this enabled us to identify the minimal set of parameters that need to be the same or tuned across the three platforms to achieve a consistent scenario. The results of the case study provided insight on the choice of next set of parameters that need to be focused on for a consistent scenario development.

A series of simulations were conducted to study the closeness of the performance evaluation results. To study impacts of traffic and vehicle control strategies on mobility and environmental impacts, important network traffic characteristics, such as average travel time and average speed, in the network were studied. In addition, the distribution of vehicle travel characteristics were also studied. Results from a single run from the three platforms were first compared to investigate individual vehicle-level travel characteristics. For comparison of network-level traffic characteristics, results from ten simulation runs with different random seeds from the three platforms were compared. Furthermore, to investigate the sensitivity of traffic demand to model results, ten replicate trials were run for the three demand scenarios: 1) Base case: original demand levels, 2) High demand case: the demand for the network was increased by 25%, and 3) Low demand case: the demand for the network was decreased by 25%.

4.1 Comparison of Vehicle Level Performance Measures

Individual vehicle trip characteristics from the single run on the three simulation platforms were compared for the three demand scenarios – base, high demand, and low demand. Figure 3 shows the distribution of the average vehicle speed, and Figure 4 shows the distribution of vehicle travel time in the network for the three demand scenarios on the three platforms. Individual vehicle travel characteristics for the base case and low-demand case show that consistent vehicle-level results were obtained from the three platforms using the previous scenario development approach. However, results of the high-demand case in VISSIM exhibit differences in average vehicle speed and average travel time distributions compared to AIMSUN and SUMO. The results indicate that different from SUMO and AIMSUN, the scenario in VISSIM had a higher number of vehicles experiencing lower average speeds under higher demand or congestion. The differences in sensitivity of demand variation on vehicle-level performance in different software indicates a need for calibration to different demand scenarios.

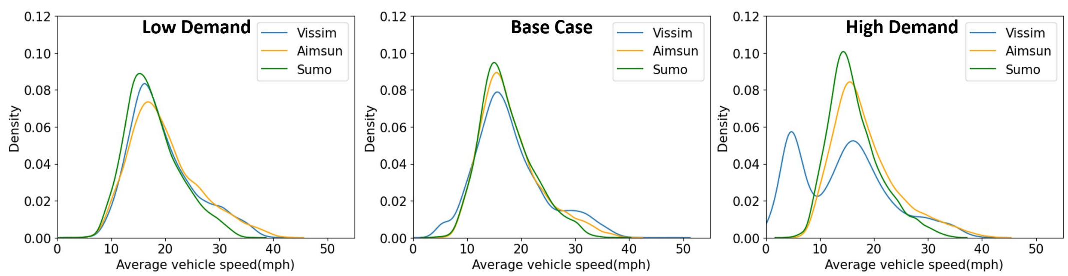


Figure 3: Kernel density estimate plots for vehicle average speed.

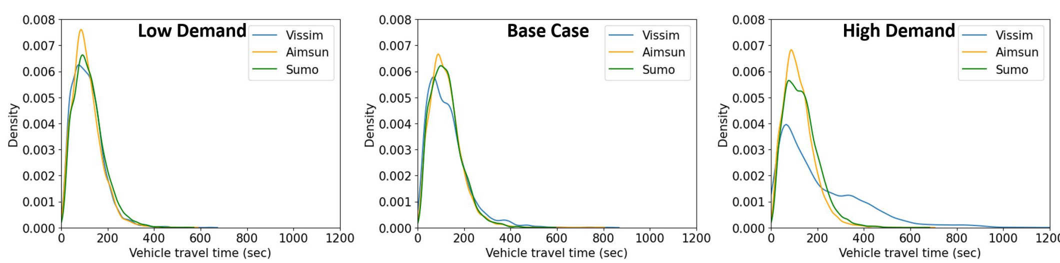


Figure 4: Kernel density estimate plots for vehicle travel time.

Figure 5 shows the distribution of instantaneous vehicle speeds observed for all vehicles in the network for the three platforms in the base case. Higher vehicle speeds were observed in AIMSUN when compared to those in the other two software for low and high demand cases. Further, the increment in the frequency of vehicles with lower speeds from low demand to base to high demand for VISSIM is evident in the figure. While the desired speed value is the same in all three software, the desired speed distribution parameters were not calibrated to be the same. The results indicate that calibration of desired speed distribution parameters for different demand scenarios is important for comparable scenario development across different platforms.

Figures 3, 4, and 5 show that the distribution of commonly used traffic performance measures - speed and travel time at the vehicle level are similar for the three software for the base case. However, for energy consumption-focused applications, acceleration values are also important. In general, microsimulation models are used to attain high fidelity (typically between 1Hz to 10 Hz) vehicle level speed and acceleration data. This data is then used to estimate vehicle energy consumption. In terms of the microscopic energy consumption model, the VT-Micro (Jaeyoung Kwak and Lee 2012), Vehicle-Specific-Power (Bin Al Islam, Abdul Aziz, and Hajbabaie 2021), and Comprehensive Modal Emission Model (Alshayeb, Stevanovic, and Effinger 2022) have been used in signal timing optimization studies.

In this case study, the polynomial fuel consumption model VT-Micro was used to obtain the energy consumption of the vehicle for the base case. Figure 6a shows the instantaneous acceleration distribution of all vehicles for base case in the range of 0 to 15 ft/s^2 while Figure 6b shows the fuel efficiency distribution. The vehicle acceleration distributions significantly differ in the three software. These differences contribute to the differences observed in the vehicle fuel efficiency distribution seen in Figure 6b. In AIMSUN, a few vehicles had very low fuel efficiency (<0.5 mpg), which is not included in Figure 6b. These vehicles also observed an unrealistic acceleration value (>24.7 ft/s^2). These findings show the importance of calibrating acceleration-related parameters such as desired acceleration/deceleration distribution, maximum acceleration/deceleration distribution, car following parameters, etc., especially for energy-focused applications. Hence, performance evaluation comparison and parameter calibration should align with the application focus for consistent scenario generation across different platforms (Figure 1).

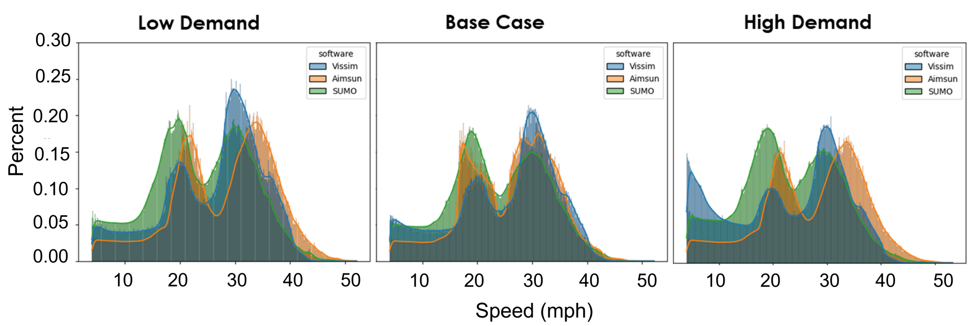
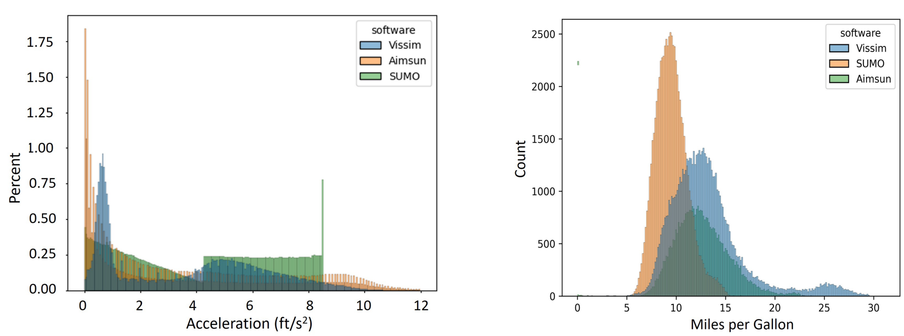


Figure 5: Distribution of instantaneous vehicle speeds (>4 mph) for all vehicles in the three platforms.



(a) Vehicle acceleration distribution

(b) Vehicle fuel efficiency distribution

Figure 6: Distribution plots in the three platforms for base case scenario

4.2 Comparison of Network Level Performance Measures

Network-level traffic performance characteristics for the three demand levels in the three platforms were compared. Performance measures – including the count of vehicles in the network, average travel time of vehicles completing the trip, and average distance traveled by all vehicles – of every 10-minute interval of the simulation period were obtained. These values were compared for the three platforms for each of the three demand cases. Moreover, to avoid making conclusions based on a single-run performance and to investigate the variations in performance measures for different random seeds, ten replicate trials were run for the three demand levels.

Figure 7 and Figure 8 show the network level performance measures observed. These plots show that the network level performance is consistent for the three platforms for the low demand scenario. The counts of vehicles in the network were consistent for low and high demand scenarios in the three platforms. However, for the high demand scenario in Figure 8, VISSIM shows different results than SUMO and AIMSUN for the average travel time by all vehicles completing the trip and the average distance traveled by all vehicles, in the 10-min time interval on the X axis. The difference in these results was observed since the second interval from the start of the simulation. Along with a difference in these values, a higher variation across different random seeds was also observed in VISSIM for average travel time.

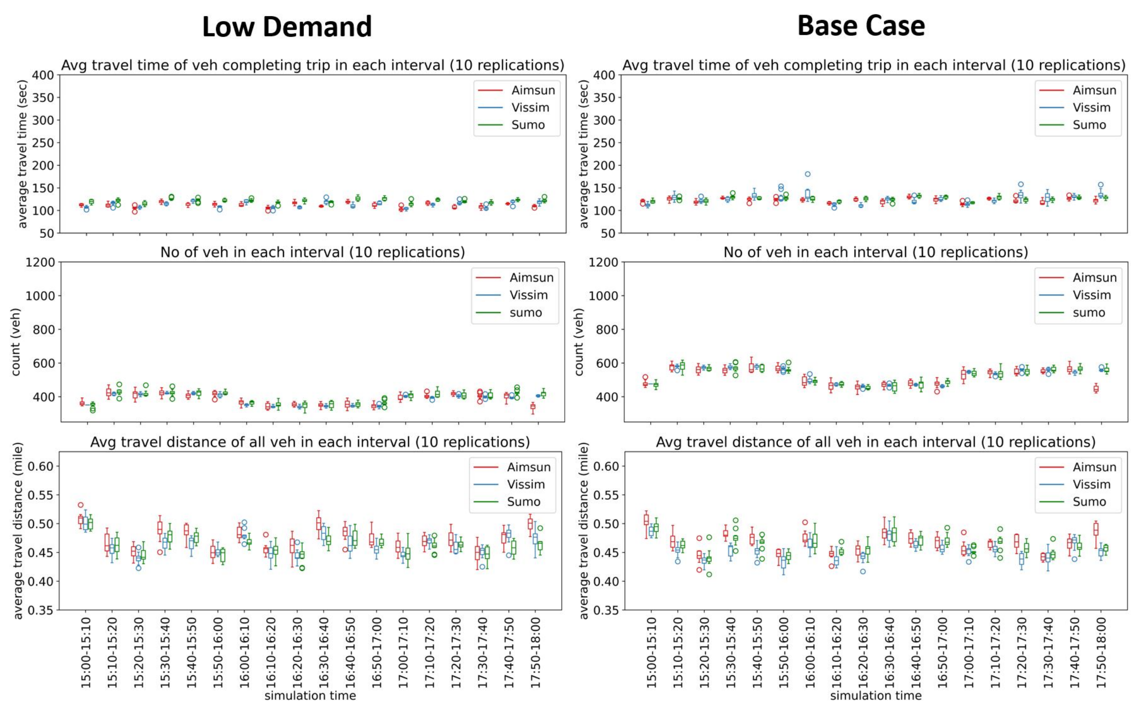


Figure 7: Comparison of boxplots of number of vehicles in network, average travel time for all vehicle ending trip, and average distance traveled in each time interval for low demand case and base case.

The differences observed in the high demand case indicate that calibration for different demand situations is needed for consistent scenario development across the platforms. In general, results of this simulation case study show that different simulation platforms require different levels of calibrations depending on the level of traffic demand. It is crucial to recognize the key parameters that impact network level and vehicle level performances in a software to attain a consistent scenario. Without a consistent scenario development and comparison methodology, traffic and vehicle control strategies can produce different impact results for energy performance in different platforms.

Lastly, vehicle routes traveled across the three platforms were compared. Many emerging vehicle and traffic control technologies aim to study route-specific energy and mobility impacts (Saroj, Roy, Guin, and Hunter 2021), such as eco–routing (Huang and Peng 2018), eco-driving, and other energy efficient vehicle control strategies (Shao and Sun 2021; Sun et al. 2022). In this case study, for demand generation, turn ratios at different junction approaches were used along with the traffic demand. This meant that the

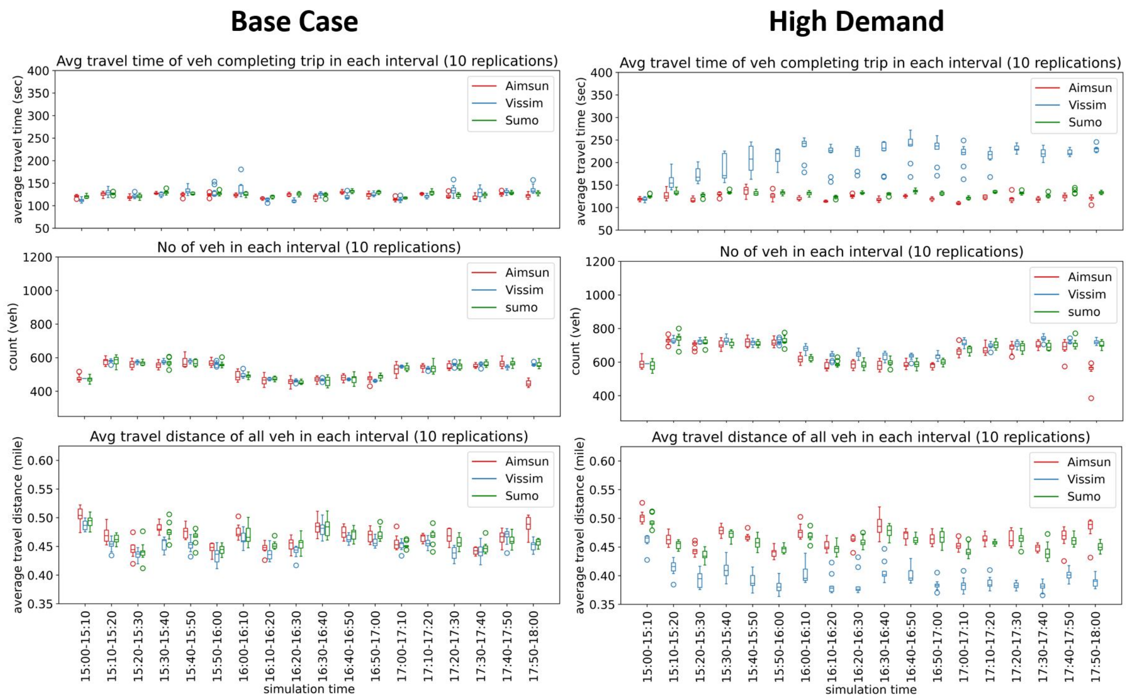


Figure 8: Comparison of boxplots of number of vehicles in network, average travel time for all vehicle ending trip, and average distance traveled in each time interval for base case and high demand case.

vehicles were assigned a turn at each junction approach based on the turn ratios in the simulation. It can lead to vehicles taking unrealistic routes like a longer U-turn. The five most frequent routes and their orders were identical in the three platforms, indicating some consistency in observed routes. However, the routes themselves may not be realistic. This routing behavior may not be a concern (Hunter 2021) when studying mobility or energy impacts at the network level where primarily only aggregated traffic performance matters.

5 CONCLUSION AND FUTURE WORK

In this study, a systematic approach was proposed to compare the development and evaluation of the traffic scenario on different traffic microsimulation platforms to study vehicle and traffic control strategies for improved mobility and energy efficiency using a case study. The approach consists of two key components: 1) Scenario Development, and 2) Scenario Performance Evaluation. The Chattanooga Downtown traffic scenario is developed on three platforms with the same demand, turn ratios, network speeds, and control strategies obtained from the field.

- From the comparison of scenario development,it is noted that OpenDRIVE files can be imported into the three software compared in this study. However, compared to AIMSUN and SUMO, VISSIM has the more comprehensive and complex underlying simulation models and requires attention to further calibrate the network layout.
- From the comparison of scenario performance evaluation it is found that for the base and the low demand cases, the network traffic characteristics and individual trip characteristics for the three software were consistent. This finding indicates the potential and effectiveness of using the scenario development approach followed in the paper to achieve consistent traffic simulation across different microscopic simulation platforms. However, higher travel times with more variations across different random seeds were observed in VISSIM compared to SUMO and AIMSUN in the high demand case. This indicated VISSIM results in more stochasticity than SUMO and Aimsun.

- Lastly, using the VT-Micro model, vehicle fuel efficiency distributions in the base case scenario in the three software are compared. The result reveals that although conventional traffic characteristics are similar across the software, the fuel efficiency distributions and acceleration distributions differ. Overall, the case study highlighted the need to calibrate driver behavior and acceleration parameters for consistent scenario generation for energy consumption-focused applications.

6 ACKNOWLEDGMENTS

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