СРПСКО ДРУШТВО ЗА ПУТЕВЕ
Пут и саобраћај
Journal of Road and Traffic Engineering
Journal homepage: www.putisaobracaj.rs

Towards a fundamental understanding on Microscopic Transportation Simulation of Autonomous Delivery Robots

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ARTICLE INFO

DOI: 10.31075/PIS.70.02.02
Professional paper
Received: 04.04.2024.
Accepted: 28.04.2024.
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Keywords
Autonomous delivery robots
ADRs
Microscopic transportation
Simulation

ABSTRACT

A large number of studies were focused into the adoption of ADRs in the current transportation and logistics, safety in practical applications, and deployment of advanced robotic technology. Only a few contributed to the simulation of microscopic transportation for autonomous delivery robots. Many researchers emphasized the importance of overcoming modelling gaps and covering the scope of simulation as realistically as possible in order to obtain reliable results from the simulation. The versatility of the technology, the nature of the logistics and components of ADR in the real world, and other challenges present challenges to the transportation modeller when it comes to thinking about the possible representation of ADRs in the simulation environment. The gradual development of both computational capacity and underlying behavioural patterns in microscopic traffic simulators opens the door for researchers to develop realistic ADRs model in the microscopic transportation simulation to investigate road interaction and the resulting impacts. This review explored and organized the currently available technologies, operational methods, and simulation components that need to be considered when modelling ADRs in microscopic traffic simulation. Furthermore, this review provides a basic understanding for modellers to address the potential challenges to cope on recent technological developments in ADR modelling and simulation.

1. Introduction

1.1 Motivation and Goal

Last-mile delivery is a problematic phase which attracts the major portion of the total delivery costs (Engesser et al. 2023; Gehrke et al. 2023). The use and popularity of ADRs will increase, as last-mile or sole package delivery, in the near future (Abrams et al. 2021) reaching a stage where it will be necessary to agree to a suitable implementation in the simulated environment before large-scale attainment in the real world. As the scope of simulation is limitless, many scenarios and provision can be evaluated without huge investment.

This emphasises the need of microscopic simulation to assess and to evaluate the impact of ADRs in the logistics. Any form of autonomous vehicle which use roads (acts on car following, lane changing, lane merging, platoon formation) such as car, truck, bus or ADR requires additional input than the conventional vehicle (Guanetti et al. 2018; Rahman et al. 2020). ADR, are relatively new, there is lack of proper provision to model them in available transportation simulation packages (Baum et al. 2019b; Othman 2021). Moreover, the process of technical development of the autonomous unit is complex and moves in three dimensions: Vehicle centric, Network centric and Driver centric as well as Vehicle architecture (Ibañez-Guzmán et al. 2012).

As a result, configuring and modelling the behaviour of an autonomous vehicle, such as ADRs, is difficult and perplexing. Every new change in an existing vehicle model or newly developed model, such as an interaction pattern, need closer monitoring and thorough evaluation to establish the connection between simulation and reality (Ibañez-Guzmán et al. 2012; Rana, Md., M. and Hossain 2023). For Transportation simulation of ADRs, there are not much previous works which can be taken as guideline or benchmark for further extension (Plank et al. 2022). This is where this review paper requires to fill the gap.

This comprehensive review highlights the versatility of the technology, operational method and simulation components that play key roles in the microscopic traffic simulation of ADRs. They are considered as principle factors of ADRs (Plank et al. 2022) which is covered in this review. This is one of the first works of its sort in the area of simulation of the ADRs. This research is organised into 8 sections. Section 2 states method which is followed to prepare this study. Section 3 states variations in critical components of autonomous delivery robot automation such as connectivity, permissibility in the useable road area, internal system architecture, optimization method, and emergency safety plan to avoid an accident. Section 4 describes the impact of logistical verities in the microscopic simulation of the delivery robots.

Component of the microscopic simulation is elaborated in Section 5. After that section 6 connects the components of the classical microscopic simulation with modelling newly introduced, delivery robots (and autonomous delivery robots). It addresses the physical representation, car-following model, lane changing model, lane merging model and lateral behaviours. This section also discusses the performance metrics which have potentiality to be Key Performance Indicator (KPI). Various challenges based on simulation of ADRs are expended in section 7. Finally, in section 8, the summary of this review paper is presented along with model building suggestion for transportation modeller.

1.2 Current State of the ADR

Autonomous vehicles are aware of their surroundings and can make decisions based on various settings such as logic and environmental perception without the need for human intervention (Zhang et al. 2019). To meet the transport demand in a safe and efficient way, researchers are pushing passenger transport and goods delivery towards autonomous technology for all modes of transport, such as public transportation, passenger car, truck and micro-mobility. Autonomous Delivery Robots (ADRs) are already being used under confined area for food and grocery deliveries, proven to be effective as last-mile logistic unit (Figliozzi and Jennings 2020; Hoffmann and Prause 2018). By design, the ADR belongs to micro-mobility family and covers relatively short range in lower speed for ensuring road safety and public acceptance (Jennings and Figliozzi 2019). They can appear as automation level between 1 to 5 (SAE 2021), as per Society of Automotive Engineers (SAE), to meet the service purpose under the economical and the technological limitation.

A level 3 ADR could be LAURA (In German words: Lauenburgs AUtomatisierte Roboter Auslieferung), functions as a last mile delivery mode, introduced by Institute for Transportation Planning and Logistics and the Institute of Logistics Engineering of Hamburg University of Technology (TUHH) (Gertz et al. 2022; Blunder et al. 2022) which is to be combined with local bus service. It is fully operated and monitored by a traffic control center. Figure 1 presents the LAURA, which is planned as the last mile in the logistic system in combined with the local bus service.

Furthermore, Starship technologies, currently considered as a worldwide leading operator of ADR based delivery, offers exclusive logistical service in minutes in the local neighbourhood. This advanced zero-emission robot has made a significant number of environmentally friendly deliveries and traveled more than 5 million miles (Fusiek 2022). The significate difference between above two examples is the dependency to involvement of local bus service. Starship only delivers the product itself, without taking any intermediate transportation.

Figure 1. LAURA, Autonomous Delivery Robot

Source: (Gertz et al. 2022; Thiel et al. 2021)

1.3 Current State of Simulation of ADR

Transportation simulation is used for assessment of different measures and implementations (Fransson 2018). It promotes robust assessment and real world representative evaluation of various depending parameters of internal or external systems, in an economical and risk-free method. The microscopic simulation offers understanding of interaction among different road agents, macroscopic simulation offers impact of utilization or decision (Kotusevski and Hawick 2009). Microscopic transportation simulators such as PTV VISSIM (Verkehr In Städten - SIMulationsmodell), SUMO (Simulation of Urban MObility) and AIMSUN (Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks), use different mathematical models for the modelling and predicting different road users i.e. Car, Bus, Bicycle. These mathematical models, which go by the names of "car following models," "lane changing models," and "lane merging models," play a critical role in simulating the behaviour of the road user (Dinar 2020; Yuting 2022). Advancement of these built-in models in the packages allow them to figure out the physical action by various real-world inputs i.e. acceleration, deceleration, size (TRB 2015).

However, in today's date, there are only a few studies that deal with traffic simulations for ADRs. It has been identified that the lack of research in the simulation of ADRs was caused from the complexity of the actual world in the depiction of simulation, the nature of realities in vehicle behaviour, the absence of a well-established theory, and mathematical representation (Pani et al. 2020; Plank et al. 2022).

As they are becoming an important part of contemporary transportation system, an evaluation of mass supply of ADRs should be conducted. The reliability of simulation is gradually improving, since computation capacity and algorithm of the computer started evolving (Kotusevski and Hawick 2009). As a consequence, complex transportation simulation is becoming a highly realistic and reliable tools for planning (Alghamdi et al. 2022).

2. Methodogy

As ADRs are a relatively recent research area, there is not much documented information available related to transportation simulation, specially towards GUI based simulators. After scanning 188 published studies, a total of 75 relevant, high-quality research papers and scholarly articles were cited, collected from many sources. These references were taken from the TUHH library and the influential journals i.e. Springler and Elsevier. The online websites were checked for their facts to ensure they were correct before they were added. Since modern disciplines such as ADR overlap with various fields such as communication, robotics and traffic engineering, it is a complex task to identify and to summarize the literature and then direct it towards a single area of research (Snyder 2019). In this work, the microscopic traffic simulation of ADRs emerged as a point of discussion.

This paper intensively included the studies as its references which are required and supportive to the microscopic transportation simulation. Table 1 shows a few keywords and their search results. There were many other keywords but follow keywords were also referring similar contents.

Table 1. Keywords and their search results

Keywords	Search results	Keywords	Search results
Delivery Robots	54	Car Following Model	15
Microscopic Simulation	32	Lane Changing Model	10
Performance metrics	18	Parcel delivery	10
Connectivity	16	Lane Merging Model	8
Autonomous Delivery Robots	16	Logistic Simulation	8

3. Automation of Delivery Robots

3.1 Connectivity in Autonomous Level

Before starting with the technical details of the automation, here are the nomenclature currently being used worldwide in research and industry. There are total 5 levels (level 1- level 5) between human-driven vehicles (HVs) and automated vehicles (AVs) (SAE 2021). Connectivity is an important topic to be discussed in the automation sector. It can be implemented by the cellular or Wi-Fi connectivity. Vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and even vehicle-to-cloud (V2C) come under the Vehicle-to-everything (V2X) network. A human-driven vehicle with V2X, is a connected human-driven vehicle (CHV). In contrary, an automated vehicle with V2X connectivity function can be named as Connected automated vehicle (CAV). Table 2 shows the combination between control and connectivity.

Table 2. Combination between control and connectivity

	Without V2X	With V2X
Controlled by Human	Human-driven Vehicle (HV)	Connected Human-driven Vehicle (CHV)
Controlled by Computer	Automated Vehicle (AV)	Connected automated vehicle (CAV)

Source: (Ersal et al. 2020; Guanetti et al. 2018)

The world of automation is steadily growing to reach the higher level of automation. Continuous research and innovation in the automation industry growing the acceptance and expectation of the end users. At this moment, up to level 2 of automation can be found in the market (Cavazza et al. 2019). These automation levels are applicable for any form of automation i.e. Micro-mobility: delivery robots. The development process is currently on the way to meet future's need and expectation. Highest level of automation (Level 5) gives higher degree of freedom on decision making process of manoeuvre, fully recognition of its surroundings and reliable automation in system (SAE 2021). Such level of automation comes with a price of infrastructural development, connectivity, public acceptance and expenses. In return, the end users might get higher degree of safety and relaxation through incrementing level of automation (Ersal et al. 2020; Yang et al. 2022; Faisal et al. 2019).

Table 3 depicts the role of driver/ remote operator for advancing automation level. This is an inspired idea from Society of Automotive Engineers (SAE 2021). Lower automation level requires fully focus driver who can run the vehicle directly. Higher automation level can totally manage manoeuvre without role of any in-vehicle driver or remote operator. They are capable to re-route and re-plan themselves. It comes with a higher cost; the intermediate level could be a good offer in such situations.

The intermediate automation level offers average automation which is relatively cheaper and easier to implement. These intermediate levels need any time takeover by the in-vehicle driver or remote operator if situation demands such as re-routing and re-planning.

Table 3. Role of end users for advancing automation level

Automation as per Society of Automotive Engineers (SAE)		
Level	In-vehicle Driver	Remote operator
0	Driver	Not applicable
1		
2		Fallback step
3	Fallback step	
4	No driver	Remote control
5		

Source: (SAE 2021)

3.2 System Architecture

Architecture of the automated driving control play a significant role in the behaviour of automated vehicles. Replacing the conventional vehicle with automation to reach a higher level of connectivity and faster reaction time, a good combination of sensors, data processing capacity and effective decision making process need to work synchronically (Blunder et al. 2022; Ziegenbein et al. 2022). It should have also emergency take over and emergency lock function. Figure 2 demonstrates the architecture of automated driving control. Automated vehicles perceive its surroundings by data collection via sensors. Manoeuvres decisions are taken with high precision. The planning and control are basically mathematical models (Kuutti et al. 2018). To make automated vehicles highly capable like the human-driven vehicle, high performance controllers are required to assure safety. Data-driven approach such as machine learning and reinforcement learning approaches can be connected with available datasets (Ersal et al. 2020).

3.3 Permissibility

Table 4 depicts the concept of the permissible area for various autonomous vehicles such as autonomous car and autonomous micro-mobility unit for any urban corridor. Any automated vehicle can be varied on access to the Drive lane, Bike lane and Sidewalk. The fastest lane for the vehicle in the street is the drive lane. It is shared by any motor vehicles such as car, bus.
The average speed varies between 40 to 60 km/h in urban drive lane area. In contrary, the bike lane mainly allows bicycles. It is also shared by e-scooters. The average speed is 16 km/h for bike lane. The slowest lane in the street area is the sidewalk (also known as footpath). The sidewalk is dedicated lane for slow road users: pedestrians, wheelchairs. The average speed is 4.5 km/h.

Based on the scope of operation of delivery robots, they are broadly classified as road-based delivery robots and sidewalk-based delivery robots (Figliozzi and Jennings 2020). Whenever necessary, they can be given priority in the mixed lane or can be kept collision free by having dedicated lane. Research has shown that higher degree of traffic performance and safety can be achieved only after a proper penetration of automation in traffic (Dinar 2020). Until the road traffic reaches a significant portion of automation in the traffic, providing dedicated lanes will not be cost worthy (CEDR 2019; Dinar 2020). Moreover, in several cases dedicated lane is not practical even through it can promote safety and public acceptance. Successful implementation of the ADRs in the warehouse with a dedicated lane is possible but they are not feasible in open places. The drive lane is accessible to autonomous car, autonomous bus and autonomous truck. There are three different concepts of delivery robots, depending on their accessibility. Starting with Type I autonomous delivery robots, these modes of transportation can operate on the sidewalk, bike lane, and driving lane. Next, type II autonomous delivery robots are not permitted in the drive lane. Finally, type III autonomous delivery robots are only permitted on sidewalks. Crossing roads, following road guidelines and priority road signs, are regulated by the permissibility plans (Figliozzi and Jennings 2020).

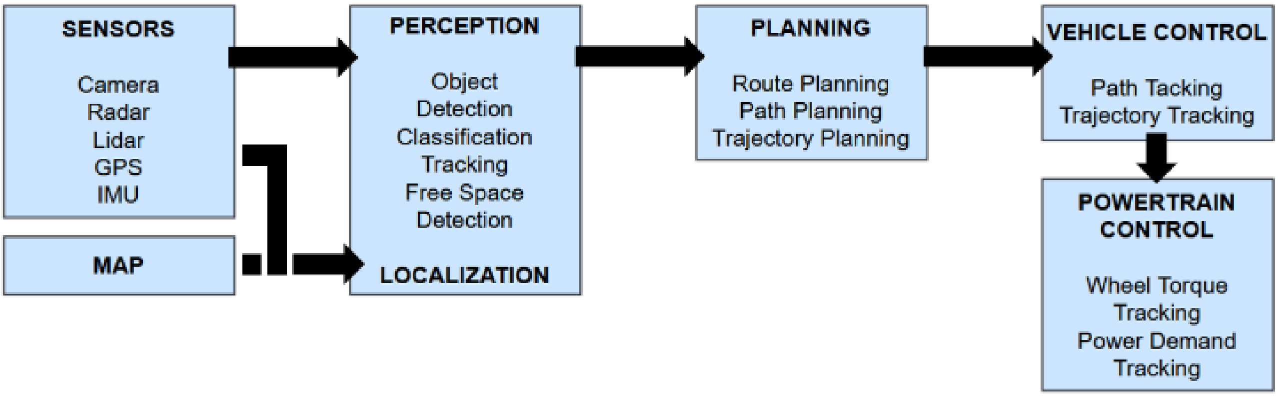

Figure 2. Typical automated driving control architecture
Source: (Ersal et al. 2020)

Table 4. The concept of the permissible area for various autonomous vehicle (Edited in Streetmix)

	Drive lane Average Speed: 40~60 km/hr	**Bike lane Average** Speed: 16 km/hr	**Sidewalk Average** Speed 4.5 km/h
Autonomous Car	✓	✗	✗
Autonomous bus	✓	✗	✗
Autonomous Truck	✓	✗	✗
Autonomous Delivery Robot (Type 1)	✓	✓	✓
Autonomous Delivery Robot (Type 2)	✗	✓	✓
Autonomous Delivery Robot (Type 3)	✗	✗	✓

Source: (Figliozzi and Jennings 2020; Fusiek 2022)

The above mentioned types of the ADR are currently seen in research and in real world. Starship technologies (Fusiek 2022) and Magna (Aurora 2022), are providing Type I, high level autonomy in the industry at this moment. In today's world, type I is often observed operating in confined places, not yet servicing a larger segment.

They can access any part of the road such as motorway and sidewalks (Aurora 2022). In contrary, the technology of type II and III need them to stay away from motorway as they are ADRs of lower autonomy. ADR development begins with Type III and intends to reach Type I during the test phase.

4. Integrated Logistic with ADRs

Previous studies have proven that ADR based logistic consist of control centre, logistic hub and autonomous delivery robot itself for effective management and operation (Gertz et al. 2022). They could be a vital component in the automated logistics (Porsche Consulting 2023). Control centre provides facilities for Fallback take over, connectivity and remote processing unit. Logistic hubs provide/ receive the goods for/from the ADRs (Porsche Consulting 2023). In the logistic hubs goods are received via various modes of transport from factory or delivery operators. Depending on how it serves a purpose, the logistics' nature may be organized. To support the shipment strategy, goods might be stored here. If the load-and-unload time for the items is long enough, delivery robots can recharge wirelessly or have their tires changed.

Road automation logistics models come in a variety of shapes and sizes. The entire delivery can be automated, including the first and last miles (Chen et al. 2021b). The most used method to indicate the part of the supply chain is concept of first/ last/ only mile: First mile delivery is the portion of the product that ships from the supplier's manufacturing facility or warehouse. Middle-mile delivery is the portion of delivery where products are transported from a fulfilment center to a fulfilment facility. Last-mile delivery is the portion of delivery in which the product is transported to the customer's doorstep (Barra 2022). If there is no intermediate stay, then no need of middle-mile logistic is required. The influence on the logistic chain cannot be assessed without addressing its components and integrated logistics behaviours in the transportation simulation. To create a more realistic model, logistical objectives like shared delivery methods, platoon building characteristics, signal slowing down, crowd response, travel plan management, scheduling, and route planning, as well as optimization based on additional factors like cost, congestion, and peak hour, could be implemented (Wen et al. 2018; Bakach et al. 2020).

4.1 Logistic Operation

In today's mobility and logistic industry, users have alternative services come with various features. In a few systems, delivery might occur immediately or at a set time if needed. In last few decades two logistic operations changed the world of passenger and courier service: Demand and Sharing facility.
Now, end users can enjoy service whenever they need and they can share the cost among different users. Figure 3 categorised various non-ownership transportation modes for passenger transport and goods delivery. In today's date, commuters and service takers have alternatives to choose fixed time or on-demand service based on the price. On-demand transportation has gained popularity and will continue to do so (Tsiamasiotis et al. 2021) in passenger transportation and logistics industry. Many of them are already adopted by big corporation i.e. Ottonomy, Magna (Aurora 2022), Starship (Mims 2020).

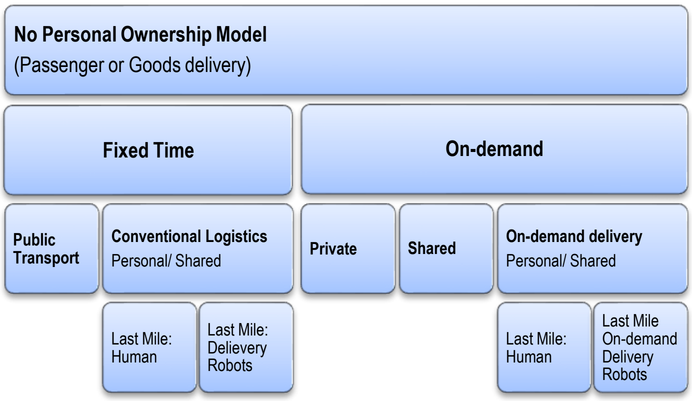

Figure 3. Transportation modes for passenger transport and goods delivery

At this stage, the Starship delivery service supports food, beverage and other parcel delivery. Although it operates primarily in campus areas, the Starship is a strong road agent in last-mile logistics because it can adhere to wild area guidelines and urban road regulations. As discussed above, based on the number of delivery in one-go, the DR logistic can be classified as personal or shared delivery. This classification influences the overall performance of the supply chain. Figure 4 shows an example of personnel and shared delivery for DRs (or ADRs). The route optimization, trip planning, and delivery priority management become aspects to be taken into account in the simulation when advanced form of delivery, and consequently, multiple-factor influenced logistic operation, is chosen.

5. Development of Microscopic simulation

It was challenging for researchers to accurately predict the potential outcomes of the simulation due to the complexity of developing such models in a transportation simulator and choosing appropriate simulation features (Bakach et al. 2020). Additionally, when it comes to delivery robots, there are few ways to calibrate the system and produce reliable results by comparing to secondary or historical data. The lack of a main stream traffic flow caused by these new transport/delivery options might be one explanation. All of this has made simulator developers and theoretical mathematicians less interested in improving the simulation and modelling of delivery robots (Boysen et al. 2018).

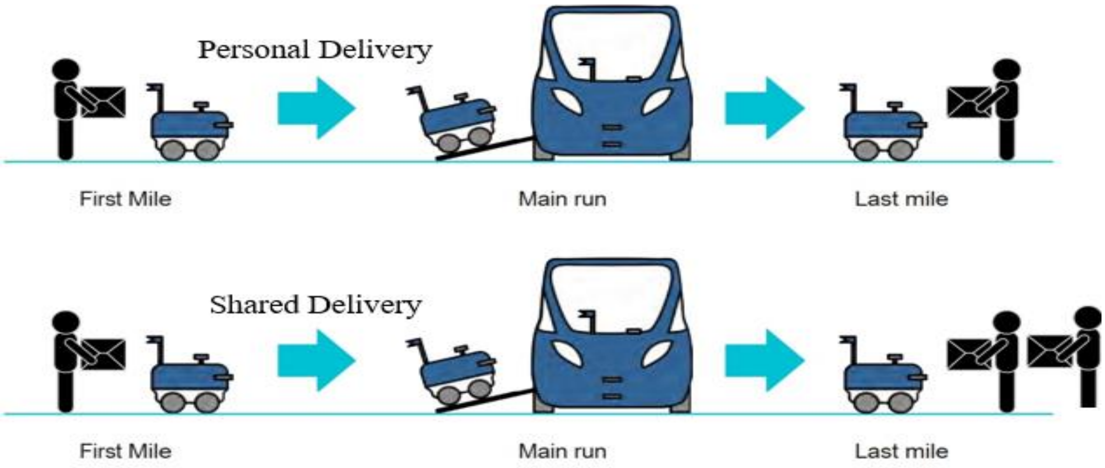

Figure 4. Schematic demonstration of personal and shared delivery covering first and last mile *Source: (Gertz et al. 2022)*

4.2 Optimization

The concept of walking neighbourhood in Europe is steadily pushing logistics into two-tiered delivery system (Poeting et al. 2019) and decision makers started seeing last-mile delivery as an important component in parcel delivery.

The human as last-mile agent in a two-tiered delivery system is expensive, physically effort demanding, and time consuming. Moreover, the irregularities/ uncertainties, generated from human, raises obstacles in logistics. In human-based logistics, irregularities and uncertainties such as delivery delays due to weather conditions, physical limitations, and so forth are typical. The optimization in human based delivery appear from multiple decisions: previous experience, shortest path, travel plan, construction area, duty break plan etc. The delivery robots are not hindered by the human factors and hence, provide wide range of advantages. The delivery system based on robot, set optimization plan in pre-set priorities and logics. It could be also dynamic to satisfy the temporal and spatial demands. Starting with route optimization in a two-tiered delivery system, operation can be maintained while priotorizing minimization of delivery and cost. Same goes for maximizing safety parameters and number of delivery in one go.

In contrary, programming based simulators i.e. MATSim, have been used for analysing the effects of new mobility in transportation system (Qurashi et al. 2020; Chen et al. 2021a) and researchers worked on test-bed to generate data but they do not reflect a complete scenario of the road traffic (Gertz et al. 2022). Figure 5 is prepared to compare different scales/ scopes of transportation simulation. To study the impact caused by any traffic and infrastructure, microscopic transportation simulation set input and analyse the situation in microscopic scale. It exclusively focuses on traffic signals, autonomous connection, driving behaviour, interaction with other road users, and safety elements such potential conflicts to study the interaction and mitigation process of any traffic in the simulated environment (Lücken et al. 2019; Kotusevski and Hawick 2009). Since full automation has not yet been implemented on roads, microscopic models undergo calibration using data gathered from human-driven traffic or test generated data in with the expectation that they will function similarly to human-driven vehicles. This advancement is insufficient and contains several incompatibilities with modelling the automation of ADRs. To achieve a robust depiction of the actual world in the simulation component of microscopic simulation, automations have to be changed to overcome data unavailability and modelling limitation.

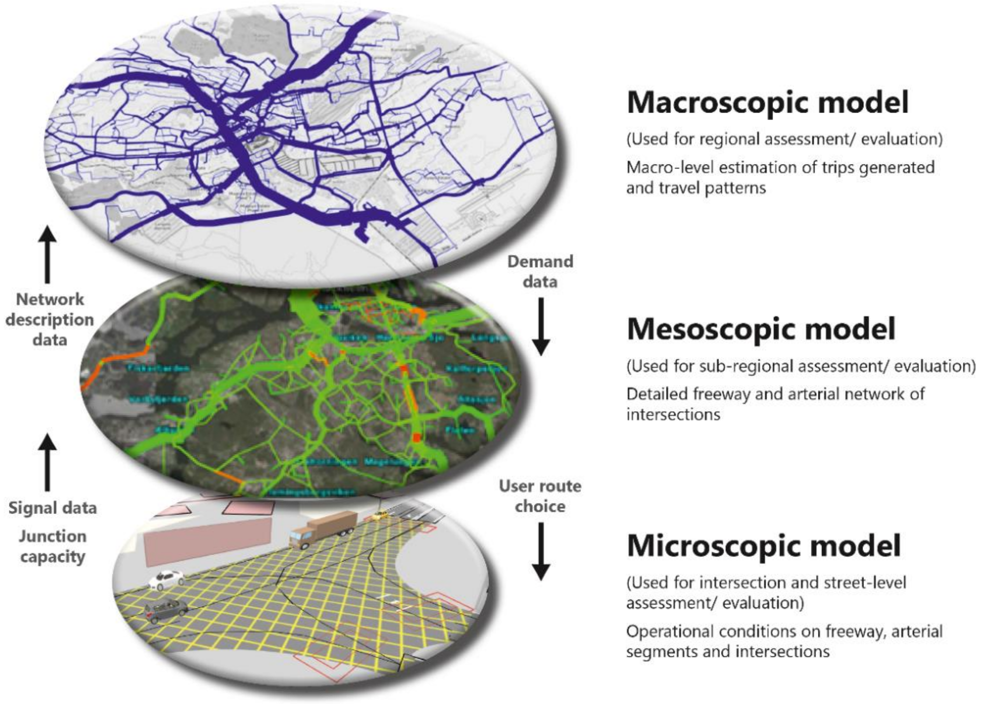

Figure 5. Comparison among different scale/ scope of transportation simulation

5.1 Transportation simulation vs. Logistic simulation

Logistics simulation is quite different from transportation simulation or microscopic transportation simulation. The scenarios and their evaluations differ significantly in the transportation simulation from the logistics simulation. Table 5 shows variation in scenario for the microscopic transportation simulation and the logistics simulation, currently seen.

Table 5. Variation in scenario for the microscopic transportation simulation and the logistics simulation

	Microscopic transportation simulation	Logistics simulation
Scope of simulation	Traffic performance, Safety concern, Interaction with other road users, connectivity, Public transport scheduling, Route planning	Cost Optimization, Storage and inventory, Production and capacity analysis, Supply route optimization, Warehouse design, Staff requirement analysis
Scenario	Number of vehicle, Time of the day, Time of the year, Travel demand and supply, Before and after implementation	Stages in delivery, Demand and supply of goods, Size and shape of the warehouse, Modes of delivery, Number of staffs
Example of Simulators	Aimsun Next, PTV VISSIM, Sumo	Anylogistix, FlexSim, Simplan

5.2 Component of microscopic simulation

The number of input and output parameters affects simulation models. Figure 6 visualizes a standard work plan for microscopic simulation, inspired by (Hellinga 1998). First, the trip description is used to determine the destination and departure time. Second, the network geometry gives physical information about the geometry: the number of lanes and the size.

The third input is traffic flow, which contains information about traffic volume. Depending on the situation, the results can include a variety of data, such as traffic performance, vehicle trajectories, and so on (Alghamdi et al. 2022). In traffic simulation, there are many influential parameters that control the behavior and interaction of the vehicles. Interaction of the vehicles control, for example, the route selection, the driving behavior and the choice of the shortest route selection.

Calibration and validation are done by adjusting such parameters. Calibration ensures that the model represents a realistic model (Dadashzadeh et al. 2019). In contrary, validation makes sure the model is universe and generate same quality of outcomes for other scenario (Brockfeld et al. 2005). Calibration and validation function on measure of effectiveness (MoE), which is real-world data, i.e. travel time, which is used to alter the input parameter in the simulation model. The settings are adjusted based on the quality of goodness of fit (GoF) (Dadashzadeh et al. 2019). Continuous development via harmonisation and calibration, as well as anticipated driving modules, aggressive-normal-cautious, is exposing automation's potential action (Sonnleitner and Friedrich 2020).

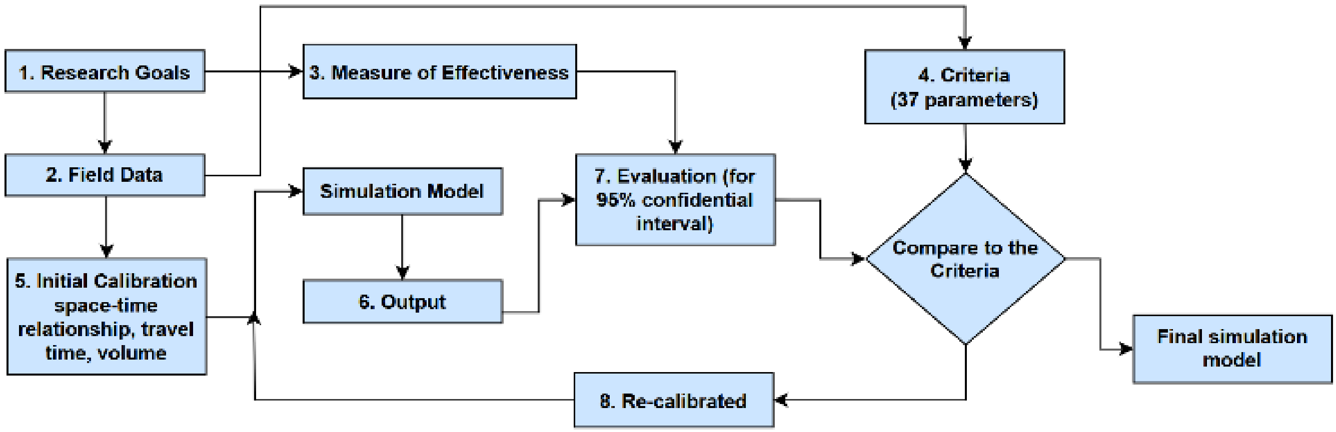

Figure 6. Standard work plan for microscopic simulation
Source: (Hellinga 1998)

During microscopic simulation more acting agents in the network will require more computational effort and time. For this reason, researchers often scale down the real world in the simulation to reduce computational effort while replicating real-world scenarios as closely as possible. In addition, similar approaches are taken when collecting real-world data, such as traffic volume or house-hold survey.

The microscopic transportation models use the random variables and sample from random distribution. By nature, the traffic in the microscopic simulation is stochastic and dynamic. It is the result of the activities of many actors and various external events (Antoniou and Wagner 2014). A single simulation iteration may significantly skip some occurrences so several iterations are necessary to cover up many occurrences as possible. Simulators average outcomes of different occurrences and matches the quality of expected values of real-world as much as possible (Antoniou and Wagner 2014). US department of transportation recommended an equation to select the number of iteration (Federal Highway Administration 2004):

$$Cl_{1-\alpha\%} = 2 * t_{\left(1-\frac{\alpha}{2}\right),N-1\frac{S}{\sqrt{N}}} \tag{1}$$

Here, $Cl_{(1-\alpha)\%} = (1-\alpha)\%$ confidence interval for the true mean, $t_{\left(1-\frac{\alpha}{2}\right),N-1}$ = statistics for the probability of a two-sided error summing to alpha with N-1 degrees of freedom, N = number of repetitions and S= standard deviation of the model results. Another method to determine the minimum number of simulations required, a simple and straightforward approach could be to run 10 iterations with different random seed (Federal Highway Administration 2004).

6. Modelling of Delivery Robots

Simulation of delivery Robots in microscopic simulation requires a sufficient information setup, comprehension of representation quality, and simulation objective. The physical properties, car following model, lane changing model, lane merging model are examples of input needed for a microscopic transportation simulation. They contain a variety of sub-controllers, including speed control mode, gap control mode, gap-closing control mode, collision avoidance control mode, reaction time, lane keeping, headway fluctuation, lane changing reluctance, breaking intensity (Lücken et al. 2019).

Car following models of ADRs in in microscopic transportation simulation directly deal with how they will manoeuvre or drive along with other road users in the sidewalks or motorways, if allowed to. This is a different scenario than the manoeuvre in warehouses where the speed, acceleration and volume of other robots are controlled. In real world, the behaviours are more diverse and unpredictable. In contrast, lane changing model for ADRs deal with the lane changing possibilities in the sidewalk, lane changing decision making process and lane changing pattern. Together with car following model, the lane changing model avoid collision and ensure safety in the traffic (Ahmed et al. 2021). Lane merging, is special type of lane changing, that take place upon shrinking of forwarding driveway. Lateral behaviour decides on distance a running ADRs and a running vehicle in the driveway or a standing vehicle. These parameters control the overall driving or manoeuvre experiences, hence determine the possible traffic conditions (Fransson 2018; Ramanujam 2007).

Figure 7 categorized driving behaviour, for the microscopic transportation simulation, into two major groups based on the topic of concern: Vehicle and Link. More input information will result in higher-quality and more realistic simulation results (Barceló and Casas 2005). To avoid the congestion and confliction states in the urban neighbourhood, a combination of ADRs with Bus or truck is one of the innovative ideas currently being thoroughly studied, both in experiment and reality (Boysen et al. 2018; Chen et al. 2021a).

It pulls the needs of different road agents for the ADRs, for example, on the sidewalk it behaves like a wheel chair or pedestrian, while in the bus stop or inside the bus it must behave like a pedestrian. These details can be a representation of any empirical relation or physical phenomenon explored from field tests.

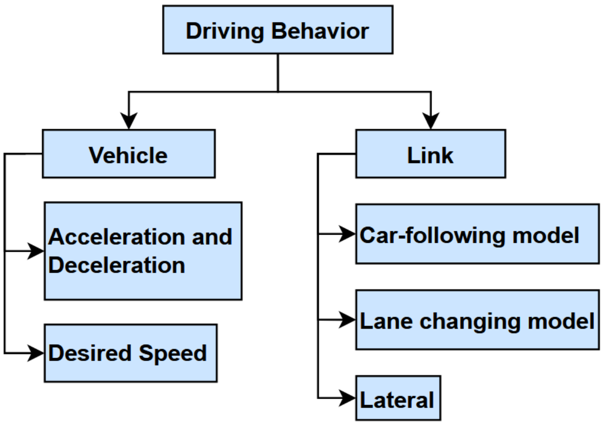

Figure 7 Component of driving behaviour for a vehicle in microscopic transportation simulation
Source: (Ahmed et al. 2021; TRB 2015)

6.1 Physical Representation

The popular and widely used commercial and open source microscopic simulators: AIMSUN, PTV VISSIM or SUMO currently do not contain any delivery robots ready to implement in the simulation run. It is necessary to appropriately define the physical parameters in the simulator to obtain interaction outcomes. Right now, the simulators contain ready physical models for the conventional vehicles such as passenger car, truck, bicycle and pedestrian. Unlike cars, bicycles, and other road users, DRs are versatile in their design and behaviours. It differs depending on the model. Fig.8 shows physical properties for the delivery robot named LAURA built by Institute for Technical Logistics (ITL) of Hamburg Uni. of Technology (Gertz et al. 2022; Thiel et al. 2021).

6.2 Car Following Model

The main objective of the car following model is to ensure that the constrained vehicle reacts to changes in the relative position and speed of the leading vehicle in a continuous stream (Ahmed et al. 2021). Broadly, car following models are divided into four groups based on their underlying concept (Olstam and Tapani 2004). Firstly, the Gazis-Herman-Rothery (GHR) models reflect the actual car following behaviour. This model counts the influential relation between a leader and a follower road user as a stimulus-response type of function. Secondly, the Safety distance or collision models of car following behaviours, ensure a safe distance between the leader and the follower road user. Thirdly, the psycho-physical or action point model works on the range of the thresholds or action points where the driver tends to change the behaviour. Finally, the Fuzzy-logic use fuzzy sets to determine what to close means. It works on conditional state such as if it is too close, it should go for emergency deceleration (Olstam and Tapani 2004). Table 6 shows a few well-known car following models.

At this moment, Gipps model and Wiedemann model are adopted by AIMSUN and PTV VISSIM, respectively for the motorway. Gipps model is a safety distance model. A car-following model based on Wiedemann's proposed psycho-physical model is also included in PTV VISSIM. GHR model supports partially in the behavioural model of MATSIM (Olstam and Tapani 2004). Social force model is being used for describing the bicycle and pedestrians. However, no driving control has been explored for the ADRs of the road (Helbing and Molnár 1995). There are plenty of scopes to explore the driving behaviour and control for the ADRs. Car following behaviours based on the data can be established from the test-bed based manoeuvres. Accurate construction of car following behaviour, lane merging or lane changing control need enough iteration and testing before implementing them in the industry.

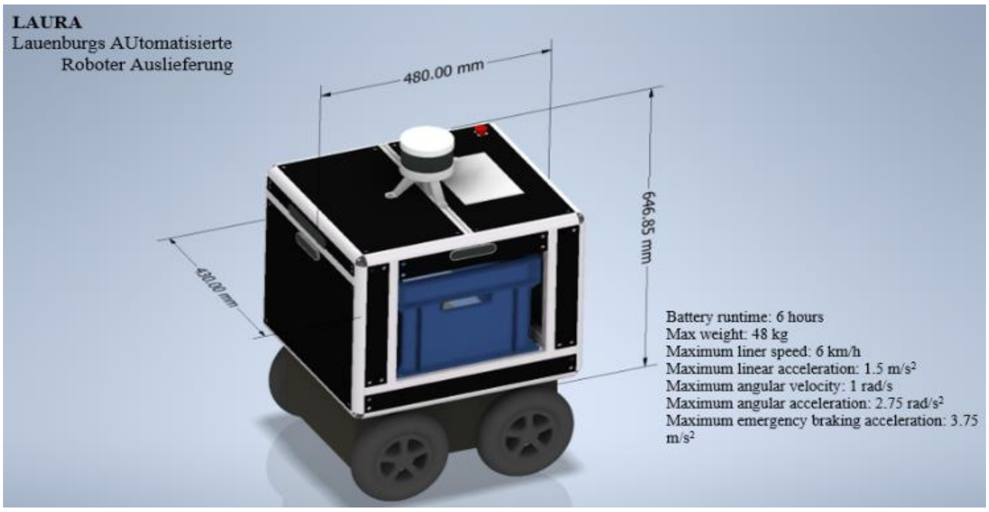

Figure 8. Physical properties of the LAURA
Source: (Gertz et al. 2022; Thiel et al. 2021)

Table 6. Car following models

Following Models	Underlying concept
Greenshields model	Linear relationship between speed and density where the road traffic flow is continuous
Pipes model	Follower tries to manage a safe distance from the vehicle in front, a distance that is proportional to the speed.
Van Aerde model	Non-linear model which is a combination of Greenshields and Pipes models and is being used in INTEGRATION as car-following behaviour
Gipps model	Speed of the following vehicle can be taken as either restricted or unrestricted by the lead vehicle
Wiedemann model	Wiedemann model presumes four different driving regions: following, free driving, closing in, or braking.
Social force model	Pedestrians move comfortably in shortest path, the motion of pedestrians is influenced from other pedestrians, it keeps distance from the boarder of the property lines and other obstacles. It also considers pedestrians are attracted to other person when necessary. This model is also useable for the bicycle.

Source: (Fransson 2018; Helbing and Molnár 1995; Gao 2008)

6.3 Lane Changing Model

When a vehicle traverses to an adjacent lane from its present lane, it comes as lane changing model. The complexity is high for the lane changing model as multiple objectives at a time interfere with each other during decision making process (Fransson 2018). Researchers and mathematicians explored the lane changing model in different methods. Based on the findings of the (Moridpour et al. 2010), the lane changing model is built on foundation of the driving assistance models and driving decision models.

The driving assistance models can be classified in two categories: collision prevention models and automation models. These models consider that the steering wheel angle and lateral motions control the lane changing action of the vehicles. Collision prevention models are developed to control drivers' lane changing manoeuvres and support them to execute a safe lane change. These models play crucial roles in safety assurance and collision avoidance. On the other side, driving decision models are classified into two categories: tactical decision models and operational decision models. This division of lane changing model focus into different traffic conditions, situational-environmental properties (Moridpour et al. 2010).

Another method to describe the lane changing model can be explained by (Mathew 2014) and (Ramanujam 2007) based on the interest of changing lane. They divided lane changing models into two categories: Mandatory Lane Change (MLC) and Discretionary Lane Changes (DLC). MLC is imposed by lane drop, any incident or approaching to final stop. In contrary, DLC works on reaching desired speed or allowing more space by the driver. (Mathew 2014) considers DLC as three steps: decision to consider a lane change, check for the feasibility and gap acceptance. Figure 9 shows the definition of Gap.

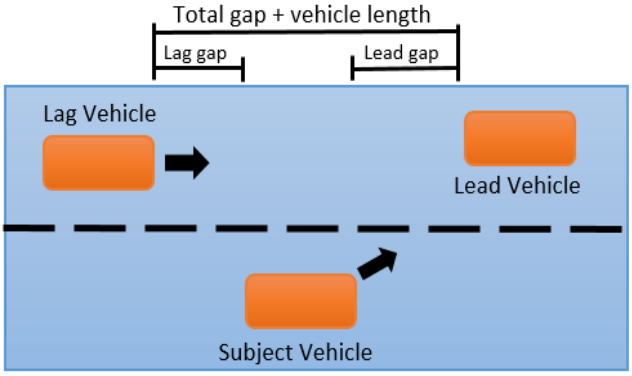

Figure 9. Definition of Gap

Source: (Fransson 2018)

MLC and DLC models also function on forced merging models and cooperative models (Fransson 2018). A forced merging model describes a situation in which the available gap on the target lane between the subject vehicle and the lag vehicle is insufficient to accommodate a lane change. The lag vehicle is forced to slow down until the gap size is large enough to be acceptable because the subject vehicle decides to change lanes despite the limited space. The cooperative model, on the other hand, does not consider gap acceptance as a criterion for making lane changes. This model is suitable for congested traffic area. It does not act on gap but takes step by cooperation with other road users. In order to facilitate the subject vehicle's lane change, the driver of the lag vehicle in the target lane will slow down (Fransson 2018).

6.4 Lane Merging Model

Merging is a type of obligatory lane change in which the lane change is required owing to a reduction in the number of lanes such as reduction of lane in ramp area. There is competition among drivers in such lane reduction areas to gain the earliest opportunity to get space in the lead lane (Li and Sun 2012). According to (Marczak et al. 2013) lane merging models utilize gap acceptance theory. (Hidas 2005) suggested complex merging model. In this model, forced and cooperative merge features are combined. However, it has no provision of cooperative merging for the subjective vehicle. (Choudhury et al. 2007) indicated a partial solution to bring cooperative merging behaviour of both vehicles: lead and lag. Simplified gap acceptance model is used by AIMSUN and VISSIM. At this moment, AIMSUN performs the merging as a modified version of (Gipps 1986).

AIMSUN added additional attributes for ensuring and controlling the state of urgency of changing the lane towards the end of the acceleration lane. Some extra parameters are added. On opposite, gap acceptance model of the VISSIM is not specified. Merging behaviour is modelled by adjusting the aggressiveness of the driver in the VISSIM (Fransson 2018). Researchers also like to consider game theory for lane merging model (Marczak et al. 2013; Fransson 2018) which is yet under experiment.

6.5 Level of Autonomy

Unlike the car, it is practical to consider the delivery robots only for simple 3 modes: Manual, Partially Autonomous and Autonomous. Manual, partially autonomous and autonomous can be related with Society of Automotive Engineers (SAE 2021) recognised autonomous level 1, 3 and 5 respectively. There is no concept need for step-wise development to cooperative adaptive cruise control (CACC), adaptive cruise control (ACC), automatic parking and automatic lane changing functions in the ADRs. ADRs are already a remotely operated road agent. They should have automatic parking as well. The development of autonomy level of ADRs can be planned in three stages.

The first stage of development is manually driven delivery robots planned for a limited area with constant human intervention. The intermediate development could be semi-autonomous delivery robots, which should only require human intervention in emergencies. Since it will travel autonomously, route mapping is important prior to implementation. The final stage of development is fully autonomous. It is expected to require human intervention only in rare cases. It features a higher level of technology. When modelling ADRs, it is important to consider the level of autonomy to achieve appropriate interaction with traffic and pedestrians. Although advanced microscopic simulators offer the possibility to manoeuvre and connect with a higher degree of autonomy, the possibilities for ADRs are still limited in today’s technology. There could be several other underlying stages (Thiel et al. 2021; Neumann 2020).

6.6 Performance metrics

The necessity and scope of the simulation are the deciding factors in the performance metrics selection. Working with simulation models with automation and a creative assessment method frequently calls out metrics that are not readily available in microscopic simulation. It is created and picked based on the specific needs. The presence of ADRs in the actual world is highly problematic because they play a role in both logistics and public transportation. Furthermore, it can use the sidewalk to react to pedestrians with a rational speed or bicycle lanes to react to micro-mobility at a faster speed. The performance metrics of ADRs are not well defined as a result of the aforementioned crisis and the complexity of technology, automation, and operating methods. Each simulation has its own performance measures based on the ADRs' requirements and accessible features.

Conventional transportation planning metrics study the traffic performance, safety and emission to measure the impact after introducing automation in the traffic stream (Dinar 2020; Kotusevski and Hawick 2009). Sustainability mobility planning metrics measures the social, economic and resource efficiency of any implemented measures. Table 7 shows the performance metrics which are currently being used for assessing automation measures. Traffic performance is measured in many various metrics: speed, travel time, total stop time, number of stop. It directly evaluates the impact of transport, measure or infrastructure in terms of action and interaction among the road users. The safety is measured in terms of many indirect parameters. One method is Surrogate Safety Assessment Model (SSAM) by Federal Highway Administration (FHWA) to detect possible crashes before they take place.

Table 7. Performance metrics used for transportation assessment from various automation

Metrics Type	Metrics
Conventional Transportation Planning	Traffic: Speed, Travel Time, Total Number of stop, Total stop time, Volume, Queue delay Safety: Number of Collision Emission: CO_2, NO_x, PM_{10} Energy: Battery consumption Economy: Total Cost, Per head cost Public Transport Metrics: Total distance covered, Total travel time, Waiting time in stop, journey time, Occupancy, seat capacity ratio, Trip length frequency distribution (TLFD) Logistics Metrics: Time per delivery, Distance covered, Required number agent Performance: HBS, Spatial index, Modal split, route choice, turn percentage Supply/ Demand: Number of vehicle, Number of order
Sustainable urban mobility indicators/ metrics	Public Transport Metrics: Affordability of public transport for the poorest group, Accessibility of public transport for mobility-impaired groups, Commuting travel time Emission: Air pollutant emissions, Greenhouse gas emissions (GHG) Noise: Noise hindrance, Safety: Road deaths, Traffic safety active modes, Security Equity: Access to mobility services, Opportunity for active mobility, Satisfaction with public transport, Quality of public spaces, Urban functional diversity, Mobility space usage Traffic: Congestion and delays Energy: Energy efficiency Performance: Multimodal integration, Modal split

The SSAM uses some useful measures to define the conflictions of the networks, such as time to collision (TTC), post-encroachment time (PET), deceleration rate (DR), gap time(GT), and proportion of stopping distance (PSD) (Federal Highway Administration 2004).

The result comes as possible collision which can be evaluated for various collision patterns: crossing conflict, rear-end conflict, lane-change conflict (Goh et al. 2014; Federal Highway Administration 2004). Emission (or environmental emission) remained an important metric in both conventional and sustainable transportation planning. The greenhouse gas (GHG) has got attention since 1997 under the Kyoto Protocol, agreed by 37 industrialized countries and the European Union (Eurostat 2015).

Other performance indicators focus on different impacts, including energy use, the economy, the efficiency of public transportation and logistics, planning effectiveness, noise, supply and demand, and supply and demand.

7. Challenges in Simulation

From the intensive literature review, it is evident that currently GUI based transportation simulation does not offer proper physical property, car following model, lane changing and lane merging to represent the ADRs in the simulation. Vehicle-to-everything (V2X), Vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-cloud (V2C), and other autonomous connectivity implications are difficult to implement in transportation simulators, making the process of configuring ADRs with traffic signals, road regulations, and other ADRs time-consuming. It currently lacks comprehensive performance indicators that account for both the evaluation of interactions in legally permitted public areas and the logistical success. The challenges which could be make the modelling of ADRs in a microscopic transportation simulator are mentioned in the Figure 10.

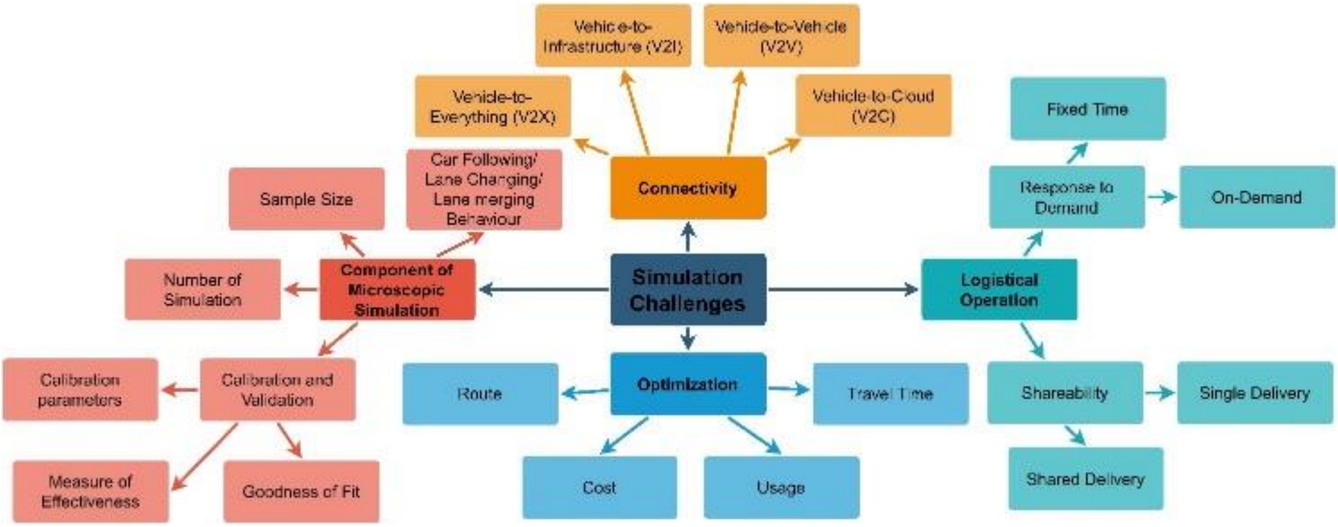

Figure 10. Challenges to model the ADRs in microscopic transportation simulator

GUI based simulators also do not support direct logistical operation such as shared and personal delivery options. It lacks drawing the demand based delivery and fixed time delivery. The route, travel time and cost optimisation are not yet introduced in GUI. Therefore, the decision process is not yet dynamic and robust, which means that the modeller's prediction may be inaccurate. This requires more experience in simulation. During Implementing the route and network for personal or shared delivery contains multiple factors which are required to be addressed. There is no provision to make it faster, efficient and cost effective (Baum et al. 2019a). In today's date the problems are solved by agent based modelling or code based simulator (Ahmed et al. 2021; Mourad 2019).

When it comes to any new mobility agent, such as ADRs, the various components of microscopic simulation themselves confine to their limits. Calibration and validation require a reliable Measure of Effectiveness (MoE) i.e. travel time, volume for both peak and off peak hours. That helps to create a universal simulation model to cover any part of the day making models robust and acceptable (Brockfeld et al. 2005). Goodness of Fit (GoF) on the other hand gives an impression how much simulated outcomes are matching the real-world data i.e. speed (Kotusevski and Hawick 2009; Dadashzadeh et al. 2019). There is no previous standard or discussion point to select an appropriate GoF for simulation of ADRs. Currently, ADRs are researched in test-beds that do not reflect real-world effects. Their use for calibration, validation and MoE therefore requires certain precautions and may involve a number of assumptions. Scaling down the simulation for ADRs could be advantageous for saving time and reducing computational effort. However, because there are currently no ADRs in widespread use in the real-world, establishing the representative number is difficult. Finally, determining the number of iterations presents a similar challenge. In these simulation components, an appropriate strategy must be used to fit the unique instance. Before deploying microscopic transportation simulation of ADRs, these key requirements needed to be investigated and considered.

8. Conclusion

The ADRs can be very diverse in terms of their physical properties, functionality and logistical operation, which makes the representation of ADRs in simulation a complicated task. To effectively cope with this complexity, the components of microscopic simulation relevant for ADRs should be categorized, defined and implemented in parallel. These gaps between components of microscopic traffic simulation and operation of ADRs can be overcome with proper provision. This review has broadened the conceptual understanding of traffic modellers so transportation modellers can apply a higher level of consideration and details to microscopic traffic simulation. It is important for traffic modellers to develop a suitable method for microscopic traffic simulation of ADRs. In this paper. some operational and technical aspects for microscopic transport simulation of ADRs are categorised. There are two major obstacles in this process. Firstly, there is a lack of default values that could be adopted from the real world to properly model ADRs in traffic simulation. Advanced forms of ADR are still in the research and development phase, which could be a starting point for modellers. In the real world, there are not many ADRs that can affect traffic and that can be simulated. Secondly, there are many variabilities in microscopic traffic simulation of ADRs. Analysing many variables at the same time could be confusing and lead to ambiguous results. Therefore, a few need to be defined and the simulation results can be compared with laboratory or test-bed data. The implementation of microscopic transport simulation for ADRs requires parallel actions: the generation of data from the laboratory or test-bed to consider the first input in the simulation, and the selection of the operation and technical aspects for the microscopic transport simulation. At this phase of advancement, the impact and evaluation of ADRs could be investigated for future exploratory study while continuing to address the mentioned components of this review. Very few earlier research papers and studies were located during the process of writing this review. Within this context, more use cases are needed to capture an integrated view of microscopic simulation of ADRs.

Acknowledgements

The authors would like to express their sincere gratitude to the partners and stakeholders of the TaBuLa-LOGplus project for their support. The authors gratefully acknowledge the contributions of Interlink, the Institute of Logistics Engineering, and the Institute of Transport Planning and Logistics at the Hamburg University of Technology.

Author contributions

YD: Concept Development, Investigation, Writing Original Draft, Editing; JM & CG: Review, Extended Concept, Supervision. All authors have approved the manuscript for submission. The content of the manuscript has not been published or submitted for publication elsewhere.

Funding

Publishing fees supported by Funding Programme Open Access Publishing of Hamburg University of Technology (TUHH).

Competing interests

The corresponding author of this review paper works as a transport modeller at the Institute of Transport Planning and Logistics at Hamburg University of Technology.

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