Effects of Vehicles with Different Degrees of Automation on Traffic Flow in Urban Areas

Von der Fakultät für Ingenieurwissenschaften, Abteilung Maschinenbau und Verfahrenstechnik der

Universität Duisburg-Essen

zur Erlangung des akademischen Grades

einer

Doktorin der Ingenieurwissenschaften

Dr.-Ing.

genehmigte Dissertation

von

Xiaoyi Ma
aus
Dalian, China

1. Gutachter: Prof. Dr.-Ing Dr. h.c. Dieter Schramm
2. Gutachter: Prof. Dr.-Ing Chang Qi
Tag der mündlichen Prüfung: 09.02.2020
Tag der Einreichung: 13.11.2020

Acknowlegement

It's not that I'm so smart, it's just that I stay with problems longer. - Albert Einstein

The present work was created while I was working at the Chair of Mechatronics in University of Duisburg-Essen. This experience of studying abroad has great influence for me. It not only made me understand the world better, but also made me understand myself better.

First of all, a very special thanks goes to my doctoral supervisor Prof. Dr.-Ing. Dr. h.c. Dieter Schramm, who not only gave me the opportunity but also always supported me. His rich knowledge, broad horizon, smart way of thinking, and good sense of humor deeply influenced me and will have lasting influences on me.

Importantly, I want to thank my motherland. The China Scholarship Council provided a four-year scholarship for me, which covered most of my expenses in Germany. The Chinese Embassy also helped me in due time. There has never been a day that I did not miss my home and my homeland.

I want also to give my thanks to my second reviewer, Prof. Chang Qi, for providing valuable comments for my thesis.

Especially, I would also like to thank my colleagues at the Chair of Mechatronics for their professional advices and the pleasant working environment. I would particularly like to thank Mira Schüller, who made my work and life in Germany colorful. I also want to thank Thomas Weber and Stephan Schweig for helping me in simulation and software.

Last but not least, I want to thank my family and friends for their patience and understanding, countless overseas calls comforted my soul in lonely festivals. In particular, I would like to thank my husband for being with me all the time.

Duisburg, im Feb. 2021 Xiaoyi Ma

Abstract

In addition to the electrification of the drive train, the development and use of autonomous and highly automated vehicles is another important contribution to the future development of individual transport. The automation of vehicle guidance is seen as a means to avoid traffic accidents, to gain leisure time in automated driving phases, but especially to improve the traffic flow and to avoid traffic jams as far as possible. While there are many obstacles to the popularization of fully autonomous vehicles in most countries, vehicles with driver assistance systems up to level 2 are already very common in different regions. A better understanding of the effects of vehicles with higher levels of automation on traffic flow can provide positive impulses for political strategies, the expansion of urban infrastructure, and the development of individual vehicles.

In this thesis, the most important driving differences between fully automated vehicles, semi-automated vehicles, and non-automated vehicles are investigated and corresponding vehicle driving models are developed. To compare the effects of these vehicle driving models in real traffic, four microscopic traffic simulation scenarios are created for two cities in two countries with different infrastructure. When comparing the simulation results for traffic with vehicles of different degrees of automation, simulation results of vehicles with a high degree of automation show a better influence on traffic in terms of traffic density, average speed, and travel time. Vehicles with high automation degree can improve the traffic situation from 3.7% to 57.4% in different aspects. Higher automation degree can bring greater impact on traffic. Based on the current development of automated vehicles in terms of technology, politics, price, and public opinion, this work estimates the penetration rate of auto-mated vehicles in the near and far future. The future traffic status is simulated based on the different penetration rates of automated vehicles. Even if only a part of the vehicles in the traffic flow is automated, this can have a positive effect on the traffic flow in many ways.

The traffic scenarios of the German city of Duisburg and the Chinese city of Wuhan created in this thesis are based on real road networks and traffic data. The scenarios can realistically reflect real traffic conditions and can also be used for further work in traffic research. The vehicle guidance model built in this thesis is based on driving experiments in a driving simulator, but it can also be combined with different vehicle models to simulate the effect of combining different drivers and vehicle types.

Kurzfassung

Neben der Elektrifizierung des Antriebsstrangs sind Entwicklung und Einsatz autonomer und hochautomatisierter Fahrzeuge ein weiterer wichtiger Beitrag für die zukünftige Entwicklung des Individualverkehrs. Die Automatisierung der Fahrzeugführung wird als ein Mittel gesehen, um Verkehrsunfällen zu vermeiden, Freizeit in automatisierten Fahrphasen zu gewinnen, aber insbesondere auch, um den Verkehrsfluss zu verbessern, bis hin zu einer weitgehenden Vermeidung von Verkehrsstaus. Während es in den meisten Ländern viele Hindernisse für die Popularisierung vollständig autonomer Fahrzeuge gibt, sind Fahrzeuge mit Fahrerassistenzsystemen bis zum Level 2 in den verschiedenen Regionen bereits sehr verbreitet. Ein besseres Verständnis der Auswirkungen von Fahrzeugen höherer Automatisierungsgrade auf den Verkehrsfluss kann positive Anregungen für politische Strategien, den Ausbau der städtischen Infrastruktur und die Entwicklung von Individualfahrzeugen bringen.

In der vorliegenden Arbeit werden die wichtigsten fahrtechnischen Unterschiede zwischen vollautonomen Fahrzeugen, teilautomatisierten Fahrzeugen und nichtautomatisierten Fahrzeugen untersucht und entsprechende Fahrzeugführungsmodelle erstellt. Um die Auswirkungen dieser Fahrzeugführungsmodelle im realen Verkehr vergleichen zu können, werden vier mikroskopische Verkehrssimulationsszenarien für zwei Städte in zwei Ländern mit unterschiedlicher Infrastruktur erstellt. Beim Vergleich der Simulationsergebnisse bei Verkehr mit Fahrzeugen unterschiedlichen Automatisierungsgrads zeigen Simulationsergebnisse von Fahrzeugen mit hohem Automatisierungsgrad einen größeren Einfluss auf den Verkehr in Bezug auf Verkehrsdichte, Durchschnittsgeschwindigkeit und Fahrzeit. Fahrzeuge mit hohem Automatisierungsgrad können die Verkehrssituation in verschiedenen Aspekten von 3,7 % bis 57,4 % verbessern. Ein höherer Automatisierungsgrad kann größere Auswirkungen auf den Verkehr haben. Basierend auf der aktuellen Entwicklung von automatisierten Fahrzeugen in Bezug auf Technologie, Politik, Preis und öffentliche Meinung schätzt diese Arbeit die Durchdringungsrate von automatisierten Fahrzeugen in der nahen und fernen Zukunft. Der zukünftige Verkehrsstatus wird auf der Grundlage der unterschiedlichen Penetrationsrate von automatisierten Fahrzeugen simuliert. Auch wenn nur

ein Teil der Fahrzeuge im Verkehrsfluss automatisiert ist, kann sich dies in vielerlei Hinsicht positiv auf den Verkehrsfluss auswirken.

Die in dieser Arbeit erstellten Verkehrsszenarien der deutschen Stadt Duisburg und der chinesischen Stadt Wuhan basieren auf realen Straßennetzen und Verkehrsdaten. Die Szenarien können die realen Verkehrsbedingungen realistisch wiedergeben und können auch für weitere Arbeiten in der Verkehrsforschung verwendet werden. Das in dieser Arbeit aufgebaute Fahrerzeugführungsmodell basiert auf Fahrexperimenten in einem Fahrsimulator, es kann aber auch mit verschiedenen Fahrzeugmodellen kombiniert werden, um den Effekt der Kombination verschiedener Fahrer und Fahrzeugtypen zu simulieren.

Contents

List of Figures

List of Tables

Notation

Symbols

Latin letters

Symbols	Unit	Meaning
a	$\frac{m}{s^2}$	Maximum acceleration of the vehicle type
a_n	$\frac{m}{s^2}$	Maximum desired acceleration of the following car
$a_n(t)$	$\frac{m}{s^2}$	Acceleration of the following car
a_s	$\frac{m}{s^2}$	Desired acceleration of the following car
b	$\frac{m}{s^2}$	Maximum deceleration for $\epsilon = 0$
b_c	$\frac{m}{s^2}$	Comfortable deceleration
b_n	$\frac{m}{s^2}$	Maximum deceleration of the following car
$\hat{b}_{n-1}$	$\frac{m}{s^2}$	Estimate of maximum deceleration of the following car
d_0	m	Maximum distance
d_1	1	Acceleration exponent
d_n	m	Distance to the leading car
$d(v_n, \Delta v_n)$	m	Desired minimum gap
$g_n(t)$	m	Gap between the leader and the follower
J	$\frac{1}{h}$	Global flow
M	kg	Vehicle mass
n		The following car
$n-1$		The leading car
p_b	1	Brake pedal position
p_g	1	Drive pedal position
p_p	1	Output pedal position
s_{n-1}	m	Effective size of the leading car
r	1	Randomness of fuzzy control model
t_l	1	Time step
T	s	Desired time gap
T_i	s	Time for acceleration from 0 to maximum velocity
V_{max}	$\frac{m}{s}$	Maximum allowed velocity
V_n	$\frac{m}{s}$	Desired speed of the following car
$\langle v \rangle$	$\frac{km}{h}$	Mean velocity

Notation

v_{n-1}	$\frac{m}{s}$	Velocity of the leading car
v_n	$\frac{m}{s}$	Velocity of the following car
v_s	$\frac{m}{s}$	Safe velocity of the following car
$v(t+\Delta t)$	$\frac{m}{s}$	Velocity of follower after the reaction time of τ
Δv_n	$\frac{m}{s}$	Velocity difference from the leading car
$\dot{v_n}$	$\frac{m}{s^2}$	Acceleration of the following car
x	1	Vehicle position
ΔY	s	Space headway at time$(t-\tau)$

Greek letters

Symbols	**Unit**	**Meaning**
α	1	Constant
β	1	Model parameter
γ	1	Model parameter
δ	1	Acceleration exponent
η	%	Random number in $[0,1]$
λ	1	Sensitivity factor of the control mechanism
ρ	$\frac{1}{km}$	Global density
τ	s	Reaction time of the following car
ϵ	1	Noise amplitude
φ	1	Radom perturbation

Abbreviations

Abbreviations	**Meaning**
AA	Adaptive Automation
ACC	Adaptive Cruise Control
AIC	Autonomous Intelligent speed Control
AIMSUN	Advanced Interactive Micro-Simulation for Urban and non-urban Networks
CA	Cellular Automata
CC	Cruise Control
DFA	Dynamic Function Assignment
DLR	German Aerospace Center (in German: Deutsches Zentrum für Luft- und Raumfahrt eV)

DUE	Dynamic User Equilibrium
FCD	Floating Car Data
GM	General Motors
IDM	Intelligent Driver Model
ITS	Intelligent Transport Systems
LCV	Light Commercial Vehicle
LKA	Lane Keeping Assistance
LNG	Liquefied Natural Gas
LOA	Level of Automation
LPG	Liquefied Petroleum Gas
LuST	LUxembourg SUmo Traffic
MPV	Multi-Purpose Vehicle
OSM	Open Street Map
PARAMICS	PARAllel MICroscopic Simulation
PELOPS	Program for the dEvelopment of Longitudial microscOpic traffic Process in a System relevant environment
SAE	Society of Automotive Engineer
SUMO	Simulation of Urban MObility
UOC	University of Catalonia
WBD	Wirtschaftsbetriebe Duisburg (German)
TAZ	Traffic Assignment Zone/Traffic Analysis Zone
TraCI	Traffic Control Interface
TRANSIMS	Transportation Analysis and SIMulation System

1 Motivation and instruction

This Chapter describes motivation and structure of this work. The current state of the art in the field and the research questions to be answered in this thesis are presented.

1.1 Motivation

As the urban population grows continuously, traffic jams, traffic accidents and other negative effects of the traffic are getting more and more attention. The United Nations predicts that, the proportion of global urban population will increase from 55% in 2018 to 68% in 2050 (United Nations). The development of urbanization not only increases the residents' demand of urban mobility, which burden the urban transportation system, but also brings traffic safety issues to mind. Each year about 1.2 million people die in vehicle-related traffic accidents (Kalra and Groves 2017). The resulting medical, legal, property, insurance and quality of life losses exceed 1 trillion US dollars (Blincoe et al. 2015). Most traffic accidents can be attributed to human error, e.g. driving under drunk, drowsiness or distraction. A study by the University of Indiana showed that in a sample of 2,258 cases, 93% of accidents were mainly due to human error (Treat et al. 1979). Another study has shown that 95% of traffic accidents are at least partially attributable to human error, while 65% of traffic accidents can even be attributed entirely to human error (Sabey and Taylor 1980).

With the expansion of driving assistance technology, autonomous driving will become an option, which may offer the prospect of reducing the accident rate in road traffic. Autonomous vehicles replace fallible human drivers with sensors, cameras and radars, which cannot be drunk, do not burn out and cannot be distracted. Autonomous vehicles or intelligent vehicles can be of great importance for the development of public health. Autonomous driving systems do not only reduce fatalities of traffic accidents, but they can also improve human's quality of life (Fagnant and

Kockelman 2015; Kalra and Groves 2017). In energy consumption, partial automated vehicles might reduce greenhouse gas emissions and energy consumption by nearly half (Wadud et al. 2016).

Before the realization of fully autonomous vehicles, many challenges are still faced by the development of autonomous technology (Marshall 2017). The new technology needs extra new sensors, communications and software for each automobile, which increase the vehicle costs significantly. An estimation shows that, most current civilian and military applications cost of autonomous vehicles are over 100,000 US dollars (Dellenback 26.May.2013). Comparing to the price of top selling vehicles, the cost of autonomous vehicle is unaffordable for most consumers. From a technological point of view, improving the visual capabilities of autonomous vehicles is one of the biggest challenges besides the required algorithms. In harsh environment such as rain, fog and snow, it is hard for autonomous cars to detect surrounding vehicles, lanes, pedestrians, traffic signs, etc. (Rasshofer et al. 2011). In terms of social acceptance of autonomous driving, the acceptance differs with varying levels of automation levels (Rödel et al. 2014). The acceptance rates for fully autonomous cars are around 68% (Payre et al. 2014; Schoettle and Sivak 2014a). Moreover, there are still many ethical and legal dilemmas that have not yet been resolved. Laws in related fields are not yet mature. These ethical and legal dilemmas have considerably prolonged the market penetration of autonomous vehicles.

Although accompanied by many difficulties, many simulation experiments and field trials are implemented to promote the development of autonomous driving technology. By August 2019, 90 cities worldwide had pilot projects for autonomous vehicles (Philanthropies). So far, investments in the development of autonomous driving technologies have exceeded 80 billion US dollars and are likely to show an further upward trend (Kerry, Karsten 2017). Nevertheless, it can be concluded from the significant advances in automotive technology that the widespread use of autonomous vehicles will come at least in the medium to long term. Thus, an early understanding of the impact of new driving technologies on transportation can give transportation planning departments the opportunity to prepare.

The applications of advanced technologies have never been done overnight, as is the application of autonomous driving technology. For over a century, automobile technology is evolving gradually. Vehicle automation has been around with the first automatic gearboxes since 1940s (Young et al. 2007). However, the relationship between the driver and the automation technologies will not always be supporting each other. Shladover compares automation technologies according to different approaches (Figure 1.1).

With the help of modern assisted driving technology, we have already found that our driving behavior has changed (Jamson et al. 2013b). In fact, increasingly advanced automotive technologies influence far more than just the driver itself. Furthermore, the impact of different degrees of automation on traffic flow cannot be ignored. Knowing beforehand of the impact of these technologies on traffic flow would have multiple advantages. In this work, the vehicle technologies commonly used for assisting, the technologies to be applied in the future for assisting and the autonomous driving technologies are discussed. This research may have positive impact on political strategies such as road planning, urban infrastructure construction and industrial applications such as vehicle design and product development.

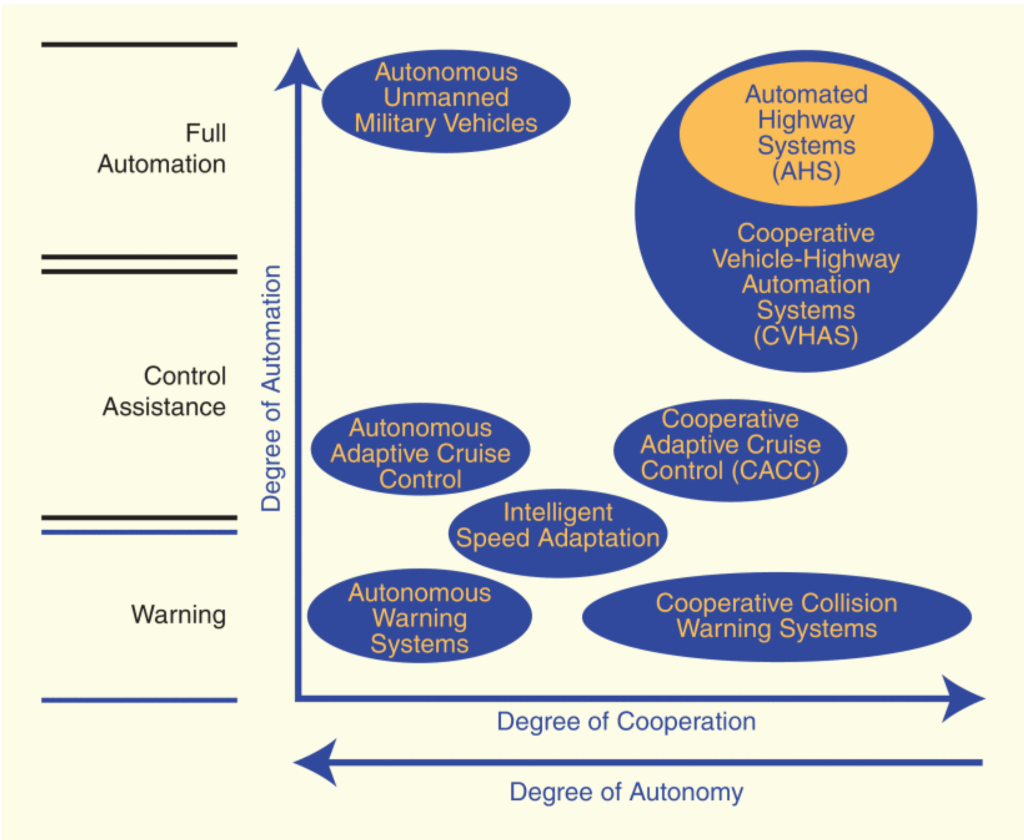


Figure 1.1: Degrees of automation and cooperation (Shladover 2009)

According to the different aggregation levels, traffic simulation can be categorized into macroscopic simulation, mesoscopic simulation and microscopic simulation. While microscopic models describe the traffic flow from the perspective of the individual driver and vehicle, macroscopic models reflect the collective state. That is to say, macroscopic models have a holistic view in spatiotemporal fields and focus on the local density, speed, and flow (Treiber and Kesting 2013). In order to analyze the behavior of each vehicle, this work focuses on the microscopic simulation level.

1.2 Objective of the work

Many manufacturers are developing autonomous vehicles and highly automated vehicles. At the same time, the influence of these emerging technologies on traffic flow have not been comprehensively researched.

In order to research the influence of vehicles with different automation levels on traffic flow, traffic simulation models with different degrees of automation need to be established. A classification system based on different degrees of automation was first published by the SAE (Society of Automotive Engineer) International in 2014, this classification system is based on the amount of driver intervention and attentiveness required, rather than the vehicle capabilities. In 2016, SAE updated its classification (Automated Driving 2014). In the current work, three levels of automation are selected: level 5 (full automation) presents vehicles in the future, level 2 (partial automation) presents vehicles that are mature in technology but do not have been widely used on road and level 0 (no automation) presents most vehicles currently running on the road. With different percentage of the vehicles in these three automation levels, future traffic flow changes in 2030 and 2050 due to vehicle technology upgrades are investigated in simulations.

The scenarios in the simulation are extracted from the present real world, including real lane distribution, the location of traffic lights and actual amount of traffic flow recorded by detectors. Furthermore, simulated road conditions are also compared with real data collected from detectors including inductive loops and cameras in certain points of the simulated area and the accuracy of the simulation is ensured from the comparison.

This work may offer a new perspective to automobile manufacturers and suppliers, political and government institutions and other related personnel in automobile industry.

1.3 Structure of the work

In the first chapter of this work, motivation and structure are introduced. Beginning with Chapter 2, this work is divided into two main parts, one related to the simulation scenario and the other related to the driver model in the simulation. Finally, these two parts are put together to run the simulation. The structure can also be seen in Figure 1.2.

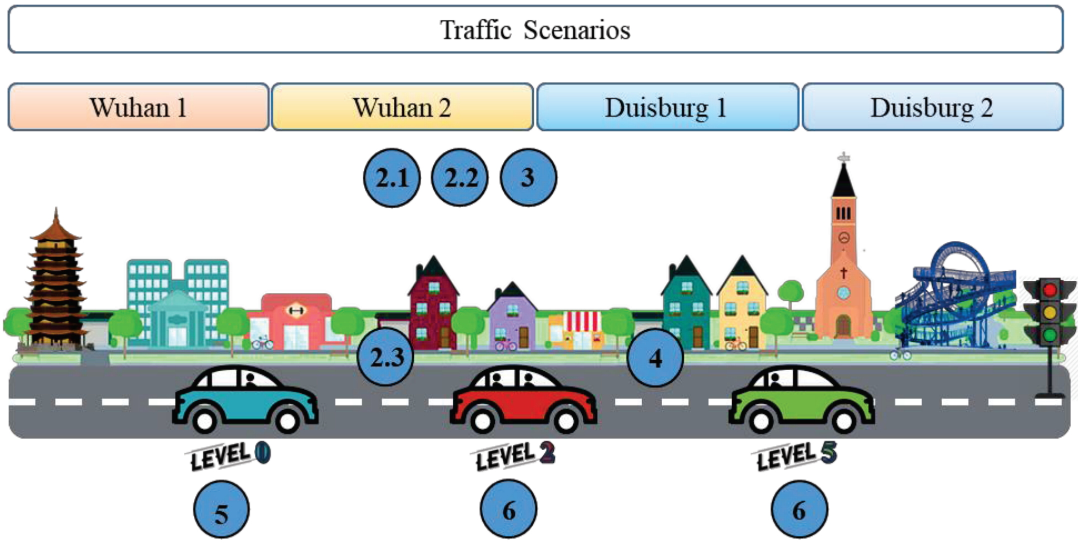


Figure 1.2: Chapter distribution of the work

The second chapter introduces the fundamentals and the current state of research in this field. In Section 2, 2.1 introduces the evolution and classification of different traffic simulation models from the past to the present. Section 2.2 introduces the traffic simulation software commonly used worldwide. These two sections are related to the simulation scenario part. Section 2.3 introduces the definition and current development of vehicles with different degrees of automation. In this section, the three studied degrees of automation are also determined, representing the present, the near future, and the long distant future respectively. This section is the basis of the driver model part.

Chapter 3 introduces the simulation scenarios in this work, the selection, construction and comparison of four different simulation scenarios in two cities. In Chapter

4, the process of establishing a driver model for each studied degree of automation is introduced in detail and implemented in the MATLAB.

Chapter 5 to Chapter 7 describe the simulation results of vehicles in different scenarios and conditions. In Chapter 5 the simulation results of ordinary cars without automation in four different scenarios are presented. Since this represents the current automation level on the road, the actual data from detectors are used to calibrate the driver model built in Chapter 4. Next, in chapter 6, the vehicles with the three investigated degrees of automation (representing the current state, the state of near future or in the far future) are simulated on the basis of two different scenarios. The effects on the traffic flow are then analyzed by comparing the results. In chapter 7, the mixing of the vehicle stock with partially and fully automated vehicles in the years 2030 and 2050 is simulated. In this chapter, the vehicles with different degrees of automation are simulated with different penetration rate of the traffic flow. Finally, in Chapter 8, a conclusion with scientific contribution and limitation of this work is given.

2 Fundamentals and state of research

This Chapter introduces first the macroscopic and microscopic simulation models used in traffic simulation. Next, the software systems widely used by researchers worldwide are presented and compared. The current state of related work using these software packages is also presented. Finally, the last part of this chapter introduces the classification of level for automation of motor.

2.1 Traffic simulation models

Road traffic is a dynamic problem with a multitude of system components that interact in a rather complex manner. It is obvious that a variety of factors will influence traffic flow. The basic purpose of a traffic flow simulation is to predict the effects on traffic of changes in the behavior of road users and the surrounding traffic infrastructure. The accuracy of the traffic simulation directly determines whether the simulation results are reliable enough to base decisions on them or not. Depending on the knowledge to be gained from the simulation, different software systems are used. Among all these simulation software packages, the evaluation criteria are the same. That is, the more similar it is to actual traffic, the more reliable the results of the simulation are. According to the different aggregation levels, traffic simulations can be categorized into macroscopic scale simulation, mesoscopic scale simulation and microscopic scale simulation, respectively.

2.1.1 Macroscopic traffic flow models

In the case of a macroscopic modeling, traffic flow models formulate the relationships among traffic flow characteristics and no distinction can be made between the individual vehicles. Only the macroscopic quantities resulting from the vehicle dynamics are considered. These are essentially the global traffic flow J, the global density ρ and the mean velocity v on a road section of given length. The size is linked by the hydrodynamic relation.

$$J = \rho\langle v\rangle. \tag{2.1}$$

This class of simulation approaches includes hydrodynamic and gas kinetic approaches. The basis of the models here is the equation of continuity, which describes the number of vehicles. The mathematical foundations of this approach originate from hydrodynamics and gas theory:

$$\frac{\partial}{\partial t}\rho(x,t) + \frac{\partial}{\partial x}J(x,t) = 0. \tag{2.2}$$

The spatial change of the local flow $J(x,t)$ causes a temporal change of the local density $\rho(x,t)$ (Neubert 2000). Other extensions are also made by lots of researchers, for example the propagation of kinematic waves (Lighthill and Whitham 1955), discontinuous density change (Prigogine and Herman 1971) and detailed applications (Lee et al. 1998).

2.1.2 Microscopic traffic flow models

Microscopic models are the dynamic and stochastic modeling of individual vehicle movements within a system of transportation facilities. To analyze the behavior or reactions of a single vehicle, the use of microscopic models is appropriate. There are lots of microscopic traffic flow models which describe different aspects of vehicle behavior. All these models can be divided into four main categories: route choice models, lane change models, gap acceptance models and car following models (Berthaume 2015).

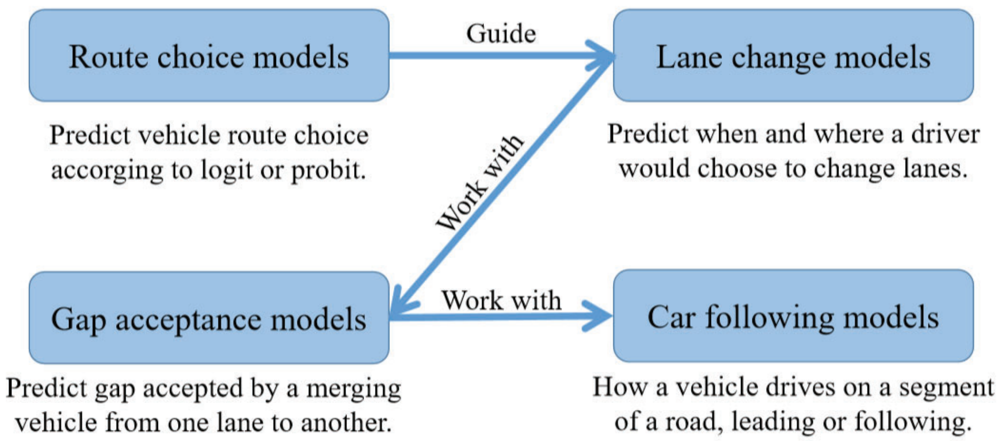


Figure 2.1: Four main categories of microscopic traffic flow models

These models present different aspects working together, simulating human drivers' behavior. Route choice models decides which road to go, guide lane change models take actions to choose another lane or stay in the same lane. Gap acceptance models are prerequisites to lane change models. When a driver tries to change to another lane, the gap on the target lane becomes a critical parameter for gap acceptance models. After determining if the driver accepts the gap or not (by the gap acceptance model), the lane change models describe the next step. Although all four models work together during the simulation, it is the car-following model that is active most of the time. From this perspective, car following models are the most important.

General Motors (GM) model

As early as in the 1950s, the study of car following models have started (Bengtsson 2001). The general form was based on the assumption that the behavior of a driver n is determined by the driver in front $n-1$. Initial approaches have been proposed as a distance and speed difference perceived model (Pipes 1953). On the assumption that the driver is able to percept the space headway and the relative speed difference, a linear car-following based on general stimulus-response relationship was introduced (Chandler et al. 1958). The model can be mathematically expressed as:

$$a_n(t) = \frac{\lambda}{M}[v_{n-1}(t-\tau) - v_n(t-\tau)] \tag{2.3}$$

where

$a_n(t)$ = acceleration of the following car,

λ = sensitivity factor of the control mechanism,

M = vehicle mass,

τ = reaction time of the following car,

v_{n-1} = velocity of the leading car,

v_n = velocity of the following car.

Based on (2.3), the General Motors (GM) nonlinear model was developed (Gazis et al. 1961). This model can be expressed as

$$a_n(t) = \alpha \frac{v_{n-1}(t)^{\beta}}{\Delta Y(t-\tau)^{\gamma}}[v_{n-1}(t-\tau) - v_n(t-\tau)] \tag{2.4}$$

where

α = constant,

β = model parameter,

γ = model parameter,

$\Delta Y(t-\tau)$ = the space headway at time$(t-\tau)$.

At low traffic densities, this model performs better because of the relationship between the space headway of the vehicles and a sensitivity factor was introduced. In the following research, the GM model has been improved by determining parameters (May and Keller 1967), adding an alternative approach based on the visual angle (Pipes 1953), extend to a nonlinear headway-dependent term (Addison and Low 1998). After all, the GM car following models are still based on the relationship between the space headway and the vehicle speed. These insurmountable characteristics bring some flaws. At low speed or when traffic stops, some models do not work. Besides, GM models ignore any unsatisfied desires for mobility (Berthaume 2015).

Wiedemann's model

After the GM model dominated in the 1960s, the German psychologist Rainer Wiedemann developed an advanced model in the early 1970s with the so-called psycho-physical spacing model.

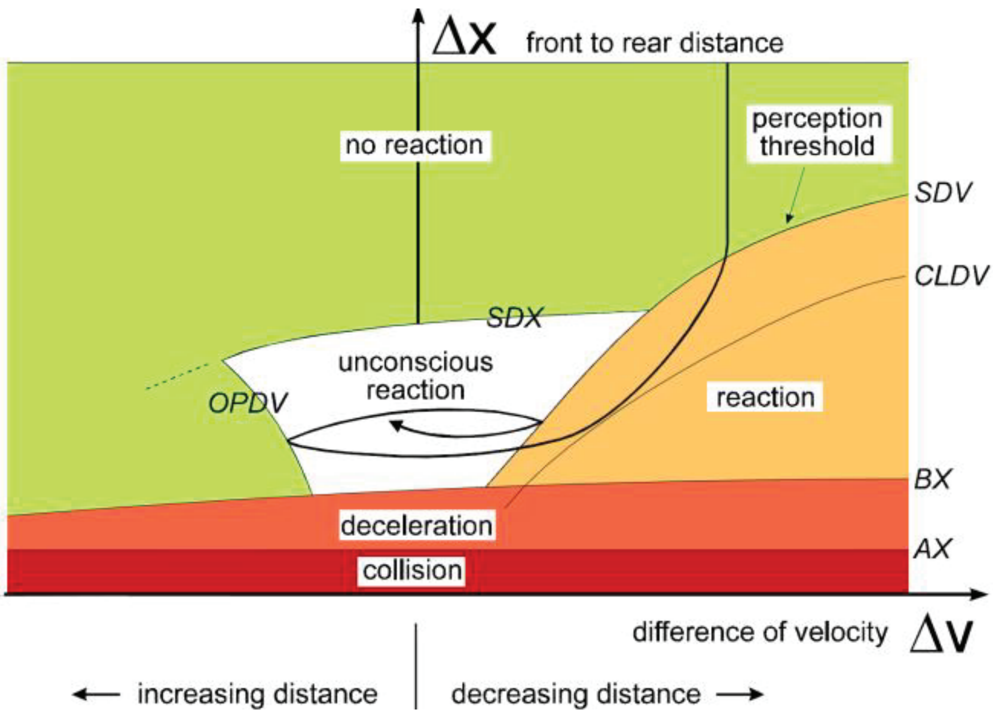


Figure 2.2: Wiedemann's psycho-physical spacing model (Wiedemann 1974)

Figure 2.2 shows Wiedemann's model on a graph depending on relative velocity and relative distance. Wiedemann divided driver behavior into four driving situations, uninfluenced driving (desired speed), approaching (consciously influenced driving), braking (consciously influenced driving) and car following (unconsciously influenced driving). Individual driving parameters are introduced in different driving situations, desired speed, desire for safety and reaction time, these driving parameters are used to determine the levels of perception of drivers.

Wiedemann's model is still in use today, e.g., the microscopic traffic simulation software VISSIM (VISION 2014) is based on this model. PELOPS (Program for the dEvelopment of Longitudial microscOPic traffic process in a System relevant environment) created by IKA (Institute for Automotive Engineering Aachen) and BMW AG is also using Wiedemann's car following model (Neunzig et al. 1998).

Although Wiedemann's model is proven to be an improvement in microscopic car following models, the calibration of so many coefficients make it difficult in using. The perceptual threshold may change with different driving behaviors. Lots of factors can have influence on this threshold, such as driver gender, age, residential country, vehicle type, the presence of passengers and so on. A comprehensive, reliable, robust database based on lots of surveys is required in using Wiedemann's model.

Gipps' model

In the 1980s Gipps employed an assumption that the driver sets a safety rule to determine vehicle spacing. The desired speed of a driver should ensure that he can perform a safe stop even if the leading car stops suddenly (Gipps 1981). The Gipps model is an optimistic model, if everyone drives like the description in this model, there will be no rear-end collisions. However, in reality, not all drivers will leave enough room for safety. Especially in the city center with high vehicle density, the gaps between vehicles are hard to reach the ideal level in Gipps' model. Mathematically, the model can be expressed as:

$$v_n(t+\tau) = \min\left[v_{a,n}(t+\tau), v_{b,n}(t+\tau)\right] \tag{2.5}$$

where

$$v_{a,n}(t+\tau) = v_n(t) + 2.5 \cdot a_n \cdot \tau \cdot \left[1 - \frac{v_n(t)}{V_n}\right] \cdot \sqrt{0.025 + \frac{v_n(t)}{V_n}},$$

$$v_{b,n}(t+\tau) = b_n\tau + \sqrt{\begin{matrix} b_n^2\tau^2 - b_n \cdot 2[x_{n-1}(t) - s_{n-1} - x_n(t)] \\ -v_n(t) \cdot \tau - \frac{v_{n-1}^2(t)}{\hat{b}_{n-1}} \end{matrix}},$$

$x =$ vehicle position,

$a_n =$ maximum desired acceleration of the following car,

$V_n =$ desired speed of the following car,

$b_n =$ maximum deceleration of the following car,

$s_{n-1} =$ effective size of the leading car,

$\hat{b}_{n-1} =$ estimate of maximum deceleration of the following car.

Although it is introduced that the vehicle space is changeable, Gipps' model does not accurately reflect driving behavior of most drivers on the road.

Krauss' model

In the 1990s, car following models developed rapidly. Like Gipps' model, Krauss' model is also based on safety distance. It is assumed that, the following vehicle will maintain a safe distance from the leading vehicle and select its speed to avoid collision (Krauss). Mathematically, the model can be expressed as:

$$V_n = \min[v_n(t) + a_n\tau, v_s, V_{max}] \tag{2.6}$$

$$v(t+\Delta t) = \max(0, V_n - \epsilon\, a\, \eta) \tag{2.7}$$

where

$v_s = v_{n-1}(t) + \frac{g_n(t) - v_{n-1}(t)\tau}{\frac{v_n(t)+v_{n-1}(t)}{2b} + \tau} =$ safe speed of the vehicle,

$V_{max} =$ maximum allowed velocity,

$b =$ maximum deceleration for $\epsilon = 0$,

$\epsilon =$ noise amplitude,

$\eta =$ random number in $[0,1]$,

$g_n(t) =$ gap between the leader and the follower,

$v(t+\Delta t) =$ the speed of follower after the reaction time of τ.

Krauss' model can be seen as a variant of Gipps' model. It defines the amount of noise ϵ that introduces stochastic behavior to the model. The safe velocity v_s is also the maximum velocity that the follower can drive when he/she wants to be sure to avoid a crash. It is assumed that neither the leader nor the follower will ever decelerate faster than b. The desired velocity V_n is the minimum out of: current velocity plus acceleration, safe speed, maximum allowed velocity.

IDM (Intelligent Driver Model)

The Intelligent Driver Model (IDM) (Treiber et al. 2000) is a continuous function incorporating different driving models for all velocities in freeway as well as city traffics. In addition of vehicle gap and actual speed, IDM puts velocity differences Δv_n on an important position. In the case of approaching to the leading car or keeping safe distance, it provides a relative more accurate model (Kesting et al. 2009). The model does not consider a reaction time, so its expression is an ordinary differential equation. In the IDM, acceleration of the following car can be calculated as:

$$\dot{v}_n = a\left\{1 - \left(\frac{v_n}{V_n}\right)^{\delta} - \left[\frac{d(v_n, \Delta v_n)}{d_n}\right]^2\right\}$$

where

$$d(v, \Delta v) = d_0 + \max\left(0, T v_n + \frac{v_n \Delta v_n}{2\sqrt{a b_c}}\right),$$

$$a = \text{maximum acceleration},$$

$$\Delta v_n = \text{speed difference from the leading car},$$

$$d_n = \text{distance to the leading car},$$

$$d(v_n, \Delta v_n) = \text{desired minimum gap},$$

$$T = \text{desired time gap},$$

$$b_c = \text{comfortable deceleration},$$

$$\delta = \text{acceleration exponent},$$

$$d_0 = \text{minimum distance to the leading car}.$$

After all, although the car following models are becoming increasingly complex, with more and more parameters, many models even involve complex machine learning methods like the neural network structures, and the advanced algorithms, etc.

However, complex models do not automatically mean higher accuracy. For example, in a comparison of four models (Newell's, Gipps', IDM, MITSIM) with real traffic data, the simplest Newell's model (Newell 2002) performed the best (Punzo and Simonelli 2005). Without large database support, lots of models cannot reach high accuracy.

2.2 Traffic simulation software

A reliable description of traffic flow is a really important topic. So far, there are lots of models present. Unfortunately, none of them can be considered as an ideal or, at least universal one (Maciejewski 2010).

2.2.1 SUMO

SUMO (Simulation of Urban MObility) is an open source microscopic traffic flow simulation system developed by German Aerospace Center (DLR) since 2001 (Krajzewicz et al. 2012). In SUMO, multimodality is concerned. That is to say, in a city where public transportation is very convenient and fast, people will choose a multimodal transportation. For example, walking to the bus station, drive to the train station or continue travel by other means of transport.

The simulation of vehicles in SUMO is time discrete and space continuous. Moreover, its car following models are all continuous. In the traffic simulation models introduced above, it includes the safe distance Krauss' model and the IDM model. The routing model in SUMO follows Dijkstra routing algorithm, which means the vehicles compute the nearest way from the origin to the destination through the network. To make up the defects of all vehicles going to the same road and generate congestion, Dynamic User Equilibrium (DUE) developed by Christian Gawron (Gawron 1998) are recommended to be used in SUMO.

SUMO provides 2D graphical visualization of microscopic traffic simulation (Figure 2.3), it also enables various vehicle types, driver models, traffic signal plans and choices of public transportation. In the new version SUMO 1.6.1, more functions like Traffic Assignment Zone (TAZ), pedestrians, visible routes in network, etc. are added to the software package.

SUMO is conceived to simulate a traffic road network of the size of a city and capable to read different source formats (origin destination matrices, traffic counts, etc.). So far, traffic simulations of some cities have been made. Berlin was simulated by the developer of SUMO as an example of city traffic simulation. In project ITS (Intelligent Transport Systems) Austria West, a scenario of Upper Austria was built (Kastner et al. 2014). Because of the efficiency of SUMO decreased below real time, they tried to build a parallelization of SUMO. Then they made some improvements, including an online monitoring system and real floating car data comparison (Kastner and Pau 2015). Meanwhile, a traffic scenario of city Bologna in Italy was built (Bieker et al. 2015). Combined by three small scenarios, the simulation was in the end compared to the real-world measurements. Due to the small size of network, route choice in the scenarios are very limited, that leads to an inaccuracy. Afterwards, a 24-hour scenario of Luxembourg City was built (Codeca et al. 2015), the system called LuST (LUxembourg SUmo Traffic) contained morning and evening rush hours, buses and bus stations. In addition to Europe, city simulation in Asia were subsequently emerged. A simulation of Kobe-city in Japan was carried out (Yuta et al. 2015). In this simulation, because of the lack of government help, origin destination matrices data source was not available for the simulation, so a sub-program in SUMO called ActivityGen was used to generate traffic demand. They also found, by changing the speed limit of the road, the simulated data will be closer to the traffic census data than default setting.

2.2.2 VISSIM

VISSIM is a commercial behavior-based system developed by PTV Group (Fellendorf 1994). It has been used worldwide for over 25 years (Fellendorf and Vortisch 2010). Users from consultancies, industry, public agencies and academic institutions find it suited for traffic engineering. VISSIM provides multimodal traffic flow simulation contains cars, trucks, buses, trams, rails and even pedestrian, bicyclists and motorcycles.

In the car following model, which is based on the VISSIM model, the psycho-physical model by Wiedemann is used (Wiedemann 1991). The same applies to the lane change model. VISSIM has a structure of one-way links connected with connectors, instead of nodes and links. This allows the representation of almost any structure of the road systems.

Figure 2.3: A screenshot of SUMO Interface

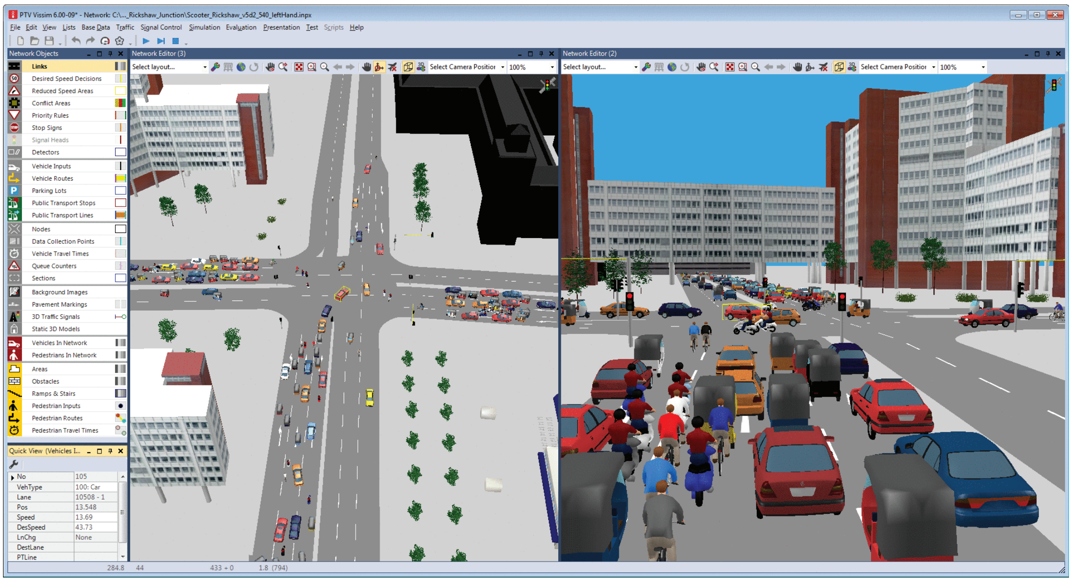


Figure 2.4: Simulation of mixed traffic with PTV VISSIM (from PTV website)

As can be seen in Figure 2.4, VISSIM provides a variable 3D visualization which has quite a high degree of reproduction of traffic condition. It provides not just precise modeling of vehicles but also road infrastructure with a high level of detail, which makes the realism level of vehicle dynamic in VISSIM higher than in most traffic simulation software packages.

At the same time, VISSIM is also an expensive commercial software and the simulation speed is relatively low. From a user's point of view, VISSIM is very user-friendly, and therefore suitable for beginners. The powerful and intuitive graphical environment also helps for government report, corporate project promotion and so on.

2.2.3 TRANSIMS

TRANSIMS (Transportation Analysis and SIMulation System) is an open-source, regional analytical traffic simulation system (Smith et al. 1995). It is a complete modeling and simulation system which contains population synthesis, activity generation, route plan, and microsimulation.

The Microsimulator is the last module of the process in TRANSIMS. It is based on cellular automata (CA) theory and uses the commonly recognized Nagel-Schreckenberg model (Nagel and Schreckenberg 1992) which is time and space discrete. For this reason, each road is divided into small cells of the same size, the default size in TRANSIM is 7.5 m. The cells can be in one of the two states: occupied or empty.

TRANSIMS offers large scope area, but the precision is limited. For the reason of cellular automata, a lot of emphasis was laid on the adjustment of cell size. But by changing the cell size from default 7.5 m to 3.75 m and 1.5 m, the decrease of the cell size causes impreciseness in simulations (Maciejewski 2010).

Because of the simplicity of the CA theory, the calculation speed of TRANSIMS is fast. At the same time, TRANSIMS presents not only macroscopic characteristics of traffic flow, but also microscopic characteristics like velocity, displacement and headway of each vehicle. It is also possible to obtain the state of all cells at a specified time. Although TRANSIMS can express some properties of microscopic traffic flow models, compared to other microscopic models, TRANSIMS is not suitable for small area traffic simulation. The driving behavior simulated with TRANSIMS significantly differs from human driving behavior. The simulation rule set of TRANSIMS knows only three categories: free driving, following and rapid deceleration. Although some random conditions are developed, the inherent nature of the model leads to software inadequacies and makes it impossible to reproduce complex driving behavior. However, traffic simulation of an extreme large area, for example a whole country is possible with TRANSIMS. There is experience of simulating the complete road network of Switzerland (Raney et al. 2002).

2.2.4 AIMSUN

AIMSUN (Advanced Interactive Micro-Simulation for Urban and non-urban Networks), developed by University of Catalonia (UPC), Barcelona, Spain, is primarily a microscopic traffic simulation package. For different traffic networks, AIMSUN is capable to reproduce real traffic on a computer (Barceló and Casas 2005).The software now includes macroscopic, mesoscopic and microscopic models.

The microscopic car following and lane changing model implemented in AIMSUN are both proposed by Gipps. The car following model in AIMSUN can be considered as an evolution of this empirical model because the model parameters are not global. Local parameters depending on the type of driver, the road characteristics, the influence of vehicles on adjacent lanes, etc., have impact on model parameters (Barceló and Casas 2005). The model is based on an assumption that the driver would try to drive at his maximum desired speed when he drives freely without any other vehicle affecting his behavior. Unlike Gipps' one-dimensional model that considers only the vehicle and its leader, AIMSUN also considers the influences of adjacent lanes. The car following model in AIMSUN determines a new maximum desired speed of a vehicle in the section, and allows a maximum difference of speed.

AIMSUN provides a basic three-dimensional preview of the simulation and the user can add as many cameras as needed to capture all the points of interest of the traffic network, as in Figure 2.5. At the same time, when three-dimensional preview with multiple viewpoints are used together, the simulation dropped in frames per second rapidly. What's more, AIMSUN can function as either a stochastic model with vehicles based on turning probabilities, or a traffic assignment model using origin destination matrices. Dynamic traffic assignment and ITS are also available in AIMSUN.

2.2.5 PARAMICS

PARAMICS (PARAllel MICroscopic Simulation) is a three dimensional microscopic traffic simulation suite developed by Quadstone Limited, a Scottish company (Cameron and Duncan 1996). Unlike the other microscopic simulation programs, PARAMICS is UNIX-based. But through the use of a Microsoft Windows-based software Called Exceed by Hummingbird, the X-Windows platform can be emulated on a standard Workstation computer.

2.2 Traffic simulation software

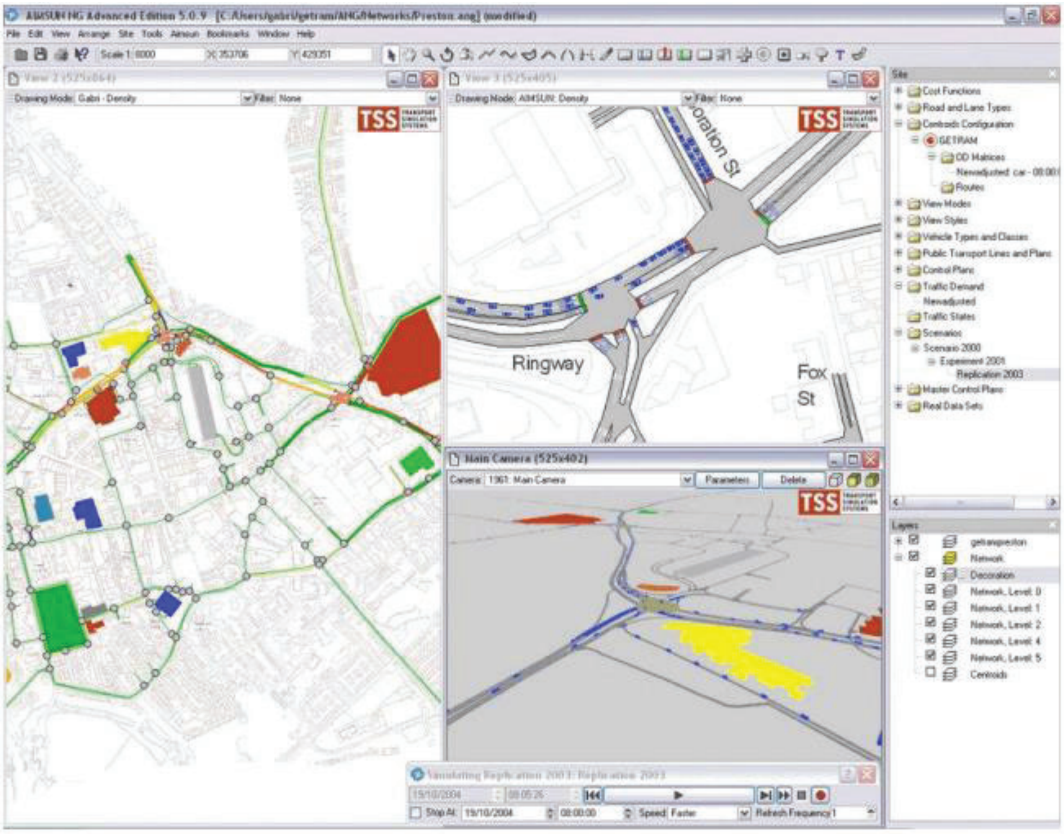


Figure 2.5: Multiple views of AIMSUN traffic simulation package (Kotusevski and Hawick 2009)

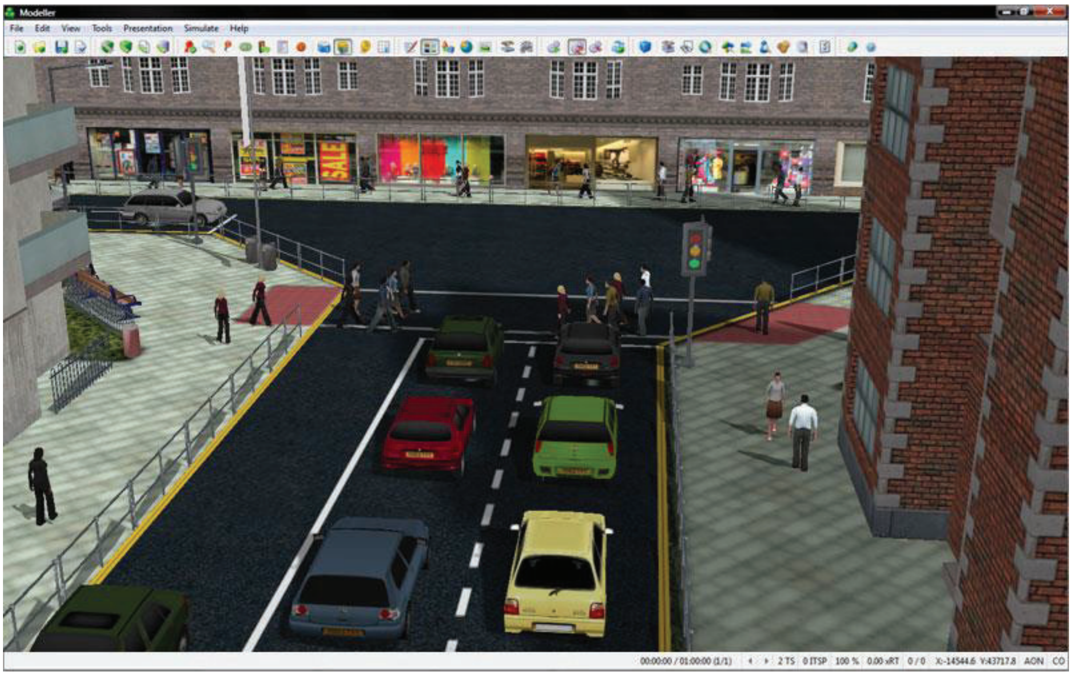


Figure 2.6: Three-dimensional representation in PARAMICS (from PARAMICS website)

Interfaces from PARAMICS to urban traffic systems are available which allow the simulation models to be used to develop ITS control strategies. Since the interactions between vehicles are modelled, the application of microsimulation to large area models is also possible.

The PARAMICS modeler has the best graphics representation of all packages. As in Figure 2.6, a complex 3D model is presented including vehicles, pedestrians, city buildings, traffic lights, etc., with lots of details. Libraries of textures are included in PARAMICS, which makes the simulation look much more realistic than the other packages. Like AIMSUN, PARAMICS users can also add as many cameras as needed to view the simulation from different points of reference. The detailed three-dimensional representation of PARAMICS and VISSIM make them always being compared with each other. In simulation accuracy, PARAMICS uses link-based routing which can result in inaccurate lane utilization for closely-spaced intersections. The path-based routing in VISSIM eliminates this problem (Choa et al. 2004).

2.2.6 Selection of the software utilized for this thesis

For the purpose of simulating the effects of vehicles' different degrees of automation on traffic flow, a basic scenario with detailed characteristics will be used. Considering simulation accuracy, scalability, model adjustability, input data extensiveness, verification convenience, microscopic traffic simulation package SUMO is chosen in building the scenario in this work.

Since the car following model will be used in SUMO, interaction between the car following model and other models (lane changing model, dynamic assignment model, etc.) must be considered. Models with high complexity would have negative impacts which are not easy to resolve (Bjärkvik et al. 2017), Krauss' model was chosen as the basic car following model in this work, and the following driver models based on different automation level will be modified on this basic model.

2.3 Current status of vehicles' automation level

2.3.1 Definition of level of automation

The tasks allocation between human and machine is probably the most important step in human-machine systems design (Wei et al. 1998), and it has early been considered by Sheridan (Sheridan 1992). Rouse described the process as three stage interactive design process: allocation, design and evaluation (Rouse et al. 1992). Several approaches have defined the assignment of functions to people and automation in terms of a more integrated team approach. One of them seeks to optimize the assignment of control between the human and automated system by keeping both involved in system operations, which has been labelled Level of Automation (LOA) (Draper 1995). Another recognized that control must be passed back and forth between the human and the automation over time, depending on the situation needs, and seek ways to use this understanding in improving human performance. This is marked as Adaptive Automation (AA) or Dynamic Function Assignment (DFA) (Corso and Moloney 1996). These can be seen as the most basic classification principles of automation.

Subsequently, the automation levels are defined by the amount of automation autonomy and the amount of human activity (Kaber and Endsley 2004). Ten automation levels were proposed as the basis of the classic man-machine task distribution principle (Sheridan and Verplank 1978). A four-stage model of human information processing was connected to automation classification (Parasuraman et al. 2000), for each stage of information processing/each function in model, either human or machine or some combination was held responsible for the effects on task performance due to the automation (Jeong et al. 2017). This can be seen as the theoretical basis for the widely recognized classification of automation.

A classification system based on six different levels was published in 2014 by SAE International, an automotive standardization body, as J3016 (Automated Driving 2014). This classification system is based on the amount of driver intervention and attentiveness required, rather than the vehicle capabilities. It is meanwhile widely accepted by researchers and automotive industry. This classification was updated by SAE in 2016, called J3016_201609, and in 2018, called J3016_201806. Basically, vehicle automation has been categorized from Level 0, corresponding to no automation, to Level 5, corresponding to full automation. The five levels of automation are depicted as follows.

Level 0 – No Automation:

> In this level, human driver is responsible for all aspects of driving tasks for the full-time including control of the car as well as monitoring the road and environment around the car. Automated system issues warning and may momentarily intervene but has no sustained vehicle control.

Level 1 – Driver Assistance (hands on):

In this level, the execution of either steering or acceleration/deceleration is done by driver assistance system but not both. It uses information about the driving environment and the human driver is expected to perform all remaining aspects of the dynamic driving task. For example, systems like Adaptive Cruise Control (ACC), Parking Assistance, Lane Keeping Assistance (LKA), etc. are classified in Level 1.

Level 2 – Partial Automation (hands off):

In this level, the execution of both acceleration/deceleration and steering control are done by a driver assistance system, while the human driver monitors the road and environment around the car. All the remaining aspects of the dynamic driving task are still performed by the human driver and continuous supervision of the human driver is also required. The human driver must be prepared to intervene immediately at any time if the automated system fails to work properly.

Level 3 – Conditional Automation (eyes off):

In this level, all aspects of the dynamic driving task are taken by the automated driving system and the driver can safely turn their attention away from the driving tasks. For situations that call for an immediate response, the automated driving system will handle. But the driver must still properly response to a request to intervene within limited time. Therefore, it requires partial supervision of the driver.

Level 4 – High Automation (mind off):

In this level, the automated driving system takes on all aspects of the dynamic driving task, even if a human driver does not respond appropriately to the intervention request. This level is basically unsupervised, the driver may safely go to sleep or leave the driver’s seat. However, the automated driving system supports only limited spatial areas or special circumstances. Outside of these areas or circumstances, the system will safely abort the trip.

Level 5 – Full Automation (steering wheel optional):

In this level, the automated driving system takes place on all aspects of the dynamic driving tasks under all road and environmental conditions. This level does not require a driver at all, the full automation vehicles can also be called self-driving vehicles. An example would be a robotic taxi.

2.3.2 Current automation level of vehicles on road

Although autonomous assisted driving technologies have developed into a relatively high level in the mass production process, consumer enthusiasm is not high due to factors such as price. Among the 20 best-selling vehicle models worldwide in 2018 (excludes LCV, includes pickups), published by Jato, the highest level of automation that can be selected is Level 2. Eight of the 20, Honda Civic (No.3), Honda CR-V (No.6), VW Golf (No.7), VW Passat (No.8), Chevrolet Silverado (No.9), Ford Escape (No.18), Hyundai Tucson (No.19) and Honda Accord (No.20) have the option of Level 2 automation and none of them is equipped Level 2 as a standard configuration. Only 5 of the 20 best-selling models are equipped with Cruise Control (CC), (the basic driving assistance technology) as standard configuration: Ford F-Series (No.1), Honda CR-V (No.6), VW Passat (No.8), Chevrolet Silverado (No.9) and VW Polo (No. 14). CC makes these five models' automation level at least at Level 1 for certain road conditions.

If passenger cars are divided into four categories, A-segment/city cars, B-segment/small cars, C-segment/medium cars and D-segment/large cars, most A and B segment cars stay with no automation or just Level 1 and some of them have an option to reach automation Level 2. For C and D segment cars for example BMW 5 Series, Audi A8, Mercedes-Benz S-Class, driving assistance technologies like ACC and LKS are in standard configuration, which make these cars' automation level at least at Level 2.

Level 3 is a relative dangerous automation level because it needs driver observe traffic situation for all the time without driving the vehicle. In this situation, drivers tend to pay attention on other aspects, such as replying messages or even watching movies. When the vehicle needs the driver to intervene, it needs it without any time delay. The reaction time of the driver in a higher-level automation vehicle may be even longer than in a no automation vehicle. From this perspective, driving assistance technology may even cause danger. This possibility of danger is difficult for consumers and transportation department to accept, so most automobile manufacturers do not focus on Level 3. Some manufacturers have already claimed to skip Level 3, including Google, Ford and Volvo.

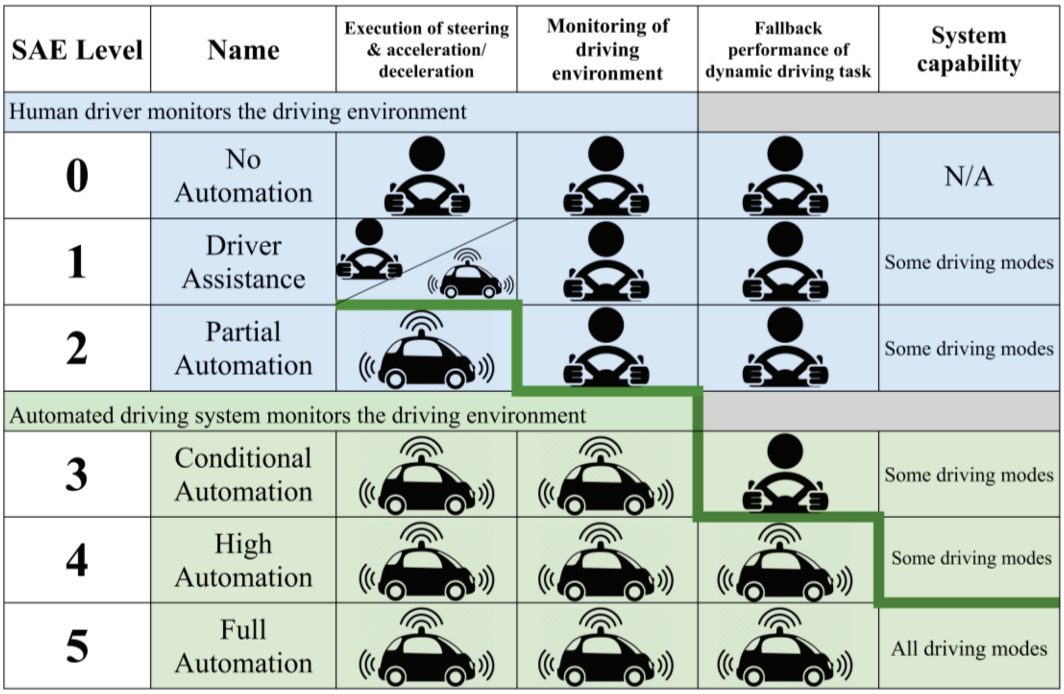


Figure 2.7: SAE defined level of vehicle automation

Figure 2.8: Waymo autonomous car Firefly and Chysler Pacifica minivan equipped Waymo technology. (Source: waymo.com)

2.3.3 Autonomous car

The difference between Level 4 (high automation) and Level 5 (full automation) is whether the vehicle can drive autonomously in all driving modes. This "all" driving modes require to cover a wide range and are therefore difficult to meet. Manufacturers who research autonomous driving always focus on the Level 4 and are committed to increasing driving modes.

Waymo is the leader in American autonomous driving technology. From December 2018, Waymo has launched a commercial autopilot service called Waymo One, and give passengers ride experience in form of self-driving taxi in Phoenix, USA (LeBeau 2018).

In the current autonomous driving research, the road test distance can be said to be one of the most important indicators for the recognition of system stability. Waymo announced in October 2018 that it has completed 10 million miles on the roads of 25 cities in USA. Of all the companies that tested autonomous vehicles in California, Waymo's detachment rate (the number of times a driver needs to take over the steering wheel when the vehicle itself is inoperable) is by far the lowest.

Other traditional automobile manufacturers are also interested in autonomous cars, Cruise Holding from General Motors developed a Level 4 autonomous vehicle which has been tested in New York, and will provide Level 5 full autonomous cars without steering wheels and drive pedals (Rocco 2014). Nissan Infiniti Q50 Prototype claims to have Level 4 automation degree and will be tested in 2020 (Greimel 2019). BMW claims that their Vision iNEXT will achieve Level 3 in 2021 and Level 4 in 2024 (Etherington 2019). Daimler and Volkswagen believes that Level 4 and Level 5 automatic driving will be released in 2025 (Shepardson 2014; Volkswagen AG 2019).

Of course, with the development of autonomous driving technology, many barriers have followed, for example the safety issues. The driver's death and pedestrian death caused by the detection problem in self-driving mode made the public feel that the technology is not yet mature. Besides, the transport laws and division of responsibility also slows down the popularization of autonomous driving technology. However, the problem will always be solved and the technology will always improve. We are getting closer and closer to the realization of autonomous driving.

2.3.4 Studied LOA in this work

In order to compare the different effect of vehicles with different degrees of automation, three categories of automation level will be studied in this work, representing the present, near future and long distant future, respectively.

Even though most new car buyers have the option of equipping basic driving assistance technologies like CC or ACC to make it Level 1, lots of them will choose not to because of some factors like extra cost. Considering of the percentage of old cars, trucks and the limited driving scenarios of these basic assistance technologies, ordinary driving in cities for most drivers stays no automation at all. Hence, Level 0 (no automation) is chosen to present the current automation level on road.

For most manufactures, Level 2 are easy to achieve. The technologies are already mature, the time of popularization is just depending on the price. For some countries, some automation functions (such as cruise control, lane keeping systems) have already been or will be required by law in the near future. Thus, it is not hard to believe, in the near future, Level 2 will be a standard configuration for most cars. Level 2 (partial automation) is chosen to present the automation level on road in the near future.

In the end, although nobody knows how long it will take, autonomous cars will be mature and eventually drive into everyone’s garage. For that time, Level 5 (full automation) is chosen to present the automation level on road in the long distant future.

3 Establishment of simulation scenarios

The simulation scenario is an important part of traffic simulation and is critical to the accuracy of the simulation. This Chapter introduces the process of creating a simulation scenario and the selection of a simulation scenario prototype. Two cities in different countries are selected as scenario prototypes and their maps are extracted into SUMO for simulation.

3.1 Extraction of real scenes

3.1.1 Open Street Map

There are many ways to import maps from actual cities into SUMO, the easiest and most convenient way is through OSM (Open Street Map). OSM is a volunteered geographic system to create a free editable map of the world. With over two million registered users (Neis and Zipf 2012), OSM collects data using manual survey, GPS devices, aerial photography and other free sources. Compared with other volunteered geographic information systems like WikiMapia, Google Map Maker, Yandex Map editor, OSM provides a free and relatively comprehensive map for cities. Compared with proprietary data sources, such as TomTom, NAVTEQ, and ATKIS, OSM is also favorable (Zielstra and Hochmair 2012).

However, OSM also has uneven quality across the world. Figure 3.1 describes OSM GPS point's distribution map, as can be seen in the picture, Europe has much more points than the rest of the world.

3.1.2 Network verification and calibration

Even in Germany, where OSM data is comprehensive, OSM data may differ from real situations. Thus, a street view map is needed for verification.

In most districts of Europe and the America, Google map provides frequently updated street view map covering most parts of the streets. But Google doesn't have accurate streetscapes of all parts of the world, sometimes local map companies have an advantage in getting more accurate map data. For example, in China, Baidu's streetscape is more accurate than Google's, the covered area are larger and map updates are more frequent. With the help of the street view maps, real street scenarios are compared and corrected.

Inaccurate intersections

Among all the inaccuracies of the map exported from OSM, errors in intersections are the most common errors and have the biggest impact on traffic simulation. Especially the OSM in China, the wider roads lead to larger intersections, these intersection areas are often marked by OSM as several different intersections. If a viaduct is passing by above the intersection, possible errors will be more. These extra intersections block vehicles in all directions. Therefore, intersections are also the key point of map verification and correction.

Normally all the intersections will be numbered after selection of simulated area in order to facilitate later verifications. Numbers of lanes, direction of each lane, allowed vehicle type of each lane, speed limit of each road section, etc. will be compared between OSM and street view.

Figure 3.2 is an example of OSM deviation in an intersection in Wuhan, China. The upper left picture shows the original map of this intersection in SUMO imported from OSM. There are five small intersections with five unrelated traffic lights. In simulation, these redundant intersections create unrealistic congestion problems.

As in the upper left picture of Figure 3.2, all vehicles are stuck in this intersection, their red color represents their low speed. In the satellite image of this intersection (in upper right in Figure 3.2), only one large intersection can be seen. Then, at the street view (lower left), at this 360-degree panorama, it is very obvious that there is only one intersection. The two north-south roads are viaducts and cannot be directly connected to the intersection on the ground level. Based on the street view, network in SUMO has been modified. The final version of the intersection can be seen in the lower right image. With the same traffic demand, adjusted network of the same intersection has a smooth traffic.

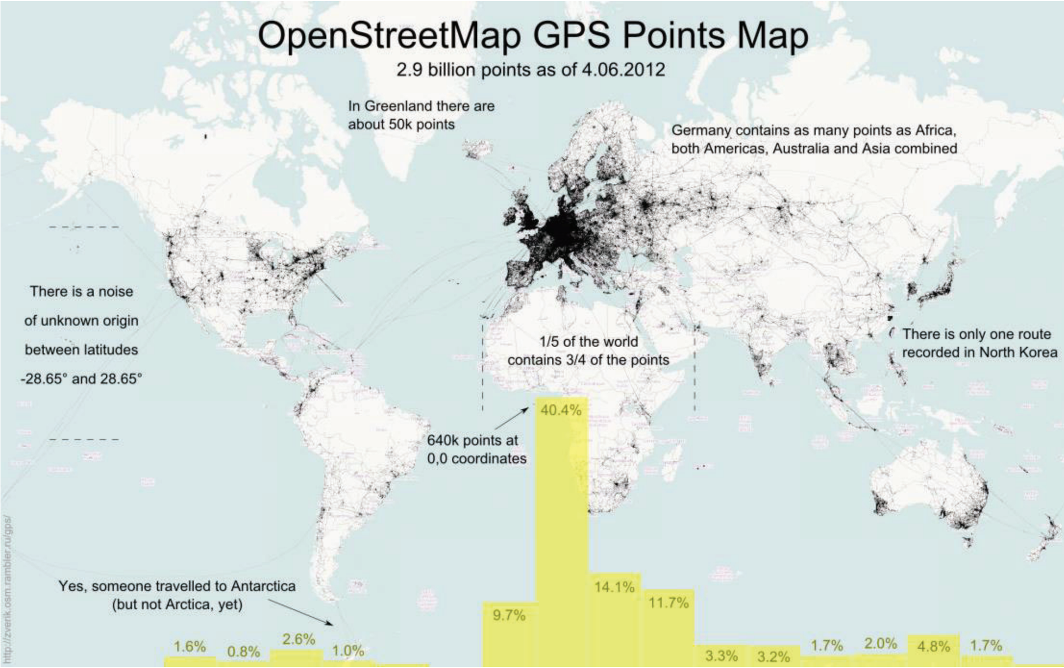


Figure 3.1: OSM GPS points map (Source: wiki.openstreetmap.org)

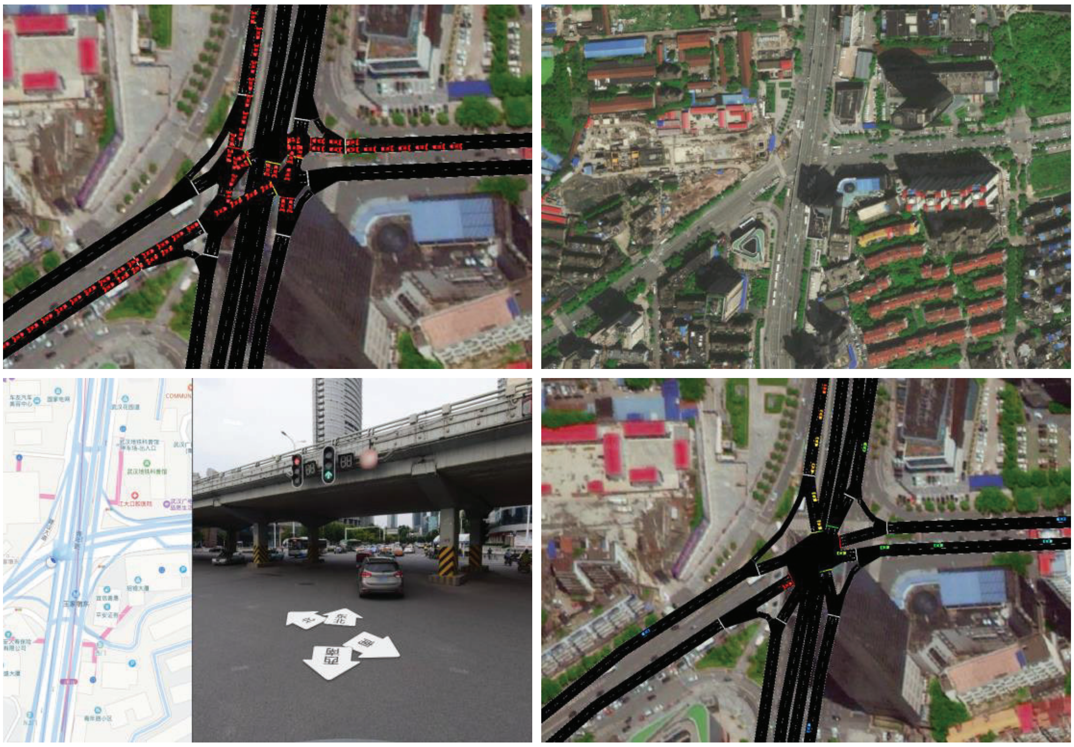


Figure 3.2: An example of OSM intersection deviation and correction.

Extra roads

In some cases, extra roads may appear in maps exported by OSM. These road areas are usually non-motorized roads or dedicated roads. In this work, non-motorized roads in the parks, by the rivers and in residential areas are often found. And also dedicated roads including tanker roads, driveway inside the zoo, farm interior roads and so on are sometimes considered as public roads on the map. An effective way to identify these extra roads is through the street view map provided by map companies.

Figure 3.3 shows an example of extra roads, which is found during the establishment of the city of Duisburg scenario. The upper left picture is a screenshot of the original road network in SUMO, the roads in black are imported directly from OSM. The blue lane in the picture is found unreachable while generating trips for vehicles. Therefore, the real scene from satellite image (upper right) and street view map

It can be seen in the lower left picture of Figure 3.3, that two barricade pillars in red and white are placed at the intersection entering this road. Obviously, the blue road in the upper left picture is a non-motorized road, for the other road entering from this intersection, the case is the same. After removing the extra roads, the adjusted road network of this area is shown in the lower right picture of Figure 3.3.

Missing roads

The missing roads also need to be manually added in the network imported from OSM. The most common of these are the two-way roads that are widespread in residential areas. Many people's houses have a single lane road leading to their garage. This single lane road is responsible for both the incoming and outgoing directions. However, in SUMO, there is only one direction for each lane. And the single lane leading to the houses with two driveways does not exist. Therefore, in the process of importing road structures from OSM into SUMO, one of the driving directions is missing. In this case, a reverse lane will be added manually in SUMO.

(lower left) are checked.

In addition, some special road sections may also have missing paths. Figure 3.4 shows an example of a dead-end road leading to a parking lot in the city of Duisburg. The upper left picture is the original network of SUMO. The light blue road leads to the green lane, but the reverse direction of the green lane only has a dead end. The satellite image (upper right) of this region shows that inside the parking lot there is a ring road. In the street view (lower left), it can be seen that there is a blue circle on the map and the vehicles can drive on the ring road. Thus, the missing road is added manually in SUMO and the result can be seen on the lower right picture. From the blue road, both of the two green roads are available, and there is no dead-end road in the picture.

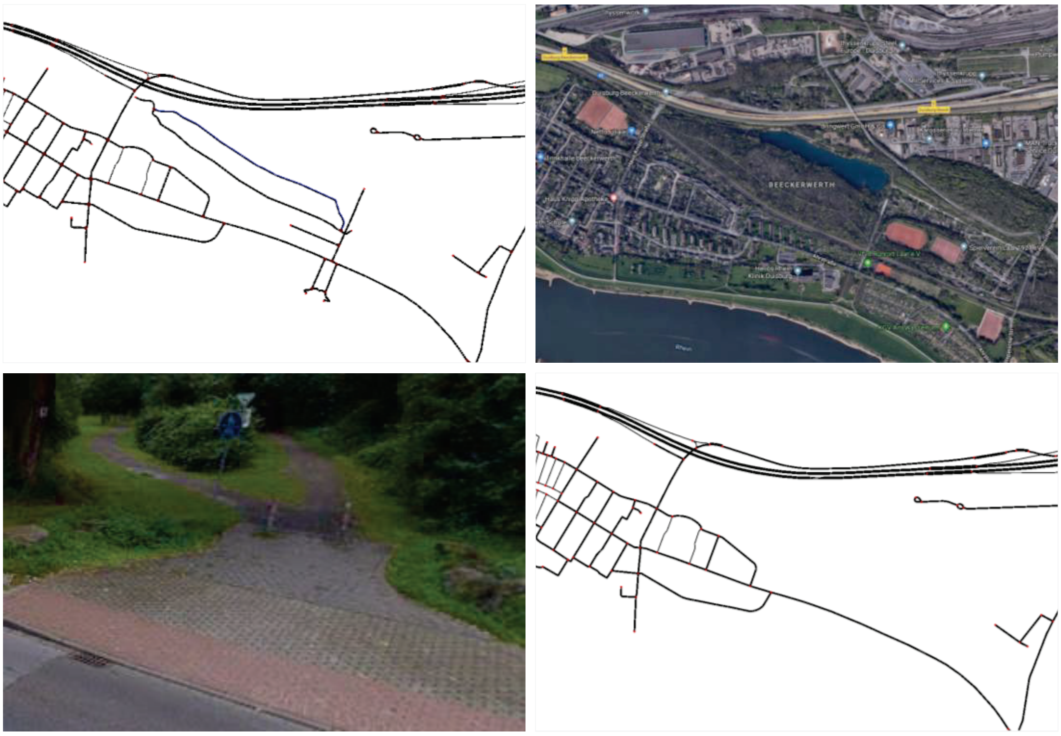


Figure 3.3: An example of extra roads inside a park in Duisburg.

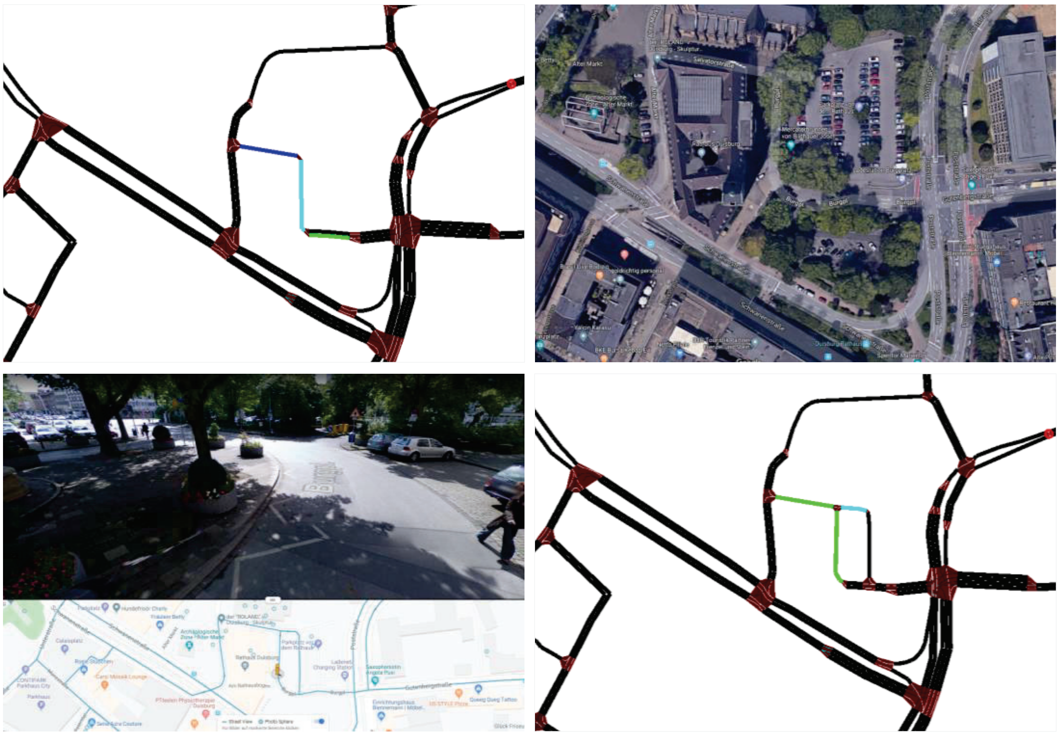


Figure 3.4: An example of missing roads in a parking lot in Duisburg.

Reverse direction roads

In addition to the general errors mentioned above, there are a few individual errors. Figure 3.5 shows a particular error near an intersection. The blue road in the upper left picture shows that it goes through the intersection, but cannot lead to other roads of the intersection. Driving directions are marked by red arrows. The upper right picture shows the further connected sections. The roads shown in the picture have two completely different directions: the road on the upper right (in blue) goes up and the road on the lower left goes down. Street view (lower left) helps in finding the right direction for this weird road and the reversed road is eventually turned over (lower right).

Map comparison and calibration is a very time-consuming task. Due to the different size of the maps, the numbers of intersections needed to be calibrated are huge. But at the same time, this work has to be done. Accuracy is the core of traffic simulation, and carefully restored map has a major impact on the accuracy. Hence, if time is limited, it is better to build a relatively small scenario and calibrate than to handle a big scenario without calibrating each intersection.

3.1.3 Visualization of scenarios

In the establishment of simulation scenarios, in addition to the roads themselves, there are roadside buildings, rivers, mountains, meadows and so on. The shapes and locations of these other scenes are described in detail in OSM and can be easily edited in Java program. But unfortunately, most of these scenes are lost in the process of importing into SUMO. Importing OSM into SUMO requires separate introduction of road information and other information such as buildings, rivers, etc. Road information can be completely imported into SUMO without being affected, but only some of the other information can be identified. Most of this information is lost because SUMO does not recognize it.

By adding the other missing information to SUMO, manual operation is needed. Basically, it is drawing all the edge points of a building or a lake and then connect them into a polygon. The time spent on this work is not worth the benefits it brings. Therefore, in the establishment of scenarios, it is decided to use a background picture under the SUMO road information. To make a better visualization, satellite map is selected.

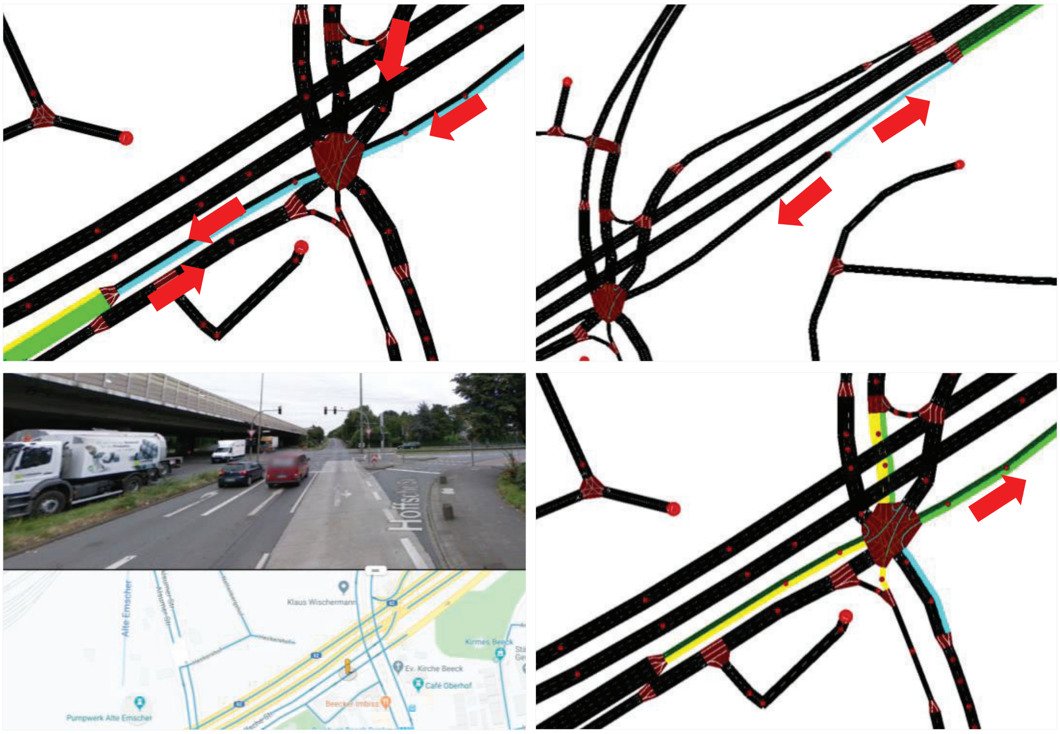


Figure 3.5: An example of the opposite direction of a road.

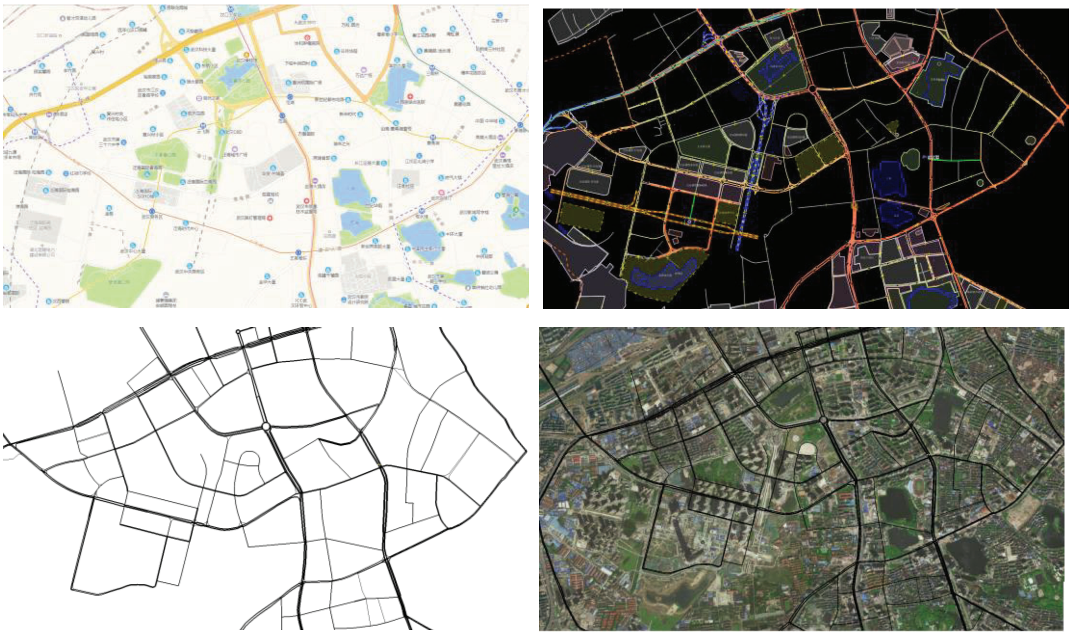


Figure 3.6: An example of map visualization in SUMO.

Figure 3.6 describes a visualization example using satellite map as background in SUMO. The selected area is in Wuhan, China. From the road map (upper left) it can be seen that this area contains several lakes and parks in blue and green, respectively. In the Java program, the OSM contains all the information (upper right). Only the road information from OSM is imported into SUMO. The lower left picture is the network from SUMO. Without other information, the road sections look clear but not that intuitive. The lower right screenshot is after putting a satellite map as a background behind the roads. This method brings a better visualization even with a facile progress.

Placing a background image is not the perfect method, if the simulated area is large enough. The background picture will be hard to match all the roads in simulation. One of the possible reasons is that the satellite view has a slight spherical deviation. When the sphere is turned into a plane, the deviation between OSM and the satellite map is different, and making the background difficult to match. Therefore, in the case of a large simulation scenario area, multiple background images can be used separately. Although the inevitable map seam will be generated, the matching degree between the roads and the background will be improved.

3.2 The city of Wuhan Scenario

3.2.1 Natural conditions of the city of Wuhan

Located in the middle of China, the city of Wuhan is the capital of Hubei Province. It has a reputation of "nine-province thoroughfare (九省通衢 in Chinese)", means an important transportation hub in China. As of 2018, the city of Wuhan has 13 districts with a total area of 8494.41 square kilometers and a resident population of 11.081 million. The population and location of the city of Wuhan are representative of major cities in China. Therefore, the traffic scenario of the city of Wuhan can represent the traffic scenarios in major cities in China.

Wuhan is located in the eastern part of the Jianghan Plain, and is in the middle of the Yangtze River, the longest river in Asia. The Yangtze River and the Han River traverse the center of city Wuhan and divide the city into three parts. There are many rivers in Wuhan, and the water area accounts for about one quarter of the city's total area. Because of its special location and topography, the city of Wuhan is the largest water, land and air transportation hub and shipping center in the interior part of China.

Like many metropolises, Wuhan is also facing traffic jams, especially in densely populated areas. Figure 3.7 is a spatial distribution of population density in Wuhan, the degree of red in the picture represents the degree of population density (deeper red = denser population). The population data source is street population in China's sixth population census in 2010. As can be seen in the figure, the most densely populated area is Jianghan Zone (江汉区) on the left side of the river. According to the data of Wuhan Municipal Transportation Bureau, the most serious traffic jam happens also in Jianghan Zone.

3.2.2 Scenario of Jianghan Zone

Jianghan Zone is an old district in Wuhan with over 500 years of history. It is also the earliest formed business district. Until now, it is still the largest and most prosperous commercial district in the city of Wuhan. With the development of the economy, the price of land in this area is getting more and more expensive, which makes it more and more difficult to widen and change roads. Therefore, it is particularly important for a scientific road planning in this region. This is also one of the reasons why Jianghan Zone was chosen for building scenario in this work.

As mentioned in 3.1.2, the accuracy of OSM data in China is poor. The directions of lanes, number of lanes, intersection construct, and speed limit of roads can be to a large extend wrong. As a result, to ensure the accuracy of network in SUMO, long time has been spent in the calibration process. For the scenario of Jianghan Zone, Baidu map was used because of its comprehensive street view data.

The planning of traffic lights also plays an important role in the accuracy of the scenario. Unfortunately, there is no official cooperation with the government of the city of Wuhan and the data on traffic light planning is not available. Thus, the traffic light plan in this scenario is the default setting of SUMO.

At the beginning, bus lines and bus stations are added into the scenario. But due to the computing capability of SUMO and the large population in this area, calculating private cars and public transportations in the same time will make later iterations impossible. As a result, in this scenario, the bus lines are not included and only the private cars are simulated.

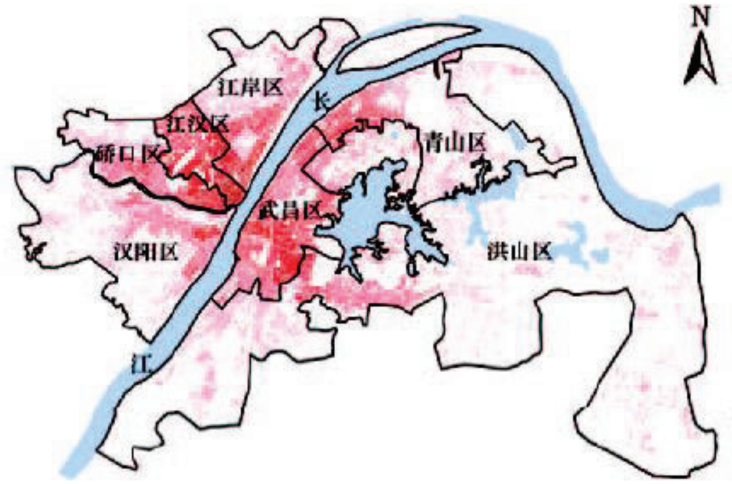


Figure 3.7: Spatial distribution of population density in Wuhan (Xu et al. 2017).

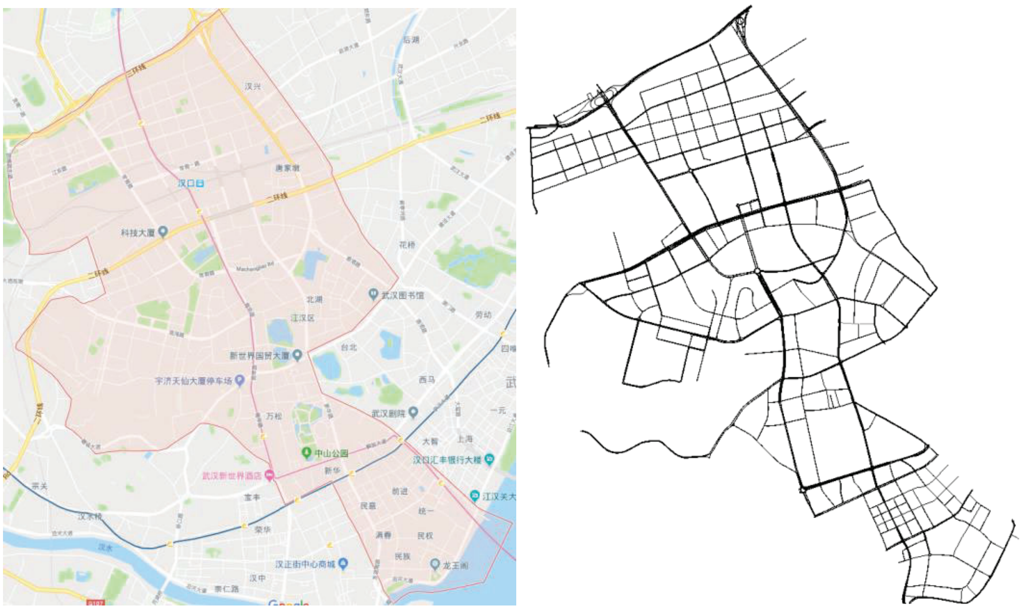


Figure 3.8: Original Map and abstracted road network of Jianghan Zone.

(a) Locations of schools and kindergarten

(b) Roads for vehicles

Figure 3.9: Selected school intensive area in Jianghan zone, Wuhan.

3.2.3 School intensive area

One feature of the city of Wuhan and even whole China is the uneven distribution of high-quality educational resources. From a national perspective, high-quality educational resources are gathered in big cities. But from a city's point of view, outstanding teachers and schools are located in the city center. In order to give their children a better educational environment, parents are willing to spend a high price for a small and old houses in the city center. In this way, their children are able to gain admission into a great school. Meanwhile, the living environment of good school districts is usually very limited. So many parents choose to live in the suburbs and drive their children to school every day. In order to analyze the extra traffic brought by key schools, the intensive part of educational resources in Jianghan Zone of Wuhan is selected as a scenario.

Figure 3.9 is the map of the school intensive area. Figure 3.9 (a) shows the distribution of schools and kindergarten in the selected area. The locations and shapes of schools are marked and numbered in red, kindergarten locations are marked and numbered in pink points. Figure 3.9 (b) shows all the vehicle roads of this area in green. The selected area has only 2.45 square kilometers, but there are 21 primary schools and 16 kindergartens in this area. As the scenario of Jianghan Zone, traffic light data is the default setting from SUMO. For the bus lines, there is no practical significance because the small size of this area.

3.3 The city of Duisburg Scenario

3.3.1 Natural conditions of the city of Duisburg

The city of Duisburg is located in the northwestern German state Nord Rhine-Westphalia. Lying on the confluence of the Rhine and the Ruhr rivers, Duisburg is one of the largest cities in the Ruhr area. Its 498,110 (2017) inhabitants make it Germany's 15th largest city. The city of Duisburg lies on both sides of the Rhine, with the city center and most boroughs on the river's right bank. What is more, Duisburg has the world's largest inland port. The city of Duisburg is a type of medium-large-scale European city, which is also the most important class of cities in Europe in demographic terms (Giffinger et al.). Therefore, the traffic scenarios of city Duisburg is built to represent common cities in Europe.

As the first pair of sister cities between China and Germany, Duisburg and Wuhan have established their friendly relations since 1982. These two cities have many similarities: both cities are steel centers, both cities are located at the river junction and are divided into two parts by a major river, the automotive industries of both cities are well developed. Since 2015, the starting and arriving stations of the new China Europe train are exactly the city of Wuhan and the city of Duisburg. For these reasons, it is interesting to build and compare two scenarios of two cities with similarities while in different continents.

As shown in Table 3.1, there is a huge difference in population between Duisburg and Wuhan. Unlike Europe, where population is generally used as a standard for ranking large cities, Wuhan, with a population of more than 10 million, is not a first-tier city in China. Wuhan has a population density six times more than Duisburg, which can be horrible for city traffic. Fortunately, Wuhan has a higher public transportation sharing rate. According to the data from Wuhan Municipal Transportation Commission, the public transportation sharing rate is 58.6% (2016), much higher than most cities in China (Wen et al.) and Europe cities like Berlin (26%), Vienna (39%), and Prague (43%) (Land Transport Authority 2014). This means that more than half of all the travel in Wuhan is carried out by public transport, which greatly reduces the traffic pressure.

3.3.2 Scenario of the whole city of Duisburg

Since the urban area of the city of Duisburg is not very large, it is possible to establish a traffic scenario of the whole city. In Duisburg, there are two horizontal (east-west) expressways namely A 42 and A 40, and two vertical (north-south) expressways A 59 and A3. The expressways, also known as Autobahn or Bundesautobahn, are federal controlled-access highway system in Germany.

These 4 expressways can be seen in Figure 3.10, A42 (horizontal, upper, more north) connects Kamp-Lintfort as west end with Castrop-Rauxe as east end, A40 (horizontal, lower, more south) connects Straelen as west end with Dortmund as east end. A59 (vertical, left, more west) connects Dinslaken and Bonn, A3 (vertical, right, more east) links the German border with Netherlands to the south at the Austrian border. The highway A3 is a major connection between the Rhine-Ruhr area and southern Germany, resulting in heavy traffic.

3.3 The city of Duisburg Scenario

Thanks to the support of the City of Duisburg and WBD (Wirtschaftsbetriebe Duisburg), OD (Origin-Destination) matrix data, and detector data (including inductive loops and cameras) are provided for this thesis. The OD matrix data consists of two parts, the first part is the selected area which will be divided in many sections, and these sections are considered as points where traffic starts and ends. The other part is a matrix that describes the traffic volume from each section/point to another in a certain time. According to the provided OD matrix data, the city of Duisburg is divided into 596 inner city traffic sections and there are 153 outer city traffic sections around the city of Duisburg. The outer city traffic sections contain city Mülheim an der Ruhr, Oberhausen, Dinslaken, Hünxe, Wesel, Rheinberg, Kamp-Lintfort, Neukirchen-Vlyn, Moers, Krefeld, the northern area of city Düsseldorf und Ratingen. The OD matrix data was calibrated to an average working day with the reference year 2015.

In Figure 3.11(a), the boundary of these inner and outer city traffic sections can be seen in shapefile software QGIS, and the red points are the center points of the traffic sections. Each point represents a traffic section in OD matrix data, but not each point has its boundary on Figure 3.11(a). Some points describe more peripheral areas of the city of Duisburg, whose exact boundary are not given. Therefore, on the edge of the outer city traffic sections, there are many points in one traffic section. Besides, the Düsseldorf airport is separately defined as a traffic section without boundary in Figure 3.11. Therefore, the total number of traffic sections defined by OD matrix data are 908, including 596 inner city traffic sections with boundaries, one inner city traffic section without boundary, 153 outer city traffic sections with boundaries and 158 outer city traffic sections without boundaries. The matrix contains the traffic volume between these 908 sections/points in 24 hours of a day.

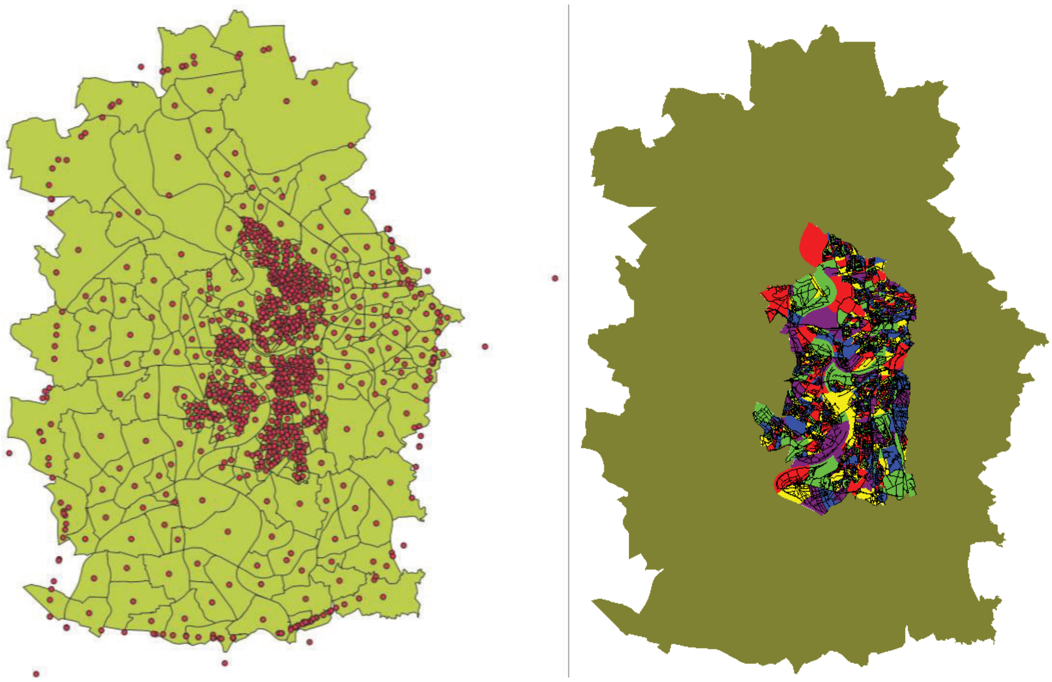
Coordinate transformation

The Duisburg city netfile mentioned above is extracted by OSM, and the OD matrix data is given in shapefile. As a result, a unification and transformation of the two coordinates is needed. In order to transfer the OD matrix traffic section data into SUMO, the polygons are exported from the shapefile with all sections described by geo-coordinates (latitude and longitude). There are two methods of performing coordinate transformations in SUMO, one is using TraCI (Traffic Control Interface) and the other is using sumolib. In this work, TraCI is used for transforming the geo-coordinates into network-coordinates (horizontal meters and vertical meters).

Table 3.1: Comparison of population and area between Wuhan and Duisburg

Cities	City area	Population	Population density
Wuhan	8,494.41 km^2	11,081,000	1,282.36 $/km^2$
Duisburg	232.82 km^2	498,110	2,100/km^2

Figure 3.10: Map, extracted network and OD matrix partition of the city of Duisburg.



(a) Traffic sections in QGIS

(b) Traffic sections in SUMO

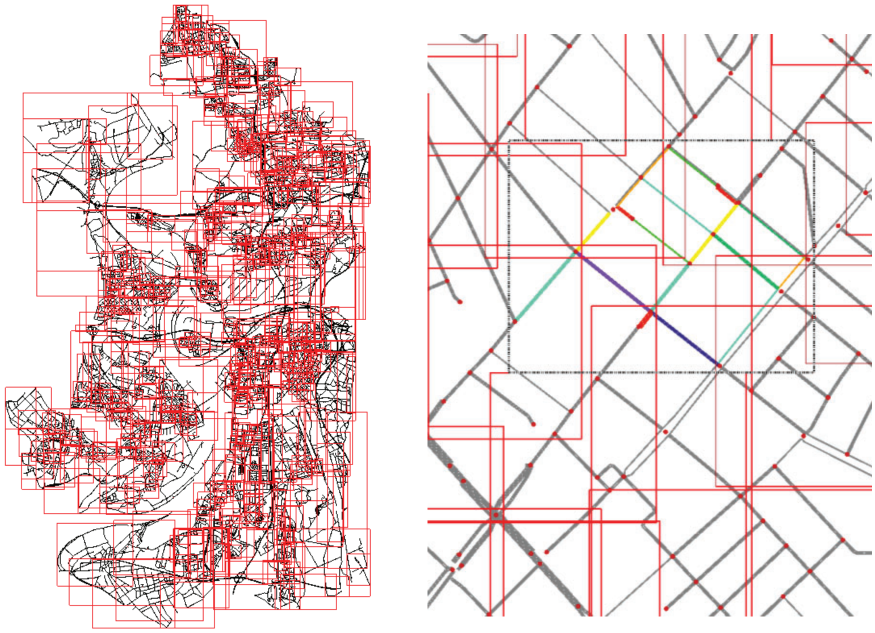
Figure 3.11: Distribution of traffic sections of the city of Duisburg.

By means of transforming coordinates with TraCI, the OD matrix traffic section data are shifted to polygons in SUMO netfile. Figure 3.11(b) shows these polygons/traffic sections in different colors. The olive color area are outer city traffic sections and the inner city traffic sections are in five different colors (red, green, blue, yellow and purple), and the black lines in the picture represent the roads. As can be seen, the sections are not divided into the same size, while the areas with more roads are divided into smaller traffic sections. This kind of segmentation for traffic sections can reflect the traffic volume more accurately between each traffic section/point and another.

Road mapping

The new version of SUMO (Version 1.6.1) unifies polygons and traffic sections into TAZ (Traffic Assignment Zone/Traffic Analysis Zone). A TAZ in SUMO is described by its ID and its corresponding streets/edges. In the process of coordinate transformation, the original IDs of the traffic sections are kept, so the IDs of TAZs can be consistent with the IDs in the OD matrix. Figure 3.12(a) shows the area of each TAZ in red boxes in SUMO. Each red box represents a traffic section in Figure 3.12(a), and Figure 3.12(b) shows a selected TAZ in black dotted box, and the streets in this box is marked in various colors.

Through a python tool in SUMO called edgesInDistricts.py, the streets/edges in a TAZ are written into the description file of this TAZ. As the TAZs or so-called traffic sections are seen as points in OD matrix, in this part the allocation of vehicles is also considered. In other words, the OD matrix just describes the traffic volume from one TAZ to another, but in the simulation, the vehicles do not start from one point, but from different roads. Therefore, the length of each street in a TAZ is also recorded into the TAZ file, and according to the length, the weight of road allocation in one TAZ will be decided.



(a) TAZ regions in SUMO (b) A TAZ and its streets

Figure 3.12: TAZ sections and its corresponding streets.

Traffic demand

Different from the traffic demand source mentioned in 3.2.2 and 3.2.3 for the city of Wuhan, in the city of Duisburg, traffic demand is defined by the OD matrix. The OD matrix data given by the city include Duisburg and the surrounding areas, and at the same time our simulation area is only the city of Duisburg. In order to resolve this difference, four cases of the simulation of the city of Duisburg were implemented and compared. For Case A, only the traffic inside the city is considered. This means that extra-urban traffic and traffic between surrounding areas is ignored. Only the traffic with both the starting point and the ending point inside the city is included. In Case B, all the trips of the city of Duisburg and the surroundings are included, but the scope of simulation has not been expanded. In other words, the outermost streets of the city of Duisburg carry the traffic of surrounding area. In this case, if a vehicle's starting point is at the surrounding area of the city of Duisburg (not in the map), it will start from a road nearest its starting point in the map. In Case C, only the trips with either the starting point or the ending point inside the city are included. That is, Case C does not contain the trips with both starting point and ending point outside the city. And in Case D, the simulation scope is expanded into the city and its surrounding areas and all trips are included. A comparison of these four cases is summarized in Table 3.2.

In all the four simulations, the OD matrix traffic demand is assigned to trips for 24 hours in a day with a sub-program in SUMO called od2trips. Then, another sub-program in SUMO called DUAROUTER is used to generate the exact route for each vehicle from the trip file. All the four cases have been simulated separately, the results of the four simulations are presented in 5.3.

Table 3.2: Scope of map and traffic of 4 different simulation cases of the city of Duisburg.

Simulation Scope		Case A	Case B	Case C	Case D
Traffic	Inner city	Yes	Yes	Yes	Yes
	In to out/ out to in	No	Yes	Yes	Yes
	Out to out	No	Yes	No	Yes
Map	Inner city	Yes	Yes	Yes	Yes
	Outer city	No	No	No	Yes

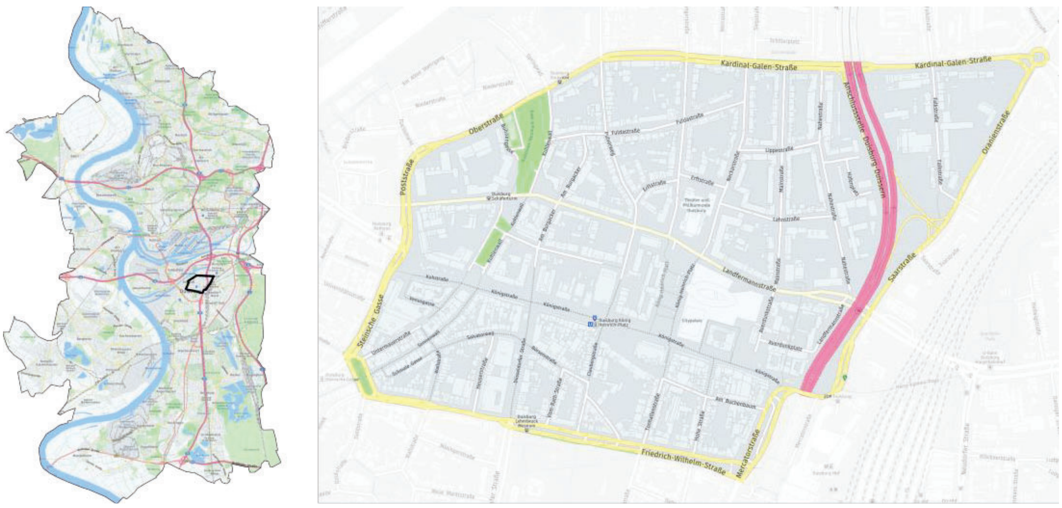


Figure 3.13: Location and range of inner ring Duisburg. (Source: Here map)

3.3.3 Scenario of Duisburg inner ring

Like many big cities, Duisburg city center is the most bustling and densely populated area. Figure 3.13 shows the range of the inner ring. The yellow roads are the main roads of this zone and the red road is a part of the highway A 59. The inner ring contains several shopping malls and is passed by all three subways in Duisburg.

The main railway station of the city of Duisburg is also located next to the inner ring. After the re-planning of the bus lines in 2019, there are 25 bus lines in the city of Duisburg, 9 of them pass the inner ring area. Therefore, the inner ring area bears multiple functions of transportation hub, shopping and entertainment.

Besides the quick bus line SB 40 (Schnellbus 40 in German) that only has one stop in the inner ring, the other eight bus lines (920, 921, 926, 928, 930, 931, 933, 934) can all transport passengers within the 16 bus stations of the inner ring. The locations of bus stations and time plan are from public information of local transport company: DVG (Duisbruger Verkehrsgesellchaft) and VRR (Verkehrsverbund Rhein-Ruhr).

The information of traffic detectors is also supported by WBD, including data collected from induction loops and cameras. Different from the scenario of the whole city of Duisburg introduced in the previous section, all the detectors with valid data in the inner ring are reproduced in this scenario. Moreover, traffic demand of this scenario is also provided by the detector data. On one hand, the OD matrix data has already divided the city into zones, and for a small area like the inner ring, the zones of OD matrix are too large to describe the traffic demand. On the other hand, data from traffic detectors can describe the traffic activities more precisely, it is more useful for accurate simulation in a small area.

The traffic light plan of the inner ring area is not provided; however, the locations of traffic lights are provided by WBD. All the 21 intersections with traffic lights are shown in Figure 3.14. The blue numbers are traffic lights with static plans and the red numbers (606, 701, and 727) are traffic lights with dynamic plans, which change with the wishes of pedestrians. The public transport stations are also shown in Figure 3.14, bus stations are marked with the H sign in yellow and green, and subway stations are marked with the U sign in blue and white.

3.4 Comparison of city Scenarios

In this chapter, four scenarios for two different cities in China and Germany are built. Scenario 1 is based on the Jianghan area in Wuhan, China. Although no real traffic light map was accessible, information about bus lines and train stations was incorporated in this scenario. Scenario 2 is based on a small section of Jianghan area, which is heavily polluted by school traffic. Due to its small size, no bus lines were added in this scenario. Scenario 3 and 4 are based on the traffic plan of the city of Duisburg, Germany. Scenario 3 covers the entire city, while scenario 4 covers the inner part of the city.

Figure 3.14: Location of traffic lights in Duisburg inner ring.

Table 3.3: Comparison of four scenarios built in SUMO.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
City	Wuhan	Wuhan	Duisburg	Duisburg
Area	33.43 km^2	2.45 km^2	232.82 km^2	ca. 0.7 km^2
Number of lanes	1243	445	23758	369
Number of junctions	562	193	9736	167
Number of residents	683,500	ca. 70,000	498,100	-
Real traffic light plan	no	no	yes	yes
Bus lines and stations	yes	no	no	yes

Comparison of the four investigated scenarios is shown in Table 3.3. The number of lanes, and the number of nodes is counted in the SUMO network. Based on these four scenarios, simulations are performed in the following chapters.

4 Driver models with different degrees of automation

In this chapter, the driver-vehicle separated models are first introduced and the advantages and possibilities brought by these models are discussed. The mathematical expressions of the driver models are then introduced. Finally, parameters of different automation levels are incorporated in the driver model to represent the driver behavior of different automation levels.

4.1 Driver-vehicle separated models

4.1.1 Traditional driver-vehicle unit model

In traffic simulation, the traditional vehicle guidance model considers driver and vehicle as a whole, and studies the overall characteristics. As shown in Figure 4.1, the driver and the vehicle are treated as a unit and all internal interactions are ignored. In this model, the input is the parameter of the leading car and the output is the status of the following car, including the speed, the acceleration, etc.

The advantages of building a unit model are obvious. Since human drivers and vehicles are complex simulation objects, the driver-vehicle unit model greatly reduces the complexity of the simulations. However, the interaction between the driver and the vehicle cannot be reflected in the simulation. Therefore, the accuracy of the simulation is diminished. In order to conduct a more accurate simulation, in this thesis, driver model and vehicle model are separated, as shown in Figure 4.2.

4.1 Driver-vehicle separated models

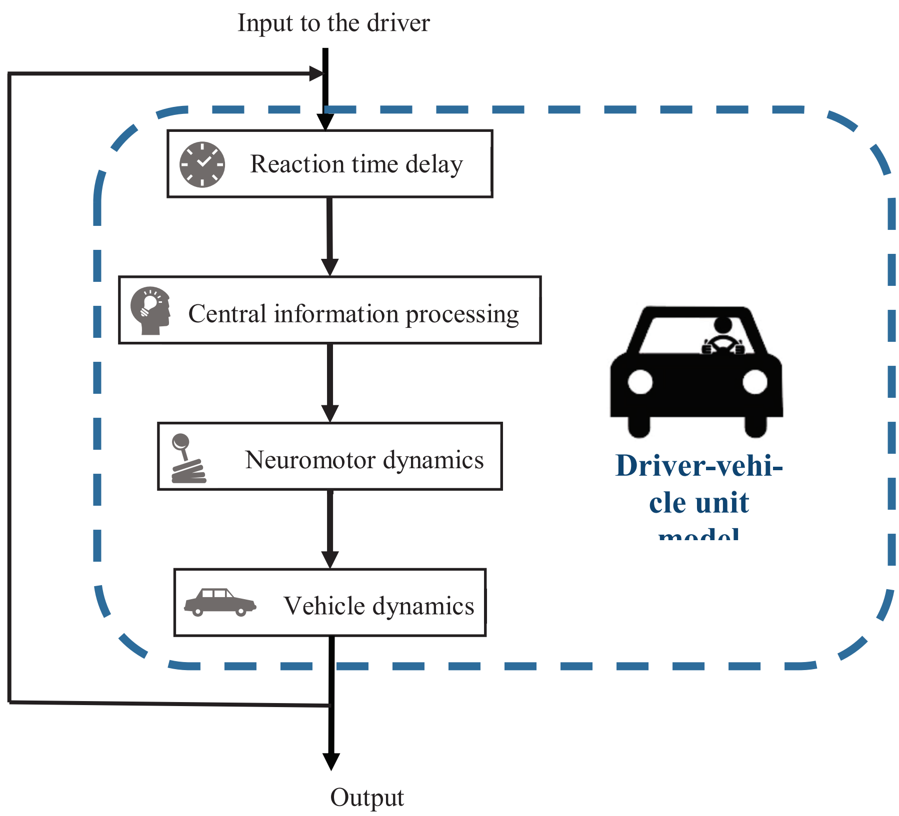


Figure 4.1: Structure of traditional driver-vehicle unit model.

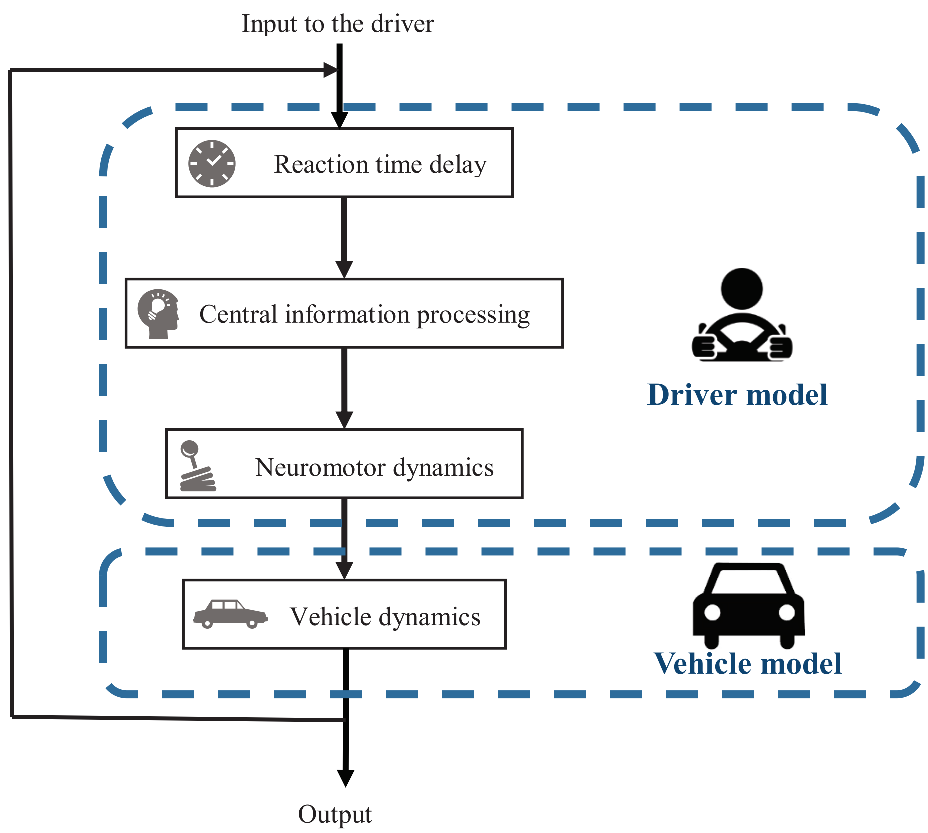


Figure 4.2: Structure of driver-vehicle separated models.

In driver-vehicle separated models, the input of the driver model are the parameters of the leading vehicle, including the position, the velocity, and the acceleration, etc. The outputs of the driver model are operating parameters of the following car, such as the drive pedal/clutch position, the gear shift level, the steering wheel angle, etc. For the vehicle model, the output of the driver model is exactly its input, which are the operating parameters. The output of the vehicle model is the status of the following car, including the velocity, the acceleration, the yaw angle, etc.

The separated models of driver and vehicle are better suited to examine the effects of different drivers and vehicle types on the overall vehicle behavior.

4.1.2 Possible classification of the driver model

With the deepening of research on driving behavior in recent years, drivers have been classified according to various methods. Therefore, the corresponding driver models also need to be established.

One classification method is to distinguish driver models by age and gender of the drivers, and sometimes their ethnicities (Tillyer and Engel 2013). Therefore, one driver classification method is to classify the drivers by physiological characteristics (age, gender, race, etc.), and the corresponding driver model can also cover elderly men, middle-aged women, young black men, etc.

Another more scientific classification is to classify through the driver's driving behavior. The categories may vary depending on the purpose of studies, but basically drivers are divided into aggressive drivers, normal drivers, timid drivers, and slow drivers. Sometimes distracted drivers are also placed in a separate category, e.g. with regard to calls, SMS or makeup.

With the development of automotive technology, the type of driver is not limited to human drivers. In today's situation where autonomous driving is not yet widely used, co-driving of human driver and vehicle brain also creates a new driving mode that requires new driver models. Co-driving drivers can be divided into different driver types according to the level of automation. In this work, three driver models are focused according to SAE classification, automation Level 0 driver model for the present driving status, automation Level 2 driver model representing the near future and automation Level 5 driver model representing the long distant future.

Due to the great discrepancy between the vehicle's control intelligence and the human brain, the differences in the driving style of different human driver types with different personalities traits are less obvious. As a result, the drivers' own characteristics such as age, gender, preferences, etc., are no longer considered in this work.

4.1.3 Possible classification of vehicle model

Compared to the relatively ambiguous classifications of driver models, the classifications of vehicle models are specific and clear, and the main reason is the clear classifications of vehicles themselves.

The most basic vehicle model classification is to divide it into passenger car models and truck models. Due to the significantly difference between the two categories in terms of driving capability, braking force, etc., same vehicle model cannot be used for both, passenger cars and trucks in traffic simulations. Of course, passenger car models can be further classified into more categories according to the type of cars: city car, mid-size car, full-size car, sport car, SUV, etc. Due to the differences in wheelbase and engine displacement, different types of passenger cars will have different feedbacks for the same commands given by driver, so in a more detailed simulation, it is also necessary to build a vehicle model separately.

According to the type of fuel sources used, vehicle models can also be divided into traditional fuel vehicles and new alternative vehicles. Traditional fuel vehicles are gasoline vehicles and diesel vehicles. Obtained through petroleum refining, gasoline and diesel are very suitable for spark ignition engines and compression ignition engines due to their high energy density, low price, non-perishable, and easy transportation. Until now, they are indispensable fuel for motor vehicles. However, because of the energy crisis and environmental issues, new alternative fuel vehicles have gained in importance. Electric vehicles, hybrid vehicles, LNG (Liquefied Natural Gas) vehicles, LPG (Liquefied Petroleum Gas) vehicles, alcohol fuel vehicles, and fuel cell vehicles have emerged. The fundamental differences in engines make the dynamics of these new fuel vehicles different from those of the traditional fuel vehicles. Therefore, vehicle models that differ depending on different fuel source can better reflect the different characteristics of vehicles.

In today's society, vehicles are often modified to suit different special uses in urban cities, which makes their characteristics different. Ambulances, fire trucks, tank trucks, bulletproof cars, construction vehicles, and even buses and taxis bear important responsibilities for the normal functioning of our society. Their special construction and different driving rules also require separate vehicle models in traffic simulation.

4.1.4 Advantages of driver-vehicle separated model

The biggest advantage of a separated model of driver and vehicle is that it enables to have different combinations of drivers and vehicles. For instance, the elderly driver model and the electric vehicle model can be matched to simulate the difference between the elder driving the electric vehicles and the traditional fuel vehicles. Another example can be the combination of an aggressive driver model and relatively slow speed truck to simulate the impact of aggressive drivers driving vehicles with different speed limit. Separated models for driver and vehicle can also make it possible to investigate specific issues. The combination of an aggressive driver model and an ambulance vehicle model can be used to find out if a specific driver is more qualified for this type of work or not. The combination of different automation level driver models and special purpose vehicle models can also simulate whether autonomous vehicles are more suitable for dangerous vehicles such as fire trucks and tank trucks. This may provide effective advices for government procurement. For ordinary people, classifying themselves according to driving behavior and combining their own driver model with different vehicle models will also provide a reference for their car purchase or job selection.

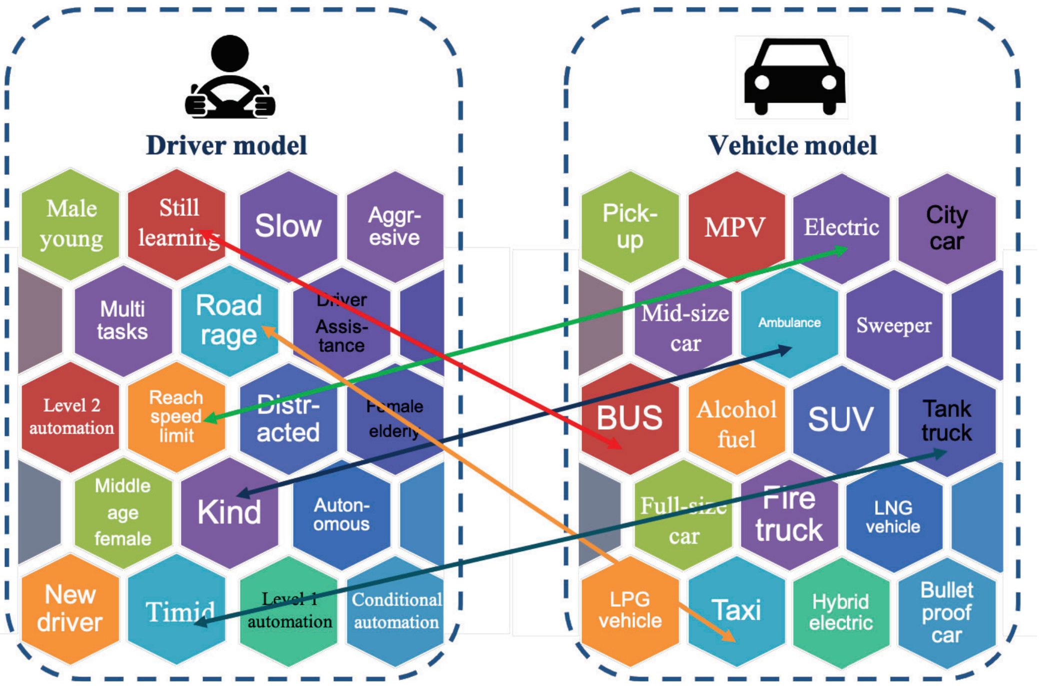


Figure 4.3: Examples of different combination of driver models and vehicle models.

4.2 Driver model algorithmic expression

4.2.1 Original Krauss model and its implementation in SUMO

As introduced in 2.1.2, there are many microscopic car following models that can be used in traffic simulation. Based on multiple considerations of robustness, stability and accuracy aspects, the Krauss' model is chosen as the basic car following model in this thesis.

Equation (2.6) describes the core of the Krauss model: the desired velocity V_n is defined to be the minimum of the three velocities, i.e. the safe speed of the following vehicle v_s, the speed limit of the following car V_{max}, and the maximum achievable speed $v_n(t) + a_n\tau$, respectively. This means that a driver's expected speed in the Krauss' model is the maximum speed that can be obtained under safe conditions and respecting the speed limit. The safe velocity v_s is calculated from the leading vehicle velocity $v_{n-1}(t)$, the following vehicle velocity $v_n(t)$, the gap between them $g_n(t)$, the maximum deceleration b and the reaction time τ.

In Krauss' first paper related to his car following model, lots of parameters were simplified, for example, time step and reaction time were both set to 1s. Later in his dissertation in 1998, to achieve better universality, these parameters were redefined and listed as variable parameters. The safe velocity can be regarded as the key point of Krauss' model. In his first model (Krauss et al. 1997), the safe speed is expressed as:

$$v_s = b(\alpha_{\text{safe}} + \beta_{\text{safe}}) \tag{4.1}$$

where α_{safe} is given by

$$\alpha_{\text{safe}} = \left[\sqrt{2\frac{d_p+g_n(t)}{b}+\frac{1}{4}}-\frac{1}{2}\right] \tag{4.2}$$

and $[\,.\,]$ denotes the integer part of the number, d_p is the braking distance of the leading vehicle. One year later, Krauss gave a more specific expression of the safe speed in his dissertation (Krauss):

$$v_s = v_{n-1}(t) + \frac{g_n(t)-v_{n-1}(t)\tau}{\frac{v_n(t)+v_{n-1}(t)}{2b}+\tau} \tag{4.3}$$

At such a safe velocity, even if the front car suddenly decelerates, the following car could remain safe. The maximum acceleration and the maximum deceleration were first set equal to the maximum achievable speed b, but then were distinguished by a_n and b. Thus, the maximum achievable speed has changed. And the expression of desired speed has also changed from $V_n = \min[v_n(t)+b, v_s, V_{max}]$ to $V_n = \min[v_n(t)+a_n\tau, v_s, V_{max}]$. In order to ensure that the vehicle does not go backward, that is, the velocity is greater than 0, the velocity of the next time step has also been changed to

$$v(t+\Delta t) = \max(0, V_n - \varphi) \tag{4.4}$$

where φ is a random perturbation to allow for deviations from optimal driving. The random perturbation was assumed by Krauss based on that the driver does not have sufficient proficiency to adjust the vehicle to the desired speed.

In the SUMO platform, there are also modifications in the implementation of the Krauss' model, the car following model called MSCFModel_KraussOrig1 is based on the work of Krauss in 1998 (Lopez et al. 2018). The random perturbation was split into three parts: ϵ, a and η. Parameter ϵ is set as noise amplitude, representing the deviation of imperfections when the driver handles the desired speed. $\epsilon \in (0,1)$, the larger value of ϵ means the less driving skill the driver has, and the greater difference between the actual velocity and the desired velocity. Parameter a is the acceleration ability of the following car type and η is a random number between 0 and 1. Under these circumstances, the velocity of the next time step in SUMO is:

$$v(t + \Delta t) = \max(0, V_n - \epsilon\, a\, \eta) \tag{4.5}$$

In the original Krauss car following model, the safe speed is formulated as:

$$v_s = -\,\tau\, b + \sqrt{(\tau\, b)^2 + v_{n-1}(t)^2 + 2b\, g_n(t)} \tag{4.6}$$

The vehicle position in the next time step is

$$x(t + 1) = x(t) + v_n(t)\, t_l \tag{4.7}$$

where t_l is the time step of the simulation. What's more, reaction time in SUMO is set equal to the simulation time step, so the desired speed is formulated as

$$V_n = \min[v_s,\ V_{max}, v_n(t) + a_n t_l] \tag{4.8}$$

The final original Krauss model in SUMO is

$$v_n(t) = \max[0, V_n - \epsilon\, a\, \eta] \tag{4.9}$$

4.2.2 Extension of the Krauss model

In addition to the original Krauss model, there are other improved models given in the SUMO platform. Firstly, a model named MSCFModel_Krauss in SUMO improved the case of faster start. If the driver wants a faster start, when high acceleration is required at a low speed, equation (4.9) will change to

$$v_n(t) = \max[0, V_n - \epsilon\, v_n(t)\, \eta] \tag{4.10}$$

Another improvement is in the minimum velocity part. Instead of being calculated from the normal deceleration, the deceleration in emergency was introduced for the minimum velocity. These two improvements make the Krauss model suitable for more circumstances.

Considering the role of the vertical direction, the model called MSCFModel_ KraussPS changed the acceleration and the velocity by slope. The maximum velocity V_{max} is calculated in the situation of vehicles driving on the slope.

Some drivers would like to choose to start slowly, this condition is concerned in the model named MSCFModel_KraussX. In this model, two new parameters representing imperfect driving are involved. They replace the original imperfection driving parameter in two situations (start slowly and over braking) respectively.

In addition to the developers of the SUMO software, other researchers also contribute in optimizing the Krauss model. For example, the acceleration and deceleration of the vehicle in the Krauss' model takes the form of abrupt changes, that is, when the driver decides to accelerate, the vehicle speed reaches the maximum velocity instantaneously. Of course, the sudden acceleration capabilities are highly unrealistic, not only because they do not fit the laws of vehicle dynamics, but rather, because everyday's experience tells us that we must slowdown in advance to avoid a collision.

Considering that the deceleration operation of the leading and following vehicle is a gradual process, the Krauss' model was improved by Han et al. (Han et al. 2012). The improved safe speed expression is

$$v_s = -\,b(\tau + T_i) + \sqrt{[b(\tau + T_i)]^2 + \left(v_{n-1}(t) + b\frac{T_i}{2}\right)^2 + 2b\,g_n(t)} \quad (4.11)$$

where T_i is the time the vehicle needs to accelerate from 0 to its maximum velocity. Except for the algorithmic change of the safe speed, other expressions are the same as in the Krauss' model.

More complex models have more advantages at the microscopic level. However, traffic simulation cannot be based on a single model, conversely, it needs the coordination of multiple models. Therefore, more complex models are more likely to cause conflicts with other models, leading to more unrealistic simulation results. In this work, the complexities with less impact on the simulation results are discarded and the MSCFModel_Krauss in SUMO is taken as the basic model. To make the Krauss' model coincide with different degrees of automation, some adjustments of parameters in the Krauss' model will be made in 4.3.

4.2.3 Fuzzy control model

If a model is seen as a black box and more attention is paid to the input and output of the model, big differences will be found between the driver-vehicle separated model and the driver-vehicle unit model. For the driver-vehicle unit model, as can be seen in Figure 4.4, the input and output parameters are all vehicle external parameters, which means, the overall vehicle data such as speed, position, acceleration, etc. are all outside the black box. The interaction between the driver and the vehicle is ignored.

For driver-vehicle separated models, driver model and vehicle model are separated boxes with their separate inputs and outputs, and the output of the driver model is the input of the vehicle model. As in Figure 4.5, the communication between these two boxes are vehicle internal parameters, which means, these parameters can be directly read by the vehicle, including the drive pedal position, the steering direction, turning light on or off, etc.

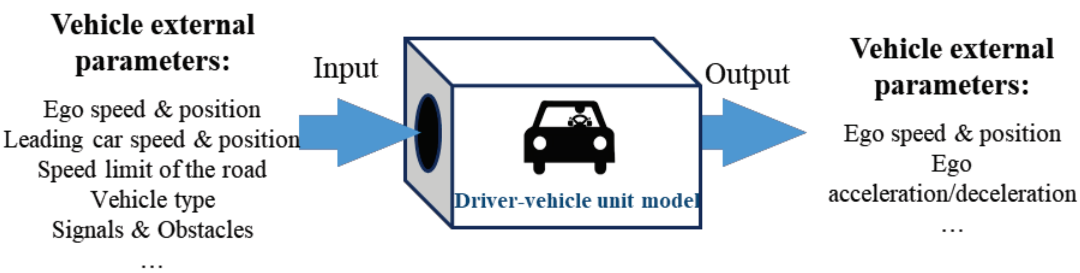


Figure 4.4: Input and output of driver-vehicle unit model.

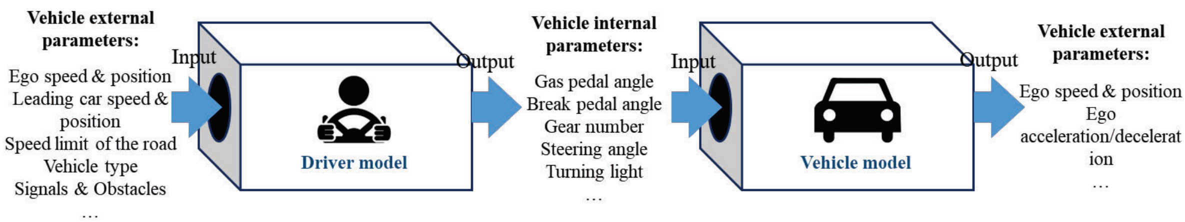


Figure 4.5: Input and output of driver-vehicle unit model.

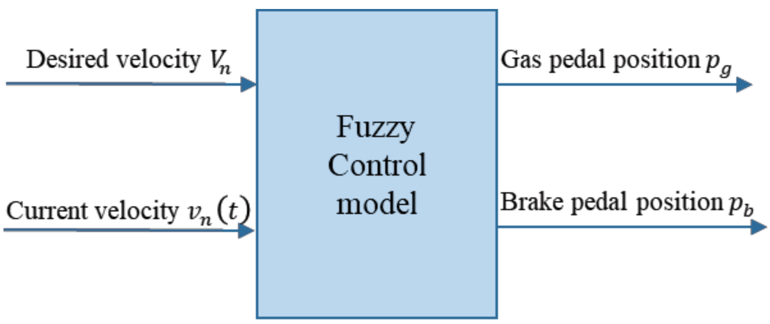


Figure 4.6: Fuzzy control model system.

To adjust the output to the vehicle internal parameters mentioned above, a fuzzy control model is used. The fuzzy method is a type of uncertainty reasoning and fuzzy control is a control method that uses the control rules of fuzzy reasoning theory to control systems. Unlike the precise mathematical model control theory, fuzzy control uses non-precise mathematical models to achieve adaptive control and the controlled object can be a non-time invariant system.

Usually Fuzzy control is used for two purposes, apart from constructing nonlinear controllers, there is also one for adding human intelligence to the controllers. Under these circumstances, fuzzy control is a kind of bionic method, which simulates the abstract thinking level of human brain. For example, when a human driver drives a car, he does not accurately measure how much the current speed is, how many meters from the obstacle ahead, but simply divides into levels like "fast, middle or slow speed", "far, not far, near". And based on this inaccurate information, the driver makes inferential decisions, decides "light step, no step or heavy step" on drive or brake pedal. Fuzzy control is a process of simulating human thinking in mathematics, it is also often listed as a branch of artificial intelligence. Due to the effectiveness and convenience of fuzzy control, it is very suitable for our conversion model for drive pedal and clutch position.

Among the parameters that the driver model transmits to the vehicle model, the drive pedal position and the clutch position are the most important ones. Depending on the difference between the desired velocity V_n and the actual velocity $v_n(t)$ of the following car, the fuzzy control model determines a desired acceleration a_s.
As shown in Figure 4.6, the fuzzy control model is a function with two inputs (desired velocity V_n, current velocity $v_n(t)$) and two outputs (drive pedal position p_g and brake pedal position p_b). The implementation through programming and the verification of the fuzzy control model will be described in 4.4.6.

4.3 Parameterization of different degrees of automation

Over the last thirty years, studies and experiments on the driving behavior of automated vehicles have led to the discovery of various types of specific variations of driving behavior. For example, it is revealed that drivers using high automation level vehicles prefer less lane changing in order overtake slower moving traffic than when driving manually (Jamson et al. 2013a). Another study revealed that the distance between an autonomous car and the leading car is obviously smaller than that of a human driver, the time headway of automatic driving can reach 0.3-0.5s. At the same time, the human driver's time headway is 0.9 to 2s (Wagner 2015). Different degrees of automation affect driving behavior in many ways. In our model, the main influenced parameters are reaction time and imperfection factor. In this section, how to determine these parameters for the chosen levels of automation are discussed.

4.3.1 Reaction time τ

The driver's reaction time is relatively difficult to model because there are too many factors associated with the reaction time. These factors all have a large impact on the reaction time, so from this point of view, these are all important factors. Moreover, the total reaction time averaged only two seconds, and the reaction time calculated by the complex model has little effect on the overall simulation. Sometimes, in a vehicle platoon, the order of braking is not completely in accordance with the sequence, from the front to the back. Too precise reaction time does not represent the exact actual action time. Therefore, in this work, the reaction time is determined with parametric approach.

The research on human driver response time has long been an object in the field of physiology and psychology. A summary in 1954 shows that, reaction time can be affected by age, gender, sleep loss, drugs, temperature, altitude, acceleration, vigilance, etc. (Teichner 1954). A 321 drivers' measurement of brake reaction time reveals that, in an anticipated situation on the road, the estimated brake reaction time should be 0.9s. For all sudden accident situations, the reaction time would be longer, about 1.2s (Johansson and Rumar 1971).

In recent years, research has often set the reaction time in a range, such as 0.5s to 2s (Orosz et al. 2004). In traffic simulation, the reaction time is usually reduced to 1s, which is the same as the simulation step time. For autonomous cars, setting the reaction time to 0.5s can not only fit the simulation step in SUMO, but also reduce the simulation time (Wagner 2015).

For the degree of automation of this thesis, the reaction time of Level 0 (no automation) is the reaction time of human driver, consequently $\tau = 1$ is set. For Level 5 (full automation), which presents the long distant future, reaction time is set as $\tau =$

0.5 representing the rapid response of mechanical brain. For Level 2 (partial automation) stands for the near future, the automatic driving can only be used in specific scene as an aid to the human driver, the car is mainly controlled by the driver. If some kind of danger suddenly occurs, it is also the human driver who is reacting. Therefore, the reaction time of Level 2 automation is set as $\tau = 1$, same as that of Level 0.

4.3.2 Imperfection factor ϵ

The imperfection factor ϵ was originally proposed by Krauss in his model (Krauss et al. 1997). This parameter represents the proficiency of the driver. The more qualified the driver's driving skills are, the smaller the difference between his actual speed and his desired speed is. Conversely, the less driving skills the driver has, the greater is the difference between his actual and his desired speed.

The reasons for the speed deviation are manifold. First, as stated in 4.2.3, human drivers do not accurately calculate the distance to the leading vehicle and then decides how many angles of pedal to step on, but use a fuzzy concept as "not far" or "hard step". These fuzzy concepts create the possibility that the human driver does not reach his desired speed. Next, the irregular reaction points of humans also contribute to imperfect driving. Research on human drivers found that the important difference between human and machine driving lies in the action point mechanism (Todosiev and Barbosa 1963). The action points of human drivers are abruptly changing, and the machine action points are always the same (Wagner 2011). The action points at different time of course have impact on the final actual speed, which is one of the reasons for imperfect driving of human drivers. With these differences, Krauss suggests that the imperfection factor should be chosen to be $\epsilon = 0.4$ for normal human drivers.

In this thesis, the imperfection factor of Level 0 (no automation) is chosen to be the same as normal human driver, which is $\epsilon = 0.4$. For autonomous vehicles, which is level 5 of automation, the electronic brain's control of the vehicle is not affected by human imperfect driving, so the desired speed of the vehicle will be reached under the vehicle's control. Hence, for vehicles of automation level 5, the imperfection factor is $\epsilon = 0$. In automatic driving modes, partial automated vehicles can also avoid the disadvantages of human imperfection driving. For example, when the driver wants to accelerate his/her car to 200 km/h, but he/she does not know exactly how many angles of the drive pedal should be stepped on, and because he/she is unskilled, he/she may have just accelerated to 150 km/h. Vehicles in automatic driving modes can accurately control the pedal position without the influence of human irregular action points. Therefore, automation level 2 vehicles can also avoid the errors mentioned above, as the fully automated vehicles, the imperfection factor of automation level 2 vehicles is also chosen as $\epsilon = 0$.

4.3.3 Randomness of fuzzy control model r

The fuzzy control model generated in this thesis represents an average driving behavior of the participants in driving experiment. Therefore, the fuzzy control model can represent the driving behavior of machine drivers better than human drivers. In order to imitate human drivers better, a randomness factor r has been used to describe the randomness in fuzzy control model. The output pedal position of fuzzy control model p_p can be represented as

$$p_p = \begin{cases} (1 \pm r)\, p_g, & p_g \neq 0 \\ -\,(1 \pm r)\, p_b, & p_g = 0 \end{cases}$$

where p_g is drive pedal position and p_b is brake pedal position.

The automation level 0 group is driven by human drivers. According to the analysis of experimental data from different participants, $r = 0\%$~50% randomness of pedal position had been set for the automation level 0 group. For level 2 and level 5 groups, randomness is set to 0.

4.3.4 Other parameters

The many differences between human driving and machine driving can of course not be fully summarized by three parameters. In this work, only the most important parameters for the difference between autonomous driving and human driving are distinguished and assigned. For vehicles with different levels of automation, there are more characteristics that are different from human drivers.

Smaller time headway of automated driving is one of these characteristics. The distance control between the autonomous car and the front car is implemented through autonomous intelligent speed control (AIC) (Kesting 2008). There are a variety of adaptive distance adjustment and open control algorithms for autonomous vehicles that are currently in use (Urmson et al. 2008; Levinson et al. 2011; Campbell et al. 2010). Although technically speaking, these control systems are not perfect, there is still room for progress, because of the huge difference in maximum deceleration between human and machine, the time headway of autonomous vehicles are still much smaller than that of human drivers (Wagner 2015).

However, these characteristics are difficult to quantify according to different levels of automation, so they are not considered in this work. In addition to the input parameters, other parameters of the driver model are listed in Table 4.1.

Table 4.1: Parameters of different degrees of automation models.

Parameter name and symbol		Level 0 No automation	Level 2 Partial automation	Level 5 Full automation
Reaction time	τ	1	1	0.5
Imperfection factor	ϵ	0.4	0	0
Time step	t_l	1	1	0.5
Randomness of fuzzy control model	r	[0, 0.5]	0	0

4.4 Programming and verification of Driver model

4.4.1 Driver model and vehicle model

Through the several sections described above, a complete driver model is obtained, the overall flow chart can be seen in Figure 4.7. First, the driving data is extracted from SUMO and transmitted to the modified Krauss model, including the ego vehicle data (current velocity, acceleration, deceleration, etc.), the leading vehicle data (current velocity, gap between the leading vehicle and the following vehicle, etc.) and the road information (maximum allowed velocity of the road). After the calculation in the Krauss model, desired velocity and current velocity are transmitted to the fuzzy control model. Here, the drive and brake pedal positions are calculated by a fuzzy control model verified by the real data. Together with the lane change request, drive and brake pedal positions are transmitted to the vehicle model.

4.4 Programming and verification of Driver model

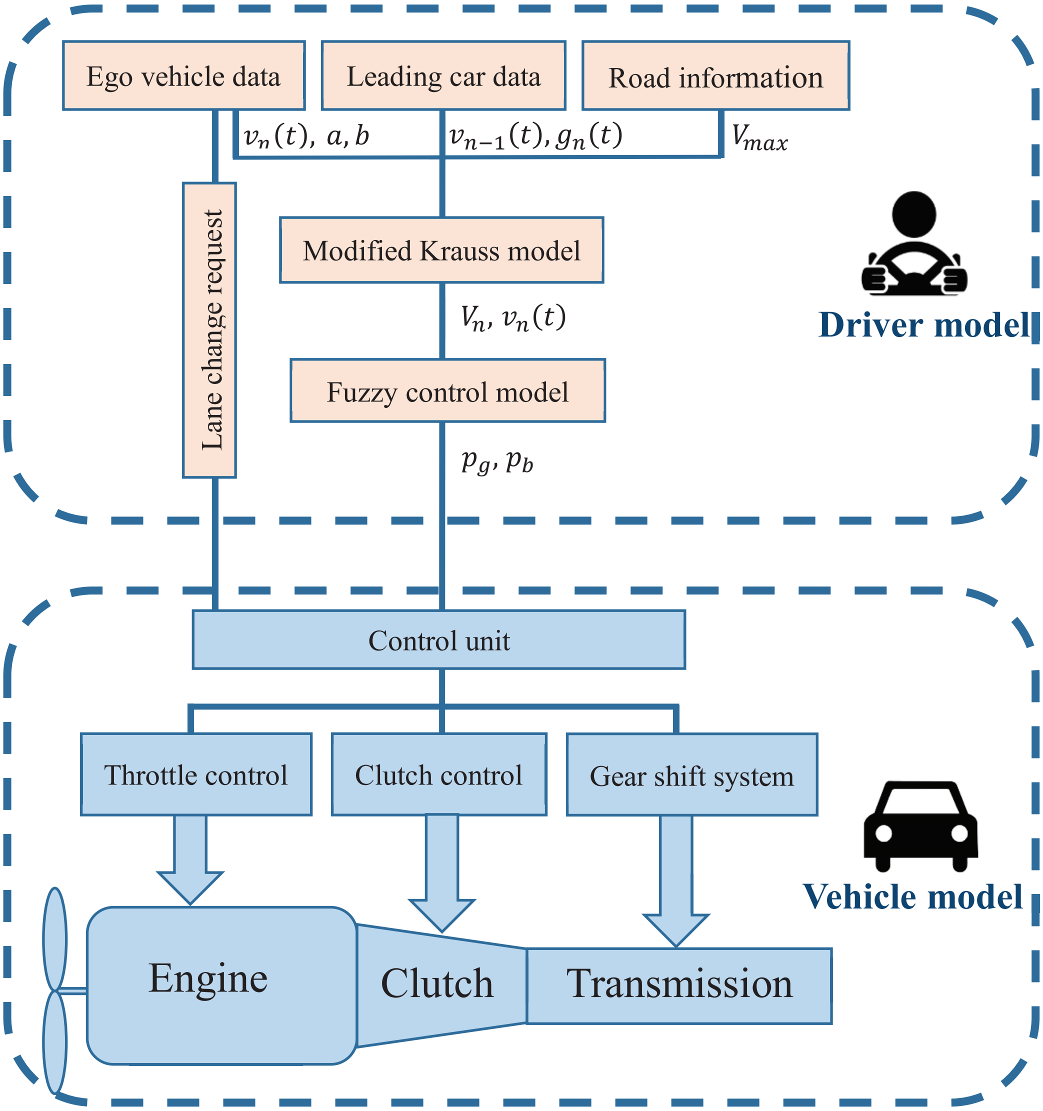


Figure 4.7: Driver model and vehicle model system.

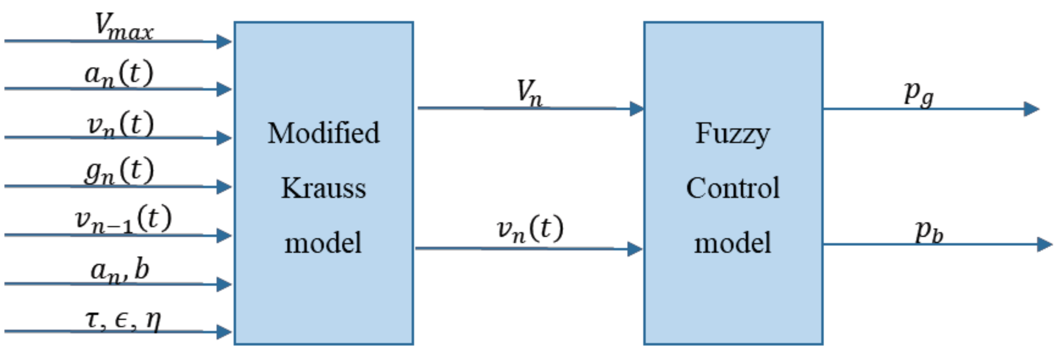


Figure 4.8: Overall structure of driver model.

In the vehicle model, the control unit receives the data and distributes them to the individual vehicle components according to the logical processing of the vehicle model. Different vehicle models will also have great impact on traffic simulation in various aspects, such as fuel economy, travel time, average speed, etc. Since the vehicle model is not the focus of this work, the relevant description will not be detailed here. To highlight the impact of different driver models on the traffic simulation, the vehicle model used in this work is a simple driving force-driving resistance model.

4.4.2 Structure of the driver model

The driver model in this work consists of two parts: one is the modified Krauss model and the other is the fuzzy control model. The inputs and outputs of the two parts can be seen in Figure 4.8. Firstly, according to many inputs, the modified Krauss model generates the desired velocity V_n. These inputs include the parameters from the ego vehicle (acceleration $a_n(t)$, velocity $v_n(t)$, acceleration time T_i, etc.), the parameters from the leading vehicle (velocity $v_{n-1}(t)$, gap between the leading vehicle and the ego vehicle $g_n(t)$), the parameter of the road (maximum velocity V_{max}), and the parameters determined by the different degrees of automation (reaction time τ, imperfection factor ϵ).

Next, the velocity of the ego vehicle $v_n(t)$ and the desired velocity V_n are entered into the fuzzy control model, based on a fuzzy control strategy described in the next section, the drive pedal position p_g and the brake pedal position p_b are determined. Along with lane change intention of the driver, drive and brake pedal positions will be transmitted to the vehicle model as input for subsequent simulations.

Determination of the parameters in the driver model is also divided into two parts as above. The Krauss model is already a mature model in microscopic traffic simulation, and many works have proven its rationality and accuracy. With the adjustment in 4.2.2, there are good reasons to believe that the modified Krauss model can well express the human process of generating desired speed from external driving environmental parameters. For the fuzzy control model, used for transforming the desired speed and current speed into pedal position, an experiment is used to determine the parameters, which is described in detail in the next section.

4.4.3 Driving experiment

In order to obtain the real data for fuzzy control model of human driver, a driving experiment was performed in a dynamic driving simulator. In the experiment, 37 drivers with valid driver license took part in, and the age range of the subjects were 23 to 40. All subjects were informed beforehand that they could end it any time without reprisal. During the experiment, the adaptation of the simulator and comfort of the subjects were also asked, in case of a physical discomfort occurred by the participants (Ma et al. 2021a).

Driving simulator

The dynamic driving simulator used in this work is a human-centered driving simulator which is capable of giving a tactile feedback to the driver to increase the degree of immersion. (Maas et al. 2014). Thus, the driver's cabin is mounted on a motion platform to realize the movements of the cabin. In this way, the driver gets a dynamic feedback for his/her inputs to the simulator. In addition to the cabin and the platform, there is also a round screen drawn around the vehicle with an angle of 250 °, so that the driver's field of vision is completely covered. The schematic structure of the driving simulator is illustrated in Figure 4.9 (Maas 2017).

Actuated by three electromechanical linear actors, the motion platform can reproduce the dynamic properties of real driving operations up to a frequency of 40 Hz with an acceleration of up to 2g. Thus, working with a reduced weight cabin, the motion platform covers a large range of acceleration behaviors.

The interior of the cabin is modelled as a real vehicle in order to achieve the highest possible degree of reality. Figure 4.10 presents the interior environment of the cabin, the fuel gauge/odometer display and the rear-view mirrors are shown by three digital displays. Near the steering wheel, another display is used in showing driving task in the present study.

The virtual scenario in this study is an area with inner-city sub-areas, rural routes and highways (Schweig et al. 2018). The scenario covers an area of 3×3 km, due to the changeable driving task, the subjects are asked to drive only on the highways. The highways of this scenario are infinite (without dead-ends), this characteristic supports the realistic impression.

Figure 4.9: Schematic structure of dynamic driving simulator.

Figure 4.10: Interior of the simulator cabin.

Experimental arrangement

The driving experiment in this work is aimed to find out how the human drivers react according to a target/desired speed. The design of this experiment comes from the speed limit board on roads. When a driver comes across a speed limit board on road, his desired speed will be adjusted to the limit speed. If the driver is speeding, he will slow down to drive below the speed limit, and when a higher speed is allowed, he tries to reach the limit speed. In this study, the target speed is given to the participants on the display near the steering wheel. The participants are asked to achieve this target speed, and their driving behaviors including drive and pedal position are recorded by the simulator.

In addition to longitudinal driving task, the participants also need to keep the ego vehicle in lane without collision to other traffic users (including vehicles and pedestrians). In the experiment, 1 from 37 subjects could not accomplish the driving task because of the control problem of the simulator. He could either accomplish the longitudinal or the lateral driving task, that is to say, either keeping the ego vehicle in lane, or achieving the target speed is possible for the participant. Because normal vehicle driving is not a problem for him, it is considered that his control problem of the driving task comes from the minor adaptation to the simulator. Another two subjects encountered physical discomfort by driving the simulator at the beginning of their experiment, and they interrupted their tests at their requests. Finally, 34 subjects accomplished the driving test.

The process of an experiment is as follows: the participant first familiarize him/herself with the driving simulator system through a test drive. There are 86 steps of the experiment, i.e., 86 target speeds are provided to the participant in order. When the actual speed of the simulator stays in ±2 km/h of the desired speed for 5 seconds, the next step/target speed is shown on the display with a “Beep” sound. Therefore, the time taken by each participant depends on the ability of their driving behavior. The drivers who have difficulty in maintaining the target speed take longer time. The total time is from 18.5 min to 64.3 min for the 34 subjects with valid experimental data.

Data analysis

From the driving simulator, numerous data were recorded, including the simulator time, target/desired speed, actual speed, drive pedal position and brake pedal position. MATLAB was used to analyze the recorded datasets. Each dataset of one participant was split up into 86 segments and each segment described one target/desired speed. Two sub-segments from each segment were extracted according to driving situation. First sub-segment described the velocity change, from which the pedal position causing the velocity change can be determined. The other sub-segment described the steady velocity, in other words, what pedal position made the velocity steady. For example, if the segment is a driving task from 40 to 70 km/h, the first speed rise from 42 to 68 km/h was extracted as sub-segment 1, and the last 5 seconds for keeping velocity between 68 to 72 km/h was recorded as sub-segment 2. After all parts of each segment were processed separately, data from the same sub-segment of different participants were averaged.

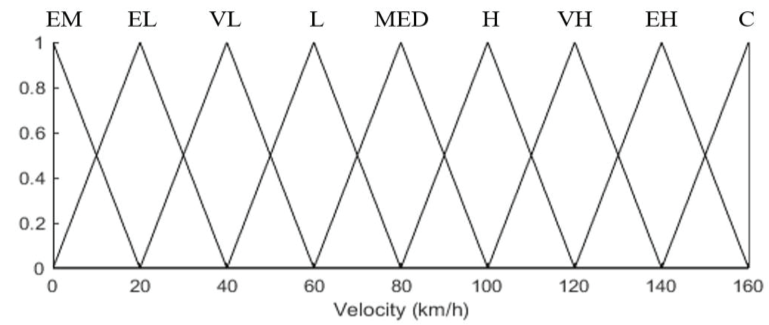
4.4.4 Fuzzy control model rules

As discussed in 4.2.3, two inputs and one output were determined for the fuzzy control model. According to the driving experiment, the rules of fuzzy control model were determined as in Table 4.2, and the corresponding inputs and outputs are shown in Figure 4.11.

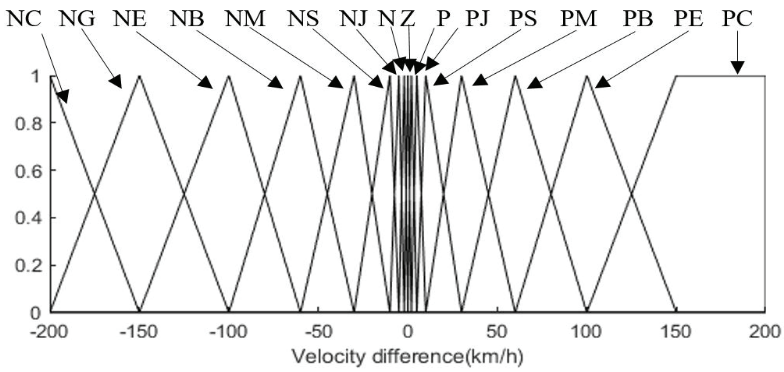
Depending on the difference between the desired speed V_n (input 1) and the actual speed v_n (input 2), the fuzzy controller determines a target pedal position (output). The positive pedal position means accelerating and the negative pedal position means braking. The driving experiment has covered all the driving situations listed in Table 4.2, and the generated rules in the table are also based on actual driving experiment. The rules marked in grey are manually added rules, these are the impossible driving situations, such as negative speed or speed out of the range of the simulator.

Table 4.2: Fuzzy control model rules based on driving experiment.

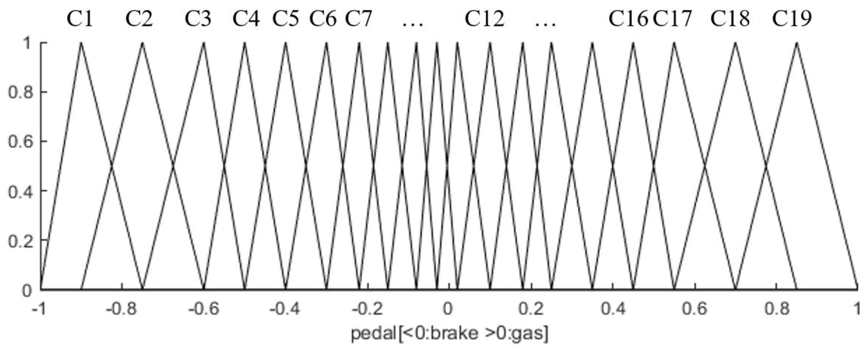
		V_n															
	&	NC	NG	NE	NB	NM	NS	NJ	N	Z	P	PJ	PS	PM	PB	PE	PC
v_n	EM	C0	C1	C1	C1	C2	C3	C8	C10	C10	C11	C12	C14	C17	C17	C18	C18
	EL	C0	C1	C1	C1	C2	C3	C8	C10	C10	C11	C13	C14	C14	C17	C18	C18
	VL	C0	C1	C1	C1	C3	C3	C10	C10	C11	C11	C13	C14	C15	C17	C18	C18
	L	C0	C1	C1	C1	C2	C3	C10	C10	C11	C11	C13	C14	C16	C16	C18	C19
	MED	C0	C1	C1	C2	C2	C3	C10	C10	C11	C12	C13	C14	C16	C17	C18	C19
	H	C0	C1	C1	C2	C2	C4	C11	C11	C11	C12	C13	C14	C16	C17	C18	C19
	VH	C0	C1	C1	C2	C3	C4	C11	C12	C13	C13	C14	C15	C16	C17	C18	C19
	EH	C0	C1	C2	C2	C3	C4	C11	C12	C13	C13	C14	C15	C16	C17	C18	C19
	C	C0	C1	C1	C2	C3	C5	C11	C12	C14	C13	C14	C15	C16	C17	C18	C19



a). Input 1:actual velocity



b). Input 2: velocity difference



c). Output: pedal position

Figure 4.11: Inputs and outputs of fuzzy control model.

4.4.5 Verification of fuzzy control model

To verify the reproduction of the fuzzy control model, a comparison test was carried out in MATLAB. The fuzzy control model is considered as a driver to finish the 86 steps driving experiment, and the vehicle model used in this test has been adjusted based on the driving simulator. To imitate the human driver better, randomness was introduced to the fuzzy control model. Based on the driving behavior analyses of the participants, up to plus and minus 50% randomness of pedal position has been added as the randomness in the fuzzy control system. Under the same driving situation, i.e., same initial speed and target speed, a comparison between a human driver and the fuzzy model driver has been made through MATLAB simulation.

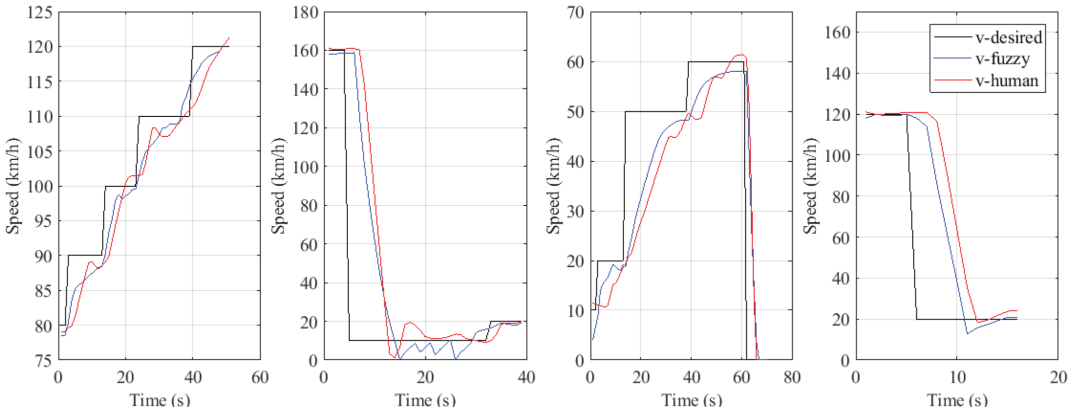


Figure 4.12: Comparison result of fuzzy control model and real data.

Figure 4.12 compares four exemplary diagrams of the experimental results of participants and fuzzy model simulation in the same driving situation characterized by the same initial velocity and target velocity. The black lines are the target speed of the situation, and the human driver (red lines) and the machine driver (blue lines) react according to the given target respectively. From the selected four driving segments, it was proved that the fuzzy control model can well represent the driving behavior of the driver in various driving situations, including the continuous acceleration, the high velocity, the deceleration and the low velocity situations.

In terms of total time, the fuzzy control model always takes a shorter time than the human drivers because the machine driver doesn't have problems of faulty manipulation. In terms of driving behavior, there are hardly any significant differences in the deceleration characteristics between human and model. On the contrary, the acceleration characteristics of the two had relatively large differences. In general, the fuzzy control model has a smoother acceleration curve during acceleration. Moreover, when the actual speed is closer to the target speed, the acceleration value is smaller. However, the human drivers are less sensitive to the difference between the current speed and the desired speed. In general, the driving behaviors of the fuzzy control model are close to the human driver and the former can reflect the driving behaviors of the latter greatly.

4.4.6 Driver models used in this work

As discussed in section 4.3, different degrees of automation are distinguished by parameters. Figure 4.13 shows the overall driver model with different degrees of automation. The driver model consists of model K (modified Krauss model) and model F (fuzzy control model). Model K receives traffic data and generates desired speed V_n, then model F generates pedal position p_p with randomness of fuzzy control model. At last, VM (Vehicle Model) generates vehicle speed based on vehicle parameters and gives it back to the simulation. The vehicle model (VM) with different levels of automation used in this work are the same, but model K and model F were set with different parameters for different automation levels.

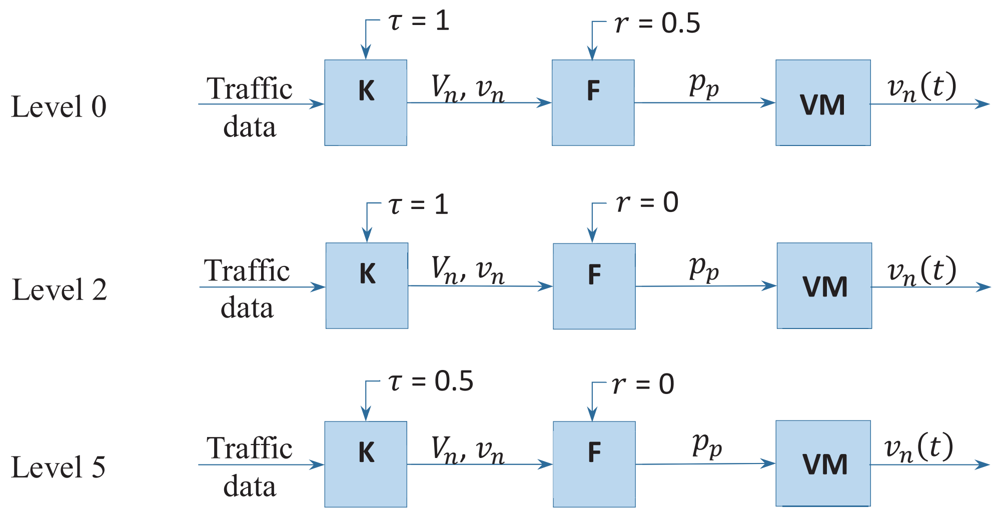


Figure 4.13: Driver model with different degrees of automation.

For the convenience of programming, MATLAB is used to write the driver model and assign the parameters of different automation levels to the corresponding model. Due to the simulation scenario is still implemented in SUMO, TraCI is used as an interface between MATLAB and SUMO.

5 Traffic flow of no automation group

In order to test SUMO's ability of reproducing traffic and provide a no automation control group for different levels of automation vehicles, in this chapter, several simulations are implemented. The simulation results are compared with the real traffic data and the reliability of the results derived by SUMO is discussed.

5.1 Simulation of Jianghan Zone in Wuhan

5.1.1 Traffic demand

Traffic demand determines the number and path of vehicles in reality and simulation. There are many ways to describe the traffic demand. The best source to get such information is the OD matrix. It presents the volume of traffic flowing from one point/region to another over a certain period of time. As long as the simulation area are divided into enough small regions, OD matrix can reproduce the traffic flow with high accuracy. Otherwise, if the simulated area is divided into few or even several small areas, the accuracy of the OD matrix will be greatly affected. However, the acquisition of the OD matrix is not very convenient. First, the city needs to be divided into several regions, then the traffic volume between each region in a certain period of time needs to be detected. Moreover, the acquisition of the OD matrix requires professional traffic statistics, along with the assistance of lots of hardware equipment, including the induction loops, the cameras, etc. Therefore, lots of work and financial support are required.

Since there was no official cooperation with Wuhan Municipal Government to achieve the traffic data, the OD matrix in Wuhan was not available for this study. For the traffic needs of Jianghan Zone in this study, ActivityGen is used to generate the traffic demand.

ActivityGen is a sub software in SUMO. The main idea of this software is computing the activities happening in the city including the commuting demand, the shopping demand, the entertainment demand etc., through detailed city information such as residence location, work location, number of workers and so on. Fortunately, all this information of Jianghan area can be found in a Chinese website. Table 5.1 lists all the information needed in ActivityGen, and the data sources. Unlike in Europe, China's privacy policy is not comprehensive, and the public is not as concerned about privacy as Europeans, that makes it possible to acquire these kinds of information on the websites of the data sources in Table 5.1. The open information provides the possibility to generate traffic demand of Jianghan Zone.

Table 5.1: Information for generating traffic demand in ActivityGen.

Item	Amount	Data Sources
Inhabitants	683,500	Jianghan District People's Government
Number of households	154,850	Hubei Provincial Bureau of Statistics
Retirement age	50-60	State Council of China
Car rate	0.28	Hubei Provincial People's Government
Unemployment rate	0.02	Human Resources and Social Security Department of Wuhan
Primary school age limit	6-11	Ministry of Education of China
Primary school students' number	30,531	Hubei Provincial Bureau of Statistics
Middle school age limit	12-14	Ministry of Education of China
Middle school students' number	13,420	Hubei Provincial Bureau of Statistics
High school age limit	15-17	Ministry of Education of China
High school students' number	7,537	Hubei Provincial Bureau of Statistics
Vocational school students' number	5,527	Hubei Provincial Bureau of Statistics

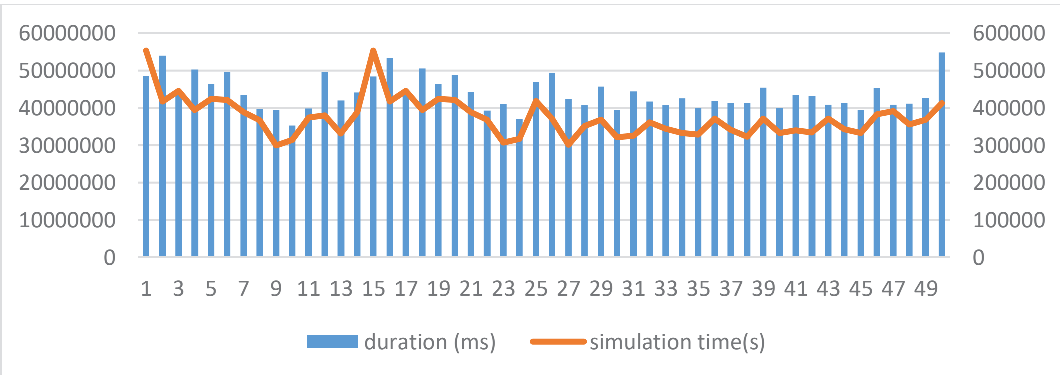


Figure 5.1: Duration and simulation time for Jianghan Zone iteration with all residents.

In addition to the basic data about the simulated zone listed in Table 5.1, there are also some parameters that need to be set. In this part of the simulation, in SUMO default settings, foot distance limit is set to 1000 meters, car preference is set to 30%, free time activity rate is set to 0.3, random traffic rate is set to 0.05, and departure variation is set to 600 seconds.

The most important part of using ActivityGen to generate traffic demand is to assign the quantity of residents and the job positions on each road in the program. In the urban areas of China, especially in big cities, there are all kinds of real estate agents. They open detailed statistics on all the communities in the urban area, including the number of buildings, the number of households in each building, the area of apartments, the apartment floor plan, etc. Using these data, knowing the number of residents on each road becomes possible. For the acquisition of the number of workers on each road, the method used in this work is to find out the name of the respective enterprise on the map, and then query the number of registered employees on the website of the Industry and Commerce Bureau. School information and public transportation information are also obtained online.

After all the needed data has been acquired, each path in SUMO was linked to the actual path, and the numbers of residents and workers were written into the statistic file. A route file based on the network file and the statistic file was generated through ActivityGen. This route file describes when and where each car does depart in the simulation, which path it goes through, and where it finally arrives.

5.1.2 Dynamic route planning

The route planning using ActivityGen in SUMO is based on the Dijkstra algorithm, also known as the shortest path method (Dijkstra 1976). This means that for each vehicle, once its starting and destination points are known, the shortest route to the destination can be calculated, which the vehicle can then follows. If the vehicles in the simulation do not interfere with each other, the shortest path results in the shortest travel time. But in the case of mutual intervention, travel time of each vehicle running in the simulation depends on the number of vehicles in the network. Sometimes from the starting point to the destination are two parallel roads and the distance difference is quite small, but based on this method, all vehicles will choose the slightly shorter route, and thus cause unrealistic congestion.

To avoid the unrealistic traffic congestion caused by this algorithm, SUMO provides a solution called Dynamic User Equilibrium (DUE). DUE uses iterative assignment to calculate a user equilibrium, i.e., it tries to find a route for each vehicle such that each vehicle cannot reduce its travel time by using a different route. Therefore, the more iterations are implemented, the more possibilities are given to find the shortest travel time for all vehicles. For the simulation of Jianghan Zone, although it is only a district in the city of Wuhan, there are still more than 680,000 residents inside. The excessive population makes SUMO take too long a time in the interactive process. In the first 50 times iterations, the average duration time is 44,334,028 ms, which means, each iteration needs more than 5 days. Even worse, the simulation time for the 24-hour simulation has not significantly reduced.

Figure 5.1 also shows that the simulation time is initially reduced from 553,391 to 299,476 s, but then increases again. Even the lowest simulation time in these 50 times iterations is far more than 82,800 seconds, for the normal 24 hours simulation time. This iteration failure caused by overpopulation can only be solved by reducing the population in the simulation.

It is interesting that although in the simulation the congestion does not dissolve because of the large population, in the real world of the Jianghan zone, no congestion develops that cannot be dissolved. After detailed research, it is found that the share of public transportation in Wuhan is very high, reaching almost 60%. This means that nearly 60% travel in this district is carried out by public transportation systems, and the map temporarily does not include the public transportation systems such as subways (underground) and light rails (elevated) that are not on the ground level. Therefore, in the following simulation of Jianghan Zone, by adjusting the population, only those who travel by private cars are simulated.

5.1.3 Verification of traffic data

In order to verify the accuracy of the generated simulation, a comparison of the simulated results and the real traffic conditions was carried out. For the simulation in Jianghan Zone, a local Chinese map called AutoNavi map was selected to provide actual traffic conditions in the real world. AutoNavi map (also known as Gaode Map) is a map website controlled by Alibaba Group, which provides detailed map data in China and also provides map data of China for Apple Maps and Google. With over

100 million users, AutoNavi is one of the most popular map softwares in China. Furthermore, AutoNavi Navigation occupies the largest share in the market. With a large number of data from mobile phone users, private car users, taxi users, rides-haring users like Uber, and some fixed monitoring points to provide traffic data, it is possible for AutoNavi to provide accurate real-time traffic conditions on its map.

AutoNavi users provide 85% real time traffic data; they upload their current speed while using the navigation system from AutoNavi. The remaining 15% data are collected from the cooperation with local traffic departments of the local cities, who control the fixed-point detections like cameras and induction loops. The detections can provide a more accurate data to calibrate the user uploaded data. In some cities, AutoNavi also cooperates with taxi companies. The floating car data (FCD) from taxis upload detailed data including speed, acceleration, etc. in real time. The emerging network transportation companies such as Uber and Didi also contribute to real time traffic state map. From the amount of travel point of view, with 550 million users, Didi is the world's largest travel service platform. By putting all these data together with a sophisticated algorithm, AutoNavi can get high accuracy and fidelity real time traffic status map in most cities of China.

The traffic conditions displayed on AutoNavi's map are indicated by three different colors: red means traffic congestion and the average speed in this road section is less than 5 km/h; yellow represents slow driving with an average speed between 5 and 30 km/h; green means smooth traffic and the average speed is over 30 km/h. It is not possible to verify the simulation results and actual traffic conditions at all points on the map, so eight representative road sections are chosen for verification.

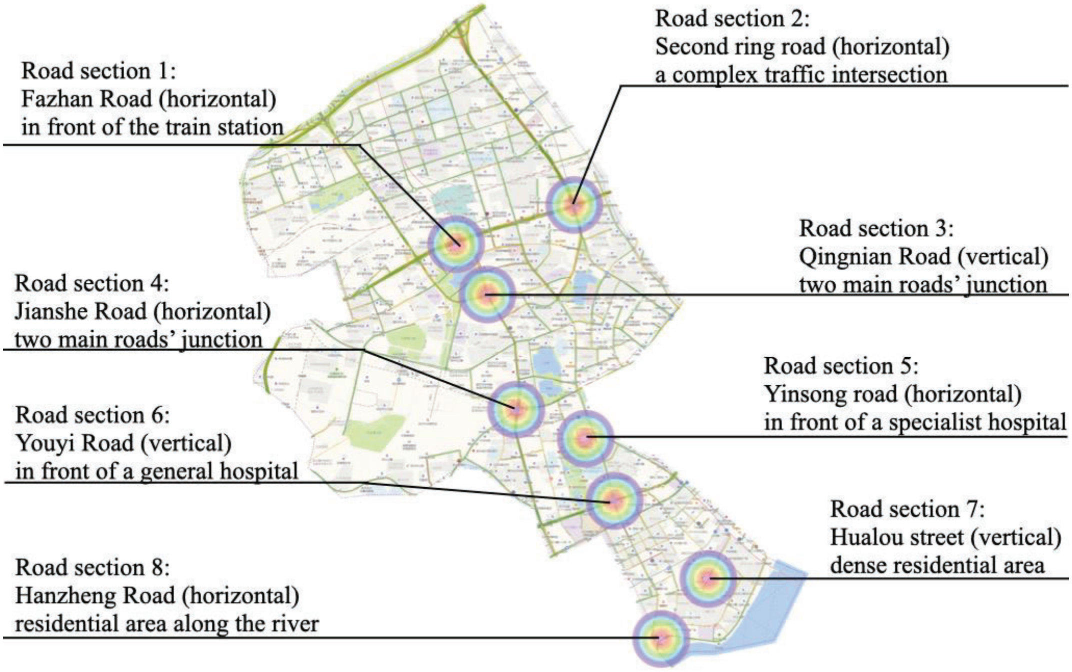


Figure 5.2: Locations and features of eight selected road sections.

The eight verification sections are shown in Figure 5.2, which are numbered in a way from north to south. Road section 1 is a part of a horizontal road called Fazhan Road, the selected section is just in front of the Hankou Railway Station. As one of the three main railway stations in Wuhan, Hankou Railway Station has 18 platforms. In 2006, Hankou Railway station sent over 9 million passengers throughout the year. The huge passenger flow makes the traffic near the train station always congested. Therefore, road section 1 is also one of the most congested area in Jianghan Zone.

Road section 2 is a part of Wuhan's second ring road. Like some cities with relatively flat terrain and relatively balanced development in all directions, Wuhan is also wrapped in several ring roads. The first ring road is also known as Wuhan inner ring road, the length is 28 kilometers and the first ring road surrounds the most central area of Wuhan. Although the first ring road is more central, the second ring road carries most of the cross-zone traffic in the city because of its larger traffic capacity. There is also the third ring road in Wuhan, but its connections are all suburbs, usually the traffic on it is not dense. As a representation of the traffic entering and leaving Jianghan Zone, the road section of two main road intersections on the second ring road is selected as our verification road section 2.

Section 3 and section 4 are located in the central area of the entire Jianghan Zone. Both sections are located at important intersections. Section 3 is on a vertical road, Qingnian Road while section 4 is on a horizontal road, Jianshe Road. As intersections of two main roads, they have a lot of traffic load when the morning and evening peaks arrive. These two sections become verification sections as representatives of ordinary traffic in the city.

Road sections 5 and 6 are located close to two different hospitals. Section 5 is on a horizontal road called Yinsong Road, in front of a specialist hospital, Tongsheng Zhenggu Hospital. It is a Chinese medicine hospital specializing in orthopedics, attracting many patients because it is known for treating without surgeries. Section 6 is on a horizontal road called Jiefang Avenue. To the north of Jiefang Avenue is one of the most famous hospitals in Wuhan, Wuhan Union Hospital. It is a large hospital that occupies an entire block, and it has more than 5,000 patient beds and over 8,000 employees. These two verification road sections are selected under the consideration of traffic status in front of the hospitals.

Road section 7 and 8 are located in two most densely populated areas. Section 7 is a part of Hualou Street, a vertical street in the middle of several large communities. On the east side of Hualou Street are two communities, Wannian community with 3,987 households, 7,726 inhabitants, and Tujia community with 1,778 households, 4,213 inhabitants. On the west side of Hualou Street is one community called Dadong community with 1,447 households, 4,653 inhabitants. Hualou Street is between these three large communities and many residents drive through this road every day. Therefore, this street is often in congestion. A section near the intersection of this road is chosen as the verification road section 7. The surrounding condition of road section 8 is similar to section 7, the location of section 8 is close to two large communities with a total of 15,218 inhabitants. These two verification points represent the traffic conditions in densely populated areas.

5.1.4 Comparison of simulated and real traffic status

In order to verify whether the simulation is accurate at each time period, the current traffic condition of each hour in each road section of the simulation is recorded and expressed in red, yellow and green. The speed interval of these three colors are the same as the average speed intervals displayed in AutoNavi map. For the real traffic data, the prediction function in AutoNavi map is used. The prediction function of AutoNavi map is generated based on the hourly average values of each day of the week. For example, the traffic prediction of Monday 8:00 of a road segment is the average condition of each Monday 8:00 of this road segment. By using the prediction function, special situation on a certain day can be avoided and more universal traffic situation can be shown.

The comparison of actual and simulated traffic condition of road section 1 can be seen in Figure 5.3. The number on the first line indicates at which hour the traffic condition is recorded, the first column is in which day of the week and the last line is the simulated data. This section represents the traffic near the railway station. However, because there is no separate treatment of the railway station and the ordinary work place in SUMO, the congested traffic conditions of road section 1 are not reflected in the simulation.

Road section 2 is a part of Wuhan second ring road, undertakes traffic pressure between regions. In Figure 5.4, the real traffic status on weekdays and weekends show a big difference. The morning peaks of working days occur at 8-9 a.m., and there are no early peak on weekends. The evening peak of the working day usually appears at 18 o'clock, on Friday it is especially long, while the evening peak of the weekend is two hours earlier. It can be said that the simulation results average the real traffic conditions on weekdays and weekends and in most time periods. From a macroscopic prospect, the simulation has well reproduced the real traffic situation.

Road section 3 and 4 can also represent the ordinary traffic conditions in a city and the comparison is in Figure 5.5. Although they are at two different intersections, and one is a north-south road, the other is an east-west road, the actual traffic conditions and simulation results are very similar. Like the real traffic of road section 2, road conditions on weekdays and weekends also vary widely on section 3 and 4. There are no obvious traffic jams at the weekend, but the morning and evening peaks of the working days are obvious. The simulation averaged these two situations, making the traffic in the simulation neither as busy as the working day nor as smooth as the weekend.

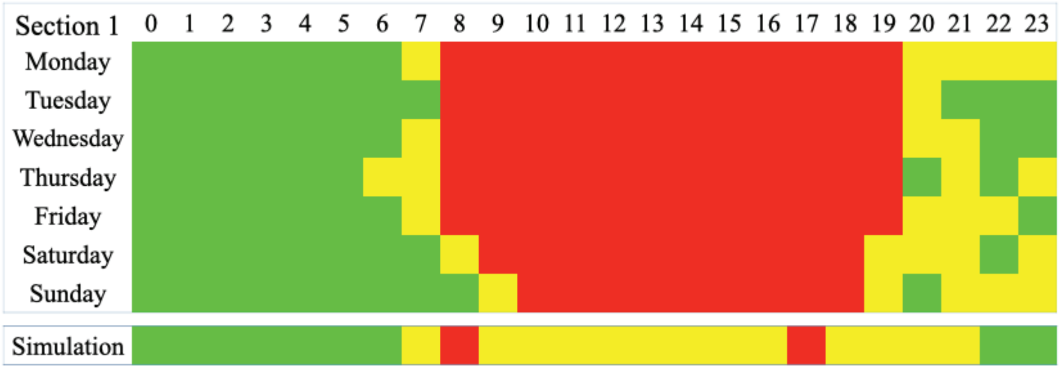


Figure 5.3: Comparison of actual and simulated traffic conditions of road section 1 (red for congestion, yellow for low speed, green for smooth traffic).

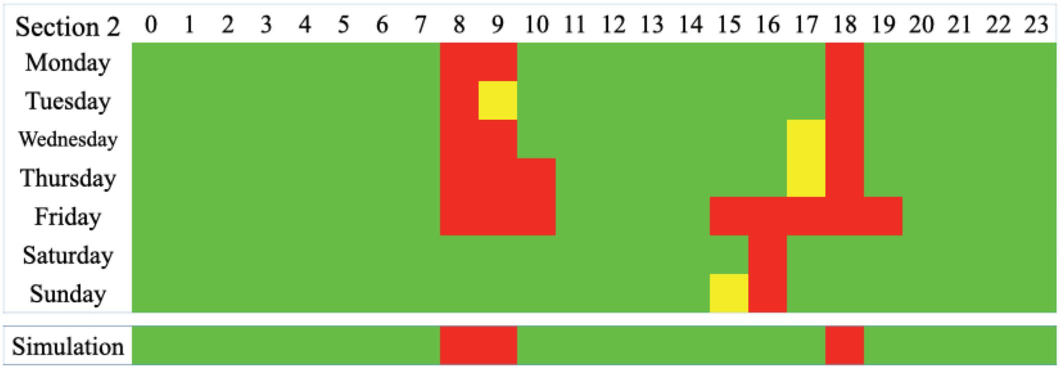


Figure 5.4: Comparison of actual and simulated traffic conditions of road section 2.

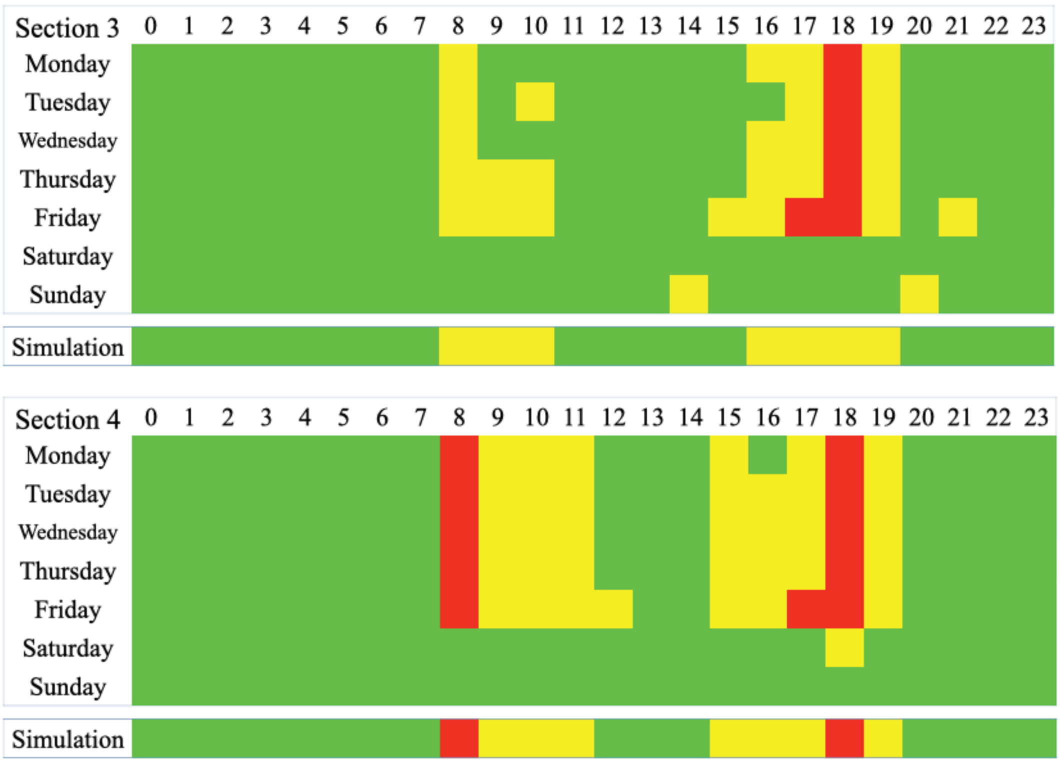


Figure 5.5: Comparison of actual and simulated traffic conditions of road section 3 and 4.

For section 5 and 6, the simulation results are not as representative as above. These two sections are near the hospital and the comparison is shown in Figure 5.6. It is seen from the actual road conditions that from 7:00 a.m. to 8:00 p.m. the roads are mostly in yellow (slow speed) state, sometimes even in red (congestion) state, on weekdays or weekends.

Unlike the blockage of road section 1, section 5 and 6 are only in slow speed status, but the reasons are similar, the hospitals are also not treated as a special model in SUMO. The traffic near the hospital is not just caused by doctors and nurses working in the hospital, the patients who go to the hospital and the family members or friends of the patients who accompany the patient cause most of the traffic needs. In China, the medical system is different from that in Europe, and the family doctors and community doctors are not common. Therefore, the patients will go to the hospital regardless of the severity of the illness. This causes huge amounts of people in Chinese hospitals. Another reason for the amount of people in hospitals is cultural differences. Many people in Europe are willing to go to see a doctor by themselves. They don’t want their family members or friends to know they are sick and what sickness they have. In contrast, in China, people think it is miserable for a person to go to the hospital alone. Most people are willing to accompany their family member or friends to hospitals. And it is also necessary in China to have accompany in hospital, because the doctors will tell the relatives about the patient’s condition instead of the patient him/herself when the illness is severe.

These differences make the traffic situation near hospitals in China problematic, and the lack of hospital models makes the simulation results not reflecting the actual situation of section 5 and 6.

In the simulation of Jianghan Zone, the most troublesome thing is the huge population. The most important manifestation is the community with the hugest population. Section 7 and 8 represent the traffic conditions in the most densely populated area, and the comparison results can be seen in Figure 5.7. In section 7, almost every day during the daytime there is a traffic jam, and on weekends the situation is even worse. The simulation result of section 7 is similar to the actual situation, it is also almost in congestion state throughout the daytime.

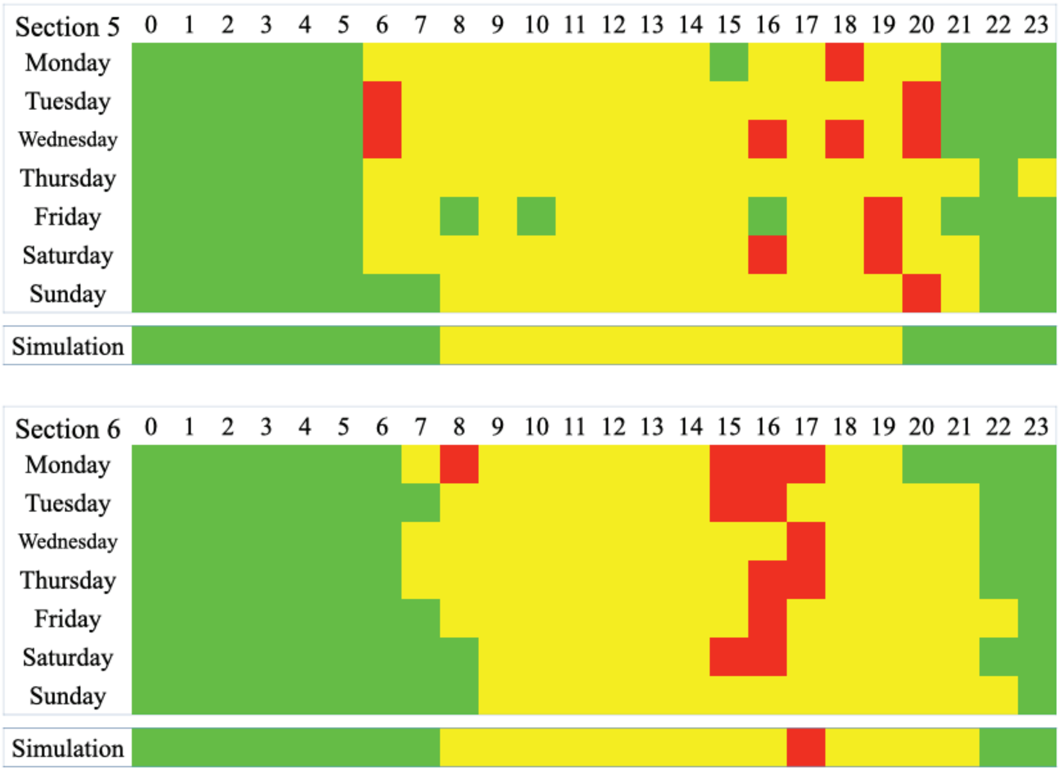


Figure 5.6: Comparison of actual and simulated traffic conditions of road section 5 and 6.

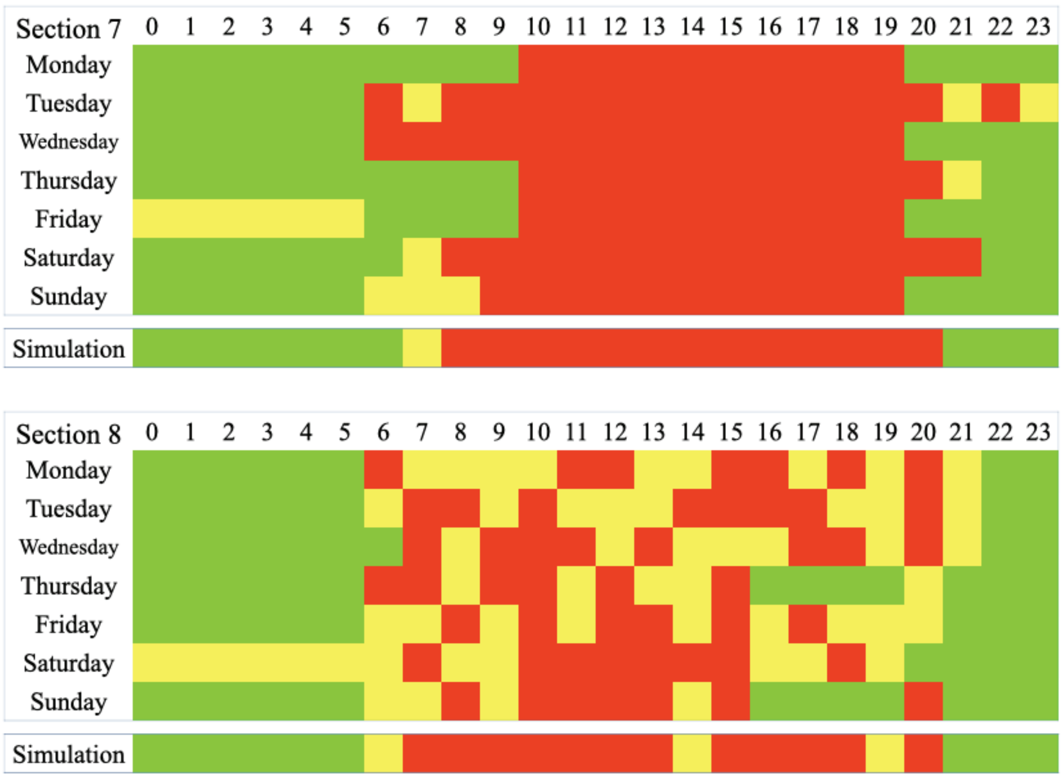


Figure 5.7: Comparison of actual and simulated traffic conditions of road section 7 and 8.

For road section 8, the congestion degree is not as serious as for section 7, but it is still either red or yellow. Residents near section 8 are not much less than those near section 7, but they have more roads to choose when going out from the community. Between 13:00 and 15:00, the simulation results show smooth traffic while actual traffic are yellow or red. In addition, the simulation result of section 8 can basically represent the actual traffic situation during the week.

In general, the simulation results in Jianghan Zone are basically consistent with the actual traffic status in Jianghan Zone, especially on ordinary urban roads and roads near residential areas. For special places such as railway stations and hospitals, accurate simulation could be conducted by establishing special models. The results of 5.1 can also prove that for ordinary urban roads, SUMO is capable of reproducing real traffic conditions through simulation.

5.2 Simulation of school-intensive area in Wuhan

5.2.1 Distribution of schools

The special traffic demand in school intensive area is caused by special social phenomena. In China, due to the uneven distribution of educational resources, the concept of "school district housing" has emerged. Of course, all housing can be assigned to schools, but only the housing around key schools are called "school district housing". All parents want their children to enroll in schools with better teachers and facilities, so the price of "school district housing" may be several times that of the non-school district in the same grade. As a result, many parents choose to purchase a small dilapidated apartment in a key school district to get the enrollment, but live in other areas.

This kind of choice of parents has greatly affected the traffic condition in school intensive areas, which are often in the city center. Figure 5.8 shows all the schools and kindergartens in the south part of Jianghan Zone. The red numbers and shapes represent the schools in this area, 21 in total; the pink numbers and dots represent the kindergartens in this area, a total of 16.

The total area of the region in Figure 5.8 is only 2.45 square kilometers (land area), but there are 13 primary schools, 7 middle schools and one high school in this region. Just the total number of students in these schools exceeds 18,000, not to mention the many kindergartens. For this area, whether the schools are in vacation or not has a great impact on the traffic of particular roads. In order to find out whether SUMO can reproduce the traffic near the schools well, this simulation is carried out.

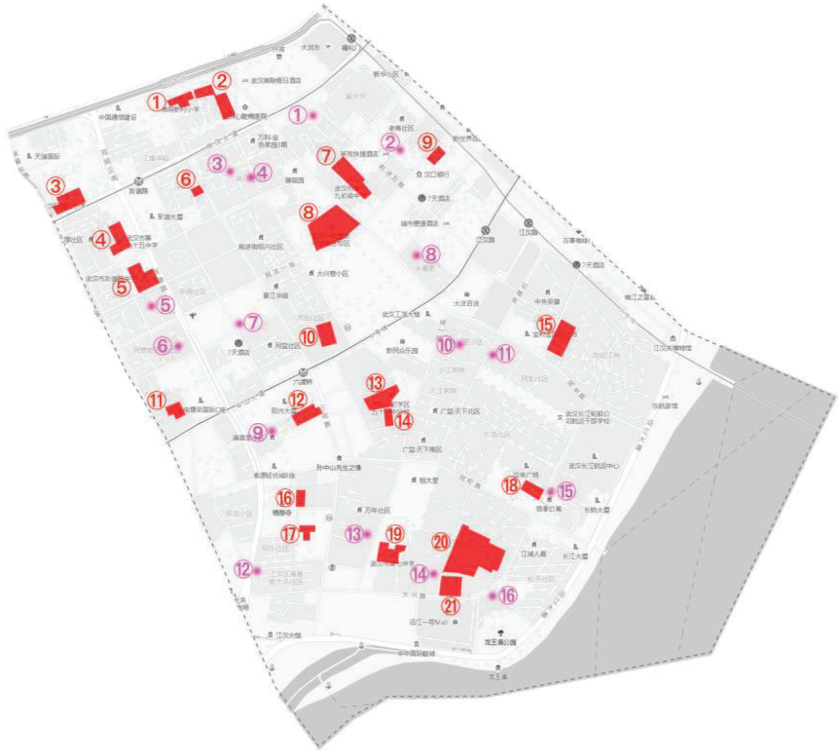
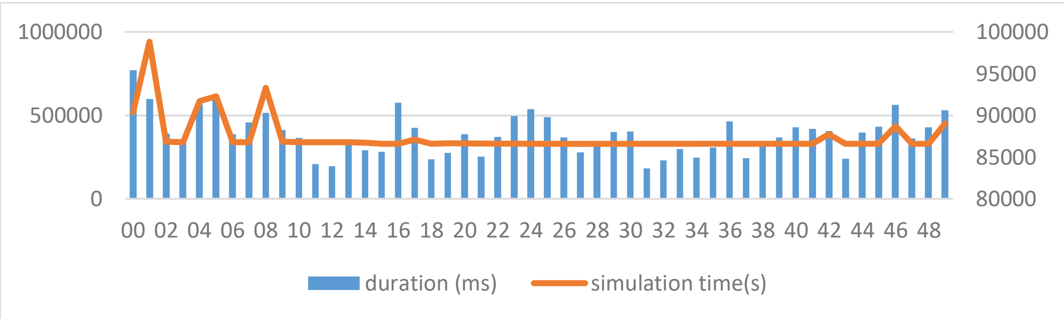
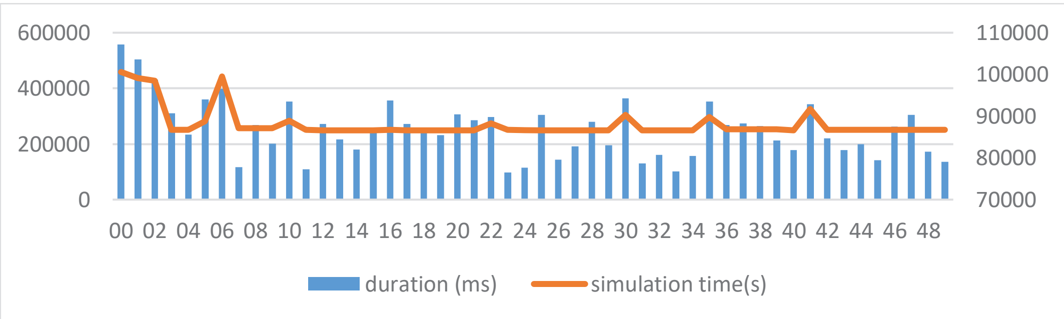


Figure 5.8: Distribution of schools and kindergartens of simulated area.



a). Situation A



b). Situation B

Figure 5.9: Iteration result of situation A and B.

5.2.2 Network and traffic demand

Like the simulation of Jianghan Zone in 5.1, the network in this section is also derived from OSM and manually corrected according to the street view in Baidu map. For traffic demand, ActivityGen is used to generate two different situations for during school semester (Situation A) and during school vacation (Situation B), respectively. In programming, the two-statistic files are represented with and without school information. In order to avoid congestion caused by the same algorithm, DUE is used, and the iteration results are in Figure 5.9.

In the iterations of the two situations, the simulation time and performance duration (iteration time) both drop sharply in the first few simulations and stabilize later. Finally, the group with the shortest simulation time in situation A and B are respectively selected as the route file for the simulations A (during school semester) and B (during school vacation).

5.2.3 Real data from semester and school vacation

As this simulation is to verify the school's impact on traffic flow, the road sections selected for comparison are all closely related to schools. As can be seen in Figure 5.10, a total of 6 road sections are selected as segments for comparing and verifying the traffic conditions. Road section 1 is on Dandong Road, on the south side of section 1 are two schools, Wuhan No. 1 Middle School with ca. 1500 students and Dandong Xincun Primary School with ca. 1300 students. Section 2 is on Qianjin fifth road, there is a school gate on the south side of section 2. Every school day, there are about 1,450 students coming in and out to Wuhan No. 19 Middle School. Road section 3 is on Qianjin second road nearby Yichu Huiquan Secondary School with over 2,000 students. Section 4 is a one-way road and Wuhanguan Primary School with about 370 pupils is on the east side. Road section 5 is in the middle of three schools, on the west side are Fujian Street Primary School with 630 students and Hankou Huimin Primary School with 380 students. On the other side of section 5 is Wuhan No. 7 Secondary School with over 1000 students. Section 6 is between residential areas, what's more, there are two schools on the south side of it, Wuhan Renmin Secondary School with 750 students and Daxing Road Primary School with about 1,600 students.

To gather the real traffic condition of the above six road sections, real time traffic screenshots on AutoNavi map are taken. In a day that all schools in this simulation map are during semester, the screenshots for every hour in the day were taken. And in a day that all schools in the simulation map are during school vacation, also 24 screenshots were made. To make the traffic data of these two days more comparable, other variables are controlled to have the same values. The weather was sunny on both days. Both days were not holiday and there were no special events in the area.

Figure 5.10: Six verification road sections of school intensive area.

5.2.4 Comparison of simulated and real traffic status

For each road section, there are four types: type 1 represents the simulation result during school semester, type 2 is real data during school semester, type 3 represents the simulation result during school vacation days and type 4 is real data during school vacation days. Figure 5.11 shows the comparison of road conditions at each hour of the six road sections.

In the comparison of type 2 and type 4 of each road section, the traffic situation of type 4 is obviously better than that of type 2. This means that in actual conditions, the schools produce extra traffic pressure during school semesters. In comparison of type 1 and 2, type 3 and 4, traffic status of simulated and actual situation, simulation is basically accurate most of the time. Only at noon time, about 12 to 15 o'clock, the simulated traffic is smoother than the actual one. The reason could be that the traffic demand caused by the parents delivering meals to their children at noon is not taken into account. In general, simulation can represent the impact of schools on traffic in various road sections. The results in section 5.3 can also be seen in (Ma et al. 2020).

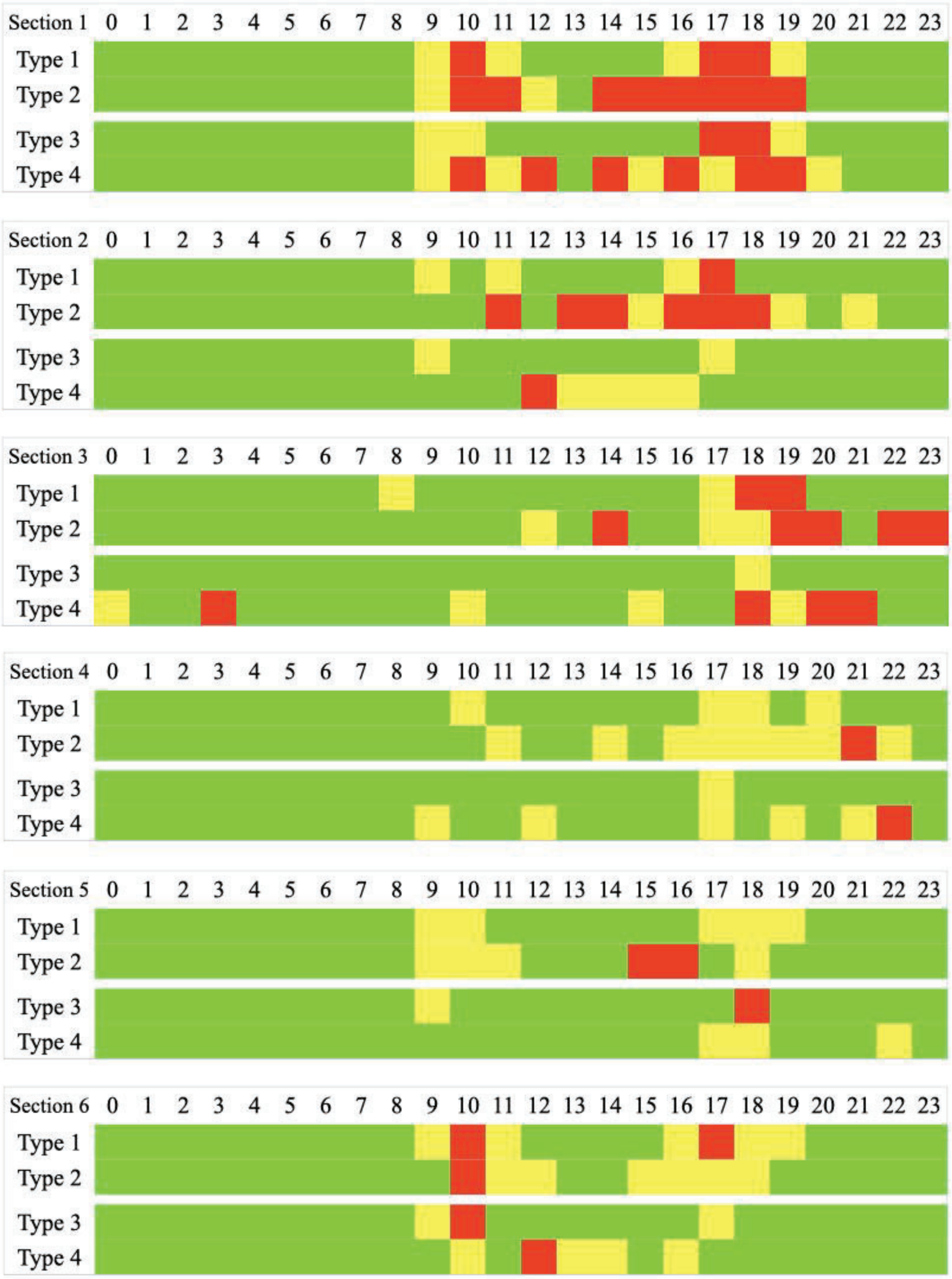


Figure 5.11: Comparison of simulation result and real data in 6 verification road sections.

5.3 Simulation of the city of Duisburg

The simulation of the city of Duisburg uses the traffic demand generated from OD matrix. Since the OD matrix only depicts the traffic volume from one area/point to another area/point in 24hours, a timeline that allocated the traffic volume of a day to each hour is required. In the simulation of the city of Duisburg, common daily time lines retrieved from cities in West Germany are used (Schmidt and Thomas 1996). For passenger cars, a time line called TGw2_PKW is used to describe the traffic distribution of a normal workday (Tuesday to Thursday). For trucks, a time line called TGw_LKW is used for the hourly traffic distribution. Figure 5.12 shows the hourly percentage of the two used time lines for passenger cars and trucks.

5.3.1 Four simulation scopes of the city of Duisburg

As described in 3.3.2, there are 4 variants for the simulation of the whole city of Duisburg. The four cases are compared in Figure 5.13, the arrow in Case C represents the trips with either departure or destination points outside the city of Duisburg are included. The other arrow in Case B represents the trips with both departure and destination points outside the city included.

The scope of the network of Case A, B and C are the same. However, with different traffic demand, the total amount of simulated vehicles differs among the three cases. In Case A, there are 756,885 vehicles in the simulation. In Case B, the total amount of vehicles is 4,338,202. In Case C, the total amount has been reduced to 1,397,578 (Ma et al. 2021b). The traffic volume of Case C is almost twice that of Case A, that means, the extra inter-city traffic demand of Case C is almost the same as the inner-city traffic demand of the city of Duisburg. The traffic volume of Case B is more than six times that of Case A, and also much more than that of Case C. This means, of all the traffic demand, the traffic outside the city still accounts for the majority. Case B and Case D share the same traffic demand with different scope of network. Therefore, the traffic volumes of Case B and Case D are quite close.

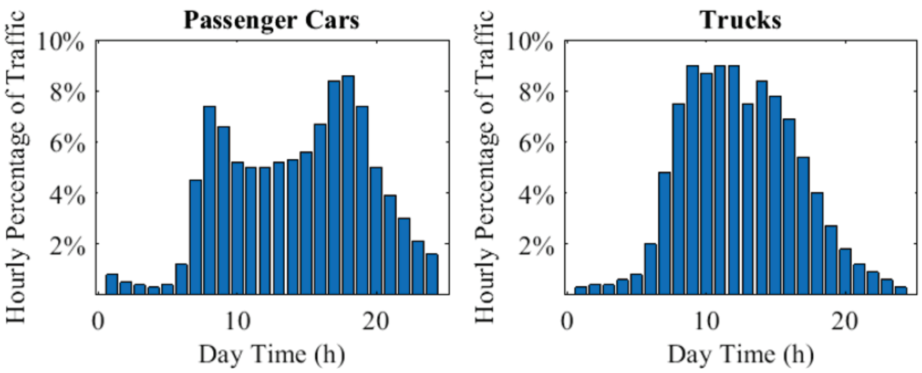


Figure 5.12: Hourly traffic distribution of passenger cars and trucks.

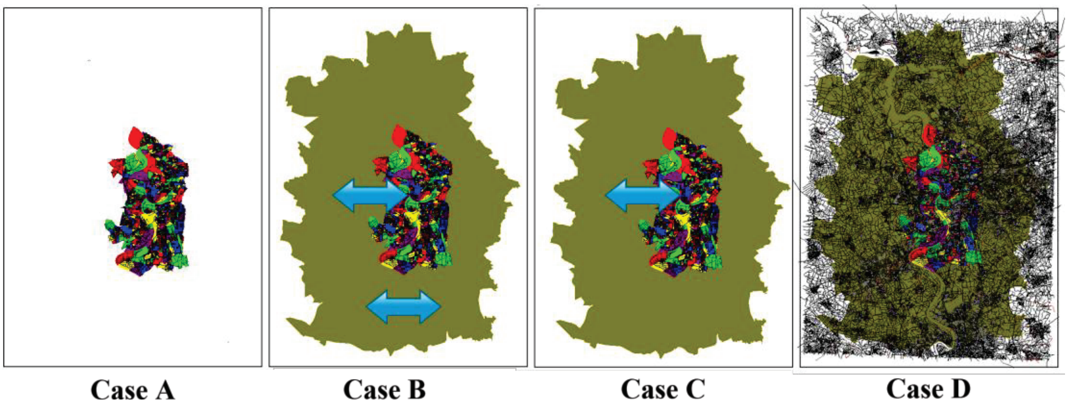


Figure 5.13: Four simulations with different scope of the city of Duisburg (olive area represents the out of city parts, other five colors represent the distribution parts of the city of Duisburg, and black lines represent the road networks).

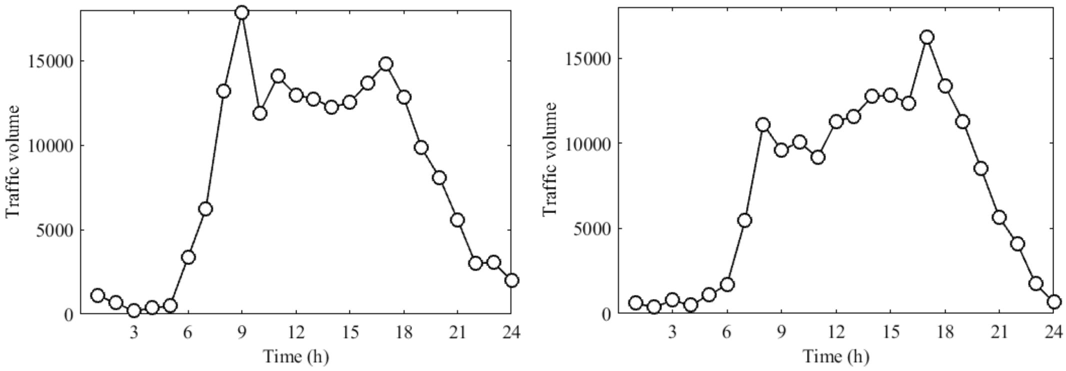


Figure 5.14: Traffic volumes of two induction loops in 24 hours.

In the four simulation scenarios, Case B has the largest traffic demand with limited network scope. Therefore, the road in the simulation of Case B is seriously overloaded. First the traffic jam happens in the sections of the city's edge, then spreads to the whole city. The simulation could hardly run after 40,000 seconds simulation time because of the large-scale traffic jam in the whole city. In addition to Case B, large-scale traffic jam also happens in the simulation of Case A and Case C. With the huge traffic volume of morning peak at around 8 o'clock, the simulated network gradually starts to congest.

The reasons for the congestion are mainly in two aspects: First, the planning data of all the traffic light in the city of Duisburg were not available for this work. In real world, traffic light plans have been modified according to the traffic volume in the years of transportation development. In some intersections in the city of Duisburg, smart traffic lights are also used. However, in the simulations, traffic lights plan still uses the default settings of SUMO. The non-optimized traffic lights make the waiting time allocation in all directions inappropriate, and cause traffic jams in some of the intersections, then spread the congestion to the entire city. Second, the path allocation algorithm used in this section is the shortest path algorithm, i.e. vehicles will use the shortest path from the departure road/edge to the destination road/edge. This means, if the departure and destination points are the same for different vehicles, they will use the same route. However, in reality, drivers with the same departure and destination points would probably not use the same route. Some drivers prefer the shortest route, some choose route for shorter time of driving according to the broadcast, and some may prefer less traffic lights, while others would choose to drive in roads with higher speed limit. In simulations, these characteristics of personalization are ignored. Therefore, there are more possibilities for the vehicles in the simulation to have traffic congestions. Due to the two reasons mentioned above, the simulated large highly-meshed road networks are prone to have traffic congestions. For Case D, the road network is much larger and more complex, therefore, the traffic congestion problem is much more severe. The simulation of Case D in 24 hours cannot be finished neither. Therefore, in the next section, only the simulation results of Case A to C are compared.

5.3.2 Verification points of the city of Duisburg

In order to verify the accuracy of the traffic volume generated from the OD matrix data, detector data collected from the real roads are used. The spread of distributed verification points can make the results more objective, therefore, nine verification points intersections in the north, south, west, east and middle of the city of Duisburg are selected. Figure 5.14 shows the traffic volume of two induction loops in 24 hours. In these two examples, the highest traffic volumes are in the morning peak and the afternoon peak, respectively. Figure 5.15 shows the location of the nine verification intersections. There are multiple induction loops at each intersection, some of them are in different lanes of the same road.

Intersection No. 116 is located in the northern part of the city of Duisburg, it is the intersection of Stockholmer Street and Duisburger Street. The induction loops are located in all four directions of the intersection, there are in total 13 induction loops in this intersection. Intersection No. 834 represents the road condition of the west side of the city. It is located at the intersection of Moerser Street and Friedrich-Ebert Street. It has two groups of induction loops on all the four directions to the intersection. Intersection No. 903 is located at the junction of Duesseldorfer Land Street and Roemer Street in the south side of the city. It is a T-junction with only two groups of detectors on the two lanes of Roemer Street. No. 656 represents the road condition on the east. Located at the junction of Kalkweg Street and Sternbuschweg Street, the T-junction No. 656 has six groups of intersection loops in all the three directions. Each direction has two lanes and there is one group of intersection loops on each lane. Intersection No. 751 represents the middle of the city. It is one of the main intersections of the city, and is located at the junction of Rheinhauser Street and Rudolf-Schock Street. In this intersection, there are over 30 camera detectors, only 14 of them on the 14 lanes are used in this work. Intersection No. 721, 723, 726 and 742 are in the inner ring area of the city, they are also selected for the verification.

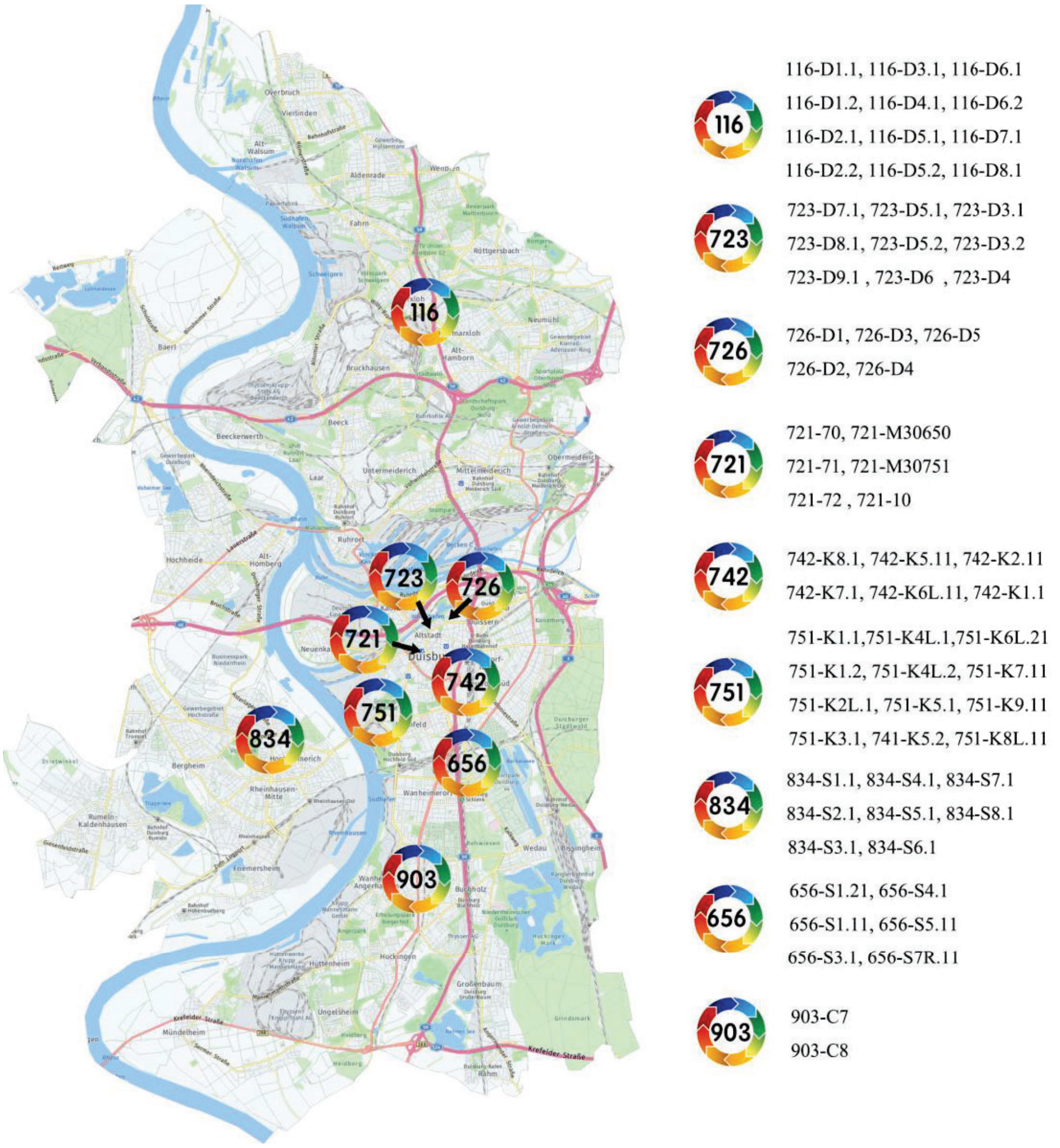


Figure 5.15: Locations of verification points for the simulation of the city of Duisburg.

Due to the non-replicability characteristic of traffic, it is impossible to reproduce all the real routes of vehicles in one day. The traffic volume recorded by a single detector may have a large difference due to the drivers' choices of lanes. Therefore, the traffic volumes of detectors on different lanes of the same road are summed. In the next section, all the simulation results compare the traffic volume of one road, instead of one detector on a lane. The real data of a week are also processed in this way.

5.3.3 Simulation results and discussion

The simulations of different cases are launched respectively, and the detectors on the network are set to record the traffic volume every 600 seconds. The simulation time step is set to 1 second. In addition to traffic demand generated from OD matrix, all other parameters in the simulation of different cases are the same. Figure 5.16 shows the simulation results of Case A, B and C with the real traffic volume collected in one week. The box graphs in dark green represent the real traffic volume in 7 days of a week. The green plus symbols represent the outliers. The black, blue and red lines represent the traffic volume of a certain detector in the simulation of Case A, B and C, respectively. The graphs only show the simulation of 8 hours, when the citywide traffic jam that affects the traffic volume in the simulations of all the cases are not severe.

In Figure 5.16, comparison graphs of four representative road sections are displayed. From all the four graphs, it can be obviously seen that the traffic volume of Case B (blue line) is larger than in all other cases, especially at the beginning of the simulations. For Intersection No. 751 and 656, the traffic volume of Case B is also much higher than the real traffic volume. However, after some time, the traffic volume of Case B decreases rapidly. The reason of this phenomenon is that, the traffic demand generated for Case B has already exceeded the total capability of the road network, and after some time, the traffic jam at the intersection makes the traffic volume reduced. Therefore, the accuracy of the simulation of Case B in reproducing the traffic situation of the city is lower than in Cases A and C.

In the comparison of case A and case C, the total vehicle quantity of the city in Case C are almost twice than Case A. From Figure 5.16 it can also be seen that the vehicle quantity of Case C (red lines) are more than that of Case A (black lines) in the four intersections. Comparing with the real data (green boxes), the vehicle quantity of Case C is closer, and the vehicle quantity of Case A is about to stay at the minimum value of the real data of the recorded week. From the comparison results of Intersection No. 727, it can be seen that the traffic volume of the three simulations decreases rapidly in the end. First the blue line represents Case B, then the red line represents Case C, at last the black line representing Case A. Because of the complexity and large scope of this traffic scenario, traffic jam happens eventually. In general, Case C reproduces the traffic situation closer to reality.

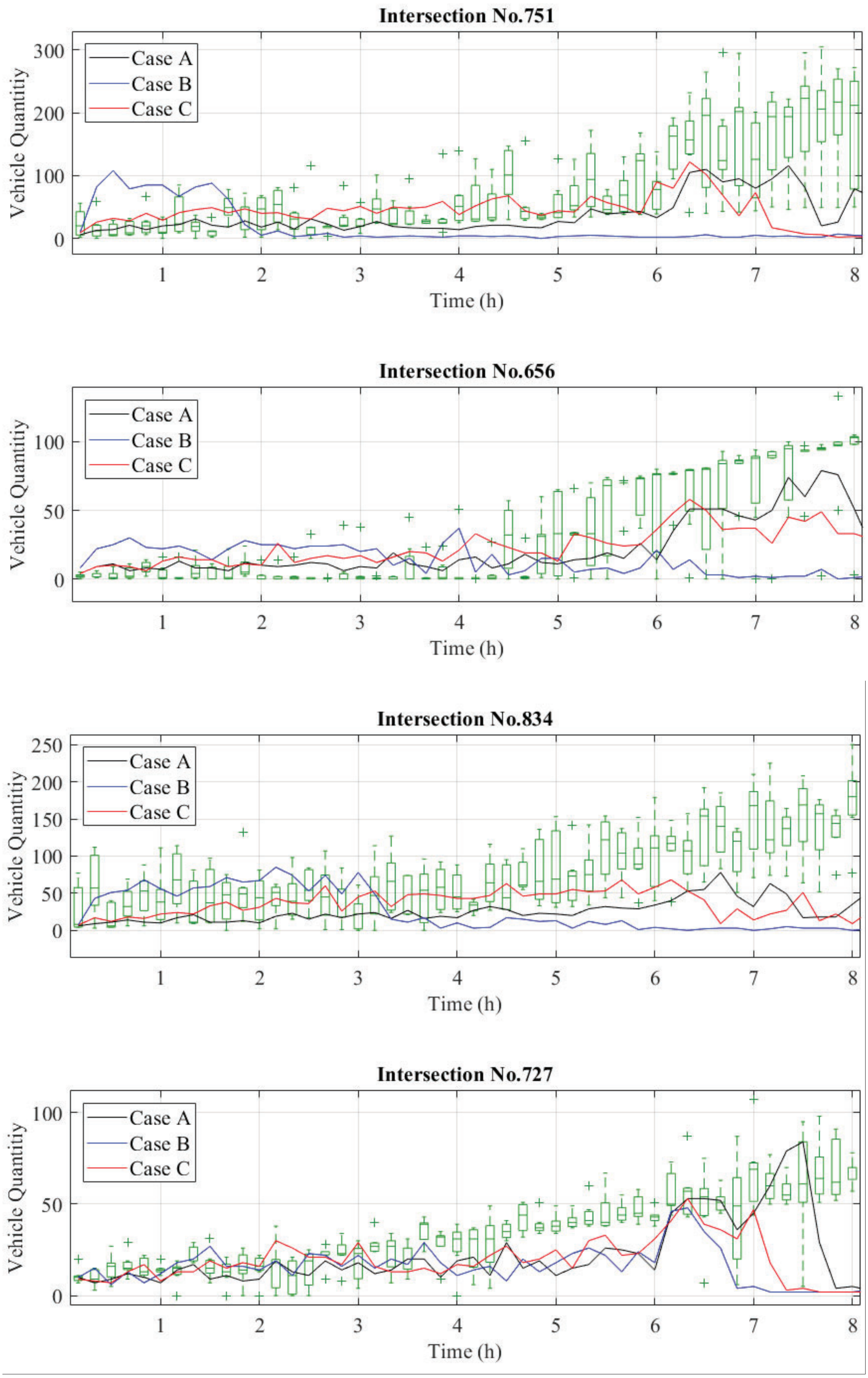


Figure 5.16: Simulation results of Case A, B and C and real traffic data in a week.

To verify the matching degree of the simulated results and the real recorded data, the proportion of the simulated data in real range is calculated. The real traffic data are recorded for one week, therefore there is a range for the real data. Figure 5.17 shows the proportion of the simulation vehicle quantity in the real recorded data range. The accuracies of Case A, B and C all increase in the first three hours, and decrease after the fourth hour. For the first two hours, Case B shows a better accuracy than Case A, but from the third hour, Case A shows better results. Of all the hours, Case C has the best reproduction rate, up to 72.22% proportion vehicle quantity are in the real recorded range.

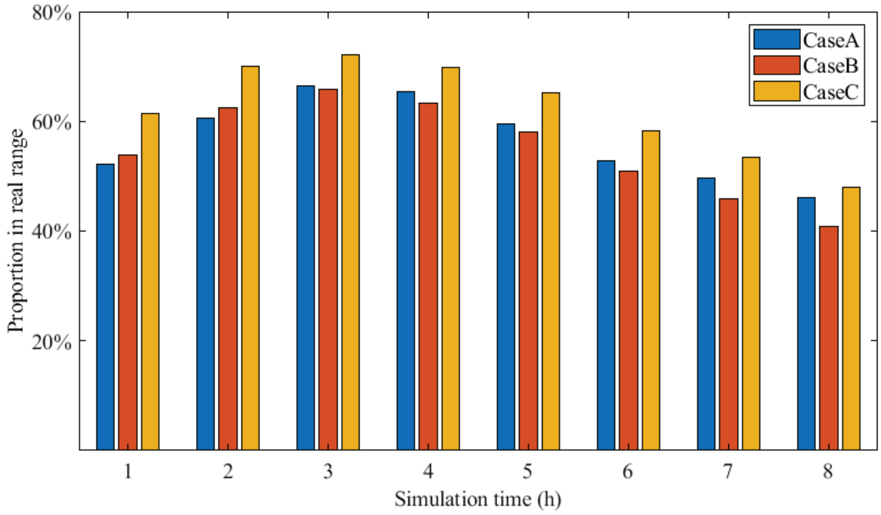


Figure 5.17: The proportion of simulated data in real range for the three cases.

Figure 5.18: Zoning of OD matrix in Duisburg inner ring.

5.4 Simulation of the inner ring in the city of Duisburg

5.4.1 Traffic demand generated from OD matrix

The inner ring area of the city of Duisburg is zoned into several parts, which are marked with different colors in Figure 5.18. According to the lengths of the roads, the traffic demand of OD matrix is assigned to the roads within their ranges with different weights.

The traffic demand generated from OD matrix in the Duisburg inner ring scenario has certain limitations. Since the OD matrix only describes the trips with origins and destinations, specific routes of vehicles are not included. Only the trips within the inner ring area are researched. The trips from the inner ring to other parts of the city are not considered in the simulation. Furthermore, the inner ring area can also be seen as a transportation hub, and there are lots of trips passing by this area; neither the departure nor the destination point is in the inner ring area. These trips can only be simulated in a larger scope.

5.4.2 Traffic demand generated from detectors

To simulate the traffic scenario with more realistic traffic volume, detector data of Duisburg inner ring area are used in generating the traffic demand. Figure 5.19 is a comparison of one intersection in layout figure (left) and in simulation (right). The intersection has both induction loops and cameras as traffic detectors. Induction loops are marked with boxes and named with D plus numbers in the layout figure on the left, and marked in pink boxes in the simulation on the right. Cameras are marked with dashed circles and named with K plus number in the layout figure, and in simulation marked in yellow boxes.

In the simulated range, there are 21 intersections with traffic lights. However, only 12 intersections have valid detector data in the given time period. In total, 76 detectors in 12 intersections are studied in this work. 53 of them are used to generate traffic demand, and 8 are used in verifying the precision of the generated traffic flow. Another 15 detectors are not used because of their unrealistic data or closeness to other detectors. Distribution of the 61 studied detectors are marked in Figure 5.20. The green arrows represent the detectors used in generating the traffic demand, and the pink arrows represent the ones used in verification. Direction of the arrow represents the direction of the recorded traffic flow.

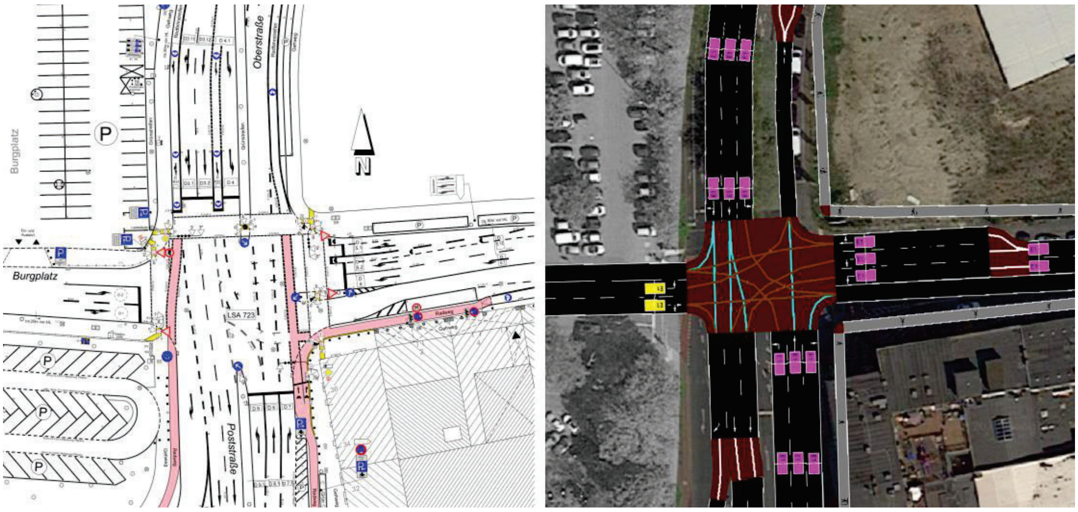


Figure 5.19: Layout (left) of an intersection with detectors and in simulation (right).

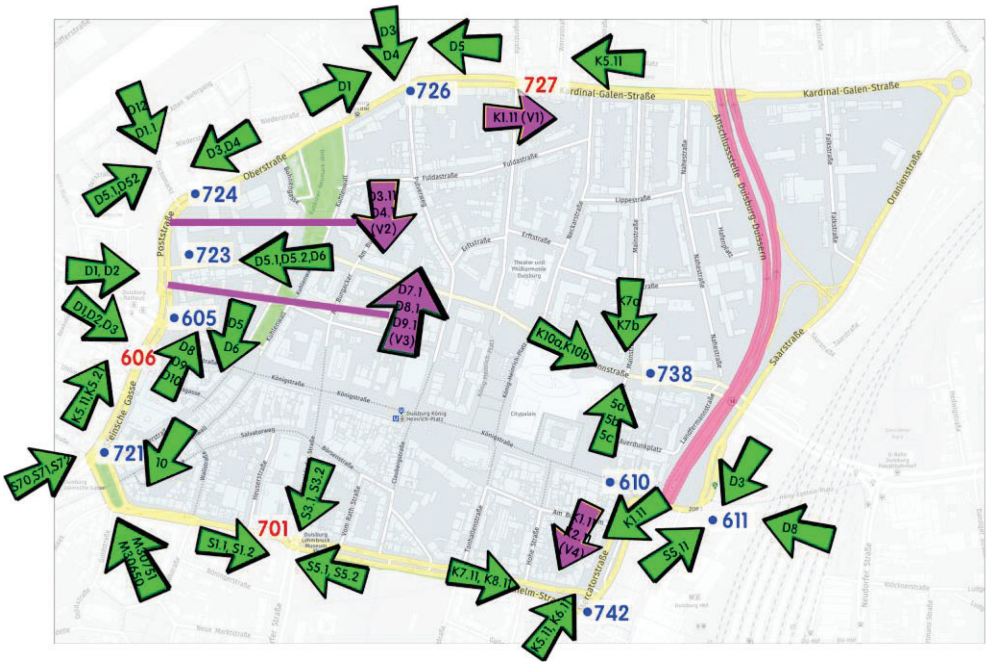


Figure 5.20: Locations of detectors and recorded traffic directions of Duisburg inner ring.

All the detectors are reproduced in SUMO as shown in Figure 5.19. The traffic volume files of the 12 intersections are modified and rewritten in a csv format file with MATLAB. Then, a sub-program in SUMO called *flowrouter* is used in generating the traffic flow. The detectors of four verification points recorded the traffic volume and average velocities of the vehicles in the simulation.

5.4.3 Verification results of Duisburg inner ring

The four verification points have 8 detectors in total. Except V1 in intersection 727, the other three verification points are roads with multiple lanes. In order to reduce the impact of different lanes on traffic flow verification, the data of multiple lanes are summed.

Figure 5.21 compares the real data and the simulation results for the four verification points in Duisburg inner ring. The upper four images are vehicle number and the lower four images are vehicle velocity of the 24 hours of a day. The black lines represent the simulation results using OD matrix as traffic demand (described in 5.4.1), the blue lines represent the simulation results using detector data as traffic demand (described in 5.4.2), and the red lines represent the real data collected from the traffic detectors.

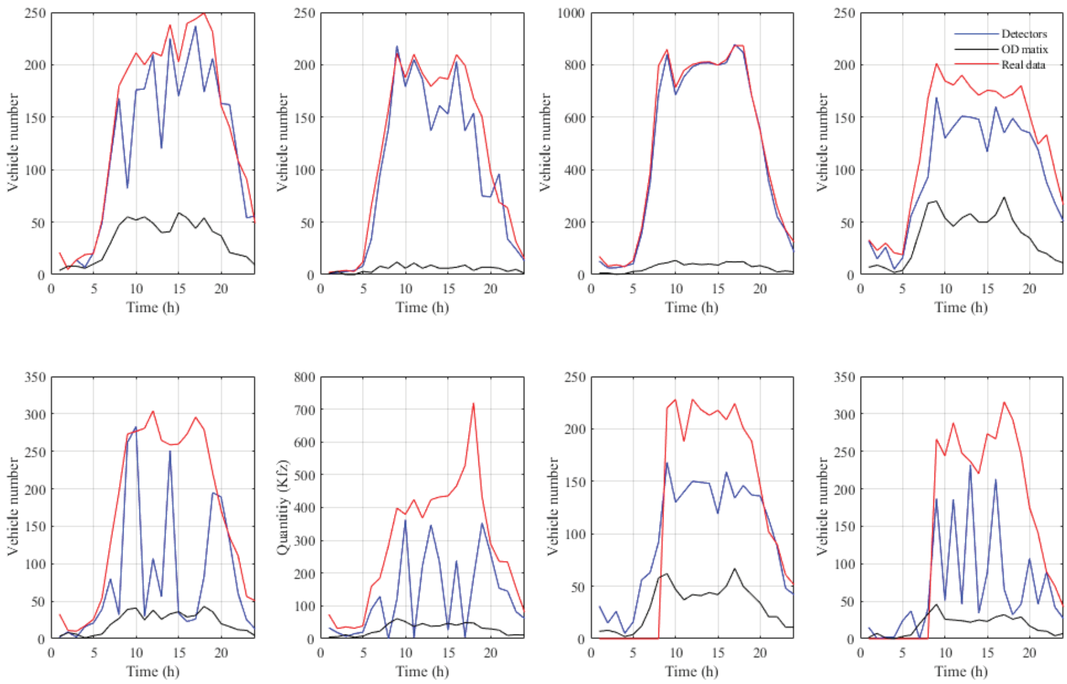


Figure 5.21: Comparison of real data and simulation results of different data sources.

As discussed in 5.4.1, the traffic volume generated from OD matrix is obviously smaller than the real data, which means, the passing-by traffic occupies a large proportion in all traffic in this area. This phenomenon is especially obvious on V2 and V3; the reason could be that, these two verification points bear more in-ring and out-ring traffic for connectivity. Meanwhile, the traffic volume generated from detectors are close to the real data. For the aspect of average velocity of the vehicles, both simulation from OD matrix and simulation from detectors are close to the real average velocity. To better reproduce the traffic status in Duisburg inner ring, the following simulation of Duisburg inner ring will use the data from detectors as traffic demand.

5.5 Discussion of simulation of different scenarios

Traffic simulations of four different scenarios are implemented in this chapter. The scenarios from the two cities in two countries show many differences in road network, population, distribution of public facilities, etc. Due to different data sources, different methods of generating traffic demand in SUMO are used. In 5.1 and 5.2, traffic demand is calculated from the geographic population information. In 5.3 and 5.4, OD matrix is used for generating the traffic demand. Traffic volume data from detectors on roads are also used for generating traffic demand in 5.4. In general, the third simulation (the whole city of Duisburg) has the largest simulated scope, while the last simulation (Duisburg inner ring) has the most accurate source data. From the comparison with verification data, a higher accuracy of simulation results can also be observed in the simulation of Duisburg inner ring.

From the simulation results of different scenarios, SUMO shows a great reliability of various simulated scopes and traffic demand sources. Whether compared with real-time traffic conditions or detector data, the traffic status generated by SUMO can reproduce the real traffic status with a high accuracy.

6 Simulation of different degrees of vehicle automation

In this chapter, vehicles with different degrees of automation are simulated in different traffic scenarios. First, a scenario of a single intersection is simulated with vehicles of automation level 0, level 2 and level 5, respectively. Then, a real traffic scenario of the inner ring area of the city of Duisburg is simulated with real traffic demand of the three automation levels.

6.1 Simulation of an intersection

6.1.1 Scenario and verification of an intersection

To distinguish the effects of different degrees of automation on traffic flow, a simple traffic scenario is needed. In this section, a simple intersection scenario is chosen for simulation. The scenario consists of two roads and one intersection, the length of east-west road is 363 meters, and the north-south road is 298 meters. There are 203 vehicles departing from the four terminal points (north, south, east and west end point) of the roads, and drive to different destinations. Figure 6.1 shows the simulation of this scenario, the yellow boxes on the three lane of roads are the induction loops in simulation, which record the amount of vehicle passing by every 60 seconds.

Three models of different degrees of automation (Level 0, Level 2 and Level 5) are simulated separately in this scenario. Apart from the driver model, all other parameters of the three simulations are the same.

6.1.2 Simulation results of the intersection scenario

The simulation results can be seen in Figure 6.2, the traffic volume of the recorded three lanes are summed and represented in three different colors. Since the induction loops in the simulation record every minute, the traffic volume corresponds to the passing number of vehicles during each minute. All vehicles depart in 660 seconds of simulation time, but in these three simulations, the respective simulation ends at different times. To be able to better compare the differences between the three simulations, scales of the horizontal and the vertical axes of the bar charts in Figure 6.2 were set the same for all cases.

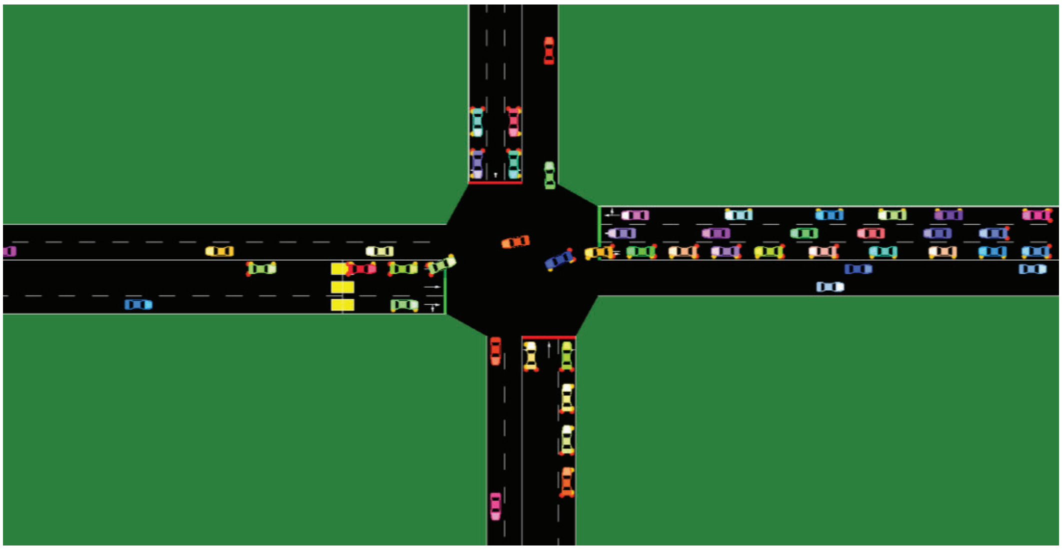


Figure 6.1: Traffic simulation of a single intersection.

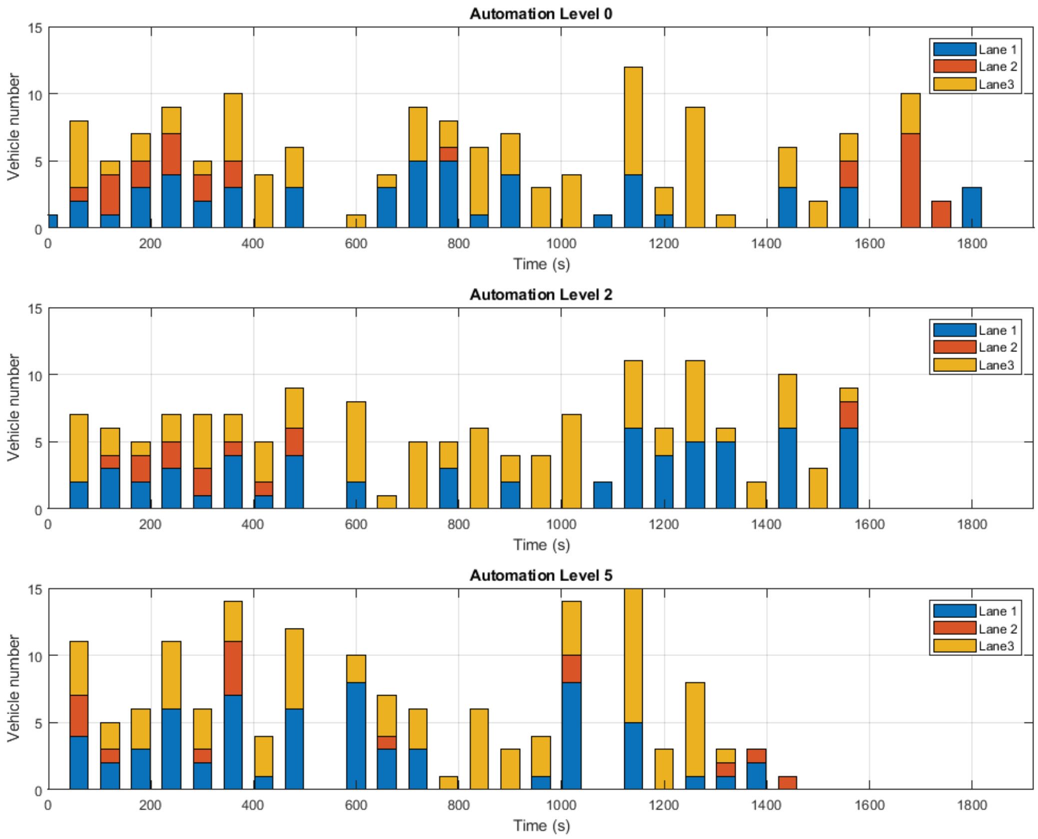


Figure 6.2: Traffic volume of vehicles with different degrees of automation in a single intersection scenario.

The simulation with Level 0 automation driver model takes the longest time (1,920 seconds) that all vehicles have left the track section of the three simulations. The second simulation with Level 2 automation driver model ends at 1,745 seconds, but the maximum traffic volume per minute remains the same with Level 0. The third simulation with Level 5 (fully autonomous/machine driver) driver model only took 1,540 seconds, and the maximum traffic volume per minute has a significant increase. Vehicles of automation Level 2 finish the driving task 9.1% faster than the no automation group, and the vehicles of automation Level 5 finish it 19.8% sooner than the no automation group.

From this simulation, the effects of different degrees of automation on traffic flow are proved in the simple intersection scenario. For a traffic scenario with heavy traffic, the differences of vehicles with different automation levels are apparent. Vehicles with a higher degree of automation facilitate a better vehicle throughput per time unit. The shorter reaction time and less randomness of operation all have a positive impact on heavy traffic scenario like in the intersection.

6.2 Simulation of Duisburg inner ring

6.2.1 Real traffic demand simulation

In this section, vehicles with different degrees of automation are simulated with real traffic demand of the Duisburg inner ring scenario. As compared and discussed in 5.4.3, traffic demand data from road detectors can represent the traffic volume in Duisburg inner ring with a higher precision. Therefore, in this section, traffic demand data are generated with road detectors. In the simulation, in total 20,952 vehicles are loaded during the simulation. Vehicles with automation Level 0, Level 2 and Level 5 are simulated separately in the scenario and road detectors in the verification points have recorded the traffic volume.

6.2 Simulation of Duisburg inner ring

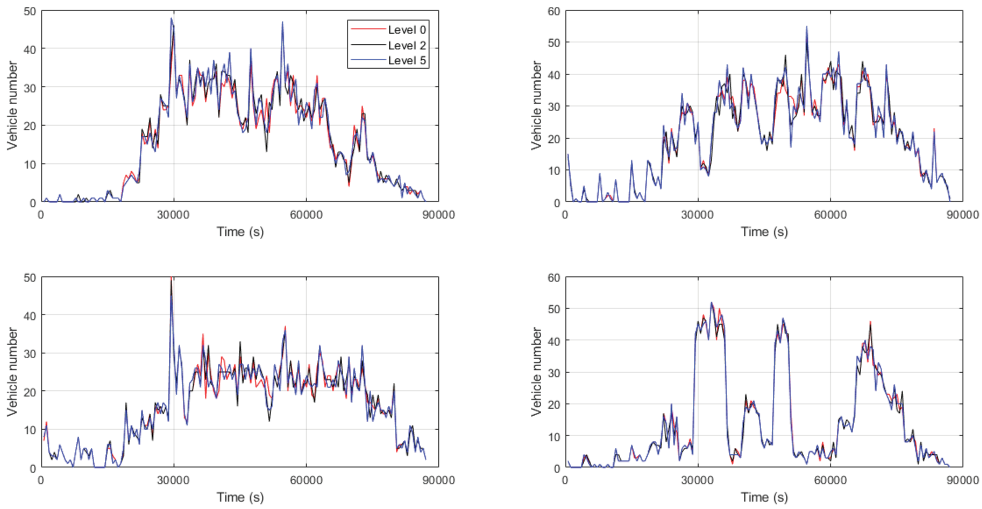


Figure 6.3: Real traffic volume simulation of different automation levels in four verification points.

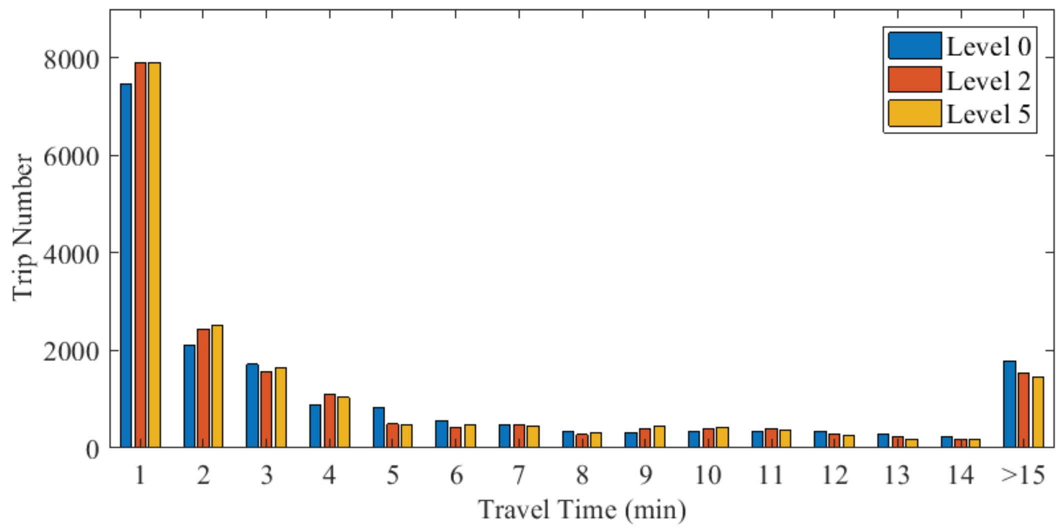


Figure 6.4: Travel time of vehicles with different automation levels in real traffic volume.

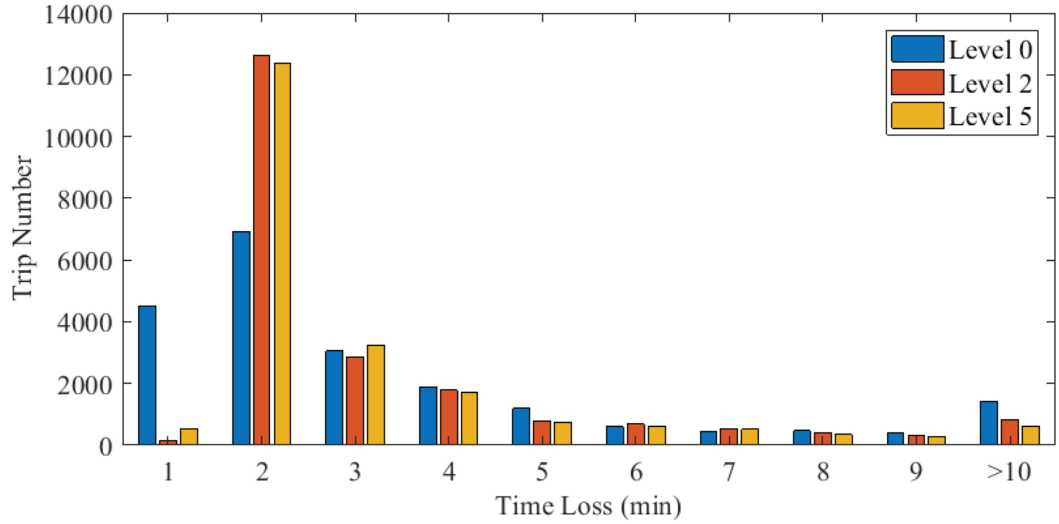


Figure 6.5: Time loss of vehicles with different automation levels in real traffic volume.

Figure 6.3 shows the traffic volume (vehicle number) of the vehicles with three different automation levels in the simulation. The red lines represent the simulation of Level 0 (no automation) vehicles, and the Level 2 and Level 5 simulations are shown in black and blue lines, respectively. The simulation is for a whole day (24 hours) and only slight differences can be seen from the traffic volume recorded by the detectors. For the same traffic volume input, the vehicles with higher automation level finish the traffic tasks earlier than the vehicles without automation. This indicates that automated vehicles have a positive impact on traffic flow, but on the condition of current traffic demand of Duisburg inner ring, the extent of impact is minor.

From the perspective of travel time, simulation of vehicles with a higher automation level tends to have shorter travel time on average. Figure 6.4 shows a comparison of travel time of a 24 hour simulation in real traffic demand. For the real traffic volume of the scenario of the inner ring area of the city of Duisburg, the median value of simulation of vehicles with automation Level 0, Level 2 and Level 5 are 1.70, 1.38 and 1.36 min, respectively. The simulations of Level 2 and Level 5 have an 18.8 % and 20% shorter median value of travel time than the simulation of Level 0 vehicle. However, the difference between Level 2 and Level 5 on the real traffic demand is not significant.

The vehicles' time loss contains vehicles' waiting time at traffic jam and approaching intersections. Figure 6.5 shows the time loss of vehicles in real traffic volume. The median of time loss of vehicles of Level 0, Level 2 and Level 5 are 44.8s 32.4s and 32.1s, respectively. From the perspective of time loss, vehicles with automation Level 2 and Level 5 can reduce the time loss by 27.7% and 28.3%, respectively. Figure 6.6 shows the average speed of vehicles and the running vehicle numbers in the 24h simulation. The average speed fluctuates sharply at the beginning, when there is just a few vehicles in simulation, but it tends to be stable as the running vehicles in simulation increases.

Figure 6.7 shows the comparison of average speed of the vehicles with different degrees of automation. The average speed of simulation of vehicles with Level 5 automation is 21.57 km/h, better than the average speed of simulation with Level 2 vehicles (20.77 km/h), and simulation with Level 0 vehicles (18.58 km/h). From the perspective of average speed, Level 2 and Level 5 vehicles can increase average speed by 3.7% and 20.7%, respectively.

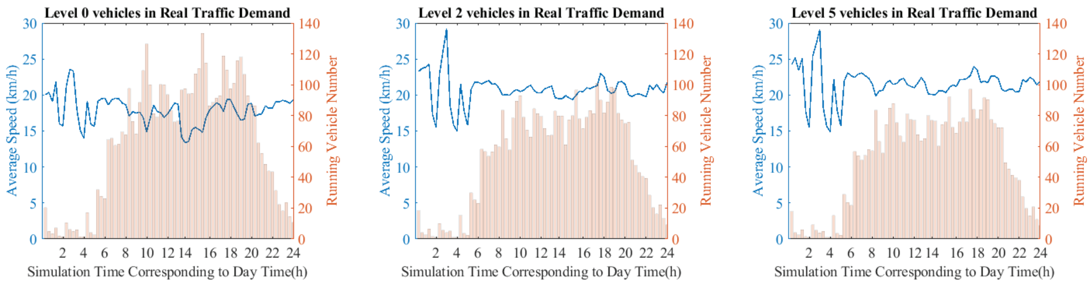


Figure 6.6: Average speed of vehicles with different automation levels in real traffic volume.

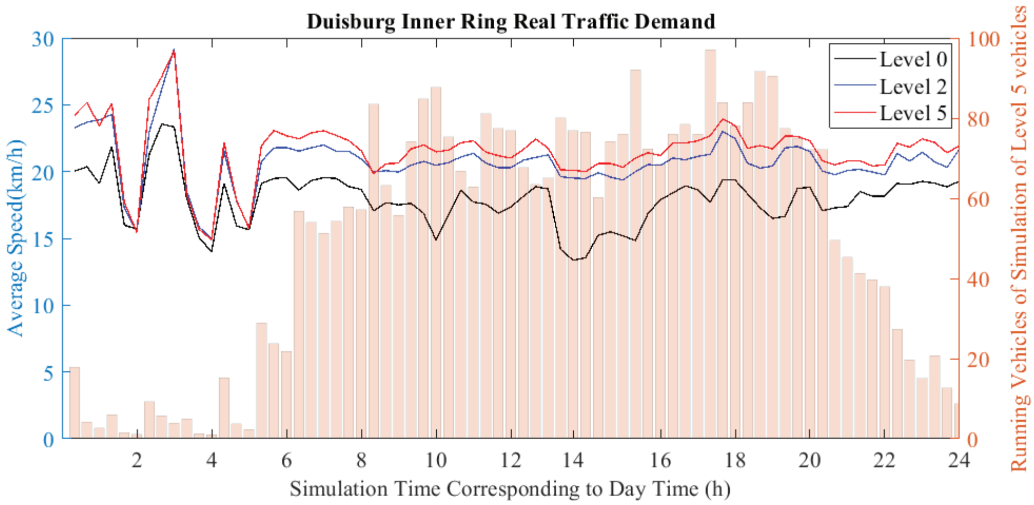


Figure 6.7: Comparison of average speed of vehicles with different automation levels in real traffic volume.

6.2.2 Heavy traffic simulation

In order to test the effect of vehicles with different degrees of automation more comprehensively, a heavy traffic situation is created based on the real traffic demand in the city of Duisburg inner ring. An extra 50% traffic volume is added to the flow in the simulation, and this time, 31,430 vehicles are loaded in the simulation.

Figure 6.8 shows the simulation results of the vehicles with three different automation levels in a heavy traffic simulation. Compared with Figure 6.3, the traffic volume of the three different automation Levels have a lager difference with each other. In general, the red and black lines (representing vehicles with Level 0 and Level 2, respectively) have less difference with each other. The Level 2 vehicles only finish the driving task slightly sooner than the vehicles of Level 0. However, the blue lines represent the Level 5 vehicles finish the driving task much sooner than the other situations.

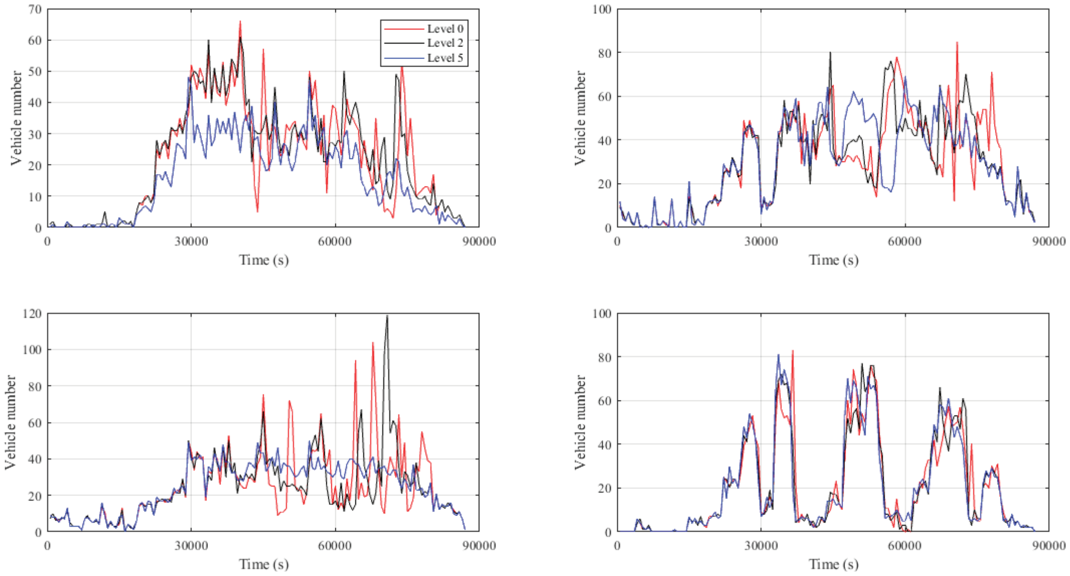


Figure 6.8: Heavy traffic simulation of different automation levels in four verification points.

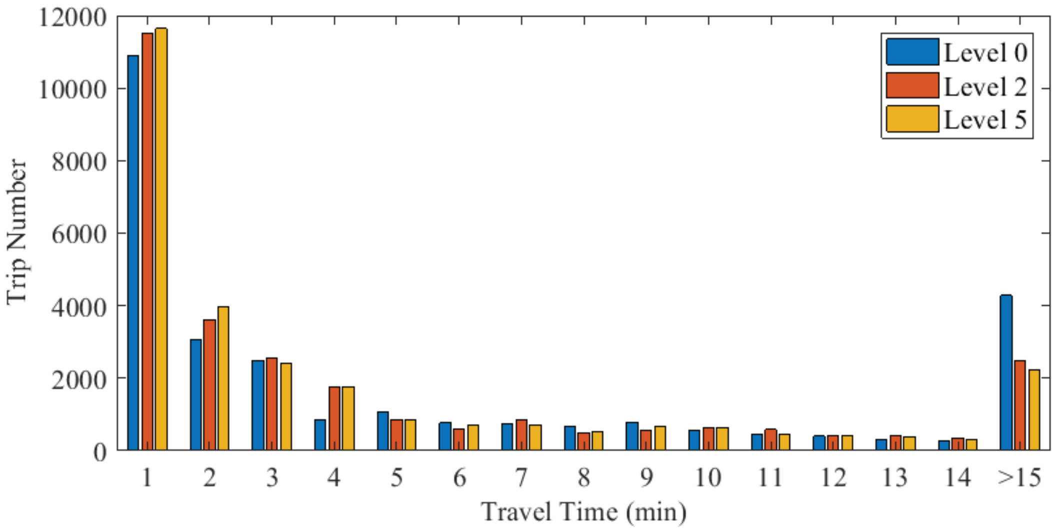


Figure 6.9: Travel time of vehicles with different automation levels in heavy traffic volume.

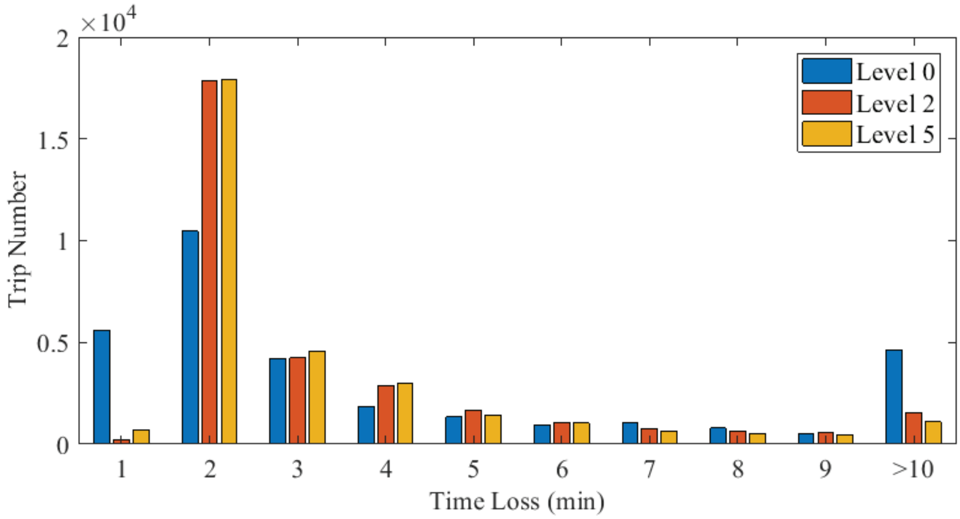


Figure 6.10: Time loss of vehicles with different automation levels in heavy traffic volume.

Figure 6.9 shows the travel time distribution of three simulations in heavy traffic volume. The median value of the simulation with Level 0, Level 2, and Level 5 vehicles are 1.88, 1.60, and 1.52, respectively. In the simulation with more traffic demand, the travel time of the vehicles becomes longer. The simulation of automation Level 5 vehicles shows a greater advantage, reducing the median value of travel time at Level 0 vehicles by 19.1%. The median of Level 2 vehicles travel time is 14.9% shorter time than Level 0 vehicles (Ma et al. 2021c).

With more traffic demand, time loss and average speed of the simulations with vehicles with different levels of automation has larger differences. Figure 6.10 shows the time loss of the simulation with heavy traffic volume. Compared with Figure 6.5, the time loss increased generally. The median value of time loss of simulation of Level 0, Level 2 and Level 5 vehicles are 56.82 s, 41.72 s and 37.67 s, respectively. In heavy traffic volume, Level 2 and Level 5 vehicles can reduce time loss by 26.6% and 33.8%. Figure 6.11 shows the relationship of average speed and running vehicle number of the three simulations. In heavy traffic volume scenario, Level 0 vehicles received the most impact comparing to Level 2 and Level 5 vehicles. As the number of running vehicles in the simulation increases, the average speed also decreases.

Figure 6.12 shows the comparison of average speed of Level 0, Level 2 and Level 5 vehicles in heavy traffic demand. The average speed of simulation with Level 0, Level 2 and Level 5 vehicles are 13.76 km/h, 20.65 km/h, and 21.66 km/h. Under heavy traffic conditions, Level 2 and Level 5 vehicles can increase the average speed by 50.1% and 57.4%.

Figure 6.13 shows the average speed of vehicles with different degrees of automation in real and heavy traffic demand scenarios. Compared with real traffic scenarios, the average speed of Level 2 and Level 5 vehicles are slightly decreased in heavy traffic scenario, however, the average speed of Level 0 vehicles are greatly impacted by the heavy traffic. Under today's traffic demand, higher level automated vehicles will have a more positive impact on traffic (increase average speed by 3.7% and 20.7%). If our traffic become more congested in the future, under heavier traffic demand, higher levels of automated vehicles will have greater impact on traffic (will increase average speed by 50.1% and 57.4%).

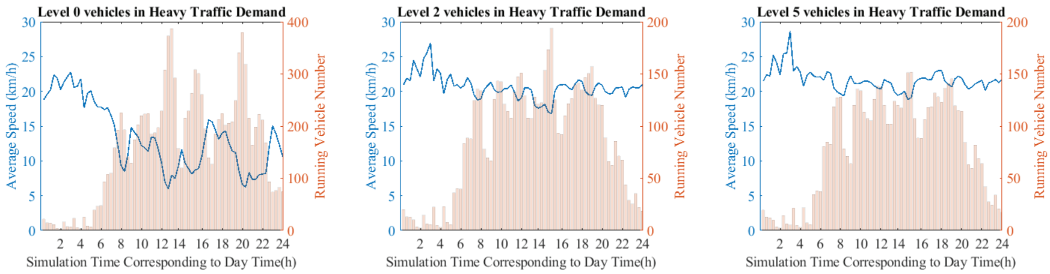


Figure 6.11: Average speed of vehicles with different automation levels in heavy traffic volume.

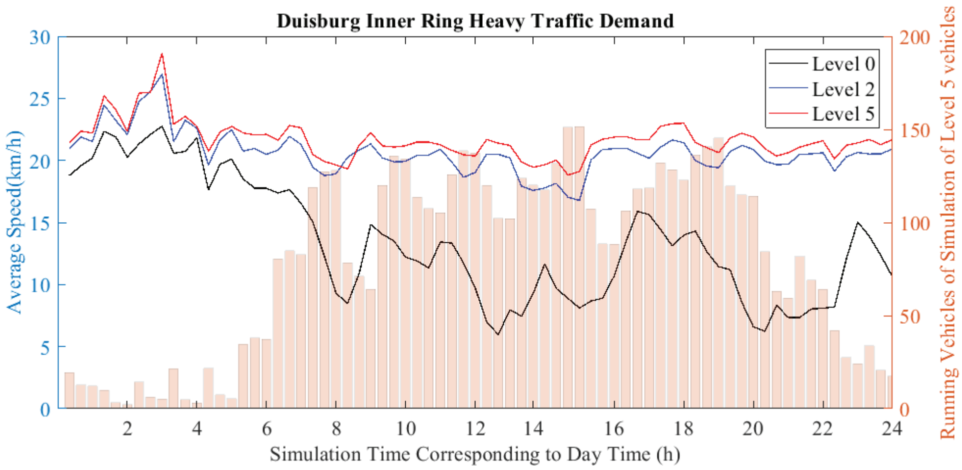


Figure 6.12: Comparison of Average speed of vehicles with different automation levels in heavy traffic volume.

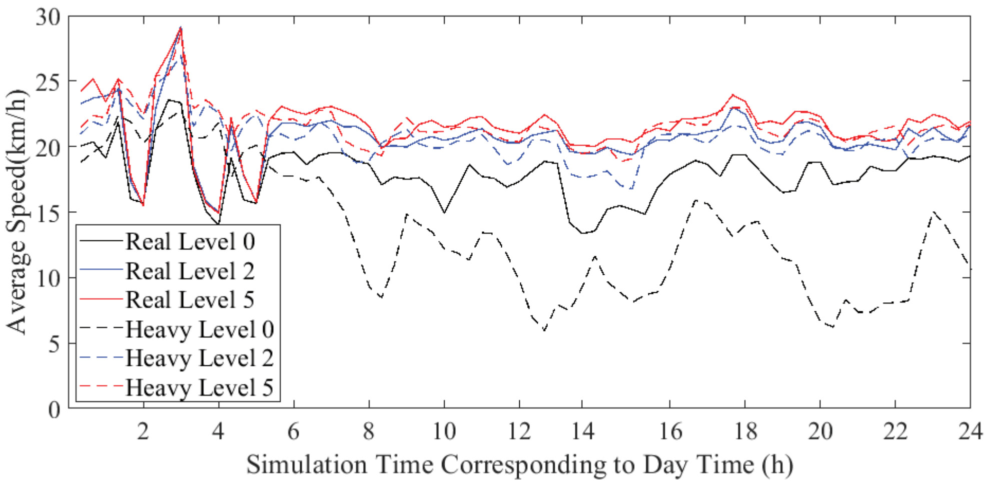


Figure 6.13: Comparison of Average speed of vehicles in real and heavy traffic scenarios.

6.3 Comparison and Discussion

In this chapter, three different simulations were carried out for vehicles with different degrees of automation. First in a simple scenario of a single intersection, vehicles with automation Level 0, Level 2 and Level 5 are simulated with the same traffic flow, respectively. Though simulation results, higher automation level has significant impact on the traffic under heavy traffic. In the scenario of the city of Duisburg inner ring, simulations with two different traffic demands are carried out. In the simulation with real traffic demand, the difference of traffic volume caused by vehicles with different degrees of automation is not obvious. In the simulation with 50% extra traffic, Level 5 vehicles finish the driving tasks much sooner than Level 0 and Level 2, and the performance of Level 2 is also better than Level 0.

From the median of travel time, Level 5 vehicles finish the driving task 20% and 19% faster than Level 0 vehicles in real and heavy traffic demand. And Level 2 vehicles have a 19.1% and 14.9% shorter travel time than Level 0 vehicles. This shows that under real traffic of inner ring area of the city of Duisburg, Level 2 vehicles can speed up traffic and shorten travel time almost as well as Level 5 vehicles. However, under heavier traffic demand, the positive impact of Level 2 vehicles is not as good as under real traffic demand. The Level 5 vehicles can shorten the travel time in both traffic demand situations by around 20% in the scenario of Duisburg inner ring. Table 6.1 shows the difference of simulation of Level 2 and Level 5 vehicles with the simulation of Level 0 vehicles. Generally, in the scenario of heavy traffic volume, all evaluations (trip time, time loss and average speed) of higher automation vehicles are better with under real traffic volume. This means, vehicles with higher degree of automation have more positive impact on traffic, the differences are greater in congestion.

Table 6.1: Effects of vehicles with higher degree of automation on the scenario Duisburg inner ring (Compared with simulation of Level 0 vehicles).

	Trip time	Level 2	Level 5
Real traffic volume	**Trip time**	18.8% shorter	20.0% shorter
	Time loss	27.7% less	28.3% less
	Average speed	3.7% faster	20.7% faster
Heavy traffic volume	**Trip time**	14.9% shorter	19.1% shorter
	Time loss	26.6% less	33.8% less
	Average speed	50.1% faster	57.4% faster

In conclusion, the automated vehicles have positive impact on traffic in the simulations, fully autonomous vehicles have the best results, and the effect of vehicles with partial automation systems on traffic flow are better than the vehicles without them. The effects of different degrees of automation are more obvious when the traffic is heavier. For the traffic situation now in the city of Duisburg inner ring, the difference is not obvious. However, if the traffic increases by 50%, the difference will be significant.

7 Simulated traffic flow for mixed traffic

In this chapter, different penetration rates of vehicles with different degrees of automation are simulated in the mixture scenario according to the estimation of near and far-distant future distribution on a time horizon up to 2030 and 2050. The most optimistic situation of the estimation is simulated, with 11% and 61% fully autonomous vehicles and 40% and 30% partial automated vehicles.

7.1 Estimation of penetration rate of automated vehicles

Before the achievement of fully autonomous mobility, there is a phase of evolution, the vehicles on the road will be described as 'mixed equipage', the combination of automated and manually controlled vehicles on road is the common situation and the percentage changes dynamically (Hancock 2015). This chapter focuses on the mixed scenario of vehicles with different degrees of automation.

7.1.1 Influence factors of estimation

Automated vehicles could have significant impacts on the transport system (Correia and van Arem 2016; Milakis et al. 2015; Fagnant and Kockelman 2015). However, many obstacles are still on the way to popularizing automated vehicles. The changes of these barriers in the future will also greatly affect the large-scale market adoption, and thereby affect the penetration proportion of automated vehicles.

Policies

Public road testing is an important step before large-scale application of automated vehicles. In the U.S., California (SB 1298) and Nevada (AB 511) have enacted legislation for automated vehicles before 2013 (Fagnant and Kockelman 2015). After 2016, driverless vehicles can also be tested in California. As of 2018, from the annual reports of the Department of Motor Vehicles (DMV), there are over 80 manufactures testing over 1400 automated vehicles in at least 36 states in the U.S. (Etherington 11 June). As a country with the largest concentration of EU vehicle manufactures, Germany approved testing of automated vehicles within small areas since 2010 (Nothdurft et al. 2011). In 2015, the A9 highway was opened for automated vehicles' testing. In 2017, the German Federal Council (Bundesrat) issued a law, which provides that fully autonomous driving system may take over the control of vehicles (Hey 2019). This law makes Germany one of the first countries worldwide to create a legal framework for autonomous driving. In China, some cities (including Beijing, Guangzhou, Hangzhou and Shenzhen) have also started allowing road testing for automated vehicles.

Many insurance and liability issues are opened up for the driverless vehicles. Until now, many crashes have occurred in the tests of automated vehicles of Tesla, Waymo, Uber, etc. Some of the accidents were fatal, drivers and even one pedestrian were killed by the automated vehicles. Who is responsible for vehicle accidents is a problem which must be solved for automated vehicles. In 2017, the UK government has issued the Automated and Electric Vehicles Bill (AEV). This new law modified the terms of mandatory liability insurance for motor vehicles, so that automated vehicles can be covered by the insurance like traditional vehicles. When an accident occurs in an automated vehicle, the victim will be compensated by the insurance company first. The insurance company has the right to recover from the vehicle manufacture in accordance with the current legal provisions. It is a major step in legal policy of automated vehicles, and the steadily updating laws make the society prepared for bigger transport revolution in the future (Schramm et al. 2020).

Technological development

Even though many manufactures announced that they have already finished the technological developments for vehicles with automation Level 4 or even Level 5, automated vehicles need many different systems' help. These systems still need technological improvements, including the navigation system, the map matching, the global path planning, the environment perception, and the vehicle control, etc. The accurate detection of other road users in real-time is a challenge for automated vehicles (Zhu et al. 2014). Some accidents of the automated vehicles are attributed to inaccurate detection.

In addition to the technologies to realize fully autonomous driving, safety technologies are also a problem that must be solved. Electronic security should always be worried about. Like in many movies and fictions, bad guys like terrorist organizations, computer hackers, disgruntled employees, and hostile nations may control driverless vehicles or even transportation systems to disturb the traffic order. Future automated vehicles will have the support from V2V (Vehicle to Vehicle) and V2I (Vehicle to Infrastructure) communications. Large-scale mesh communication system also gives more possibilities for virus-like attacks.

Vehicle cost

The cost of automated vehicle platforms is also a barrier to large-scale market adoption. Even though 20% of consumers would definitely/probably be willing to pay as much as $3,000 for autonomous driving applications (Power 2013), the more advanced sensors, such as LIDAR, cost tens of thousands of dollars (Silberg et al. 2012). Additional costs like other sensors, software, and communication and guidance technology would accrue the total cost of automated vehicles. An estimation about the most current civilian and military automated vehicle applications shows that the cost is over $100,000 (Dellenback 26.May.2013), which is unaffordable for most consumers.

However, the cost may be reduced through technological advances and large-scale production in the future. The added costs per automated vehicle may fall to $25,000 to $50,000 with mass production, and for at least 10 years, it will not fall to $10,000 (Dellenback 26.May.2013). Electric vehicle costs have been declining by 6% to 8% annually (Hensley et al. 2009). If the automated vehicles' cost decline by 8% annually, the cost would decline to $3,000 after 20 to 22 years (Fagnant and Kockelman 2015). Eventually the additional cost of automated vehicles may reach $1,000 to $1,500 per vehicle (Silberg et al. 2012).

Public opinion

Globally, lots of studies have investigated the public opinion on automated vehicles. In general, male and younger adults show greater interest on autonomous technology (Hulse et al. 2018). People who are highly educated, and live in large urban areas are more enthusiastic about autonomous vehicles (Nielsen and Haustein 2018). Public perception of automated vehicles might vary widely between countries (Haboucha et al. 2017; Lang et al. 2016; Schoettle and Sivak 2014b). In developing countries with lower GDP per capita, higher income inequality, lower vehicle usage and ownership, and greater numbers of road deaths, the respondents are more optimistic about current and future automated vehicles (Green et al.).

In addition to public concerns about safety and legal issues, the concern about privacy has raised because of the data sharing in automated vehicles. The travel data of automated vehicles, such as routes, destinations, and times of day, are likely be provided to central control system, to assist transportation planners evaluating future improvements. The data could be misused by relative employees for tracking, monitoring and surveillance (Fagnant and Kockelman 2015).

7.1.2 Penetration rate estimation

Several studies have tried to predict the time course of the spread of automated vehicles in a more general context. The public's opinions differ between different genders, income levels and current commuting methods (Howard and Dai 2014). During the Automated Vehicles Symposium 2014, a survey was held among the experts. They expected Level 3 and Level 5 vehicle would reach the market in 2019 and 2030 respectively (Underwood 2014). In an Internet-based questionnaire survey with 5000 respondents from 105 countries, 69% of the respondents estimate that vehicles with automation Level 5 would reach 50% penetration rate by 2050 (Kyriakidis et al. 2015).

As the penetration rate of automated vehicles is affected by the development of many factors mentioned in last section, the estimation should be divided into optimistic estimation and pessimistic estimation. Milakis et al. (2017) developed four scenarios of estimating the penetration rate for year 2030 and 2050. The four scenarios are constructed assuming combinations of supportive or restrictive policies and high or low technological development for automated vehicles. In the most optimistic scenario (supportive policies and high technological development), the share of vehicles with automation Level 3 to 5 reached 11% in 2030 and 61% in 2050. In this scenario, the assumption is that, technological between 2015 and 2025 is fast, and first vehicles with Level 3 launched in the market in 2018 and Level 4 or 5 vehicles reach the market in 2025.

As of 2020, the assumption of the most optimistic scenario has already been realized. In 2017, Audi launched the first Level 3 (conditional automation) system – the Audi AI traffic jam pilot. It is even one year earlier than the assumption in the most optimistic scenario. In 2018, Google Waymo launched driverless taxis in a roughly 100-mile (160 km) zone in four Phoenix suburbs. This means vehicles with automation level 4 do not have to wait until 2025 as the assumption, but have already come to our roads.

The technological development of autonomous driving is faster than the estimation of the experts. Other relative aspects such as policies, public opinions, are also developing in a better direction with the rapid progress of technologies. There are great reasons to believe that, the most optimistic scenario is credible. In this work, the penetration rate of Level 5 vehicles is set to 11% and 61% for the scenario in 2030 and 2050 respectively.

The vehicles with automation Level 2 have already reached the market for many years. Many automobile manufactures have launched their models with optional Level 2 driver assistance systems, including Tesla Autopilot, Cadillac Super Cruise, Mercedes-Benz Drive Pilot, Nissan Pro Pilot Assist, Volvo Pilot Assist, etc. These systems work under certain road conditions (such as highway over 80 km/h, urban congestion). For safety reasons, the systems cooperate with frequent driver reminder to prevent the driver from distracting. For example, in the Cadillac CT6, when the Super Cruise system is working and the driver looks away from the dashboard, the Super Cruise mode will be exited automatically. And with the Drive Pilot System in the Mercedes-Benz E-Class, the driver has to operate the steering wheel at short intervals, depending on speed and road conditions. If this is not accomplished, the system switches off automatically after several warnings. Nissan's Leaf requires the driver to have at least one hand on the steering wheel all the time when the Pro Pilot Assist system is working, otherwise after warning, it will slow down until stop. These safety assurance systems make the Level 2 vehicles reliable and stable, and alleviate the drivers' concerns about safety.

Because there are no policies or technical restrictions like fully autonomous vehicle, most of the reasons that prevent people from buying a vehicle with Level 2 assistance system are the prices. The driver assistance systems are mostly optional, Tesla Autopilot system costs four thousand Euro to add when order a vehicle, and 5 thousand as a post-purchase upgrade. Cadillac Super Cruise is a 4 thousand Euro extra available on the CT6 model, for just highway scenario. Mercedes-Benz Drive Pilot came as a part of an 8 thousand Euro options package for E400 Coupé and Volvo Pilot Assist costs only about 2 thousand Euro (for only highway scenario). The Level 2 automation vehicles have relatively less barriers and would be a common configuration in the near and far-distant future. Therefore, in this work, the assumption of the penetration rate of vehicles with automation Level 2 on road in 2030 and 2050 is 40% and 30%, respectively. In total, the automated vehicles (including Level 2 and Level 5) have the share of 51% in the near future (2030) and 91% in the far-distant future (2050) in the simulation below (Ma et al.).

7.2 Simulation of the city of Duisburg in 2030 and 2050

To find out the effects of mixture situation of automated vehicles on traffic flow in a larger range, the largest scope of traffic scenario in this work, Scenario 3 (the whole city of Duisburg) is chosen for the simulations in this chapter. To achieve a more realistic traffic flow situation, the traffic demand of Case C in 3.3.2 is used in this section. Because the road network and traffic light plans have some differences with the real ones, the traffic capacity of the simulation road network is lower than that of the real road network. Therefore, the traffic demand is lowered in the same proportion to the extent that the road network can carry. The general network is the same as in chapter 5, and the driver models used in representing vehicles with different degrees of automation are the same as in chapter 6. Because of the different penetration rate of automated vehicles, a sub-program must judge the degree of automation of the vehicle and decide the appropriate driver model for each vehicle in each simulation step. The whole process makes the simulation slower than all the simulations in previous chapters. Even with the reduced traffic demand of Case C, a simulation of 24 hours takes 4 to 8 days, depending on the computer performance. On one hand, the huge simulation scenario and numerous vehicles slow down the simulation speed. On the other hand, the communication speed of TraCI (between SUMO and MATLAB) also limits the overall speed of the simulation.

As a control group, the traffic situation of year 2020 is also simulated for the same scenario. As discussed in 2.3.2, the vehicles in scenario 2020 are set to automation Level 0, all other parameters of simulation remain the same as in scenario 2030 and 2050. Figure 7.1 shows the simulated vehicle quantity of the scenario 2020, 2030, and 2050 in black, blue and red lines, respectively. From the traffic volume recorded by most detectors, such as LSA751L, LSA724 and LSA834U in Figure 7.1, the differences between the three scenarios are not large.

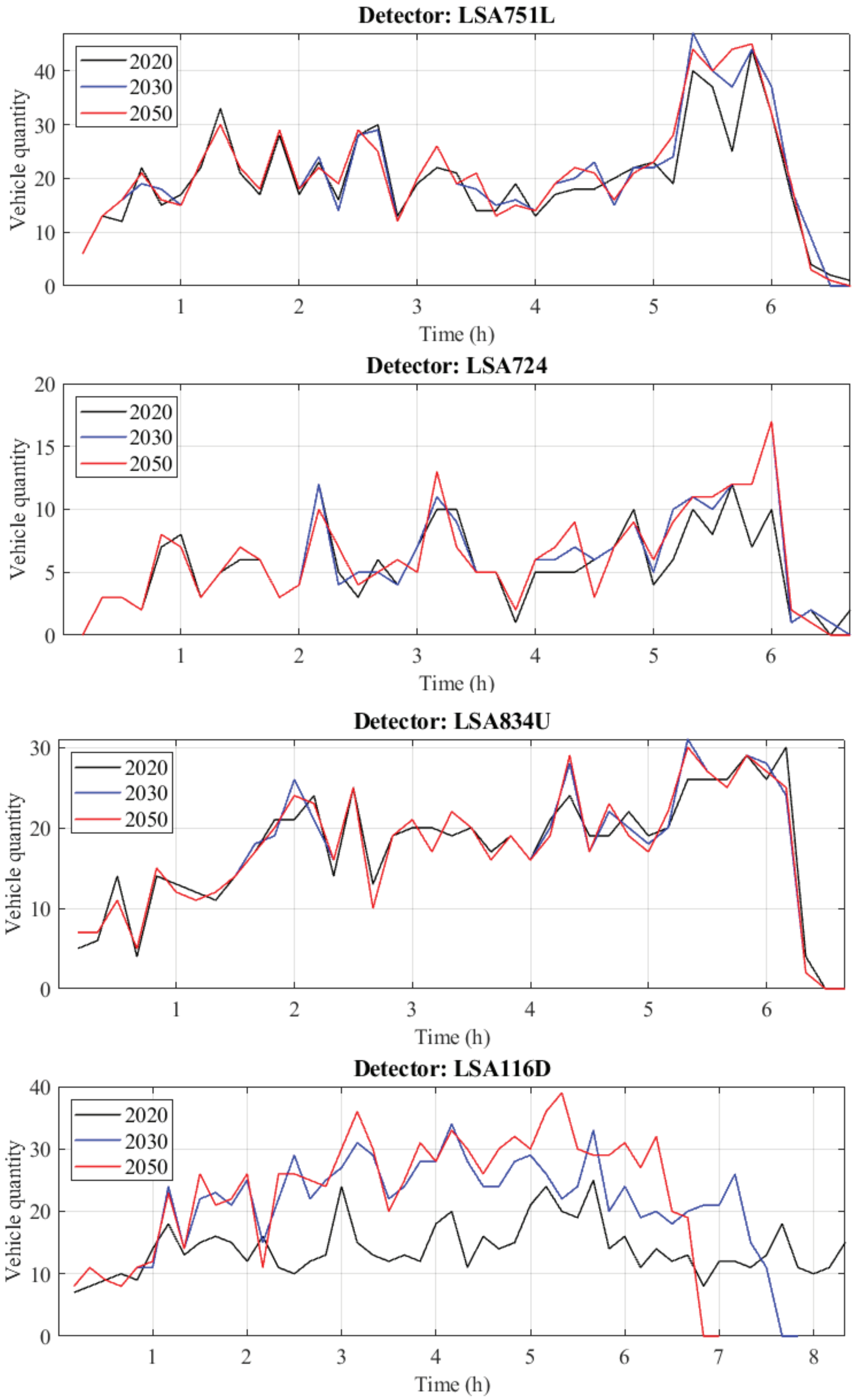


Figure 7.1: Traffic volume of the simulation scenario of year 2020, 2030 and 2050.

The red lines representing the scenario of 2050 have similar performance with the blue lines representing the scenario of year 2030, and both of them perform better than the black lines representing the scenario of 2020. For some detectors such as LSA116D in Figure 7.1, the differences are obvious. The traffic volume of the scenario of year 2050 is more than that of 2030 and much more than that of 2020.

Moreover, the simulation time of scenario 2050 is also shorter than the other two scenarios.

The differences between detectors could result in different traffic volumes. For more intensive traffic areas with more traffic jams, the scenario with higher percentage of vehicles with higher automation levels (Scenario of year 2050) have more advantages than other scenarios. For normal traffic demand such as the area of other three intersections, the positive effects of automated vehicles on traffic flow is not obvious.

The average travel time of all the trips in the simulations is another representative statistic. Figure 7.2 shows the comparison of average travel time of a six hour simulation in scenario 2020, 2030 and 2050. The median of the travel time are 8.37 min, 7.24 min, and 7.00 min, respectively. From the perspective of travel time, the vehicles in scenario 2030 can reduce the travel time by 13.5%, and the higher porportion automated vehicles in scenario 2050 can reduce the travel time by 16.4% than the scenario in 2020.

In addition to trip time, another indicator of concern is traffic jam time. In this thesis, it is expressed as time loss. Time loss refers to the time lost due to driving below the desired speed, including the time lost in traffic jams and approaching intersections. Figure 7.3 shows the time loss of all trips in the scenario 2020, 2030 and 2050. The median time loss of the three scenarios are 1.78 min (scenario 2020), 1.01 min (scenario 2030) and 0.86 min (scenario 2050). From the perspective of time loss, the vehicles in scenario 2030 can reduce time loss by 43.3%. With a higher penetration rate of automated vehicles, the vehicles in scenario 2050 can reduce time loss by 51.7% than scenario 2020.

The average speed of all vehicles in the three simulation scenarios is also analyzed, and the result is shown in Figure 7.4. The vehicles' speed is mainly limited by the speed limit of the road. In Germany, the maximum permitted speed for all motor vehicles within a built-up area is 50 km/h, as in most European countries. Outside built-up areas, it is generally to drive faster than built-up areas. And there is no speed limit for cars on the highways in Germany. The vehicles' average is 19.51 km/h in scenario 2020, 44.09 km/h in scenario 2030, and 50.69 km/h in scenario 2050. The vehicles in scenario 2050 drives closest to the speed limit of the road (it is also the desired speed of the driver) comparing to in the other two scenarios. As shown in Figure 7.4, the average speed remains high when there is less traffic in the simulation, and decreases as the traffic increases. It can also be seen in Figure 7.5, under the same traffic demand, traffic congestion has the greatest impact on scenario 2020, and has less impact on scenario 2030 and 2050.

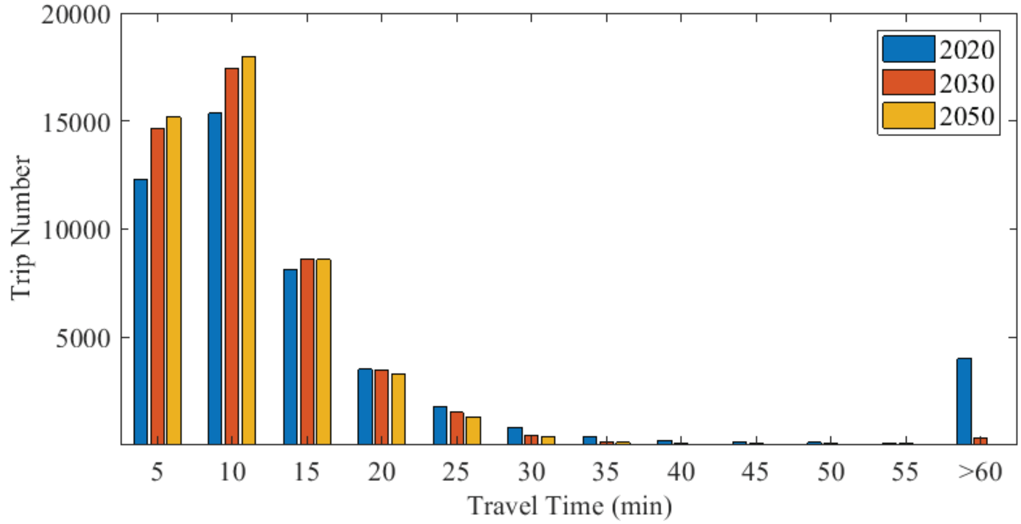


Figure 7.2: Vehicles' travel time of scenario 2020, 2030 and 2050.

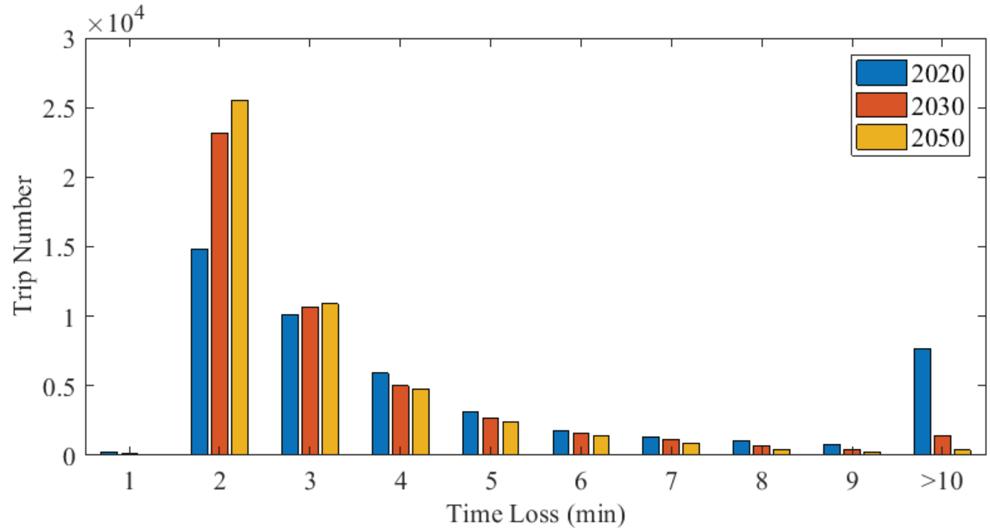


Figure 7.3: Vehicles' time loss of scenario 2020, 2030 and 2050.

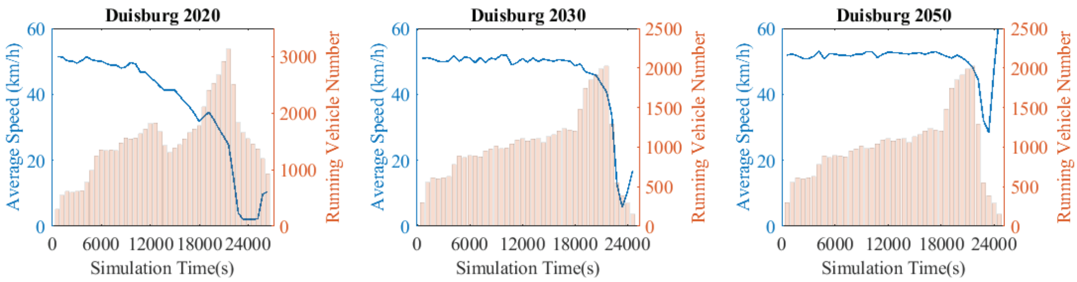


Figure 7.4: Vehicles' average speed and running vehicle number of scenario 2020, 2030 and 2050.

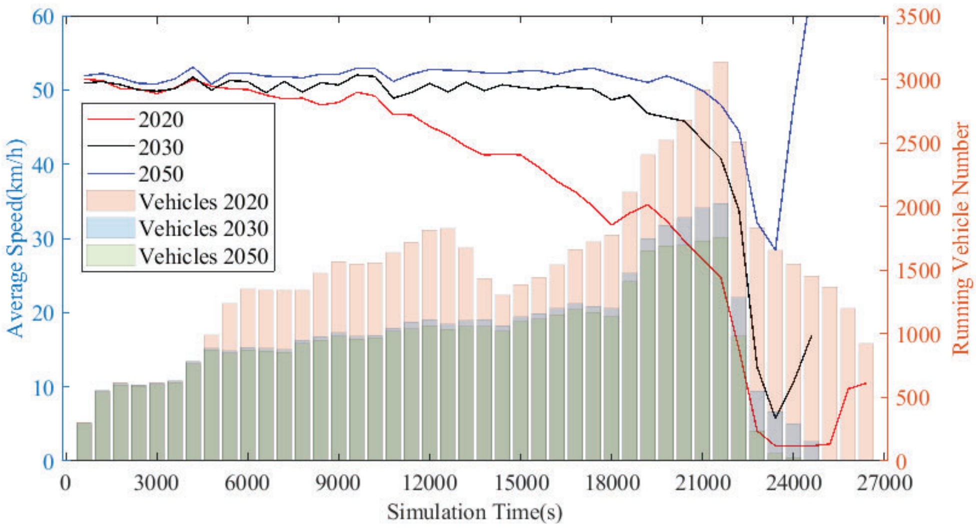


Figure 7.5: Comparison of vehicles' average speed and running vehicle number of scenario 2020, 2030 and 2050.

7.3 Comparison and Discussion

Based on the current development status of automated vehicles, this chapter predicts the future penetration rate of partial automated vehicles and fully autonomous vehicles in traffic flow in 2030 and 2050. The assumed penetration rate is then simulated in the traffic scenario of the whole city of Duisburg. The simulation results show that, if the traffic demand remains the same as nowadays, traffic intensive areas can enjoy huge advantages on traffic flow brought by automated cars, while some areas with less traffic pressure have not many differences.

For the existing traffic demand of the city of Duisburg, the proportion of automated vehicles in 2030 can reduce travel time by 13.5%, and the proportion of automated vehicles in 2050 can reduce travel time by 16.4%. The time loss of scenario 2030 and 2050 can be reduced by 43.3% and 51.7% comparing to scenario 2020.

8 Conclusions and future aspects

Automated vehicles will enter the vehicle fleet progressively. They could be the new revolution of the transportation system. The following effects of the automated vehicles on traffic are a noteworthy issue. This chapter concludes the work and discuss the limitations and future aspects of this work.

8.1 Conclusions

This thesis focuses on the effects of vehicles with different degrees of automation on traffic flow. The motivation and fundamentals of the research in this field have been introduced in Chapter 1 and 2, respectively.

Establishment of simulation scenarios

Four simulation scenarios of different scopes and cities in two different countries have been established in Chapter 3. The largest scope of simulation scenario covers a whole city. The process of generating simulation scenarios in Germany and China shows many differences. This applies to the providing of the input data for the simulation as well as to the validation of the simulation results. Due to different national conditions, road usage habits are also very different.

Establishment of driver model with different degree of automation

A vehicle guidance model with a close-to-reality driver model and different levels of vehicle automation has been built with real data of driver experiment in Chapter 4. The driver models and vehicle model used in this work have been determined and the models of vehicles with different degrees of automation have also been set with different parameters. It is also verified in this chapter that the driver models used in this work can well reproduce the human driving activities.

Simulation of non-automation vehicles in different scenarios

Based on the simulation scenarios and driver-vehicle-separate models, traffic flow of no automation group is simulated in different simulation scenarios and compared with real traffic data in Chapter 5. Simulations in the city of Wuhan were performed by using the traffic demand of geographical population distribution information and verified with average velocity ranges. By contrast, simulations in the city of Duisburg were conducted by using the traffic demand of OD matrix data or detector data and verified with precise detector data. For the relatively ambiguous traffic demand of geographical population distribution information, special public facilities such as train station, hospital and schools are considered. For relatively precise traffic demand of OD matrix, even more accurate data is used for verification. From the simulations results and comparisons in chapter 5, SUMO shows a great reliability, and the simulations can reproduce real traffic status with high accuracy.

Simulation of vehicles with different degrees of automation in scenario 4

Chapter 6 focuses on the comparison of vehicles with different degrees of automation. In the scenario of a single intersection, vehicles of automation Level 2 finish the driving task 9.1% faster than the no automation group, and vehicles with automation Level 5 finish it 19.8% sooner than the no automation group. In the scenario of Duisburg inner ring, vehicles with different degrees of automation show little difference in respond to the current traffic demand, however, on more 50% traffic status, vehicles with higher automation level have more positive effects on traffic. In the scenario of Duisburg inner ring, vehicles with automation Level 2 and Level 5 have 19% and 20% shorter travel time comparing to Level 0 on real traffic demand, respectively. For heavy traffic status, Level 2 and Level 5 vehicles have 11% and 19% shorter travel time.

Simulation of mixture situation in scenario 3

Chapter 7 makes a more specific analyses of the development of future automated vehicles, and assume that in 2030, the penetration rate of vehicles with automation Level 2 and Level 5 is 40% and 11%, respectively. Moreover, the penetration rate will become 30% and 61% in 2050, respectively. Based on the assumption, the simulations of the city of Duisburg in year 2030 and 2050 are launched, and for the traffic demand now in the city of Duisburg, a greater proportion of higher levels automated vehicles will have positive effect on traffic. In particular, the traffic intensive areas can gain more positive effects from the automated vehicles than other areas of the city. With such penetration rate of automated vehicles, the vehicles in scenario 2030 and 2050 can reduce the travel time by 13.5% and 16.4% respectively.

8.2 Scientific contribution of this work

Traditional driver-vehicle models for traffic simulation always regard the driver and vehicle as a unit. This kind of method has the advantages such as simple, easy to use, and less interference. However, with more and more technological innovations in modern automotive industry, the disadvantages of the traditional approach of treating the driver and the vehicle as a unit have begun to appear. This work separates the driver model from the vehicle model and focuses on the driver model. The driver/vehicle separate models make it possible to combine different types of vehicles and drivers in traffic simulations. For example, the performance of self-driving vehicle with electrical power vehicle can be simulated with the driver/vehicle separate models. For the future simulation of vehicles with more technological innovations, driver/vehicle separate models can bring more possibilities.

In this work, vehicles with different degrees of automation are modeled and simulated in different scenarios of real cities. Based on the major differences between human driving and machine driving, the model in this paper uses different parameters to distinguish the driver models. The vehicle guidance model of vehicles with different automation levels is established, including no automation group representing the present state, partial automation group representing the state of the near future, and fully automated group representing the state of the far future. The comparison of these three models are simulated in real traffic scenarios in Duisburg inner ring respectively. The three models are also simulated with different penetration rates in Duisburg whole city scenario for year 2030 and 2050.

The large-scale simulation scenario of the city of Duisburg is another contribution of this work. This work establishes the scenario in four cases and affirm the relative most accurate case through comparison with real detector data. The scenario of the city of Duisburg can also be used in other traffic simulations.

8.3 Limitations and future work

Even though the factors that may cause imprecision are avoided as much as possible, this work still has some limitations. In the fuzzy control model built in chapter 4, the data from a driving experiment are used. The fuzzy control rules in this work is impacted by the subjects in the driving experiment. The subjects have not covered all the age ranges, countries, driving behaviors, etc. Therefore, the driving characteristic extracted from the driving experiment cannot represent all the human drivers. The driver model with different degrees of automation in this work concentrates on the parameters that have the main influences, many other differences are not considered. For example, the simulation does only consider accident-free traffic, but in reality, the accident rate of autonomous vehicles and non-automated vehicles is different, which is ignored in the simulations.

The road network of the traffic scenarios in this work also have some limitations. The traffic light plan of all the road networks are not available, therefore, only default traffic light plan was used. Moreover, the road structures of the city of Duisburg were verified in Google street view, however, the street view of the city of Duisburg has not been updated since August 2008. In 12 years, many road structures have already been changed. These two aspects may cause inaccuracy of road networks.

As a prospect of the future work, the effects on traffic flow and fuel economy of self-driving electric vehicles can be studied. Electric vehicles have their own driving characteristics, and the combination of self-driving technology and electrical power may be interesting. If there is a chance, more accurate traffic scenarios can also be built, of course more data like traffic light plan, road network map are needed.

9 Publication bibliography

Addison, Paul S.; Low, David J. (1998): A novel nonlinear car-following model. In *Chaos: An Interdisciplinary Journal of Nonlinear Science* 8 (4), pp. 791–799.

Automated Driving (2014): Levels of driving automation are defined in new SAE international standard J3016: 2014. PA, USA. Available online at https://www.sae.org/standards/content/j3016_201609/, checked on 2/12/2021.

Barceló, Jaime; Casas, Jordi (2005): Dynamic network simulation with AIMSUN. In Ryuichi Kitamura, Maso Kuwahara (Eds.): Simulation approaches in transportation analysis: Springer, pp. 57–98.

Bengtsson, Johan (2001): Adaptive cruise control and driver modeling. Doctoral Dissertation. Lund Institute of Technology.

Berthaume, Andrew L. (2015): Microscopic modeling of driver behavior based on modifying field theory for work zone application. Doctoral Dissertation. University of Massachusetts Amherst.

Bieker, Laura; Krajzewicz, Daniel; Morra, AntonioPio; Michelacci, Carlo; Cartolano, Fabio (2015): Traffic simulation for all: a real world traffic scenario from the city of Bologna. In Michael Behrisch, Melanie Weber (Eds.): Modeling Mobility with Open Data: Springer, pp. 47–60.

Bjärkvik, Eric; Fürer, Florian; Pourabdollah, Mitra; Lindenberg, Björn (2017): Simulation and Characterisation of Traffic on Drive Me Route around Gothenburg using SUMO. In: SUMO User Conference 2017. Berlin, Germany.

Blincoe, Lawrence; Miller, Ted R.; Zaloshnja, Eduard; Lawrence, Bruce A. (2015): The economic and societal impact of motor vehicle crashes, 2010. Available online at https://trid.trb.org/view/1311862, checked on 2/12/2021.

Cameron, Gordon D. B.; Duncan, Gordon I. D. (1996): PARAMICS—Parallel microscopic simulation of road traffic. In *The Journal of Supercomputing* 10 (1), pp. 25–53.

Campbell, Mark; Egerstedt, Magnus; How, Jonathan P.; Murray, Richard M. (2010): Autonomous driving in urban environments: approaches, lessons and challenges. In *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 368 (1928), pp. 4649–4672.

Chandler, Robert E.; Herman, Robert; Montroll, Elliott W. (1958): Traffic dynamics: studies in car following. In *Operations research* 6 (2), pp. 165–184.

Choa, Fred; Milam, Ronald T.; Stanek, David (2004): Corsim, paramics, and vissim: What the manuals never told you. In: Ninth TRB Conference on the Application of Transportation Planning Methods. Baton Rouge Louisiana, United States.

Codeca, Lara; Frank, Raphaël; Engel, Thomas (2015): LuST: a 24-hour Scenario of Luxembourg City for SUMO Traffic simulations. In: SUMO User Conference 2015 - Intermodal Simulation for Intermodal Transport. Berlin, Germany.

Correia, Gonçalo Homem; van Arem, Bart (2016): Solving the User Optimum Privately Owned Automated Vehicles Assignment Problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility. In *Transportation Research Part B: Methodological* 87, pp. 64–88.

Corso, G. M.; Moloney, M. M. (1996): Human performance, dynamic function allocation and transfer of training. In *Manufacturing agility and hybrid automation*, pp. 636–639.

Dellenback, Steven (26.May.2013): Director, intelligent systems department, automation and data systems division, southwest research institute. Communication by email, 26.May.2013.

Dijkstra, Edsger Wybe (1976): A discipline of programming. pp. 154-167. New Jersey: prentice-hall Englewood Cliffs.

Draper, John V. (1995): Teleoperators for advanced manufacturing: Applications and human factors challenges. In *International Journal of Human Factors in Manufacturing* 5 (1), pp. 53–85.

Etherington, Darrell (2019): BMW and Daimler partner on autonomous driving, first results of team-up in market by 2024. In *TechCrunch*, 7/4/2019. Available online at https://techcrunch.com/2019/07/04/bmw-and-daimler-partner-on-autonomous-driving-first-results-of-team-up-in-market-by-2024/, checked on 10/20/2020.

Etherington, Darrell. (11 June): Over 1,400 Self-Driving Vehicles Are Now in Testing by 80+ Companies across the US, 11 June. Available online at https://techcrunch.com/2019/06/11/over-1400-self-driving-vehicles-are-now-in-testing-by-80-companies-across-the-u-s/, checked on 2/12/2021.

Fagnant, Daniel J.; Kockelman, Kara (2015): Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. In *Transportation Research Part A: Policy and Practice* 77, pp. 167–181.

Fellendorf, Martin (1994): VISSIM: A microscopic simulation tool to evaluate actuated signal control including bus priority. In: 64th Institute of Transportation Engineers Annual Meeting. Dallas, TX, USA, 1994.

Fellendorf, Martin; Vortisch, Peter (2010): Microscopic traffic flow simulator VISSIM. In Jaume Barceló (Ed.): Fundamentals of traffic simulation: Springer, pp. 63–93.

Gawron, Christian (1998): Simulation-Based Traffic Assignment. Computing user equilibria in large street networks. Doctoral Dissertation. University of Cologne.

Gazis, Denos C.; Herman, Robert; Rothery, Richard W. (1961): Nonlinear follow-the-leader models of traffic flow. In *Operations research* 9 (4), pp. 545–567.

Giffinger, Rudolf; Fertner, Christian; Kramar, Hans; Meijers, Evert: City-ranking of European medium-sized cities. Vienna University of Technology. Available online at http://www.smart-cities.eu/download/city_ranking_final.pdf, checked on 2/12/2021.

Gipps, Peter G. (1981): A behavioural car-following model for computer simulation. In *Transportation Research Part B: Methodological* 15 (2), pp. 105–111.

Green, William H.; Armstrong, Robert C.; Ben-Akiva, Moshe; Heywood, John; Knittel, Christopher; Paltsev, Sergey et al.: Insights Into Future Mobility: A Report from the Mobility of the Future Study. Available online at http://energy.mit.edu/publication/insights-into-future-mobility/, checked on 2/12/2021.

Greimel, Hans (2019): Nissan gives Japan version of Infiniti Q50 self-driving upgrade, more power. Edited by Automotive News Europe. Available online at https://europe.autonews.com/automakers/nissan-gives-japan-version-infiniti-q50-self-driving-upgrade-more-power, updated on 10/20/2020, checked on 10/20/2020.

Haboucha, Chana J.; Ishaq, Robert; Shiftan, Yoram (2017): User preferences regarding autonomous vehicles. In *Transportation Research Part C: Emerging Technologies* 78, pp. 37–49.

Han, Guanghui (韩光辉); Chen, Xiaorong(陈笑蓉); Yu, Yang (俞洋); Li, Yongqian (李永前) (2012): Research on Microscopic Traffic Simulation Based on SUMO Platform (基于 SUMO 平台的微观交通仿真研究). (in Chinese). In *Computer Engineering & Science (计算机工程与科学)* 34 (7), pp. 195–198.

Hancock, Peter A. (2015): Automobility: the coming use of fully-automated on-road vehicles. In: 2015 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision. Orlando, USA, March 9-12.

Hensley, Russell; Knupfer, Stefan; Pinner, Dickon (2009): Electrifying cars: How three industries will evolve. In *McKinsey Quarterly* 3 (2009), pp. 87–96.

Hey, Tim (2019): Die außervertragliche Haftung des Herstellers autonomer Fahrzeuge bei Unfällen im Straßenverkehr. Münster: Springer.

Howard, Daniel; Dai, Danielle (2014): Public perceptions of self-driving cars: The case of Berkeley, California. In: Transportation research board 93rd annual meeting, vol. 4502. Washington, D.C., USA.

Hulse, Lynn M.; Xie, Hui; Galea, Edwin R. (2018): Perceptions of autonomous vehicles: Relationships with road users, risk, gender and age. In *Safety Science* 102, pp. 1–13.

Jamson, A. Hamish; Merat, Natasha; Carsten, Oliver M. J.; Lai, Frank C. H. (2013a): Behavioural changes in drivers experiencing highly-automated vehicle control in varying traffic conditions. In *Transportation Research Part C: Emerging Technologies* 30, pp. 116–125.

Jamson, A. Hamish; Merat, Natasha; Carsten, Oliver M.J.; Lai, Frank C.H. (2013b): Behavioural changes in drivers experiencing highly-automated vehicle control in varying traffic conditions. In *Transportation Research Part C: Emerging Technologies* 30, pp. 116–125. DOI: 10.1016/j.trc.2013.02.008.

Jeong, H.; Park, J.; Lee, B. C. (2017): Inconsistent work performance in automation, can we measure trust in automation. In *International Robotics & Automation Journal* 3 (6).

Johansson, Gunnar; Rumar, Kåre (1971): Drivers' brake reaction times. In *Human Factors* 13 (1), pp. 23–27.

Kaber, David B.; Endsley, Mica R. (2004): The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task. In *Theoretical Issues in Ergonomics Science* 5 (2), pp. 113–153.

Kalra, Nidhi; Groves, David G. (2017): The enemy of good: Estimating the cost of waiting for nearly perfect automated vehicles. Santa Monica, CA, USA: Rand Corporation.

Kastner, Karl-Heinz; Keber, Robert; Pau, Petru; Samal, Martin (2014): Real-Time Traffic Conditions with SUMO for ITS Austria West. In Michael Behrisch, Daniel Krajzewicz, Melanie Weber (Eds.): Simulation of Urban Mobility. Berlin, Heidelberg, 2014. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 146–159.

Kastner, Karl-Heinz; Pau, Petru (2015): Experiences with SUMO in a Real-Life Traffic Monitoring System. In: SUMO 2015–Intermodal Simulation for Intermodal Transport, vol. 1. Berlin, Germany, pp. 1–10.

Kerry, Cameron F.; Karsten, Jack. (2017): Gauging investment in self-driving cars. Available online at https://www.brookings.edu/research/gauging-investment-in-self-driving-cars/, checked on 2/12/2021.

Kesting, Arne (2008): Microscopic modeling of human and automated driving: Towards traffic-adaptive cruise control. Doctoral Thesis, Dresden, Germany. Dresden University of Technology.

Kesting, Arne; Treiber, Martin; Helbing, Dirk (2009): Agents for traffic simulation. In *Multi-agent systems: Simulation and applications*, pp. 325–356.

Kotusevski, G.; Hawick, K. A. (2009): A review of traffic simulation software. In *Research Letters in the Information and Mathematical Sciences* 13, pp. 35–54.

Krajzewicz, Daniel; Erdmann, Jakob; Behrisch, Michael; Bieker, Laura (2012): Recent development and applications of SUMO-Simulation of Urban MObility. In *International journal on advances in systems and measurements* 5 (3&4), pp. 128–138.

Krauss, Stefan: Microscopic modeling of traffic flow: Investigation of collision free vehicle dynamics. Doctoral Thesis, Cologne.

Krauss, Stefan; Wagner, Peter; Gawron, Christian (1997): Metastable states in a microscopic model of traffic flow. In *Physical review E* 55 (5), p. 5597.

Kyriakidis, Miltos; Happee, Riender; Winter, Joost C. F. de (2015): Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. In *Transportation research part F: traffic psychology and behaviour* 32, pp. 127–140.

Land Transport Authority (2014): Passenger transport mode shares in world cities. In *Journeys*. Available online at https://web.archive.org/web/20140715001906/http://app.lta.gov.sg/ltaacademy/doc/J11Nov-p60PassengerTransportModeShares.pdf, checked on 2/12/2021.

Lang, Nikolaus; Rüßmann, M.; Mei-Pochtler, Antonella; Dauner, Thomas; Komiya, Satoshi; Mosquet, Xavier; Doubara, Xanthi (2016): Self-driving vehicles, robo-taxis, and the urban mobility revolution. In *The Boston Consulting Group* 7, p. 2016.

LeBeau, Phil (2018): Waymo starts commercial ride-share service. Available online at https://www.cnbc.com/2018/12/05/waymo-starts-commercial-ride-share-service.html, checked on 2/12/2021.

Lee, H. Y.; Lee, H-W; Kim, D. (1998): Origin of synchronized traffic flow on highways and its dynamic phase transitions. In *Physical Review Letters* 81 (5), p. 1130.

Levinson, Jesse; Askeland, Jake; Becker, Jan; Dolson, Jennifer (2011): Towards fully autonomous driving: Systems and algorithms. In *2011 IEEE Intelligent Vehicles Symposium (IV)*, pp. 163–168. DOI: 10.1109/IVS.2011.594056.

Lighthill, Michael James; Whitham, Gerald Beresford (1955): On kinematic waves II. A theory of traffic flow on long crowded roads. In *Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences* 229 (1178), pp. 317–345.

Lopez, Pablo Alvarez; Behrisch, Michael; Bieker-Walz, Laura; Erdmann, Jakob; Flötteröd, Yun-Pang (2018): Microscopic traffic simulation using sumo. In *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pp. 2575–2582. DOI: 10.1109/ITSC.2018.8569938.

Ma, Xiaoyi; Hu, Xiaowei; Schramm, Dieter (2020): Effects of School Activities on Traffic Flow on the Example of Traffic Scenario from the City Wuhan. In Heike Proff (Ed.): Neue Dimensionen Der Mobility: Springer Gabler, pp. 153–163.

Ma, Xiaoyi; Hu, Xiaowei; Schweig, Stephan; Pragalathan, Jenitta; Schramm, Dieter (2021a): A Vehicle Guidance Model with a Close-to-reality Driver Model and Different Levels of Vehicle Automation. In *Applied Sciences* 11(1):380, pp. 1–11. DOI: 10.3390/app11010380.

Ma, Xiaoyi; Hu, Xiaowei; Weber, Thomas; Schramm, Dieter: Effects of Automated Vehicles on Traffic Flow with Different Levels of Automation. In *IEEE Access* 9, pp. 3630–3637. DOI: 10.1109/ACCESS.2020.3048289.

Ma, Xiaoyi; Hu, Xiaowei; Weber, Thomas; Schramm, Dieter (2021b): Experiences with Establishing a Simulation Scenario of the City of Duisburg with Real Traffic Volume. In *Applied Sciences* 11(3), 1193, pp. 1–11. DOI: 10.3390/app11031193.

Ma, Xiaoyi; Hu, Xiaowei Hu; Weber, Thomas; Schramm, Dieter (2021c): Traffic Simulation of Future Intelligent Vehicles in City Duisburg Inner Ring. In *Applied Sciences* 11(1), 29. DOI: 10.3390/app11010029.

Maas, Niko (2017): Konzeptionierung, Auslegung und Umsetzung von Assistenzfunktionen für die Übergabe der Fahraufgabe aus hochautomatisiertem Fahrbetrieb. Universitätsbibliothek Duisburg-Essen.

Maas, Niko; Hesse Benjamin; Koppers Martin; Schramm, Dieter (2014): Simulator setup according to use case scenarios-A human-oriented method for virtual development. In *2014 IEEE/ASME 10th International Conference on Mechatronic and Embedded Systems and Applications (MESA)*.

Maciejewski, Michal (2010): A comparison of microscopic traffic flow simulation systems for an urban area. In *Transport Problems* 5, pp. 27–38.

Marshall, A. (2017): After peak hype, self-driving cars enter the trough of disillusionment. Wired.

May, A. D.; Keller, HARTMUT E. M. (1967): Non-integer car-following models. In *Highway Research Record* 199 (1), pp. 19–32.

Milakis, Dimitris; van Arem, Bart; van Wee, Bert (2015): The ripple effect of automated driving. In *2015 BIVEC-GIBET Transport Research Day, May 28-29, 2015, Eindhoven, The Netherlands*.

Nagel, Kai; Schreckenberg, Michael (1992): A cellular automaton model for freeway traffic. In *Journal de physique I* 2 (12), pp. 2221–2229.

Neis, Pascal; Zipf, Alexander (2012): Analyzing the contributor activity of a volunteered geographic information project—The case of OpenStreetMap. In *ISPRS International Journal of Geo-Information* 1 (2), pp. 146–165.

Neubert, Lutz (2000): Statistische Analyse von Verkehrsdaten und die Modellierung von Verkehrsfluss mittels zellularer Automaten. Doctoral Thesis, Duisburg, Germany. University of Duisburg.

Neunzig, Dirk; Weilkes, Michael; Hochstädter, Almut; Ludmann, Jens (1998): Assessment of advanced vehicle control systems with the vehicle oriented traffic simulation tool Pelops. SAE Technical Paper.

Newell, Gordon Frank (2002): A simplified car-following theory: a lower order model. In *Transportation Research Part B: Methodological* 36 (3), pp. 195–205.

Nielsen, Thomas Alexander Sick; Haustein, Sonja (2018): On sceptics and enthusiasts: What are the expectations towards self-driving cars? In *Transport policy* 66, pp. 49–55.

Nothdurft, Tobias; Hecker, Peter; Ohl, Sebastian; Saust, Falko; Maurer Markus; Reschka, Andreas; Boehmer, Juergen Ruediger (2011): Stadtpilot: First fully autonomous test drives in urban traffic. In *2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC)*.

Orosz, Gábor; Wilson, R. Eddie; Krauskopf, Bernd (2004): Global bifurcation investigation of an optimal velocity traffic model with driver reaction time. In *Physical review E* 70 (2), p. 26207.

Parasuraman, Raja; Sheridan, Thomas B.; Wickens, Christopher D. (2000): A model for types and levels of human interaction with automation. In *IEEE Transactions on systems, man, and cybernetics-Part A: Systems and Humans* 30 (3), pp. 286–297.

Payre, William; Cestac, Julien; Delhomme, Patricia (2014): Intention to use a fully automated car: Attitudes and a priori acceptability. In *Transportation research part F: traffic psychology and behaviour* 27, pp. 252–263.

Philanthropies, Bloomberg: Is your city getting ready for AVs? This is a guide to who's doing what, where, and how. Available online at https://avsincities.bloomberg.org/, checked on 2/12/2021.

Pipes, Louis A. (1953): An operational analysis of traffic dynamics. In *Journal of applied physics* 24 (3), pp. 274–281.

Power, J. D. (2013): Automotive emerging technologies study results, 2013. Available online at http://www.jdpower.com/sites/default/files/2014057_US%20_Auto_ET.pdf, checked on 7/20/2015.

Prigogine, Ilya; Herman, Robert (1971): Kinetic theory of vehicular traffic. New York, U.S.: Elsevier.

Punzo, Vincenzo; Simonelli, Fulvio (2005): Analysis and comparison of microscopic traffic flow models with real traffic microscopic data. In *Transportation Research Record* 1934 (1), pp. 53–63.

Raney, Bryan; Voellmy, Andreas; Cetin, Nurhan; Vrtic, Milenko; Nagel, Kai (2002): Towards a microscopic traffic simulation of all of Switzerland. In *International Conference on Computational Science*.

Rasshofer, Ralph H.; Spies, M.; Spies, H. (2011): Influences of weather phenomena on automotive laser radar systems. In *Advances in Radio Science: ARS* 9, p. 49.

Rocco, Matthew (2014): Self-Driving Cadillac Brings Industry Closer to Autonomous Car. Fox Business. Available online at https://web.archive.org/web/20141005205008/http://www.foxbusiness.com/industries/2014/09/08/self-driving-cadillac-brings-industry-closer-to-autonomous-car/, updated on 10/20/2020, checked on 10/20/2020.

Rödel, Christina; Stadler, Susanne; Meschtscherjakov, Alexander; Tscheligi, Manfred (2014): Towards autonomous cars: The effect of autonomy levels on acceptance and user experience. In *Proceedings of the 6th international conference on automotive user interfaces and interactive vehicular applications*.

Rouse, William B.; Cody, William J.; Frey, Paul R. (1992): Lessons learned in developing human-machine system design tools. In *Information and Decision Technologies* 18 (5), pp. 301–308.

Sabey, Barbara E.; Taylor, Harold (1980): The known risks we run: the highway. In Albers W.A. Schwing R.C. (Ed.): Societal Risk Assessment. General Motors Research Laboratories. Boston, MA., U.S.: Springer, pp. 43–70.

Schmidt, Gerhard; Thomas, Bernd (1996): Hochrechnungsfaktoren für manuelle und automatische Kurzzeitzählungen im Innerortsbereich. In *Forschung Straßenbau und Straßenverkehrstechnik* (732).

Schoettle, Brandon; Sivak, Michael (2014a): A survey of public opinion about autonomous and self-driving vehicles in the US, the UK, and Australia. University of Michigan, Ann Arbor, Transportation Research Institute.

Schoettle, Brandon; Sivak, Michael (2014b): Public opinion about self-driving vehicles in China, India, Japan, the US, the UK, and Australia. University of Michigan, Ann Arbor, Transportation Research Institute.

Schramm, Dieter; Hesse, Benjamin; Maas, Niko; Unterreiner, Michael (2020): Vehicle Technology. Technical foundations of current and future motor vehicles. München, Wien: De Gruyter Oldenbourg (De Gruyter Textbook).

Schweig, Stephan; Liebherr, Magnus; Schramm, Dieter; Brand, Matthias; Mass, Niko (2018): The Impact of Psychological and Demographic Parameters on Simulator Sickness. In *8th International Conference on Simulation and Modeling Methodologies*, pp. 91–97.

Shepardson, David (2014): Daimler chief: Fully autonomous vehicles could be ready by 2025. Edited by The Detroit News. Available online at https://web.archive.org/web/20140116082928/http://www.detroitnews.com/article/20140113/AUTO04/301130112/1148/rss25, updated on 10/20/2020, checked on 10/20/2020.

Sheridan, Thomas B. (1992): Telerobotics, automation, and human supervisory control. Cambridge, MA: MIT press.

Sheridan, Thomas B.; Verplank, William L. (1978): Human and computer control of undersea teleoperators. MIT Man-Machine Systems Laboratory. Cambridge, MA.

Shladover, Steven E. (2009): Cooperative (rather than autonomous) vehicle-highway automation systems. In *IEEE Intelligent Transportation Systems Magazine* 1 (1), pp. 10–19.

Silberg, Gary; Wallace, Richard; Matuszak, G.; Plessers, J.; Brower, C.; Subramanian, Deepak (2012): Self-driving cars: The next revolution. In *White paper, KPMG LLP & Center of Automotive Research* 9 (2), pp. 132–146.

Smith, Laron; Beckman, Richard; Baggerly, Keith (1995): TRANSIMS: Transportation analysis and simulation system. In *Proceedings of the 5th National Conference on Transportation Planning Methods Application* 2.

Teichner, Warren H. (1954): Recent studies of simple reaction time. In *Psychological Bulletin* 51 (2), p. 128.

Tillyer, Rob; Engel, Robin S. (2013): The impact of drivers' race, gender, and age during traffic stops: Assessing interaction terms and the social conditioning model. In *Crime & Delinquency* 59 (3), pp. 369–395.

Todosiev, E. P.; Barbosa, L. C. (1963): A proposed model for the driver–vehicle system, The car-following problem. In *Traffic Engineering* 3, pp. 43–44.

Treat, John R.; Tumbas, N. S.; McDonald, S. T.; Shinar, D.; Hume, Rex D.; Mayer, R. E. et al. (1979): Tri-level study of the causes of traffic accidents: final report. In *Causal factor tabulations and assessments* 1.

Treiber, Martin; Hennecke, Ansgar; Helbing, Dirk (2000): Congested traffic states in empirical observations and microscopic simulations. In *Physical review E* 62 (2), p. 1805.

Treiber, Martin; Kesting, Arne (2013): Traffic Flow Dynamics. Data, Models and Simulation. Berlin, Heidelberg: Springer. Available online at http://dx.doi.org/10.1007/978-3-642-32460-4.

Underwood, S. E. (2014): Automated vehicles forecast vehicle symposium opinion survey. Automated Vehicles Symposium 2014. San Francisco, CA., 2014. Available online at https://drive.google.com/file/d/0B8gGx-CYkV-wREVMTEhH-QUxjOWM/edit, checked on 2/12/2021.

United Nations: 2018 revision of world urbanization prospects. United Nations New York. Available online at https://www.un.org/development/desa/publications/2018-revision-of-world-urbanization-prospects.html, checked on 2/13/2021.

Urmson, Chris; Anhalt, Joshua; Bagnell, Drew; Baker, Christopher; Bittner, Robert; Clark, M. N. et al. (2008): Autonomous driving in urban environments: Boss and the urban challenge. In *Journal of Field Robotics* 25 (8), pp. 425–466.

VISION, P. T.V. (2014): Ptv vissim 7 user manual. Available online at https://www.ptvgroup.com/en/solutions/products/ptv-vissim/knowledge-base/, checked on 2/13/2021.

Volkswagen AG (2019): Autonomous driving – on the way to market maturity. Available online at https://www.volkswagenag.com/en/news/stories/2019/11/autonomous-driving-on-the-way-to-market-maturity.html#, updated on 9/25/2020, checked on 10/20/2020.

Wadud, Zia; MacKenzie, Don; Leiby, Paul (2016): Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. In *Transportation Research Part A: Policy and Practice* 86, pp. 1–18.

Wagner, Peter (2011): A time-discrete harmonic oscillator model of human car-following. In *The European Physical Journal B* 84 (4), pp. 713–718.

Wagner, Peter (2015): Steuerung und Management in einem Verkehrssystem mit autonomen Fahrzeugen. In Markus Maurer, J.Chritian Gerdes, Barbara Lenz, Hermann. Winner (Eds.): Autonomes Fahren. Berlin, Germany: Springer Vieweg, pp. 313–330.

Wei, Zhi-Gang; Macwan, Anil P.; Wieringa, Peter A. (1998): A quantitative measure for degree of automation and its relation to system performance and mental load. In *Human Factors* 40 (2), pp. 277–295.

Wen, Xuli (温旭丽); Yang, Tao (杨涛); Ling, Xiaojing (凌小静): Current bus share rate in China and abroad and the Enlightenment (国内外公交分担率现状及启示). (in Chinese). Available online at https://www.cnki.com.cn/Article/CJFDTotal-GLJJ201502088.htm, checked on 2/13/2021.

Wiedemann, Rainer (1974): Simulation des Strassenverkehrsflusses. In *Vol. 8 of Schriftenreihe des IfV*, Institut für Verkehrswesen, University of Karlsruhe, Germany.

Wiedemann, Rainer (1991): Modelling of RTI-Elements on multi-lane roads. In *Advanced Telematics in Road Transport* DG XIII, edited by the Comission of the European Community.

Xu, Jiwei (许基伟); Fang, Shiming (方世明); Liu, Chunyan (刘春燕) (2017): Analysis on the Spatial Equity of Park Green Space in Wuhan City Center Based on G2SFCA (基于 G2SFCA 的武汉市中心城区公园绿地空间公平性分析). (in Chinese). In *Resources Science (资源科学)* 39 (3), pp. 430–440.

Young, Mark S.; Stanton, Neville A.; Harris, Don (2007): Driving automation: learning from aviation about design philosophies. In *International Journal of Vehicle Design* 45 (3), p. 323. DOI: 10.1504/IJVD.2007.014908.

Yuta, Asano; Nobuyasu, Ito; Hajime, Inaoka; Tetsuo, Imai; Takeshi, Uchitane (2015): Traffic simulation of Kobe-city. In *Proceedings of the international conference on social modeling and simulation, plus Econophysics Colloquium 2014*.

Zhu, Wentao; Miao, Jun; Hu, Jiangbi; Qing, Laiyun (2014): Vehicle detection in driving simulation using extreme learning machine. In *Neurocomputing* 128, pp. 160–165.

Zielstra, Dennis; Hochmair, Hartwig H. (2012): Using free and proprietary data to compare shortest-path lengths for effective pedestrian routing in street networks. In *Transportation Research Record* 2299 (1), pp. 41–47.

DuEPublico

Duisburg-Essen Publications online

UNIVERSITÄT DUISBURG ESSEN

Offen im Denken

ub | universitäts bibliothek

Diese Dissertation wird via DuEPublico, dem Dokumenten- und Publikationsserver der Universität Duisburg-Essen, zur Verfügung gestellt und liegt auch als Print-Version vor.

DOI: 10.17185/duepublico/74070
URN: urn:nbn:de:hbz:464-20210226-153702-5

Alle Rechte vorbehalten.