Review and Modelling of Shared Autonomous Vehicle Services

Master's Thesis

Technische Universität München

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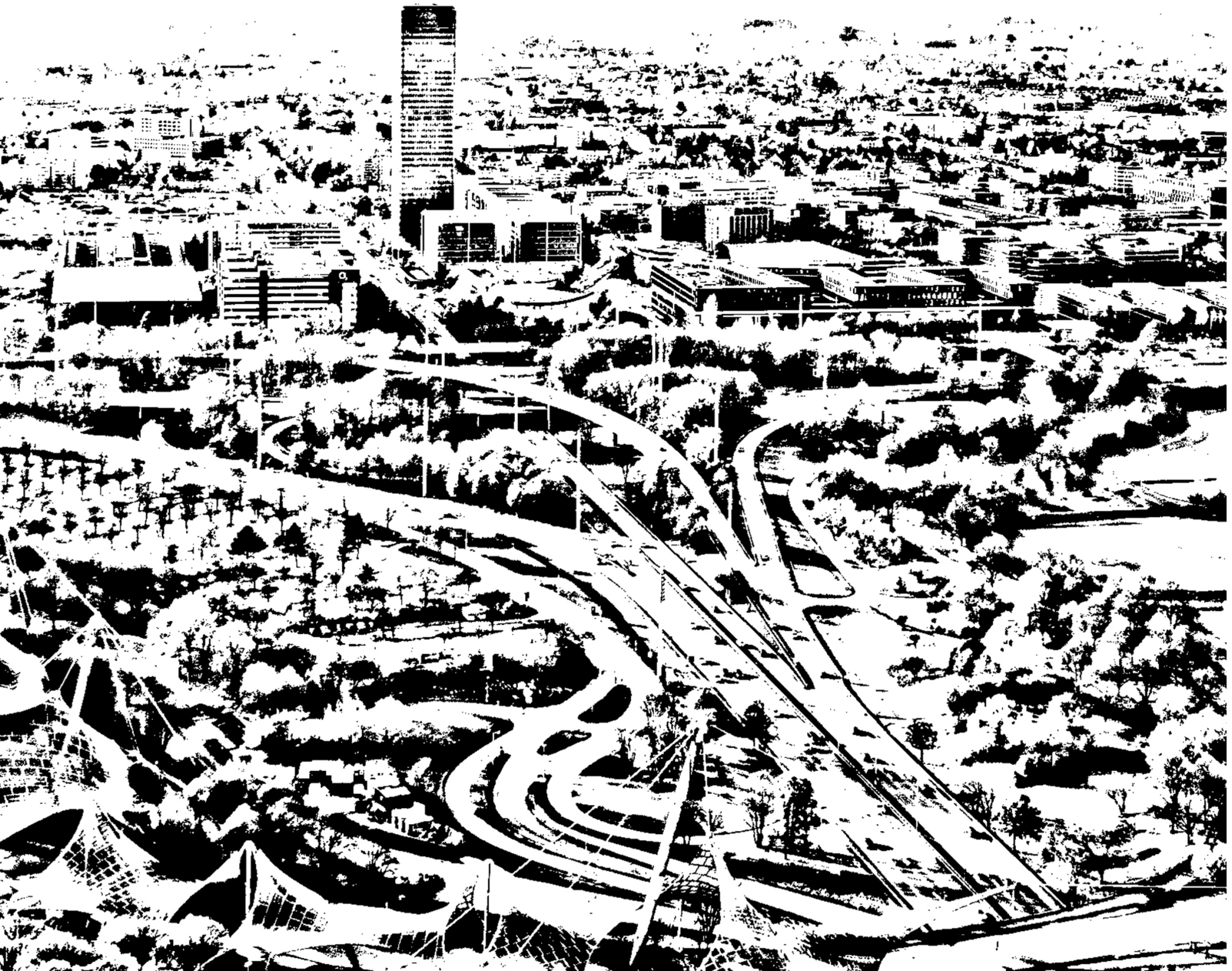

TECHNICAL UNIVERSITY OF MUNICH

CHAIR OF TRANSPORTATION SYSTEMS ENGINEERING

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Abstract

The actions of the autonomous vehicle manufacturers and related industrial partners as well as the interest from policy makers and researchers point towards the initial deployment of autonomous vehicles as a shared autonomous mobility service. Numerous research studies are lately being published regarding Shared Autonomous Vehicles (SAVs) and hence it is necessary to have a comprehensive outlook to consolidate the existing knowledge base. Hence, one of the twofold objectives of this thesis is to present a comprehensive consolidation of studies in the field of SAV services. The primary focus is the critical evaluation of the impacts which are categorised into seven groups namely Travel behaviour, Traffic, Transport Supply, Land-use, Economy, Environment and Governance. Pertinent to the evaluation of the impacts, an SAV typology is presented and the modelling approaches, expected demand and policy framework required are reviewed. The second research objective of this thesis is to formulate and solve combined Dynamic User Equilibrium and SAV Chain Formation (DUESCF) problem as a bilevel model based on game theory involving road users and SAV service operator, with the assumption that the road network in future is going to be filled with conventional private vehicles and reservation based shared autonomous vehicles. In such a scenario, road users select paths and departure times to minimize their disutility forming a DUE (fixed point problem) and SAV service operator try to maximize their performance forming appropriate SAV chains (combinatorial problem). The final objective of this formulation is a traffic assignment and SAV chain formation, such that both road users and SAV service operator obtain their optimal solutions, forming a Nash equilibrium where no player is better off by unilaterally changing their decisions. A solution approach based on Iterative Optimization and Assignment (IOA) method is proposed with path flow and SAV performance changes as convergence criteria. Further, the solution approach is tested for its robustness using an existing DUE and SAV chain formation model from the literature and the tests are performed on three different networks with varying level of complexity. A scenario analysis is also carried out to evaluate the effect of carsharing, ridesharing and vehicle occupancy on the total system travel time, traffic congestion level and vehicle requirement for the SAV service. This is the first time such a model is being formulated and solved in literature.

Acknowledgements

The completion of this thesis would not have been possible without the support and help I got throughout the past six months. First and foremost, I would like to express my sincere gratitude to my supervisors, Emmanouil Chaniotakis and Prof. Dr. Constantinos Antoniou, who always inspired me and provided me great support and guidance throughout my thesis. A special thanks to Emmanouil Chaniotakis for his patience, belief in me and free life lessons. I am happy to look back to all those arguments we had and the balancing compromises we made. Furthermore, I would like to thank Dr. Ke Han and Dr. Willem Himpe for clarifying the doubts I had on their DUE models. Last but not least, I would like to thank my brother and my friends who always supported me during my studies. Finally, I would like to dedicate this thesis to my parents who have unconditional faith in me and boundless love towards me.

Declaration

I hereby declare that this thesis is an outcome of my own efforts and has not been published anywhere else before and not used in any other examination. Also, to mention that the materials and methods used and quoted in this thesis has been properly referenced and acknowledged.

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Contents

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List of Abbreviations

AV	Autonomous Vehicle
B2C	Business-to-Consumer
CG	Cost Gap
CS	Car Sharing
CTS	Cybernetics Transportation System
DAE	Differential Algebraic Equation
DARP	Dial A Ride Problem
DNL	Dynamic Network Loading
DTA	Dynamic Traffic Assignment
DUE	Dynamic User Equilibrium
DUESCF	Dynamic User Equilibrium and SAV Chain Formation
DVI	Differential Variational Inequality
EV	Electric Vehicle
FCFS	First-Come, First-Served
FIFO	First-In, First-Out
GHz	GigaHertz
GNSS	Global Navigation Satellite Systems
IBM	International Business Machines corporation
ICT	Information and Communication Technology
ILUT	Integrated Land Use and Transport
IOA	Iterative Optimization and Assignment
LDM	Link Delay Model
LP	Linear Program
OD	Origin-Destination

P2P	Peer-to-Peer
PC	Personal Computer
PFG	Path Flow Gap
POI	Point Of Interest
PT	Public transport
RC	Route Choice
RS	Ride Sharing
SAE	Society of Automotive Engineers
SAV	Shared Autonomous Vehicle
SCF	SAV Chain Formation
SCIP	Solving Constraint Integer Programs
SRDTC	Simultaneous Route and Departure Time Choice
SUMO	Simulation of Urban MObility
VKT	Vehicle Kilometres Travelled
VMT	Vehicle Miles Travelled
VO	Vehicle Occupancy
VOT	Value Of Time

Chapter 1

Introduction

This chapter begins with a description of the thesis background followed by research objectives, questions and contributions. Finally, research framework and the structure of the report are summarized.

1.1 Background and motivation

Automated vehicles are vehicles with some level of automation to assist or replace human control. The Society of Automotive Engineers (SAE) has defined different levels of automated functionality, ranging from no automated features (Level 0) to full automation (Level 5 — commonly referred to as Self–driving or Autonomous Vehicles). Autonomous Vehicles (AV) are expected to lead the next paradigm shift in the field of transportation. While the benefits and problems associated with their introduction are still critically evaluated and discussed, the active involvement of major technology companies and car manufacturers in a race to build the first operational vehicle is on, for many years now, and has resulted in spending billions of dollars every year (e.g., Korosec, 2018; Trivedi, 2018). Given the high recent interest for autonomous vehicles, it can be asserted that such systems will eventually be introduced (Brown, 2018). The questions, however, include when, how and what will the impacts to the transportation system be. Although there still exists uncertainty with regards to their characteristics, the actions of the autonomous vehicle manufacturers and related industrial partners point towards the initial deployment of autonomous vehicles as a shared autonomous mobility service: BMW Group has partnered with Intel and Mobileye Team to produce autonomous vehicles by 2021 for the purpose of ridesharing (BMW Group, 2016). General Motors has planned to run an autonomous taxi service in 2019 (Hawkins, 2017). Ford plans to introduce their autonomous vehicles in a ride–hailing or ride-sharing service in 2021 (The Ford Company, 2016). Volkswagen Group and Hyundai have partnered with Aurora Innovations to begin autonomous on–demand services by 2021 (O'Kane, 2018). Daimler has partnered with Uber to enable introduction of autonomous vehicles in Uber's ride sharing network (Daimler AG, 2017). Toyota has also partnered with Uber with the same goal (Monaghan, 2018). Waymo has already recently started commercial autonomous ride–sharing service, available in Tempe, Mesa and Chandler (LeBeau, 2018).

Shared use of a vehicle for performing a trip is termed as shared mobility (Shaheen et al., 2015). Services such as car–sharing, bike–sharing, scooter–sharing, on–demand ride services and ridesharing fall into the category of shared services. Shared mobility services enable cost savings, convenience and reduction of vehicle usage, ownership, and vehicle miles/kilometres travelled (VMT/VKT) (Shaheen and Chan, 2015). The diffusion of growing shared mobility services and emerging autonomous vehicle technology jointly have the potential to disrupt transportation system operations, especially when combined with electrification (Sprei, 2018; Walker and Johnson, 2016; Weiss et al., 2017). Autonomous vehicle technology could accelerate the growth of shared services (Thomas and Deepti, 2018) and shared mobility can make the deployment of autonomous vehicles financially viable (Gurumurthy and Kockelman, 2018; Stocker and Shaheen, 2018). This diffusion could lead to a more sustainable future with enhanced mobility and equity, when integrated with public transport systems (International Association of Public Transport, 2017). Their development can be streamlined to achieve a beneficial change to the transportation system (Fagnant and Kockelman, 2015).

Numerous research studies are lately being published regarding shared autonomous vehicles and hence it is imperative to have a comprehensive outlook to consolidate the existing knowledge base. Given the often controversial results found in the literature, one of the twofold research gaps that this thesis aims to fill in is a comprehensive review of relevant studies in the field of SAV services, for various facets of shared autonomous vehicle deployment.

Based on operations, SAV services can be divided into dynamically operated systems (the customers can book vehicles in real time), systems based on reservation (booked in advance) and mixed systems. Regular trips like commuting trips and pre-planned trips like trip to airports are suitable for reservation based service. Reservation based operations ensure vehicle availability which could be a factor in increasing preference towards shared mobility services, influencing the mode shift of personal car users to shared operations. Certainly, in case of reservation based SAV services, SAV chain formation by the SAV operator influences the route and departure time choices of road users because of the change in traffic and the new flow pattern affects the SAV chain formation as well. Therefore, it is imperative to consider the interaction between route/departure time choice behaviour of the road users and the SAV chain formation. Modelling this interaction based on dynamic user equilibrium, i.e., a model that incorporates DUE for traffic assignment, for evaluating reservation based SAV services is still missing in literature and this is the second research gap this thesis will fill in.

1.2 Research objectives, questions & contributions

As indicated in Section 1.1, one of the twofold objectives of this thesis paper is to obtain insight on SAV services through a comprehensive review of the existing literature. The second research objective is to formulate the combined Dynamic User Equilibrium and SAV Chain Formation (DUESCF) as a bilevel model based on game theory to achieve Nash equilibrium. Figure 1.1 shows the research gaps that this thesis will fill in, major research questions that this thesis strives to answer, and the contributions that this thesis will make.

The two main research questions mentioned in Figure 1.1 introduce the following secondary research questions:

- What are the business models of SAV services that can be expected in future?
- What are the existing modelling approaches and the components involved for evaluating SAV services?
- What are the categories of impacts of SAV services?
- How much demand can be expected for SAV services in the next couple of decades?

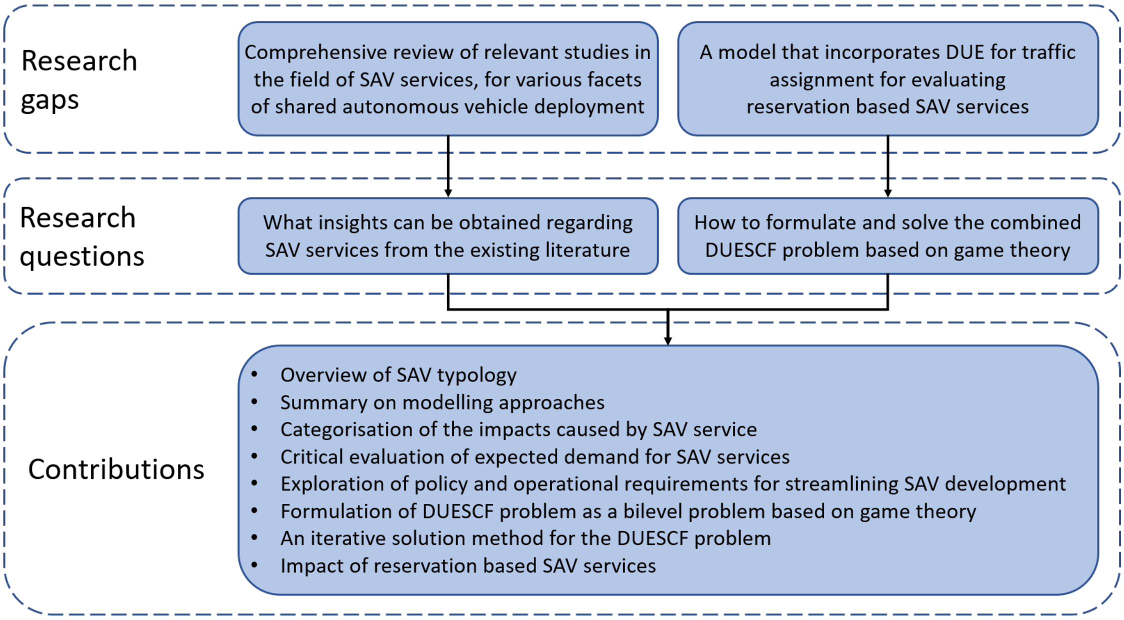


Figure 1.1: Research questions and contributions

- What are the necessary policies and operational framework required to streamline the growth of SAV services?
- Can any of the existing dynamic user equilibrium (DUE) model in the literature be adopted for use as part of the DUESCF problem?
- Can any of the existing vehicle assignment models be adopted for forming SAV chains in the DUESCF problem?
- Which is an appropriate convergence criterion for the proposed solution approach?
- How good the proposed solution algorithm performs with different networks of varying complexity?
- Based on the developed model, what will be the impact of introducing reservation based SAV services?

By answering the aforementioned research questions, this thesis makes the contributions listed in Figure 1.1. The first five contributions are based on the first research objective and the rest three based on second research objective.

1.3 Research framework

The general topic of this thesis was set out as 'Shared Autonomous Vehicles' based on the motivations explained in Section 1.1. Then a literature review on current review works on SAV services was carried out. A comprehensive review relevant studies in the field of SAV services was found out to be missing in the literature and filling this gap was set out as the first objective of this thesis. As per the first objective, the review was carried out and from the review results, it was found that a model incorporating DUE for traffic assignment for evaluating reservation based SAV services was also missing in the literature and filling this gap was set out as the second objective of this thesis. Subsequently, the model was framed as DUESCF problem by formulating it as a bilevel model based on game theory to achieve Nash equilibrium between road users and SAV operator and a solution algorithm based on an iterative approach is proposed. Existing DUE and SAV chain formation model, selected based on literature review, was used for this purpose. Later, the proposed solution algorithm was tested on three different networks of varying complexity and scenario analysis is done to evaluate the impacts of reservation based SAV services. Finally, conclusions for both the review work and the developed bilevel model are made followed by suggestions for future work. The research framework has been depicted as flow chart in Figure 1.2.

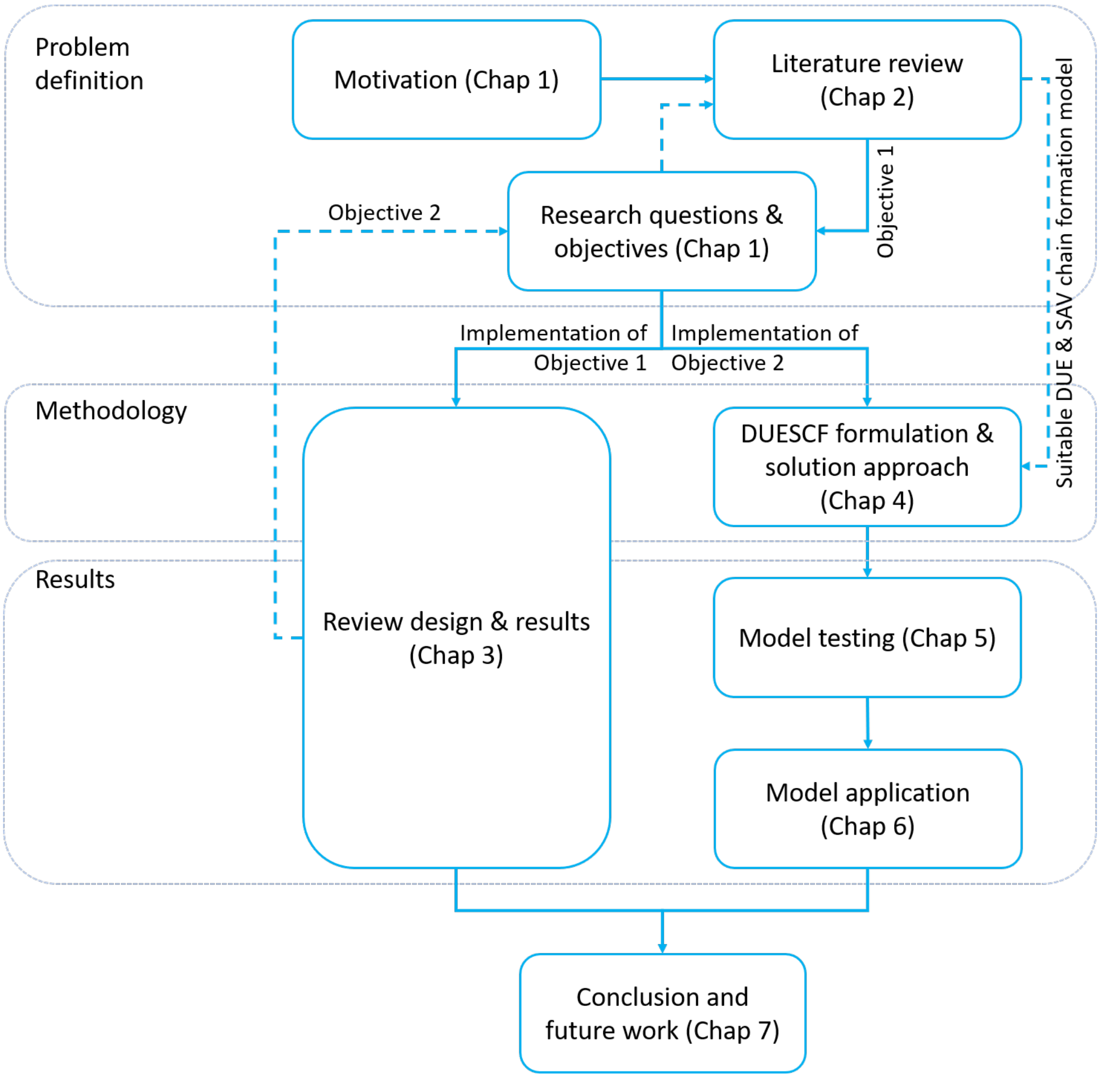


Figure 1.2: Research framework

1.4 Report structure

This thesis report is structured as follows: The literature review will be presented in the next section followed by the insights obtained from the review of relevant studies in the field of SAV services. After that, the formulation of DUESCF problem as a bilevel problem based on game theory and the proposed iterative solution algorithm are described. Later, modelling process is elucidated followed by briefing on the computation experiments performed on three different networks. Then, the results of scenario analysis are reported. Thereafter, conclusions are presented and finally, future works for the proposed bilevel model are discussed.

Chapter 2

Literature Review

The chapter is split into three parts. First, existing review works on SAV services are described. Then, existing models for evaluating reservation based SAV services are reviewed along with a briefing on DUE models. Finally, a summary relevant to the two research objectives is provided. Following research questions are answered in this chapter:

- *Can any of the existing DUE model in the literature be adopted for use as part of the DUESCF problem?*
- *Can any of the existing vehicle assignment models be adopted for forming SAV chains?*

2.1 Existing review works on SAV services

Three review studies, Becker and Axhausen (2017), Milakis et al. (2017) and Soteropoulos et al. (2018), have been found in literature related to SAV services and the author would like to bring into notice that none of them deal with SAV services exclusively. All the three studies explore both private and shared autonomous vehicles.

Becker and Axhausen (2017) review research works related to the acceptance of autonomous vehicles up to 2016. They classified studies according to the study methodology and the response and explanatory variables tested and identified the following response variable categories: the level of acceptance, the modal split, the willingness to pay, and the choice of owning an AV or using a taxi service. Similarly, groups' demographics, current behaviour, attitudes and trip characteristics were the identified categories of explanatory variables. They compared and contrasted the conclusions related to the response and explanatory variables from the studies reviewed. It is to be noted that a vast number of papers has been published on the topic of acceptance of autonomous vehicles from 2017 and important technical reports like Trommer et al. (2016) and Walker and Johnson (2016) are not included in Becker and Axhausen (2017).

Milakis et al. (2017) review studies related to the impacts of automated driving and they use the ripple model to conceptualize the sequential impacts of automated driving. The explored three levels of impact: 1. First order - traffic, travel cost and travel choices; 2. Second order - vehicle ownership, vehicle sharing, location choices and land use and transport infrastructure; 3. Third order - energy consumption, air pollution, safety, social equity, economy and public health.

Soteropoulos et al. (2018) also review studies related to the impacts of automated driving. They explore two major categories of impacts namely travel behaviour (trip generation rate, mode choice and the possible mobilisation of new user groups due to AVs like impaired people and elderly) and land use (location choices of people and firms and reductions in parking space).

Some important aspects such as impacts on entertainment and advertising industries as well as expected SAV service systems and governance implications of SAV development were found missing in the above mentioned review works.

2.2 Modelling reservation based SAV services

To the author's best knowledge, only four studies, (Bongiovanni et al., 2019; Levin, 2017; Ma et al., 2017; Shun Su, 2018), exists in literature that deals with vehicle assignment exclusively for reservation based SAV services. While Bongiovanni et al. (2019) and Ma et al. (2017) creates a formulation of their own for SAV chain formation, Levin (2017) and Shun Su (2018) base their study on the formulation of Cordeau and Laporte (2007).

Route choice between O-D pairs could affect traffic congestion and hence the travel time between an origin and destination, a traffic assignment model considering the road network is necessary. Also, when modelling reservation based SAV services, capturing the trip chaining behaviour is necessary and this requires a dynamic traffic assignment model which considers the evolution of queues and congestion over time in response to vehicle departures and arrivals. Of the four studies specified above, only Levin (2017) considers the underlying road network and the other two studies use graphs with edges that directly connected customer origins and destinations.

Levin (2017) incorporated dial-a-ride behaviour of SAVs into the system optimal DTA model of Ziliaskopoulos (2000). Though their formulation is a linear program, numerical testing on a grid network with four O-D pairs showed a high computation time (35 to 45 minutes). He concluded that his formulation and solution method might not be tractable for realistic networks and suggests using DUE models for route choice.

Ma et al. (2017) formulated an integer programming model and showed that the integer program is equivalent to linear program by proving that the constraint matrix is totally unimodular. They tested their model with New York taxi dataset by using CPLEX solver and the solution computation time was in the order of few seconds. Thus, their model is tractable for larger demands.

Bongiovanni et al. (2019) incorporated vehicle-to-depot assignment and battery-management problem in their formulation along with the usual vehicle assignment for the customers and their formulation is a mixed integer problem. The problem could only be solved for instances of up to 4 vehicles and 40 customers with a maximum computation time of 2 hours. Thus, their model is not suitable for larger demands.

Shun Su (2018) adopted the formulation of Cordeau and Laporte (2007) for forming SAV chains and used the Tabu search meta-heuristics method combined with a clustering method (K-Means and K-Medoids) as a solution algorithm. His solution method was tested with New York taxi dataset and was found to be usable for forming SAV chains for the dataset. The solution computation time was in the order of hours.

2.3 Dynamic user equilibrium models

Modelling of the network assignment of the time varying flows on road network, consistent with the established traffic flow theory and travel demand theory, is stated as dynamic traffic assignment (Friesz, 2010). A wide variety of problems fall under the category of DTA, each with different behavioural assumptions and having different capabilities in representing the traffic system (Peeta and Mahmassani, 1995).

Dynamic user equilibrium is a type of DTA wherein the effective unit travel delay for the users having same origin and destination and departing at the same time is identical and minimum (Friesz, 2010; Szeto and Wong, 2012). This is defined by generalizing wardrop conditions of the static user equilibrium case to time-dependent case wherein the user equilibrium conditions are obtained through a time-dependent extension of Wardrop's first principle. DUE is usually modelled for the within-day time scale based on the demand established on a day-to-day time scale (Himpe, 2016).

Many approaches have been proposed in literature for modelling DUE. With regards to formulation, DUE models can be formulated based on optimal control theory, variational inequality, nonlinear complementarity problem, differential variational inequality, differential complementarity system and fixed-point problem. The readers are recommended to go through Han et al. (2019) to know about the different formulations. Based on the dimension of choice considered for equilibrium, DUE models are of two types namely Route Choice (RC) model (e.g., Himpe, 2016) and Simultaneous Route and Departure Time Choice (SRDTC) model (e.g., Han et al., 2019). As the name suggests, in case of former, only route choice of the road users are considered in the formulation of equilibrium, while in the latter, both trip route and departure time choice of the road users are considered. Classification as link based, path based and destination based DUE model is another type of classification, which is based on the type of base variable, and the readers can refer to Himpe (2016) to know the principles behind them. Based on the type of route travel time considered for equilibrium, DUE models are can be of two types: 1. Reactive/instantaneous and 2. Actual/predictive (Yildirimoglu and Geroliminis, 2014). While the reactive travel time is the sum of the link travel times along the path estimated at the time of departure from origin, the predictive travel time is based on the sum of the link travel times along the path estimated at the time when drivers enter each link. Finally, based on stochasticity in the choice decision, DUE models can be divided into deterministic and stochastic DUE model (Szeto and Wong, 2012).

DUE models usually consist of two components namely: 1. Route (and departure-time) choice model and 2. Dynamic network loading (Han et al., 2019). The route choice model contains the mathematical expression for equilibrium condition. The Dynamic Network Loading (DNL) component describes the spatial and temporal evolution of traffic flows on a network that is consistent with the route (and departure time) choices established in the first model. As such, the DNL component models the network performance and this is executed using the following sub models (Friesz, 2010; Han et al., 2019):

- **Link/Path delay** - deals with calculation of link/path delay (could be travel time or a combination of travel time and arrival penalties)
- **Flow dynamics** - represents analytical relationship between flow/speed/density and link/path traversal time
- **Flow propagation constraints** - deals with propagation of traffic through links
- **Junction dynamics and delays** - modelling of traffic at junctions

Various traffic flow propagation (link travel time) models for DUE have been found in literature and they can be broadly classified into two groups namely delay-function models and the exit-flow function models (Friesz et al., 2013; Yildirimoglu and Geroliminis, 2014). Delay-function models are based on an explicit travel delay function (e.g. link delay model

(LDM)). Exit-flow function models are based on explicitly modelling the underlying flow dynamics (e.g., outflow model, cell transmission model, whole link model, deterministic queuing model and mesoscopic models).

The DNL models should possess the following properties:

- **FIFO** - vehicles entering a link first leaves out the link first
- **Positivity** - flows must be positive
- **Conservation** - continuity of flow
- **Capacity restraint** - flow in a link should be less than or equal to the capacity of the link
- **Causality** - future flows does not affect past flows
- **Monotonicity** - monotonic relationship between travel time and density
- **Consistency** - traffic flow consistent with the route (and departure time) choices established by the equilibrium condition

The readers are recommended the following works to know more about DTA and DUE models: Boyce et al. (2001); Chiu et al. (2011); Friesz (2010); Friesz and Han (2018); Garavello et al. (2016); Peeta and Ziliaskopoulos (2001); Ran and Boyce (1996); Szeto and Wong (2012); Wang et al. (2018b). The author was able to find two DUE models in literature that are available as open source scripts, Han et al. (2019) and Himpe (2016). A comparison of the two models is shown below in Table 2.1

Table 2.1: Comparison between DUE models of Han et al. (2019) and Himpe (2016)

	Han et al. (2019)	Himpe (2016)
DUE choice type	Simultaneous Route and Departure Time Choice (SRDTC)	Route Choice (RC)
Formulation type	Fixed point problem based on variational inequality	Variational inequality problem
Pros	A) Path travel time directly available B) Tested for large real-world networks	Presence of only route choice (absence of complications due to departure time choice)
Cons	A) Presence of departure time choice (affects relocation trips which are dependent on service trips) B) Only one arrival time per O-D pair	A) Path travel time needs to be calculated which is complex in case of dynamic systems B) Not tested for large real-world networks

2.4 Summary

Review on SAV services

The review work of Becker and Axhausen (2017) include research works related to the acceptance of autonomous vehicles only up to 2016. However, a vast number of papers has been published on this topic from 2017. Other existing review works, like Milakis et al. (2017) and Soteropoulos et al. (2018) discuss the impacts of automated and autonomous vehicles in general, without focusing in detail to some important aspects such as impacts on entertainment and advertising industries, as well as factors affecting SAV acceptance and governance implications of SAV development. Hence, this thesis will present a comprehensive review of relevant studies in the field of SAV services, including but not limited to impacts identified, demand estimated and policies required.

Modelling reservation based SAV services

A model that incorporates DUE for traffic assignment for evaluating reservation based SAV services is still missing in literature and this will be filled in through this thesis. Hence, a novel contribution of this thesis will be linking the DUE problem with the SCF problem by formulating and solving the combined DUESCF as a bilevel model based on game theory to achieve Nash equilibrium between roads users and SAV operator. This would enable evaluation of reservation based SAV services with consideration of network congestion. Developing a new DUE or vehicle assignment model is beyond the scope of this thesis and hence existing DUE and SCF models will be used as basis for formulating the DUESCF problem. The model of Han et al. (2019) was found appropriate for DUE traffic assignment since it has already been tested for large realistic networks. For the formation of SAV chains, the model of Ma et al. (2017) was found to be most appropriate since the resulting solution is optimal (exact solution) and the solution computation time is in the order of few seconds. A fixed point algorithm has been used to solve the DUE problem in Han et al. (2019) and a linear program solver, CPLEX, to solve the SAV Chain formation problem in Ma et al. (2017) and the same will be utilised in this thesis.

Chapter 3

Review of SAV services and their impacts

This chapter presents insights related to SAV typology, modelling approaches, impacts of SAV services, expected demand for SAV services and the necessary policies for SAV services that are obtained from the comprehensive review of relevant studies in the field ofSAV services. Naturally, the research questions that are addressed in this chapter are:

- *What are the business models of SAV services that can be expected in future?*
- *What are the existing modelling approaches and components involved for evaluating SAV services?*
- *What are the categories of impacts of SAV services?*
- *How much demand can be expected for SAV services in the next couple of decades?*
- *What are the necessary policies and operational framework required to streamline the growth of SAV services?*

3.1 Review design

A semi-structured approach was followed starting from collecting studies from SCOPUS database based on 13 keywords (shared autonomous, autonomous mobility(-)on(-)demand, autonomous taxi(s), shared automated, autonomous fleet, autonomous shared, driverless taxi(s), autonomous vehicle sharing, robo(-)taxi(s), autonomous mobility service(s), automated electric taxi, autonomous electric taxi and shared self(-)driving), for the publication year range 1950 to 2019. Screening is done on the obtained studies by characterising them based on their relevance. Additional papers were obtained from the references of the screened papers. Some studies not specific to SAVs have been included since they are applicable to autonomous vehicles in general i.e., applicable to both personal and shared autonomous vehicles. Type of documents reviewed include journal papers, conference papers and technical reports.

The collected studies are grouped into five categories viz. Typology, Modelling, Impact, Demand and Policies depending upon the subject discussed in the paper. A study could fall into multiple groups e.g., a study evaluating impacts can fall into the groups Impact and Modelling, if the study includes development of a new model or modification of an existing model. Insights are then obtained from each of the groups and the same will be presented in below sections.

3.2 SAV Typology and Characteristics

Both the concept of automation and car sharing are not new. The first known attempt for autonomous vehicles originates back in the early 20^{th} century (1925) in the form of a radio–controlled driverless car by a firm named Houdina Radio Control (Dormehl and Edelstein, 2018). Widespread exposure to the concept began in 1939 during General Motors' Futurama exhibit, where the concept of autonomous driving was presented in a massive and very costly event (Ferlis, 2007). Japan pioneered advanced automated vehicle technology development in 1977 by developing a car that follows white street markers with a speed of up to 20 miles per hour, followed by Germany and other countries (Forrest and Konca, 2007). However, it was the DARPA Grand Challenge (2004 and 2005) and DARPA Urban Challenge (2007), sponsored by the U.S. Defense Advanced Research Projects Agency (DARPA), that popularised the development of autonomous vehicles (Defense Advanced Research Projects Agency, 2014). Furthermore, foundations for current developments were laid by Carnegie Mellon University, Environmental Research Institute of Michigan and SRI International (as indicated in Stocker and Shaheen, 2017).

The first car–sharing system dates back to 1948 in Zurich, Switzerland. For nearly three decades, car–sharing systems failed to attract customers, mainly because of the availability of fast and cheap private motorization (Becker et al., 2016). However, with increasing awareness of the citizens and the diffusion of Information and Communication Technologies (ICT) and mobile services, car–sharing systems started to become successful in the 1980s, with high growth being evident in the 2000s (Ferrero et al., 2018). Specifically, from 2012 to 2014, car–sharing systems around the world experienced a 65% increase in membership and 55% increase in fleet (Shaheen and Cohen, 2016). A system combining car–sharing and automated vehicles, named Cybernetics Transportation System (CTS), was first conceptualised in the early 1990s in Europe (Parent and de La Fortelle, 2005). The concept was investigated in France by INRIA (French national research institute for the digital sciences) and INRETS (former French national institute for transport and safety research, currently called IFSTTAR); details on the concept can be found in Parent and Daviet (1993). Such a system was first introduced in Netherlands in 1977 at Schiphol airport (Parent and de La Fortelle, 2005). Though the concept was envisioned in the early 1990s, commercial deployment of such a service in an urban setting is still a challenge.

Different types of SAV systems are studied in the literature, commonly on the basis of their operation and level of their integration with other modes (Figure 3.1). The typology presented in the following paragraphs is based on the system types and characteristics identified in the reviewed literature, mainly from the impact evaluation approaches reviewed.

Based on operations, SAV services can be divided into dynamically operated systems (the customers can book vehicles in real time), systems based on reservation (booked in advance) and mixed systems. Most of the studies found in the literature are related to dynamic booking operations (e.g., Alonso-Mora et al., 2017; Fagnant and Kockelman, 2018; Gurumurthy and Kockelman, 2018; Hörl, 2017; Hyland and Mahmassani, 2018; Levin et al., 2017; Lokhandwala and Cai, 2018; Mahmassani, 2018; Wang et al., 2006), and only six studies have been found for reserved booking operation (Bongiovanni et al., 2019; Lamotte et al., 2017; Levin, 2017; Ma et al., 2017; Pimenta et al., 2017; Shun Su, 2018). The reason might be the current state of operation of shared vehicles, i.e. current request scenarios for

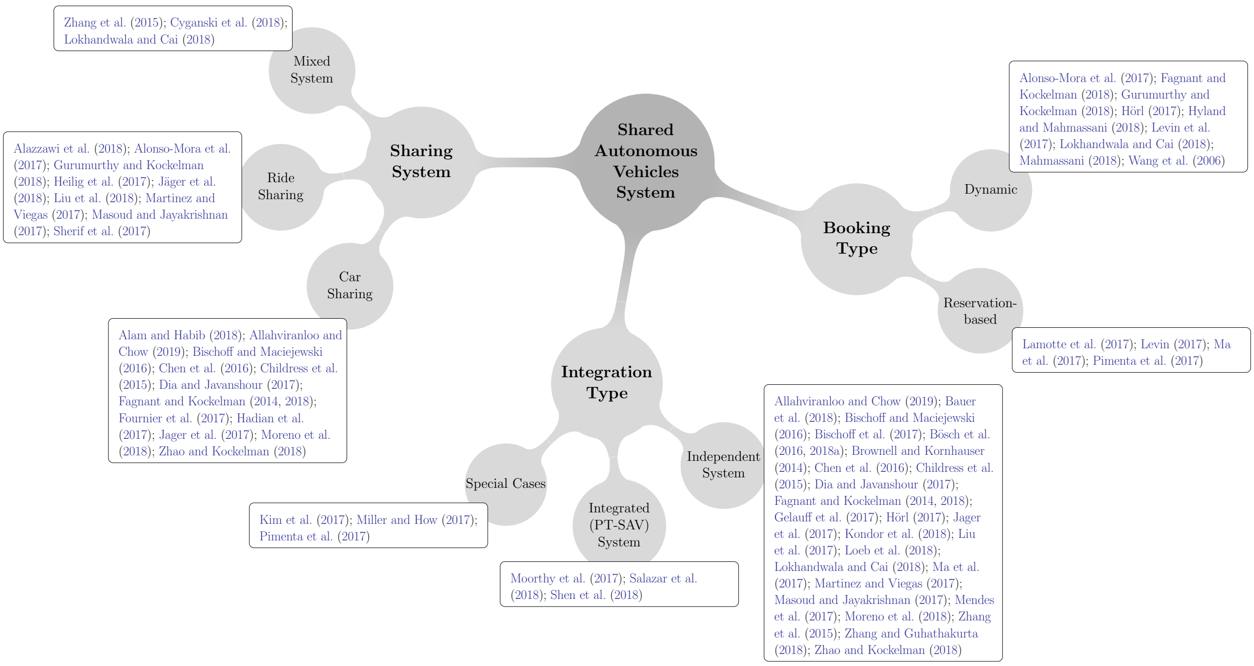


Figure 3.1: Types of SAV services explored and indicative references

shared vehicle services are primarily dynamic. However, reservation–based systems enable better planning of routes and schedules and, if optimally designed, higher efficiency, thereby reducing fleet size, empty cruising time and operating cost, as well as increasing resource utilization (Wang et al., 2014).

SAV services can be further classified into car–sharing, ride–sharing and mixed systems. In case of ride–sharing systems, two or more customers share a vehicle at the same time (Alazzawi et al., 2018; Alonso-Mora et al., 2017; Gurumurthy and Kockelman, 2018; Heilig et al., 2017; Jäger et al., 2018; Liu et al., 2018; Martinez and Viegas, 2017; Masoud and Jayakrishnan, 2017; Sherif et al., 2017), while only one customer request is served in case of a car–sharing system (Alam and Habib, 2018; Allahviranloo and Chow, 2019; Bischoff and Maciejewski, 2016; Chen et al., 2016; Childress et al., 2015; Dia and Javanshour, 2017; Fagnant and Kockelman, 2014, 2018; Fournier et al., 2017; Hadian et al., 2017; Jager et al., 2017; Moreno et al., 2018; Zhao and Kockelman, 2018). Gurumurthy and Kockelman (2018) explore two types of dynamic ride–sharing system namely (i) Origin–Destination (O–D) dynamic ridesharing and (ii) dynamic ridesharing en–route. In case of the former, travellers sharing the same origin and destination are matched in a common ride, while, in the latter case, also travellers having different origin and destination may share the ride. In mixed systems, the customers are allowed to choose between using the car alone or share with other customers (Zhang et al., 2015; Cyganski et al., 2018; Lokhandwala and Cai, 2018).

With regards to the integration type, independent systems make the service available as an independent mode (without connection to any other mode). Independent service can be further divided into two, based on who owns the vehicles. Systems similar to current mobility–on–demand (MOD) service providers (like Uber & Lyft) fall into one category (Alam and Habib, 2018; Bauer et al., 2018; Bischoff and Maciejewski, 2016; Bischoff et al., 2017; Bösch et al., 2016, 2018a; Brownell and Kornhauser, 2014; Chen et al., 2016; Childress et al., 2015; Dia and Javanshour, 2017; Fagnant and Kockelman, 2014, 2018; Gelauff et al., 2017; Hörl, 2017; Jager et al., 2017; Kondor et al., 2018; Liu et al., 2017; Loeb et al., 2018; Lokhandwala and Cai, 2018; Ma et al., 2017; Martinez and Viegas, 2017; Mendes et al., 2017; Moreno et al., 2018; Zhang et al., 2015; Zhang and Guhathakurta, 2018; Zhao and Kockelman, 2018), while the other category is a fractionally owned system, wherein e.g. a group of households share an autonomous vehicle (e.g., Allahviranloo and Chow, 2019; Masoud and Jayakrishnan, 2017). In integrated systems, the SAV services act as complimentary to existing public transport (PT) for first and last mile service and may replace PT operation in certain areas of low demand (Moorthy et al., 2017; Salazar et al., 2018; Shen et al., 2018). Special cases include SAV services inside university campuses and industries (Kim et al., 2017; Miller and How, 2017; Pimenta et al., 2017).

Foldes and Csiszar (2018) identify four SAV service types, namely: taxi, shared taxi, feeder pod and fixed route pod. The first type is equivalent to the independent car–sharing system and the second type is equivalent to the independent ride–sharing system. The latter two types fall under integrated PT–SAV systems. Both the third and fourth types serve as feeder systems to a high capacity line (e.g., a metro system), but the feeder pod system enables flexible boarding points, while —in case of fixed route pod systems— the boarding point is fixed. The study of Foldes and Csiszar (2018) describes the first three systems as demand–driven, and the last one as demand–responsive. Based on the same study, demand–driven services are provided when a request is registered, similar to a taxi system. A service based on flexible timetable and capacity with a predetermined route is called demand–responsive service.

With regards to business models, Stocker and Shaheen (2018) discuss some plausible scenarios that can be expected in the future. The study mentions six potential business models constructed based on two main aspects: vehicle ownership and network operations. The six business models are (i) Business–to–Consumer (B2C) with single owner–operator, (ii) B2C with different entities owning and operating, (iii) Peer–to–Peer (P2P) with third–party operator, (iv) P2P with decentralized operations, (v) Hybrid ownership with same entity operating, and (vi) Hybrid ownership with third–party operator. Based on vehicle capacity, the study also proposes four potential vehicle types, namely (i) large vehicles (20+ Pax), (ii) mid–sized vehicles (7 to 20 Pax), (iii) small vehicles (3 to 7 Pax), and (iv) micro vehicles (1 or 2 Pax). The study mentions that profitability of a business model will depend on many factors, including availability of technology, location of the service, vehicle types used, and the ownership schemes. Stocker and Shaheen (2018) conclude that it is possible for single–occupant vehicles to remain dominant and it is also possible for shared rides to become common, provided that the shared ride service becomes more cost–effective, less onerous to users and leads to fewer deviations, because of the efficiency of automation.

3.3 SAV modelling approaches

The diversity of SAV characteristics and the uncertainty related to their deployment has led to a development of wide range of modelling frameworks and algorithms. Although optimization algorithms can be evaluated and compared, there is a wide spectrum of methods with regards to modelling SAV services and the lack of basis for proper performance evaluation and validation makes their review eminent. A consolidation based on the prevailing methodological aspects can reveal trends, helpful for future research. This section includes elucidation on the major objectives of the three main stakeholders (customers, operators and government) of a shared autonomous vehicle service followed by a description on the components of SAV modelling and finally the tools used in modelling SAV services are presented.

3.3.1 Major objectives

Customers, operators and government (public authorities) are the main stakeholders of SAV systems identified in the literature, where each stakeholder has one or several objectives (Figure 3.2). The customers expect minimum waiting time to get picked up and minimum cost and travel time to reach the destination. They also expect maximum comfort while travelling. The usually incorporated user objective in the algorithms is minimising waiting time (e.g., Babicheva et al., 2018; Hyland and Mahmassani, 2018; Levin, 2017; Wang et al., 2006). Bai et al. (2017) use trip cost reduction as one of the objectives in their fare allocation algorithm. Reduction of customer travel time is incorporated in Salazar et al. (2018).

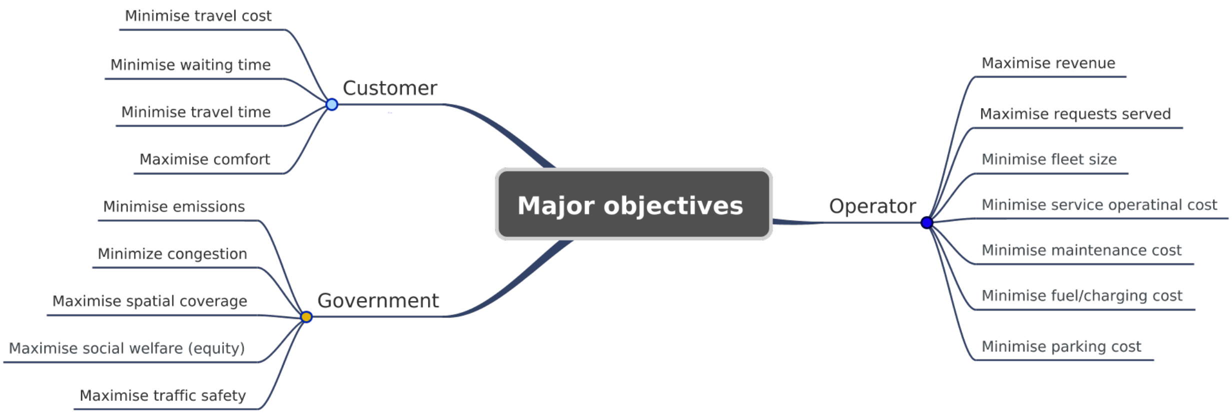


Figure 3.2: Commonly observed objectives of different stakeholders

The main objectives of the operators include decreasing the various types of cost incurred (operational, maintenance, fuel/charging cost and parking cost) and the fleet size while increasing the number of requests served and the revenue earned. One way of reducing operational cost is through reduction of total system travel time and this is one of the most common objectives found in the literature (Allahviranloo and Chow, 2019; Alonso-Mora et al., 2017; Bischoff et al., 2017; Levin, 2017; Ma et al., 2017). Reduction of total vehicle miles/kilometres travelled is incorporated in Farhan and Chen (2018) and Hyland and Mahmassani (2018). While Beirigo et al. (2018) reduce operational cost by integrating passenger and freight transport, Iacobucci et al. (2018) try to minimise charging cost. Zhang and Guhathakurta (2017) include parking cost in their study. Wang et al. (2006) and Masoud and Jayakrishnan (2017) uses reduction of fleet size as an objective. Alonso-Mora et al. (2017), Masoud and Jayakrishnan (2017) and Miller and How (2017) aim to maximise the number of customer requests served.

Government agencies aim at reducing accidents, congestion and emission while ensuring adequate spatial coverage and equity. The objectives used in a study depends on the component of the mobility service that is subjected to optimization. Explicit usage of such objectives is seldom seen in literature. Exceptions include studies that concentrate on vehicle redistribution (Babicheva et al., 2018; Iglesias et al., 2018; Rossi et al., 2018), which aims to reduce network congestion. Though direct usage of objective like minimising emissions are not seen in literature, it should be remembered that other objectives such as reduction of total system travel time and total vehicle miles/kilometres travelled compliment government's objectives.

3.3.2 Components of SAV modelling

Transportation system models that include SAVs are inherently complex and occurs with its breakdown into a series of components. From the reviewed articles, the main modelling components, as shown in Figure 3.3, can be summarised to be the following: a) Demand; b) Fleet; c) Traffic Assignment; d) Vehicle Assignment; e) Vehicle Redistribution; f) Pricing and g) Charging; h) Parking.

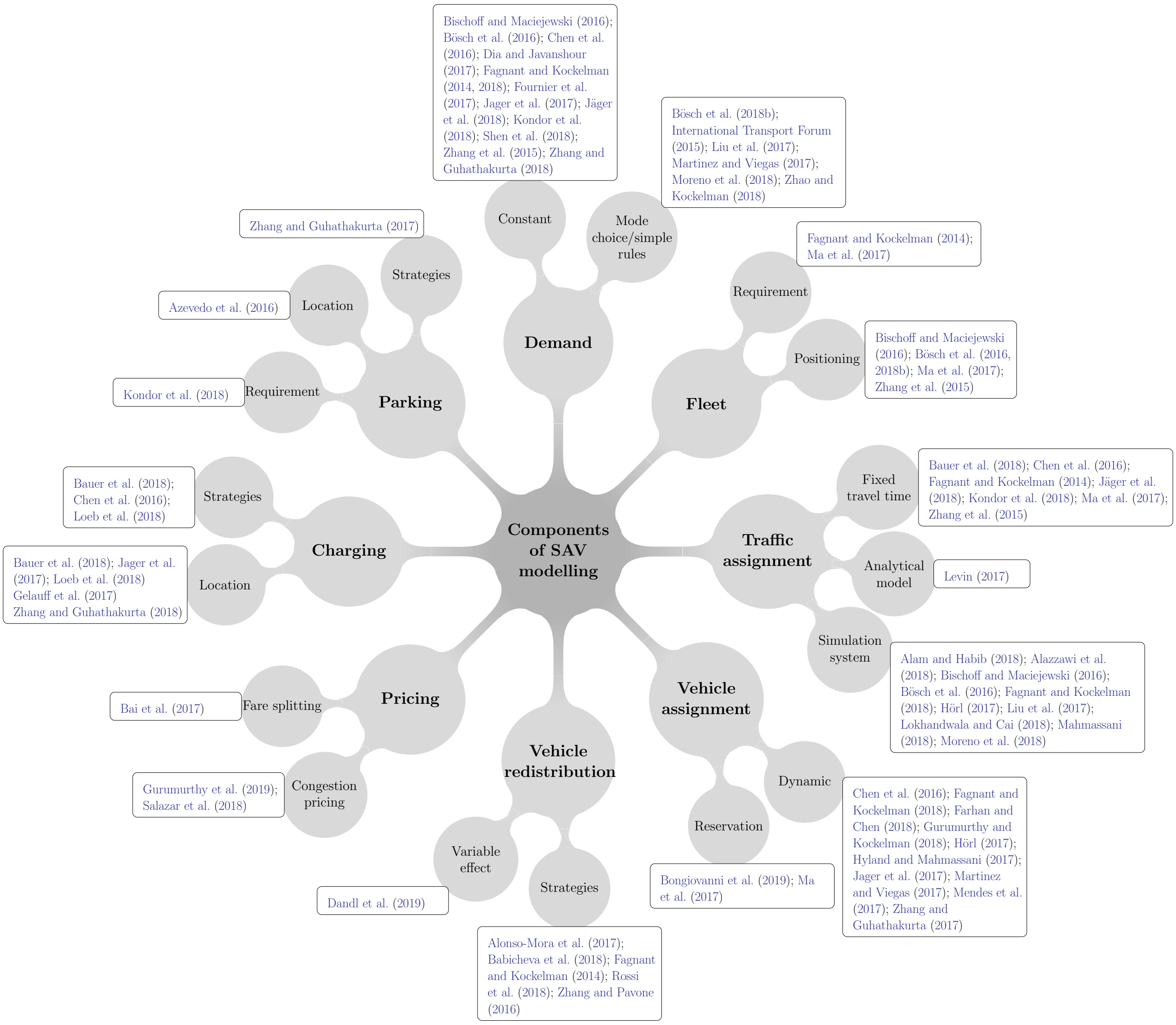


Figure 3.3: Components of SAV modelling and indicative references

With regards to **Demand**, trips are generated based on travel survey data (Chen et al., 2016; Dia and Javanshour, 2017; Fagnant and Kockelman, 2014, 2018; Martinez and Viegas, 2017; Zhang et al., 2015), data from existing land-use and transport models (Alam and Habib, 2018; Bischoff and Maciejewski, 2016; Bösch et al., 2016; Childress et al., 2015; Gelauff et al., 2017; Jager et al., 2017; Meyer et al., 2017; Moreno et al., 2018; Zhao and Kockelman, 2018), travel records from transit smart card (Shen et al., 2018), cell phone data (Gurumurthy and Kockelman, 2018; Kondor et al., 2018) or a taxi dataset (Chicago taxi dataset in Hyland and Mahmassani, 2018 and New York taxi dataset in Alonso-Mora et al., 2017; Bauer et al., 2018; Lokhandwala and Cai, 2018; Ma et al., 2017; Rossi et al., 2018; Yi et al., 2018; Zhang and Pavone, 2016. In case exact trip times are not available but only hourly or daily averages (usually the case when using travel survey data), a Poisson process is commonly used to randomly generate trip requests (e.g., Chen et al., 2016; Fagnant and Kockelman, 2014; Zhang et al., 2015). Many studies assume a constant demand (single or multiple values) for the SAV services from the total trips generated for further analysis (Bischoff and Maciejewski, 2016; Bösch et al., 2016; Chen et al., 2016; Dia and Javanshour, 2017; Fagnant and Kockelman, 2014, 2018; Fournier et al., 2017; Jager et al., 2017; Jäger et al., 2018; Kondor et al., 2018; Shen et al., 2018; Zhang et al., 2015; Zhang and Guhathakurta, 2018) and the rest use mode choice models or simple rules to estimate demand (Bösch et al., 2018b; International Transport Forum, 2015; Liu et al., 2017; Martinez and Viegas, 2017; Moreno et al., 2018; Zhao and Kockelman, 2018). With regards to constant demand, the values assumed range from 1% to 10% of the trips made in the service area (Chen et al. (2016) - 10%, Fagnant and Kockelman (2014) - 3.5%, Fagnant and Kockelman (2018) - 1.3%, Zhang et al. (2015) - 2%, Zhang and Guhathakurta (2018) - 5%). Few studies assume replacing private car trips (Bischoff and Maciejewski (2016) and Fournier et al. (2017) - 100% replacement; Bösch et al. (2016) - 1 to 10% replacement). Dia and Javanshour (2017) assumes that 25% of the conventional private car demand will be served by private autonomous vehicle and the remaining 75% by shared autonomous vehicles. Jäger et al. (2018) consider replacing existing bus system and Shen et al. (2018) consider replacing bus system in low-demand routes.

With regards to the **Fleet**, studies mainly aim at estimating the required fleet size to serve a given demand and also at fixing the initial position of the vehicles. Many simulation studies employ a warm up simulation (see Fagnant and Kockelman (2014) for the method) to determine the fleet size required. Ma et al. (2017) use a virtual link in their optimization algorithm to determine optimal fleet size required. Assuming a fixed fleet size (single or multiple values) is also commonly found in literature (Alam and Habib, 2018; Lokhandwala and Cai, 2018; Moreno et al., 2018; Shen et al., 2018). Initial fleet placement can be random (Bösch et al., 2016; Zhang et al., 2015), based on the population density (Bischoff and Maciejewski, 2016; Bösch et al., 2018b) or based on warm-start (Fagnant and Kockelman, 2014). If depots are present, then the vehicles initially start from the depot (Ma et al., 2017). For a taxonomy on SAV fleet management problems, the authors recommend reading Hyland and Mahmassani (2017). The paper describes new taxonomy categories apart from adapting existing categories.

The **Traffic Assignment** component is used to extract route flows and travel time between origin and destination nodes. In the simple case, fixed travel times between nodes are assumed. Fixed travel time commonly found in the literature is 1) the free flow travel time multiplied by a factor to represent congestion (Jäger et al., 2018), 2) average travel time of off-peak and peak hour (Chen et al., 2016; Fagnant and Kockelman, 2014; Zhang et al., 2015) and 3) an hour-based value, either extracted from Google Maps (Bauer et al., 2018) or from the transport department of the city where the analysis is done (Kondor et al., 2018). Ma et al. (2017) uses the travel time mentioned in the taxi dataset along with a correction factor when designing a reservation-based system. Dynamic traffic assignment models are closer to reality and can be divided into two categories: simulation-based and analytical methods. As the name implies, the former category involves a simulation system, while in the latter, an equilibrium assignment model based on Wardrop's principles is used. For modelling dynamic SAV services (typology presented in Section 3.2), majority of the studies use simulation systems (e.g., Alam and Habib, 2018; Alazzawi et al., 2018; Bischoff and Maciejewski, 2016; Bösch et al., 2016; Fagnant and Kockelman, 2018; Hörl, 2017; Liu et al., 2017; Lokhandwala and Cai, 2018; Mahmassani, 2018; Moreno et al., 2018). To the best of authors' knowledge and based on the studies reviewed, for reservation-based systems, only Levin (2017) uses the traffic assignment component, based on dynamic system optimal assignment, by including an analytical model.

Vehicle Assignment assigns vehicles to the customers, which can be based on certain rules, heuristics or an optimization algorithm. For modelling dynamic services, a rule-based vehicle assignment method similar to assigning nearest vehicle is usually implemented (e.g., Chen et al., 2016; Fagnant and Kockelman, 2018; Gurumurthy and Kockelman, 2018; Hörl, 2017; Jager et al., 2017; Mendes et al., 2017; Zhang and Guhathakurta, 2017). The most commonly found rule is assigning the nearest vehicle to the request. Realtime optimization models (e.g., Farhan and Chen, 2018; Martinez and Viegas, 2017) are seldomly used because of their complexity and required computation power. Hyland and Mahmassani (2017) present and compare six different vehicle assignment strategies for dynamic SAV services with no shared rides. The first strategy assigns travellers to the longest idle SAV based on first-come, first-served (FCFS) priority and the second assigns travellers to the nearest idle SAV based on the same priority. While in the first two strategies travellers are assigned sequentially, the third strategy involves simultaneous assignment of travellers. In the third strategy, only unassigned travellers are considered and in the remaining three strategies, both unassigned and assigned travellers are considered when solving the assignment problem. Fourth strategy considers idle and en-route pickup vehicles during vehicle assignment for new requests. In the fifth strategy, idle and en-route drop-off vehicles are considered. Idle, en-route pickup and en-route drop-off vehicles are considered in the last strategy. The study concludes that optimization-based strategies that consider both unassigned and assigned travellers (strategies 4 - 6) are more efficient in terms of reducing fleet miles and traveller waiting times. However, this is true only in case of high fleet utilization. Assigning nearest idle AV is comparable to the complex strategies in case of low fleet utilization. For assigning vehicles to requests in a reservation-based services, formation of SAV chains is generally found in the literature (e.g. Ma et al., 2017). Formulation for SAV chain formation is similar to dial-a-ride problem (DARP) formulation and hence, the algorithms that are used for solving DARP (Braekers et al., 2014; Cordeau, 2006; Cordeau and Laporte, 2007; Paquette et al., 2013) can be adapted to solve SAV chain formation. It is worth noting that none of the studies reviewed explored a mixed service (combination of dynamic and reservation based services).

Vehicle Redistribution, also referred as "**vehicle rebalancing or repositioning**", is used to redistribute excess vehicles from low demand areas to high demand areas when modelling dynamic SAV services (Alonso-Mora et al., 2017; Babicheva et al., 2018; Fagnant and Kockelman, 2014; Rossi et al., 2018; Zhang and Pavone, 2016). Alonso-Mora et al. (2017) and Zhang and Pavone (2016) use a linear program for vehicle redistribution. Fagnant and Kockelman (2014) explore four different relocation strategies, either individually or in combination, labelled as R1 through R4 with decreasing bound for relocation distance. They found that strategy R1, that allows larger relocation distance, results in lower waiting times for customers. All the relocation strategies resulted in increased vehicle miles travelled. Rossi et al. (2018) proposes a congestion-aware algorithm that shows good performance in terms of network congestion and customer service times by selectively redistributing vehicles through routes that do not increase congestion. Babicheva et al. (2018) evaluates six different methods to apply redistribution and their results show that the combination of simple nearest neighbours and index-based redistribution method provides very promising results. To know the effect of spatial and temporal aggregation of demand forecast which is used for vehicle redistribution, the readers are referred to Dandl et al. (2019). They conclude that higher the spatial disaggregation of demand forecast, better is the fleet performance in terms of user wait time and empty fleet miles, though the demand forecast quality is decreased at higher disaggregation. Having concluded that, they also mention that higher quality demand forecasts, especially at more disaggregate levels, enable better performance of the fleet.

The component **Pricing** includes estimation of fare of SAV trips based on spatial (customer origin and destination) and temporal parameters (demand levels at different time of the day or based on network congestion). Thought the effects of flexible pricing strategies for SAV services is still not much explored (Hyland and Mahmassani, 2017), use of congestion pricing and strategies for splitting cost between multiple customers in case of ridesharing are seen in literature. For example, Salazar et al. (2018), to explore the interaction between SAV services and public transport system when they are coordinated, designs a congestion pricing scheme to achieve maximum social welfare (system optimality). Another example, Gurumurthy et al. (2019) modelled a system consisting of SAVs with dynamic ridesharing option and introduced congestion pricing during peak periods. With regards to strategies for splitting cost between multiple customers, Bai et al. (2017) use the concept of fairness, which is based on envy freeness and maximum utility, to allocate price for different customers sharing the ride. In their scheme, the first passenger onboard can choose to allow boarding of the next passenger in exchange for a reduction of his/her trip cost.

Charging refers to monitoring battery levels of electric vehicles and strategies to charge vehicles (Iacobucci et al., 2018; Iglesias et al., 2018). While the charging vehicles are not allowed to undock and serve a new request in Chen et al. (2016), still-charging vehicles are allowed to serve a new request in Bauer et al. (2018) and Loeb et al. (2018). With regards to location of charging stations, Jager et al. (2017) locates charging stations at taxi stands or POIs and Bauer et al. (2018) uses an elimination strategy by initializing charging stations at all possible locations and iteratively removing those locations whose elimination resulted in least impact on the system. Some studies use a warm up simulation to ascertain location of charging stations (see Loeb et al., 2018, for the method).

Finally, the component **Parking** involves estimating parking requirements and also includes the strategies to park vehicles. Kondor et al. (2018) use a data-driven approach to estimate parking requirement by capping the distance that a SAV can travel to park. Azevedo et al. (2016) use an optimization algorithm (Facility Location problem) to locate charging cum parking stations. Zhang and Guhathakurta (2017) minimise cost by routing idle vehicles to low cost parking areas.

3.3.3 Tools used for SAV modelling

For algorithms involving optimization, the frequently used solver is CPLEX from IBM (Levin, 2017; Ma et al., 2017; Masoud and Jayakrishnan, 2017; Pimenta et al., 2017; Rossi et al., 2018), either in IBM's optimization studio or as a plugin in other programming languages. Other solvers used include Gurobi (Beirigo et al., 2018; Hyland and Mahmassani, 2018; Bongiovanni et al., 2019), SCIP (Yi et al., 2018) and Matlab's inbuilt solver (Allahviranloo and Chow, 2019; Iacobucci et al., 2018; Liu et al., 2018). Many researchers use Matlab to develop optimization models for assigning vehicles to customers and to build custom simulation systems (e.g., in Gurumurthy and Kockelman, 2018; Mendes et al., 2017; Zhang et al., 2015). As shown in Figure 3.4, Java (Jager et al., 2017), C++ (Fagnant and Kockelman, 2014), python (Zhang and Guhathakurta, 2018) and R (Bauer et al., 2018) are some of the other programming languages used when modelling SAV services.

The most common form of custom simulation system is agent-based simulation sys-

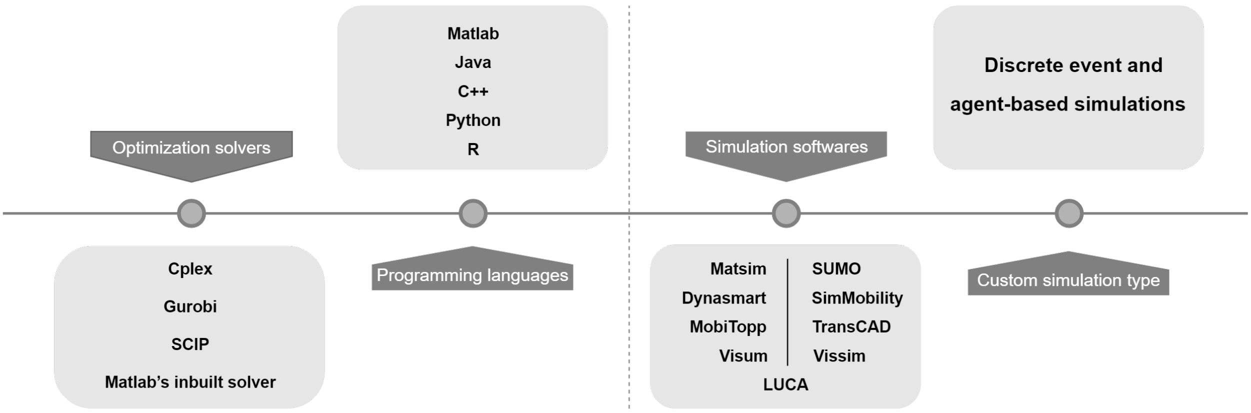


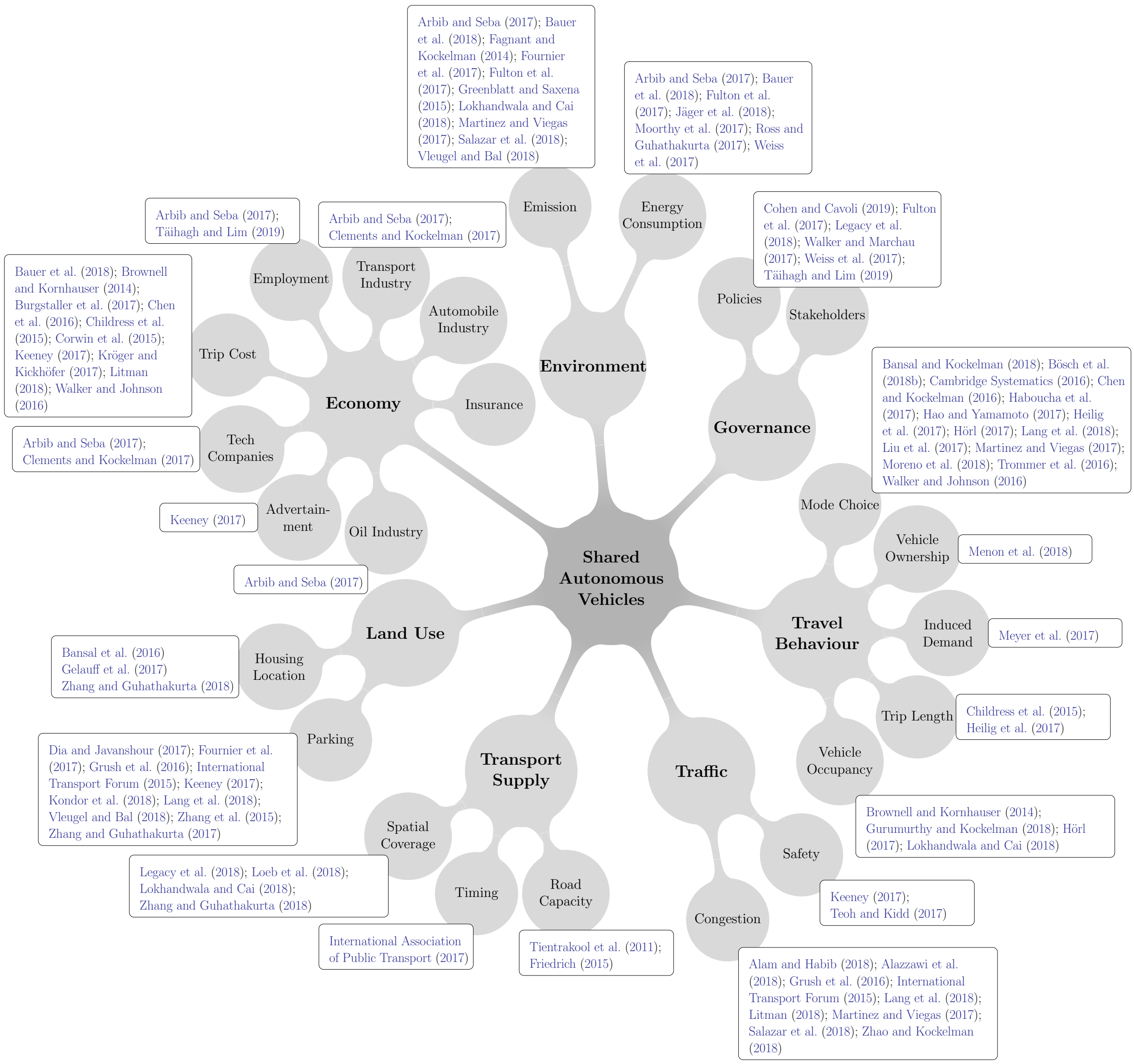
Figure 3.4: Commonly used tools for modelling SAV services

tem (e.g., in Bauer et al., 2018; Dia and Javanshour, 2017; Fagnant and Kockelman, 2014; Lokhandwala and Cai, 2018; Martinez and Viegas, 2017; Shen et al., 2018; Zhang et al., 2015; Zhang and Guhathakurta, 2018) and few studies use a discrete event simulation method (Jager et al., 2017; Jäger et al., 2018; Zhang and Guhathakurta, 2017). Matsim is the most used simulation software for simulating SAV operations (e.g., in Bischoff and Maciejewski, 2016; Bösch et al., 2016; Hörl, 2017; Liu et al., 2017; Bösch et al., 2018b; Fagnant and Kockelman, 2018; Loeb et al., 2018; Moreno et al., 2018; Wang et al., 2018a). Other simulation systems used include Dynasmart (Mahmassani, 2018), SUMO (Alazzawi et al., 2018; Friedrich, 2015), SimMobility (Azevedo et al., 2016), MobiTopp (Heilig et al., 2017), TransCAD (Zhao and Kockelman, 2018) and Vissim (Alam and Habib, 2018). The Dutch spatial general equilibrium model 'LUCA' is the only ILUT model found in the literature which has used to model SAVs (used in Gelauff et al., 2017). The programming languages and the tools listed are based on the studies that have been reviewed by the authors and there are many more tools that can be utilized, for example Xpress for optimization and DynaMIT for simulation.

3.4 Impacts

A wide spectrum of research focuses on the identification of impacts that SAVs will bring to the transportation system. Aiming at providing an overview of the various fields, where impacts are identified, a classification of the relevant studies is provided, as presented in Figure 3.5.

A detailed and structured review of the impacts identified in the literature is presented in the following paragraphs. Where applicable, the results of this analysis are presented in a tabular form and a selection of the studies is discussed. As understood, transportation system models that include SAVs are inherently complex and can be broken down into a series of components. The main modelling components are summarised in 3.3.2. In most cases, the estimation of impacts would include the use of (agent–based) simulation techniques, or the development of analytical models. Of course, the studies examined usually base their analysis on different assumptions, scenarios, contexts and methods and hence, directly comparing the results per se would not be considered appropriate, without taking the context into account. Having said that, the exploration of direction of impact and the range of values that can be expected is considered beneficial.



Note: The references for policies and stakeholders are common. Similarly Transport Industry, Automobile industry and Insurance share the same references.

Figure 3.5: Classification SAV services impacts

3.4.1 Traffic efficiency

Starting from network congestion, as presented in Table 3.1, the results of the studies examined can be considered rather controversial. On one hand, car–sharing systems are found to increase congestion (Alam and Habib, 2018; Zhao and Kockelman, 2018), while on the other hand, ride–sharing systems could reduce traffic (Alazzawi et al., 2018; Martinez and Viegas, 2017). Alazzawi et al. (2018) show that traffic would reduce with at least 50% demand for ride–sharing services. Their implementation was based on the use of SUMO for the city of Milan, with an initial demand estimated based on mobile phone data, while the matching of passengers to robo–taxis was performed using the stable marriage algorithm (McVitie and Wilson, 1970). Salazar et al. (2018) show that car–sharing system, when integrated with PT (integrated PT-SAV system), can reduce traffic. Their approach is based on mesoscopic optimization, with the goal to be the maximization of the social welfare (minimizing travelers travel time and costs along with reduction of congestion issues). Lang et al. (2018) performed a conjoint analysis of mode choice and implemented an agent based simulation framework for the city of Boston, USA. They found that, in urban areas, SAVs will replace both personal car and mass transit, while in suburban areas, they will mainly replace personal car use. Both Lang et al. (2018) and Litman (2018) support that traffic would reduce in the inner city, but increase in suburban areas. This is mainly due to the higher possibility of sharing in inner cities, which is associated with higher demand density.

Table 3.1: Summary of the Traffic–related impacts

Variable	**Study**	**Effect**
Traffic	International Transport Forum (2015)	Local networks: (+)
	Grush et al. (2016)	(+)[1]
	Martinez and Viegas (2017)	(-)
	Alam and Habib (2018)	Peak hour: First hour (-) and then next two hours (+)
	Alazzawi et al. (2018)	With at least 50% SAV demand: (-)
	Lang et al. (2018)	Speed: Downtown (PT is mainly replaced): +5.50% Outer (cars are mainly replaced): -12.10%
	Litman (2018)	Urban areas: (-) Suburban and rural areas: (+)
	Salazar et al. (2018)	(-)[2]
	Zhao and Kockelman (2018)	Average speed: (-)[3]
Safety (Accidents)	Fagnant and Kockelman (2015)	-40%
	Keeney (2017)	-80
	Teoh and Kidd (2017)	(-)

Note: Studies are sorted by year and then alphabetically on authors per each category; (+) indicates increase and (-) indicates decrease

[1]Mixed traffic (conventional + autonomous); [2]Integrated PT - SAV services compared with independent SAV services

[3]Combination of private and shared AVs

In the field of traffic safety (Table 3.1), Keeney (2017) estimates 80% reduction in accident rates. The author reaches this conclusion by adjusting the experience from the airline industry, for generally the impact of automation in car traffic. On a more targeted approach, Fagnant and Kockelman (2015) use the statistics of alcohol consumption, distraction, drug consumption and fatigue, which account for over 40% of fatal crashes in the USA, suggesting that development of autonomous vehicles could result in at least 40% reduction in fatal crashes. Though accidents can be reduced to a greater extent, it is not possible to eliminate them completely (Teoh and Kidd, 2017), as machine errors will persist (Täihagh and Lim, 2019), leading to the need of new legislative frameworks for the liability (Hayes, 2011).

Autonomous Vehicles can also be associated with security concerns. Täihagh and Lim (2019) state that data storage and transmission capabilities of autonomous vehicles might result in privacy risks and the communication networks of autonomous vehicles might be prone to malicious attacks. Petit and Shladover (2014) explore the security issues related to autonomous vehicles and conclude that the most severe and likely attacks are Global

Navigation Satellite Systems (GNSS) spoofing and injection of fake messages. GNSS helps positioning vehicles on an accurate map and the data can be manipulated to result in erratic and inaccurate manoeuvres. International Transport Forum (2018) discusses about road safety issues and security vulnerabilities associated with autonomous vehicles and gives recommendations to lessen the issues.

3.4.2 Travel Behavior

With regards to trip length, Childress et al. (2015) developed an agent based model to evaluate SAV services and tested four scenarios for Seattle, USA. A slight increase of trip length is shown, with the exception of a scenario where high cost of service is assumed (decrease of 15% in this case). Heilig et al. (2017) show an increase in trip length for a pooling–based SAV service, assuming a reduction of cost. On vehicle replacement, which represents the number of conventional vehicles that one autonomous shared vehicle can replace, a range of values from 1.17 to 11 is predicted (Table 3.2). Although it is difficult to ascertain the exact replacement value, it is asserted that SAV systems have the potential to reduce vehicle ownership, when complemented by strong policies. Mendes et al. (2017) performed various simulation experiments to test different scenarios for vehicle replacement for light rail. Their results show that 150 to 500 vehicles are needed to replace a 39–vehicle light rail system. Fagnant and Kockelman (2014) performed a sensitivity analysis of 26 scenarios using agent based simulation for a synthetic case of a mid–sized city. The aim was to understand the environmental impacts of SAVs and the result showed a maximum vehicle replacement of 10 vehicles per SAV. Average vehicle occupancy values for SAV services with ride–sharing option are rather consistent in the literature and range between 1.13 to 3. Moderate reduction in the value of time (VOT, in the order of 10%) is suggested in Singleton (2018). Singleton (2018) provide a comprehensive discussion of the pertinent studies, asserting that the VOT reduction would be lower than what is anticipated in other studies. Steck et al. (2018) assert that time is valued 10% less negative than manual driving.

An increase in vehicle miles/kilometres travelled (VMT/VKT) in general expected due to the introduction of shared autonomous vehicles (Table 3.2) (Alam and Habib, 2018; Bischoff and Maciejewski, 2016; Chen et al., 2016; Dia and Javanshour, 2017; Fagnant and Kockelman, 2014; International Transport Forum, 2015; Jager et al., 2017; Kondor et al., 2018; Lang et al., 2018; Moreno et al., 2018; Zhang and Guhathakurta, 2018), the major reason for this being empty trips. However, Rossi et al. (2018) show that it is possible to route empty vehicles without substantial increase in congestion. Though increase in VMT/VKT is a general trend, Lokhandwala and Cai (2018) show that, when shared autonomous vehicle services with ridesharing option replace the current taxi system, there is a reduction in VMT/VKT. Lokhandwala and Cai (2018) also show that usage of conventional vehicles with ride–sharing option reduces VMT/VKT to a greater extent, compared to autonomous vehicles, though the fleet requirement is high. *Thus, in terms of VMT/VMT, autonomous ride–sharing is better than autonomous car–sharing and conventional ride–sharing is better than autonomous ride–sharing.*

Bischoff et al. (2017) observe a similar trend and conclude that an autonomous ride–sharing system results in lower VMT/VKT, when compared to an autonomous car–sharing system. Heilig et al. (2017) also confirm a similar trend, i.e. reduction in VMT/VKT for an autonomous ride–sharing system; however,the study implements redistribution of vehicles only once during the night. Childress et al. (2015) also find a VMT/VKT reduction, although they did not consider ride–sharing; this is due the assumed comparatively high cost

Table 3.2: Summary of the Travel Behaviour–related impacts

Variable	Study	Effect
Average vehicle occupancy	Brownell and Kornhauser (2014)	1.17 to 2.16
	Hörl (2017)	1.13 to 1.6
	Gurumurthy and Kockelman (2018)	1.14 to 1.9
	Lokhandwala and Cai (2018)	1.2 to 3[1]
Trip length	Childress et al. (2015)	-15% to +14%
	Heilig et al. (2017)	(+)
VMT/VKT	Fagnant and Kockelman (2014)	+10%
	Childress et al. (2015)	-35%
	International Transport Forum (2015)	+6% to +89%
	Bischoff and Maciejewski (2016)	(+)
	Chen et al. (2016)	+7.1% to +14%
	Bischoff et al. (2017)	-15% to -20%[2]
	Dia and Javanshour (2017)	+10% to +29%
	Heilig et al. (2017)	-20%
	Jager et al. (2017)	+15.80%
	Masoud and Jayakrishnan (2017)	+20%
	Alam and Habib (2018)	(+)
	Fagnant and Kockelman (2018)	+4.5% to +8.7%
	Jäger et al. (2018)	10 times more[3]
	Kondor et al. (2018)	+2%
	Lang et al. (2018)	+16%
	Lokhandwala and Cai (2018)	-18% to -45%[1]
	Moreno et al. (2018)	+7.40%
	Shen et al. (2018)	-860 km (morning peak hour)[4]
	Zhang and Guhathakurta (2018)	(+)
	Zhao and Kockelman (2018)	(+)[5]
Vehicle replacement	Brownell and Kornhauser (2014)	2.72 to 4.75
	Fagnant and Kockelman (2014)	10
	International Transport Forum (2015)	5 to 10
	Pavone (2015)	1.43 to 3
	Bösch et al. (2016)	4 to 10
	Chen et al. (2016)	3.7 to 9
	Zhang and Pavone (2016)	1.4
	Dia and Javanshour (2017)	1.75 to 8.3
	Heilig et al. (2017)	6.67
	Levin et al. (2017)	3.6
	Masoud and Jayakrishnan (2017)	9
	Mendes et al. (2017)	150-500 vehicles, replace a 39-vehicle light rail system
	Fagnant and Kockelman (2018)	8.7 to 10.8
	Gurumurthy and Kockelman (2018)	6 to 8
	Lang et al. (2018)	1.18
	Lokhandwala and Cai (2018)	1.93 to 2.451
	Moreno et al. (2018)	2.5
Vehicle ownership	Menon et al. (2018)	18.6% are likely and 7.3% are extremely likely to give up their vehicle (1214 individuals surveyed)
Value of Time	Singleton (2018)	Modest VOT reductions[5]
	Steck et al. (2018)	-10% (private AVs -31%)[6]

Note: Studies are sorted by year and then alphabetically on authors per each category. Where applicable, green and red text highlights lowest and highest values respectively; (+) indicates increase and (-) indicates decrease

[1]Conventional taxis compared to ridesharing SAV; [2]Autonomous ridesharing compared to autonomous carsharing [3]Comparison with bus fleet; [4]Integrated PT - SAV system; [5]Combined results of private and shared AVs; [6]Compared to conventional cars

of SAV service ($1.03/km). Thus, many users shift to transit and walk modes and, hence, a reduction in VMT/VKT is estimated. Shen et al. (2018) show that an integrated PT–SAV system, wherein the SAV system replaces the PT system in low demand areas, could reduce VMT/VKT.

Change in VMT/VKT and vehicle replacement are the two major impact variables explored in several studies. Figure 3.6 shows a scatter plot between percentage change in VMT/VKT and vehicle replacement. As observed, most studies predict a moderate increase of VMT/VKT, which can be considered to be rather independent of the vehicle replacement rate.

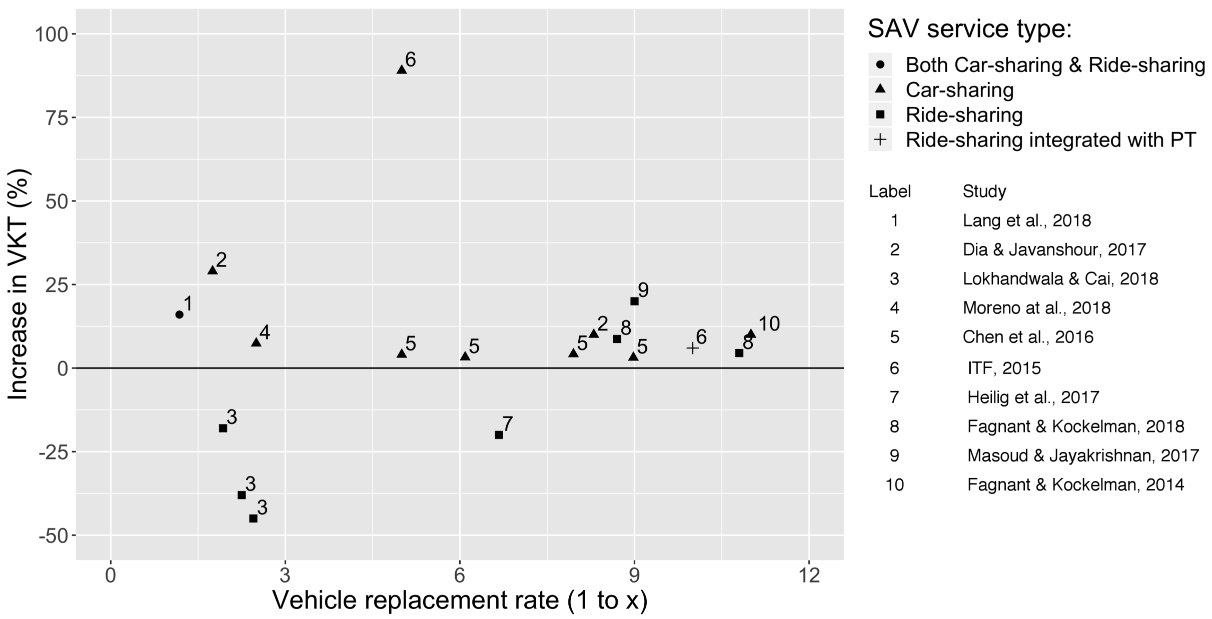


Figure 3.6: Changes in VMT/VKT for different vehicle replacement rates as found in the examined literature

3.4.3 Economy

The cost of SAV services, as predicted in the literature (see Table 3.3), ranges from $0.11/km to $1.03/km, with the range $0.19/km to $0.30/km being prominent (Bauer et al., 2018; Chen et al., 2016; Corwin et al., 2015; Keeney, 2017; Litman, 2018; Walker and Marchau, 2017). Litman (2018) provides an overview of costs and predicts that the cost will be between $0.19/km and $0.38/km for an autonomous micro–transit system and $0.38/km to $0.62/km for an autonomous taxi system. Burgstaller et al. (2017) estimate the cost to be $0.77/km, this being a conservative reduction from current costs of ride hailing services ($0.92/km). They believe that savings from the removal of drivers would be substituted by increase in operating costs and additional taxes to compensate loss of taxes from conventional taxi industries. Childress et al. (2015) assume a cost of $1.03/km, based on the price of Uber services in Seattle in 2014. Brownell and Kornhauser (2014) predict the cost for a person per day to be $16.30 to $23.50 for a smart paratransit SAV system, calculated based on the total distance of all trips and the required fleet size. Salazar et al. (2018) conclude that an integrated PT–SAV system can substantially reduce transport costs of individuals. Arbib and Seba (2017) express that the revenue sources from the entertainment and advertising industry could ultimately lead to free SAV services. Savings per family would then amount to more than $5,600 per year. Technology firms might be the highest beneficiary of AV development (Clements and Kockelman, 2017).

Table 3.3: Summary of the Economy–related impacts

Variable	**Study**	**Effect**
Cost per Kilometre ($/km)	Childress et al. (2015)	1.03[1]
	Corwin et al. (2015)	0.19
	Chen et al. (2016)	0.26 to 0.30
	Walker and Johnson (2016)	0.19
	Burgstaller et al. (2017)	0.77
	Keeney (2017)	0.22
	Kröger and Kickhöfer (2017)	0.45 (Car sharing)
		0.11 (Ride sharing)
	Bauer et al. (2018)	0.18 to 0.38
	Litman (2018)	0.19 to 0.62
Cost per person per day ($)	Brownell and Kornhauser (2014)	16.30 to 23.50
Economy	Arbib and Seba (2017)	Automobile market: (-)
		Family savings / year: $5,600
	Clements and Kockelman (2017)	Digital media & technology firms: (+)
		Auto repair, Medical industry, insurance companies & legal services: (-)
	Keeney (2017)	U.S. GDP: +$2 trillion
		Global public equity markets: +10%
		Global beverage industry: +$28 billion
		Entertainment & advertising industry: +$100 billion
	Täihagh and Lim (2019)	Increase in inequality
Revenue	Burgstaller et al. (2017)	Increase in opportunities
	Fagnant and Kockelman (2018)	+19% (profit)

Note: Studies are sorted by year and then alphabetically on authors per each category. Where applicable, green and red text highlights lowest and highest values respectively; (+) indicates increase and (-) indicates decrease

[1]Assumed to be the same as current prices of Uber.

Keeney (2017) states a 10% increase in global public equity markets. Furthermore, they proclaim that introduction of SAVs could add $28 billion to the global beverage industry, due to the absence of the need for designated drivers, and $100 billion could be added to the entertainment and advertising industry, due to the increased usage of streaming and social media services like Netflix and Facebook. Although some industries would experience a positive impact, growth of autonomous vehicles would increase economic inequality, because of employment redistribution of low–skilled workers, e.g. vehicle drivers (Täihagh and Lim, 2019). Development of SAVs could decrease revenue in auto repair shops, medical industry, insurance companies and legal services (Clements and Kockelman, 2017).

3.4.4 Transport Supply

An increase in road capacity could be expected due to the introduction of autonomous vehicles, mainly attributed to reduced headways (Friedrich, 2015; Tientrakool et al., 2011). The increase in road capacity is estimated to be between 40% to 273% (larger values are due to the efficient communication between the autonomous cars based on Vehicle–to–Vehicle (V2V) technologies combined with decreased headways). SAV services can be made available 24x7 and hence, if seen as an extension of Public Transport, can enable provision of services during extended operating hours (International Association of Public Transport (2017)).

With regards to spatial coverage of SAV services, Loeb et al. (2018), Lokhandwala and Cai (2018) and Zhang and Guhathakurta (2018) conclude that suburban areas will be under–served and the quality of service will be better in urban areas. In all three cases, the conclusions have been based on a combination of agent–based simulation tools.

On accessibility, Meyer et al. (2017) found that most municipalities in Switzerland would experience an increase of accessibility (85% of the cases), while for the remaining 15% of the cases (mostly cities), there would be a substantial loss of accessibility of up to 29%. Meyer et al. (2017) assume different scenarios and examine various values of road capacities. Through the impact they have on congestion and induced demand, changes in accessibility have been evaluated and the results are in the same direction with Childress et al. (2015).

Table 3.4: Summary of the Supply–related impacts

Variable	Study	Effect
Accessibility	Meyer et al. (2017)	+1.4% to +10.3%
Road capacity	Tientrakool et al. (2011)	+43% to 273% (highway)
	Friedrich (2015)	+40% (Urban) +80% (Highway)
Spatial coverage	Legacy et al. (2018)	Certain areas will be under-serviced if not strongly regulated
	Loeb et al. (2018)	Urban areas served better
	Lokhandwala and Cai (2018)	Suburban areas under-served[1]
	Zhang and Guhathakurta (2018)	Urban areas served better compared to suburbs

Note: Studies are sorted by year and then alphabetically on authors per each category. (+) indicates increase and (-) indicates decrease

[1]Conventional taxis compared to SAVs with ridesharing

3.4.5 Land use

In the majority of the studies that focus on parking–related aspects of land use (Table 3.5), a substantial reduction in parking space requirements is concluded (Dia and Javanshour, 2017; Fournier et al., 2017; International Transport Forum, 2015; Keeney, 2017; Kondor et al., 2018; Lang et al., 2018; Vleugel and Bal, 2018; Zhang et al., 2015; Zhang and Guhathakurta, 2017). In many of the studies examined, it is asserted that, with the introduction of SAV, on–street parking can be reduced significantly; Zhang et al. (2015) simulate the choices of agents, aiming at the exploration of the effect of SAV on parking and conclude that the reduction could reach 90% for a business–as–usual day, but allowing empty vehicle cruising. Based on two simulated scenarios for Melbourne, Australia, Dia and Javanshour (2017) estimate a reduction of up to 89%. Also using simulation–based methods, Zhang and Guhathakurta (2017) suggest a reduction of 4.5% for a penetration of 5%, mentioning that each SAV can free more than 20 parking spots. On a different note, Grush et al. (2016) expect that parking demand will increase in the next three decades, because of mixed traffic (non–, semi– and fully autonomous vehicles) and increased car usage.

Table 3.5: Summary of the Land–Use–related impacts

Variable	**Study**	**Effect**
Parking	International Transport Forum (2015)	On-street: -20%
		Off-street: -80%
	Zhang et al. (2015)	-90%
	Grush et al. (2016)	(+)[4]
	Dia and Javanshour (2017)	-58% to -83% (on-street)
	Fournier et al. (2017)	(-)
	Keeney (2017)	-250 million spaces (USA)
	Zhang and Guhathakurta (2017)	-4.5% (for 5% penetration)
	Kondor et al. (2018)	-50%
	Lang et al. (2018)	-48%
	Vleugel and Bal (2018)	-50%
Residential Location Choice	Bansal et al. (2016))	A) Larger households and Individuals with Bachelor's degrees or higher - move away from central Austin
		B) Full-time working, tech-savvy and higher income people - move closer to central Austin
	Gelauff et al. (2017)	Urbanisation
	Zhang and Guhathakurta (2018)	A) No chaotic sprawl
		B) Elder - move slightly closer to the CBD
		C) Younger - move out, within 25 miles from CBD

Note: Studies are sorted by year and then alphabetically on authors per each category. Where applicable, green and red text highlights lowest and highest values respectively; (+) indicates increase and (-) indicates decrease

[1]Mixed traffic (conventional + autonomous)

Gelauff et al. (2017) indicate that introduction of SAV services will result in urbanisation, while Zhang and Guhathakurta (2018) mention that introduction of SAV services will not result in unfettered sprawl. Elder generations might move slightly closer to the city centre. Although younger generations might move a little away from the city centre, they would stay within 25 miles from the city centre. Bansal et al. (2016) conclude that larger households and individuals with bachelor's degrees or higher would move away from the downtown and full-time working males, tech-savvy and higher income individuals would move closer to the downtown.

3.4.6 Environment

Results related to energy consumption are mainly connected to the anticipated use of Electric Vehicles (EV) in SAV services and show a decrease in consumption (Arbib and Seba, 2017; Bauer et al., 2018; Fagnant and Kockelman, 2018; Fulton et al., 2017; Jäger et al., 2018; Moorthy et al., 2017; Ross and Guhathakurta, 2017). Bauer et al. (2018) state that, unless there is a dramatic drop in oil prices or conventional car prices, electric vehicles will become cheaper. In an exploration of different scenarios, Fulton et al. (2017) concluded that the decrease of energy consumption would only be present with an electric fleet and, if the vehicles would be conventionally powered, then any improvements in efficiency would be compensated by the increase in VKT that shared autonomous systems will bring.

Studies related to emissions show that emissions would be significantly reduced, again, especially with the application of electric vehicles (Arbib and Seba, 2017; Bauer et al., 2018; Fagnant and Kockelman, 2014; Fournier et al., 2017; Fulton et al., 2017; Greenblatt and Saxena, 2015; Lokhandwala and Cai, 2018; Martinez and Viegas, 2017; Salazar et al., 2018; Vleugel and Bal, 2018). Salazar et al. (2018) conclude that integrating SAV services with public transport would result in reduced emission along with reduction in traffic and transport cost. Electricity demand will be peak during mid-day and overnight (Weiss et al., 2017).

Table 3.6: Summary of the Environment–related impacts

Variable	Study	Effect
Emissions	Fagnant and Kockelman (2014)	(-)
	Greenblatt and Saxena (2015)	-87% to -94% (per km)
	Arbib and Seba (2017)	-90%
	Fournier et al. (2017)	-10% to -35%
	Fulton et al. (2017)	-80%
	Martinez and Viegas (2017)	-40%
	Bauer et al. (2018)	-73%
	Lokhandwala and Cai (2018)	- 725 metric tonnes per day[1]
	Salazar et al. (2018)	(-)[2]
	Vleugel and Bal (2018)	(-)
Energy Consumption	Arbib and Seba (2017)	-80%
	Fulton et al. (2017)	-70%
	Moorthy et al. (2017)	-37%
	Ross and Guhathakurta (2017)	(-)
	Weiss et al. (2017)	Peak charging for EV: Overnight & mid-day
	Bauer et al. (2018)	-58%
	Jäger et al. (2018)	-56%[3]

Note: Studies are sorted by year and then alphabetically on authors per each category. Where applicable, green and red text highlights lowest and highest values respectively; (+) indicates increase and (-) indicates decrease

[1]Conventional taxis compared to SAVs with ridesharing; [2]Integrated PT - SAV services compared with independent SAV services; [3]Comparison with bus fleet

3.4.7 Governance

Legacy et al. (2018) expect merging of private and public transportation. The role of public transport authorities will change from owning and managing the transportation assets to managing SAV service providers to ensure equitable and sustainable transport service and also to curtail the possible vested interests of corporations. Fulton et al. (2017) also express a similar train of thought, and put emphasis on regulatory controls to direct the growth towards sustainability. All these would result in new stakeholders entering the mobility market and new forms of cooperation would thus emerge (Weiss et al., 2017). Apart from the formation of new forms of cooperation, apportioning liability and insurance risks between different parties involved in autonomous vehicle designs call for a new legal framework (Täihagh and Lim, 2019).

From the above, it can be understood that SAVs replacing the current conventional taxi system and integrated with public transport, instead of completely replacing public transport, is a more sustainable paradigm, and several studies recommend this route (Bösch et al., 2018b; International Association of Public Transport, 2017; Fraedrich et al., 2018; Salazar et al., 2018). Currie (2018) explains why public transportation systems need to be promoted and concludes that public transport fusion (adoption and integration of best features of different modes into public transport modes and services) is a better solution for the future. Furthermore, new forms of cooperation between private operators and government bodies are required, along with regulatory measures to support shared services and at the same time to control the vested interests of corporations. With these things taken care of, the introduction of SAVs could potentially lead to a better transportation system.

3.5 SAV Demand: Penetration, Acceptance, and Mode Choice

Estimating the impact of SAVs is related to the estimation of the actual demand that SAVs will attract. However, predicting the demand for SAVs involves uncertainty. Methods that are used to estimate the demand for SAV services include technology adoption S–curves (Trommer et al., 2016; Walker and Johnson, 2016), disruption framework (Arbib and Seba, 2017) and stated preference surveys. Technology adoption S–curves denote the life cycle of technological adoption and technological diffusion, while disruption framework is a technology adoption framework that considers technologies and innovations converging together to cause a substantial disruption. In the third method, researchers conduct stated preference surveys and predict the demand either descriptively from the surveyed data (Bansal et al., 2016; Bansal and Kockelman, 2018; Krueger et al., 2016; Haboucha et al., 2017; Pakusch et al., 2018; Nazari et al., 2018; Zmud and Sener, 2017), or by using the data as an input to a discrete choice model, which is part of a simulation system (Moreno et al., 2018). The addition of an SAV mode into an existing simulation system to predict demand without any new survey data is also found in literature (Liu et al., 2017; Heilig et al., 2017).

3.5.1 SAV Penetration

Most of the reviewed studies converge to penetration rates, in terms of trips performed using SAV services in the near future, much lower than 100%. The only study that gives a value closer to 100% penetration rate is Arbib and Seba (2017) and the study concludes that 95% of the passenger miles (considered here as proxy to SAV penetration rate) travelled

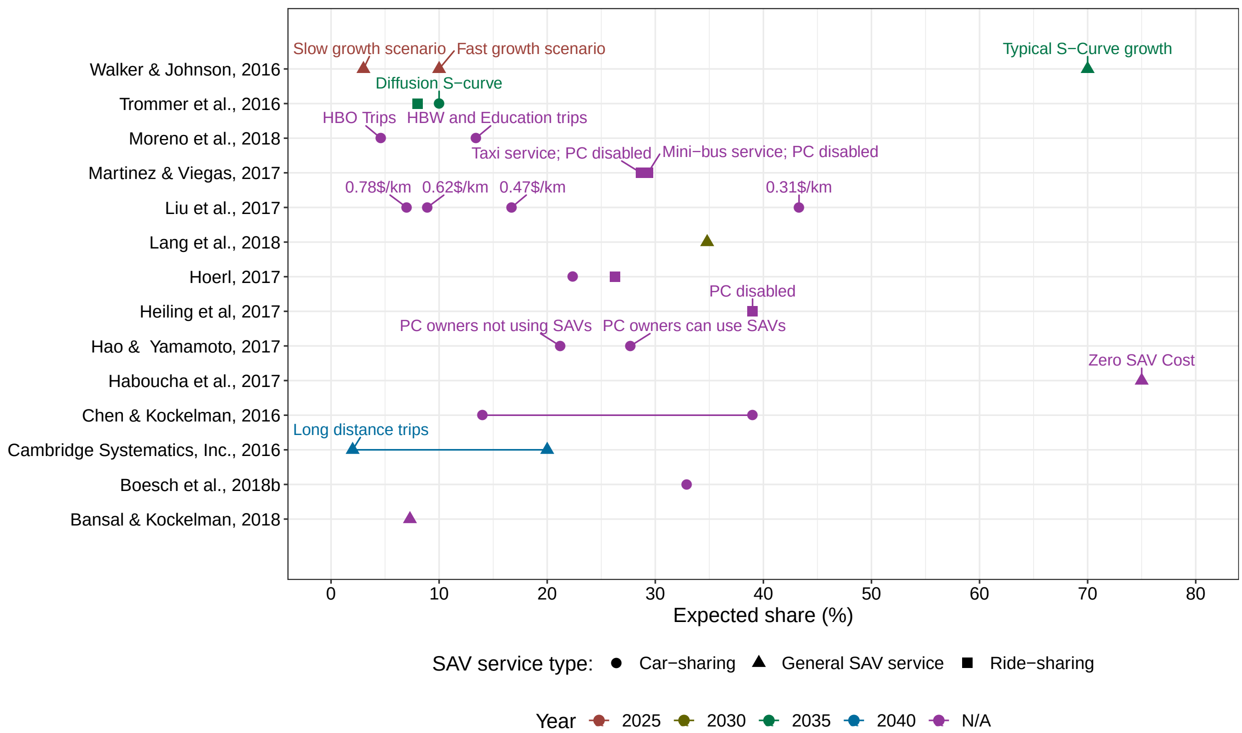


Figure 3.7: Expected demand for SAV services from different studies. Straight lines represent intervals

in USA will be in a shared autonomous vehicle by 2030. In fact, Bösch et al. (2018a) and Pakusch et al. (2018) affirm that private cars will continue to exist. Watkins (2018) states that loss aversion would be a reason hindering the individuals from giving up their personal car(s). Menon et al. (2018) found that 27.5% of the 1214 respondents surveyed are extremely unlikely and 26.7% are unlikely to relinquish their personal vehicle. Haboucha et al. (2017) show that 100% penetration rate of SAV service might not be achieved, even if the service is offered for free. Based on the range of values observed in the literature (Figure 3.7), the authors expect that the mode share of SAV services would be less than 50% in the next 10-15 years.

The authors would like to note that the development of a shared autonomous mobility service still requires a wide variety of developments, ranging from data security and road safety measures to vehicle and mobility service system design. Pendleton et al. (2017) review the development of autonomous vehicle software systems and conclude that there are still issues to be solved to enhance the driving capabilities of autonomous vehicles. Schatzinger et al. (2018) assert that shared autonomous mobility services are least likely to be implemented anytime soon because of the technical and social complexities associated with autonomous technology.

3.5.2 Effect of SAV service on mode choice behaviour of people

A common observation found in the literature is that SAV services will mainly attract users of sustainable modes of transport, PT, walking and bicycling (Bösch et al., 2018b; Cyganski et al., 2018; Pakusch et al., 2018). Lang et al. (2018) conclude that both public transport and personal car usage will be replaced in urban areas and in suburban areas and areas outside the city proper, car usage will be mainly replaced. The conclusions of Liu et al. (2017) also support this, stating that SAVs will be preferred over conventional private cars in rural areas at lower fares ($0.31 or $0.47 per km compared to $0.62 and $0.78 per km). In a situation wherein private car usage is disabled, Heilig et al. (2017) found that the majority of car users would switch to SAV services (and not PT or other modes). Users who did short trips (less than two kilometres) formerly in cars shifted to walking and bicycling. Some previous car users shifted to PT.

While younger people, students and more educated citizens would be the early adopters (Haboucha et al., 2017), very rich, tech–laggards and people from highly rural areas would be non–adopters (Arbib and Seba, 2017). Bansal et al. (2016) predict that the frequent users of SAV services will be high income tech–savvy males, individuals living in urban areas and densely populated neighbourhoods and individuals having greater crash experience. Non–frequent users will be licensed drivers and older persons. Krueger et al. (2016) state that multi–modal users are expected to use SAV systems more and users who only use private cars are expected to be reluctant to shift to shared mobility services. PT users are more likely to switch to autonomous car sharing systems, while current carsharing users are more likely to switch to an autonomous ride sharing system.

3.5.3 Suitability of SAV services

Bösch et al. (2018a) state that SAVs can serve the demand efficiently wherever substantial bundling of demand is not possible, i.e. SAVs can be an efficient mode in suburban and rural areas. However, it should be remembered that, in suburban and rural areas, SAV services may not be profitable to the operators, when compared to urban areas, and can also result in increased VKT. Where substantial bundling is possible, public transport may be more suitable.

Though many positive impacts from autonomous ride–sharing services are expected, Cyganski et al. (2018) observe a lower acceptance for ridesharing, compared to autonomous taxi–based services in Brunswick (Germany). Lang et al. (2018) make a similar observation for Bostonians (USA). Tachet et al. (2017) propose a simple model to ascertain potential for ride sharing in any city based on the taxi requests and conclude that the potential for sharing is high, even for low trip density of taxi requests. Although the model is built upon the data of conventional taxis, the authors believe that the conclusions will also be applicable to autonomous vehicles. The study considers only spatial and temporal aspects and not people's willingness to join such systems. It is in the hands of public authorities to motivate people and increase willingness for ride–sharing.

3.5.4 Factors affecting the acceptance of SAV services

Nazari et al. (2018) conclude that adoption of SAVs might be hindered, due to safety concerns, and that policies aimed at reducing such safety concerns would be beneficial. Philipsen et al. (2019) identified exact pickup time at the origin and arrival time at the destination as important factors for SAV acceptance, while route of journey and determination of co–passengers had minor importance. Vehicle equipment and entertainment systems (including Wi–Fi) were unimportant. The majority of the users were unwilling to pay extra charges for individualization (ride sharing to car sharing). Amanatidis et al. (2018) conclude that users have different expectations for autonomous vehicle user interface, based on whether the vehicle is owned or shared. This shows the different trajectory of development required between personal and shared autonomous vehicles. Dowling et al. (2018) explore the socio–material relationship that an individual has with the shared car and how the sharing experience could be disrupted in the presence of an issue. Understanding this would help one to comprehend why and how private users could be shifted to a car sharing system. Also, it could help to design the car sharing system in a way attractive to people, which will in turn boost the share of this market. Becker and Axhausen (2017) gives an overview of variables that affect acceptance of autonomous vehicles (both personal and shared), based on a review of different research works that are published before 2017.

3.6 Policy and operational framework

Technological advances in transport will not necessarily positively impact the performance of the transportation system by their own; in many of the policy related papers reviewed, regulation is found to be required in order to make the introduction of autonomous vehicles sustainable (Sprei, 2018; International Association of Public Transport, 2017). Cohen and Cavoli (2019) substantiate the necessity for streamlining autonomous vehicle development, absence of which might result in socially undesirable outcomes. They discuss the effect of a laissez–faire governance approach, when governing autonomous vehicle development, concluding that, with such an approach, the outcomes will be less sustainable and an interventionist approach is needed to achieve a more socially desirable outcome.

From a policy makers perspective, on a municipality level, the study of Fraedrich et al. (2018) explores the effects of autonomous vehicles (both private and shared) and their compatibility to municipalities' existing objectives. Fraedrich et al. (2018) concluded that autonomous vehicle development should be steered in a way to complement public transport. Along the same lines, International Association of Public Transport (2017) insist that it is the right time to create a suitable policy framework for AVs and recommend introduction of AVs as shared autonomous vehicles in a way reinforcing public transport system and supporting walking and cycling. The study suggests promotion of shared mobility services along with the creation of multimodal mobility platforms. Sprei (2018) concludes that automation should be steered towards sustainability in combination with shared mobility system.

Interventions for enhancing sustainability in the era of (Shared) Autonomous Vehicles are suggested in the categories of planning/land–use, regulation/policy, infrastructure/technology, service provision and economic instruments (Sprei, 2018). Given the high uncertainty involved, Walker and Marchau (2017) propose a dynamic adaptive policy framework to govern the growth of shared autonomous services. The policy system consists of five steps and allows for adaptations over time as knowledge about performance and acceptance of the shared autonomous service system evolves. On infrastructure, Schlossberg et al. (2018) suggest street redesign strategies for urban arterials and residential streets, considering the opportunities that would be available due to the development of autonomous vehicles. Their strategies range from reduction of lane width to removal of certain lanes. Szigeti et al. (2017) present a system architecture and propose a functional model for managing demand responsive SAV services. The system architecture includes six components, namely (i) Smart passenger, (ii) Operational control centre, (iii) Traffic control centre, (iv) Autonomous road vehicle, (v) Smart stop and (vi) Maintenance. Foldes and Csiszar (2018) emphasize the need for coordination between the operation service centre, traffic control centre, local municipalities and infrastructure operators. They describe two planning functions required for SAV operations, namely preliminary service planning and operative planning.

To conclude, the current policy system should be adapted in a way to streamline the growth of autonomous vehicles and accept the uncertainties involved in their development.

Close cooperation is required between operational control centre, traffic control centre and the transport network operator. Stocker and Shaheen (2018) summarise the current pilot projects and policies related to SAVs in USA. European Commission (2018) gives an overview of the stand of EU commission on the development of autonomous vehicles. Bloomberg Philanthropies (2017) provide a comprehensive overview of pilot projects and policy initiatives related to autonomous vehicles started in different cities around the world. The data is continuously updated and includes data of 123 cities as of February 2019.

Chapter 4

DUESCF formulation and solution

The DUESCF problem is formulated and a solution algorithm along with a convergence criterion are proposed in this chapter. The combined problem of DUESCF is formulated as a bilevel model based on game theory and an iterative approach is proposed as a solution technique to solve it. Research questions that are dealt with here include:

- *How to formulate and solve the combined DUESCF problem?*
- *Which is an appropriate convergence criterion for the proposed solution approach?*

4.1 DUE problem

4.1.1 Notations

P:	Set of paths in the network
W:	Set of O-D pairs in the network
k:	Vehicle type
l:	A set of demand and expected time of arrival
Q_{ij}:	O-D demand between $(i, j) \in W$
Q_{ijk}:	O-D demand between O-D pair (i, j), corresponding to vehicle type k
Q_{ije}:	Demand corresponding to SAV empty trips
PR:	Penetration rate for SAV services
P_{ij}:	Subset of paths that connect O-D pair (i, j)
P_{ijk}:	Subset of paths that connect O-D pair (i, j), corresponding to vehicle type k
P_{ijl}:	Subset of paths that connect O-D pair (i, j), corresponding to vehicle type k and set of demand and expected time of arrival 'l'
$[t_0, t_f]$:	Planning horizon starting and ending time
t:	Continuous time parameter in the planning horizon $[t_0, t_f]$
$\wedge$:	Set of feasible path departure vector
$h_p(t)$:	Departure rate along path p at time t
$h(t)$:	Vector of departure rates; $h(t) = (h_p(t) : p \in P)$
h:	Matrix of departure rates
h^*:	Matrix of departure rates corresponding to DUE

$P_{\wedge_0}[.]$: Minimum-norm projection operator
Ψ: Effective delay operator (could be combination of travel time, arrival time & road pricing)
$\Psi(h^*)$: Matrix of travel cost (effective delay) under departure profile h^*
$\Psi_p(t, h)$: Travel cost along path p with departure time t, under departure profile h
α: A fixed constant
v_{ij}: Dual variable
S: Set of origins
P^o: Set of paths originating from $o \in S$
$D_o(t)$: Demand at origin $o \in S$ at time instant t
M: A large arbitrary number, e.g. larger than the flow capacity of link j
$A^J(t)$: Flow distribution matrix of junction J at time instant t
$D_p(t, h)$: Travel time in path $p \in P$ at time instant t, under departure profile h
$S_i(t)$: Supply of link i at time instant t
$D_i(t)$: Demand in link i at time instant t
$f_i^{in}(t)$: Inflow of link i
$f_i^{out}(t)$: Outflow of link i
$N_i^{up}(t)$: Cumulative link entering count
$N_i^{dn}(t)$: Cumulative link exiting count
C_i: Capacity of link i
L_i: Length of link i
v_i: Speed of forward-propagating waves in link i
w_i: Speed of backward-propagating waves in link i
ρ_i^{jam}: Jam density of link i
$\rho_i(t, x)$: Traffic density in a link i at time instant t and location x
$\mu_i^p(t, x)$: Percentage of flow on link i that belongs to path p at time instant t and location x (link entrance and exit); Path disaggregation variable
$\alpha_{ij}(t)$: Turning ratios of cars discharged from link i that enter downstream link j, calculated at time instant t
$[a_i, b_i]$: Entrance and exit of link i
$\Theta(.)$: A junction model
m: No. of incoming links to a junction
n: No. of outgoing links from a junction
$q_o(t)$: Volume of point queue at the origin node $o \in S$
$\tau_i(t)$: Entry time of link i corresponding to exit time t
$\lambda_i(t)$: Exit time of link i corresponding to entry time t
K: Iteration count of the fixed-point algorithm
β: Path flow adjustment parameter (step size) of fixed-point algorithm

4.1.2 Formulation and solution

The objective of the DUE model is to find dynamic user-optimal flows over the network. Recently, Han et al. (2019) developed a fixed point algorithm to solve a SRDTC DUE model formulated as a fixed-point problem as shown in Equation 4.1.

$$h^* = P_{\wedge_0}[h^* - \alpha\Psi(h^*)] \tag{4.1}$$

$$\wedge = \left\{ h \geq 0 : \sum_{p \in P_{ij}} \int_{t_0}^{t_f} h_p(t)dt = Q_{ij} \quad \forall (i,j) \in W \right\} \tag{4.2}$$

Equation 4.1 represents the fixed-point re-statement of the DUE problem using optimal control theory (See Friesz (2010) fo more info) and the expression for set of feasible path departure vector is shown in Equation 4.2. The DUE problem from Han et al. (2019) allows for only one type of vehicle class and in order to model different classes of vehicles, i.e., conventional private vehicles and SAVs, the author duplicates the path set (P_{ij}; the set of paths that connect each O-D pair), one set per vehicle type. This would allow easy extraction of path and departure time choice of the trips belonging to the respective classes, although vehicle characteristics of the two classes were not differed. A new index, $k \in K$ (Equation 4.3), has been introduced for the path set of each vehicle class. Similarly, Han et al. (2019) allows for only one set of demand and expected time of arrival per O-D pair. Though the users (both vehicle type) travelling between an origin and destination might have a single expected time of arrival, the expected time of arrivals for SAV empty trips (dispatch, relocation and collection trips) would be different and this necessitates the inclusion of multiple sets of demand and expected time of arrival per O-D pair. In order to overcome the limitation in the original model, again path duplication is implemented and the number duplicated sets depend on the number of sets of demand and expected time of arrival per O-D pair. As done for previous case, a new index, $l \in L$, has been introduced to represent each path set corresponding to one set of demand and expected time of arrival. The following holds upon inclusion of the two above mentioned indexes:

$$k = \begin{cases} 1, & \text{for private vehicles} \\ 2, & \text{for SAVs} \end{cases} \tag{4.3}$$

$$P_{ij} = P_{ij1} \cup P_{ij2} \quad \forall (i,j) \in W \tag{4.4}$$

$$P_{ijk} = P_{ijk1} \cup P_{ijk2} ... \cup P_{ijl} \quad \forall k \in K \tag{4.5}$$

$$\sum_{p \in P_{ijk}} \int_{t_0}^{t_f} h_p(t)dt = Q_{ijk} \quad \forall k \in K \tag{4.6}$$

$$Q_{ijk} = \begin{cases} (1 - PR)Q_{ij}, & \text{if } k = 1 \\ PR(Q_{ij}) + Q_{ije}, & \text{if } k = 2 \end{cases} \tag{4.7}$$

Han et al. (2019) formulated DNL as a Differential Algebraic Equation (DAE) system and the same is presented below:

$$\frac{d}{dt} q_0(t) = \sum_{p \in P^0} h_p(t) - min\{D_0(t), S_j(t)\} \tag{4.8}$$

$$D_0(t) = \begin{cases} M, & \text{if } q_0(t) > 0 \\ \sum\limits_{p \in P^0} h_p(t), & \text{if } q_0(t) = 0 \end{cases} \tag{4.9}$$

$$D_i(t) = \begin{cases} f_i^{in}\left(t - \frac{L_i}{v_i}\right), & \text{if } N_i^{up}\left(t - \frac{L_i}{v_i}\right) = N_i^{dn}(t) \\ C_i, & \text{if } N_i^{up}\left(t - \frac{L_i}{v_i}\right) > N_i^{dn}(t) \end{cases} \tag{4.10}$$

$$S_j(t) = \begin{cases} f_j^{out}\left(t - \frac{L_j}{v_j}\right), & \text{if } N_j^{up}(t) < N_j^{dn}\left(t - \frac{L_j}{w_j}\right) + \rho_j^{jam} L_j \\ C_j, & \text{if } N_j^{up}(t) < N_j^{dn}\left(t - \frac{L_j}{w_j}\right) + \rho_j^{jam} L_j \end{cases} \tag{4.11}$$

$$N_i^{dn}(t) = N_i^{up}(\tau_i(t)), \quad N_i^{up}(t) = N_i^{dn}(\lambda_i(t)) \tag{4.12}$$

$$\left([f_i^{out}(t+)]_{i=1,...,m}, [f_j^{in}(t+)]_{j=1,...,n}\right) = \Theta\left([D_i(t)]_{i=1,...,m}, [S_j(t)]_{j=1,...,n}; A^J(t)\right) \tag{4.13}$$

$$\mu_j^p(t, a_j) = \frac{f_i^{out}(t)\mu_i^p(\tau_i(t), a_i)}{f_i^{in}(t)} \quad \forall\, p\ s.t.\ \{i, j\} \subset p \tag{4.14}$$

$$A^J(t) = \alpha_{ij}(t); \quad \alpha_{ij}(t) = \sum_{p \ni i,j} \mu_i^p(\tau_i(t), a_i) \tag{4.15}$$

$$\sum_{i=1}^{m} f_i(\rho_i(t, b_i)) = \sum_{j=1}^{n} f_j(\rho_j(t, a_j)) \quad \forall\, t \in [t_0, t_f] \tag{4.16}$$

$$f_i(\rho_i(t, b_i)) \leq D_i(\rho_i(t, b_i-)), \quad f_j(\rho_j(t, a_j)) \leq S_j(\rho_j(t, a_j+)) \;\; \forall\, i \in \{1, ..., m\},\ j \in \{1, ..., n\} \tag{4.17}$$

$$\frac{d}{dt} N_i^{up}(t) = f_i^{in}(t), \quad \frac{d}{dt} N_i^{dn}(t) = f_i^{out}(t) \tag{4.18}$$

$$D_p(t, h) = \lambda_s \circ \lambda_1 \circ \lambda_2 ... \circ \lambda_K(t) \quad p = \{1, 2, ..., K\} \tag{4.19}$$

Equations 4.8 and 4.9 are related to the point-queue model, which is included to take care of dynamics at the origin nodes. If the departure rate from an origin node exceeds the flow capacity of the first link, a queue is formed. Equation 4.8 conveys that the change in volume of point-queue per time instant is the difference between the flow entering the queue and the flow exiting the queue. Link supply and demand, which indicates the maximum flow that can enter and exit a link, based on variational formulation (Lax-Hopf formula) is given by the Equations 4.10 and 4.11. The relationship between cumulative link entering and exiting counts is shown in Equation 4.12. Equation 4.13 represents a junction model for modelling the dynamics at the junctions (nodes with incoming and outgoing links), whose inputs will be $D_i(t)$, $S_j(t)$ and $A^j(t)$ and outputs will be outflows from the incoming links and inflows to the outgoing links. The flow distribution matrix ($A^j(t)$) required for the junction model is formed using Equation 4.15 and the path disaggregation variable, which is necessary for forming the flow distribution matrix, is calculated using the Equation 4.14. The junction model should satisfy the flow conservation constraint (4.16) and the demand-supply constraints (4.17). Equation (4.16) means that the total flow through a junction is conserved and Equation (4.17) ensures the physical feasibility of the flows through a junction. The change in cumulative link entering count per time instant for link i is equal to the inflow to the link i and the cumulative link exiting count is equal to the outflow from the link i, as shown in Equation 4.18. Finally, Equation 4.19 gives the path travel time corresponding to the departure time t with departure rate h. To summarize, Equations 4.8 and 4.9 are related to queueing at the origin nodes (source model), Equations 4.10, 4.11 and 4.12 to the link dynamics (link model) and Equations 4.13, 4.14, 4.15, 4.16 and 4.17 to the junction dynamics (junction model). While Equation 4.18 is used to calculate the cumulative link entering and exiting link counts for subsequent time instants, Equation 4.19 is used to calculate path travel time for a vehicle departing at time instant t.

The above presented DAE system is time-discretized and solved in a forward fashion as shown in Figure 4.1.

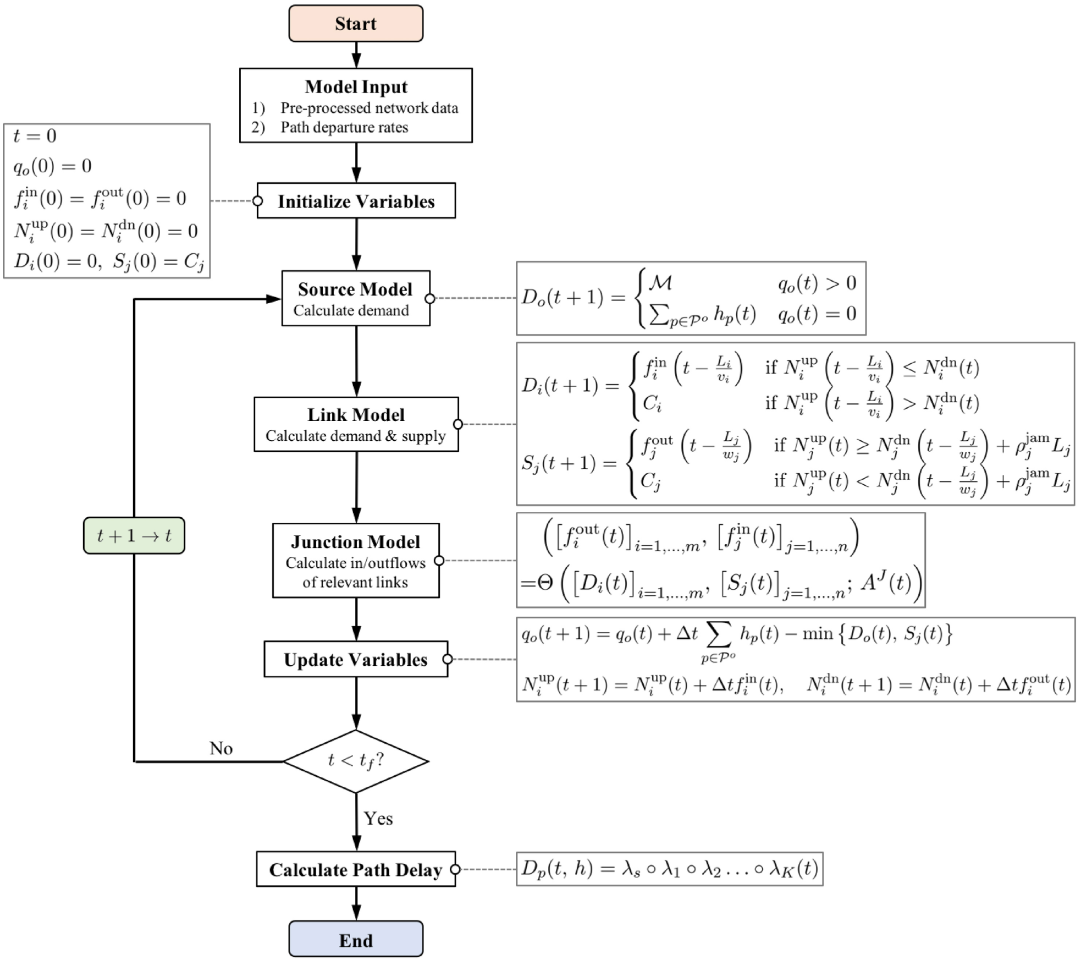


Figure 4.1: DAE system solution approach (Han et al., 2019)

Following solution approach for DUE developed by Han et al. (2019) is implemented:

Step 0: **Initialization** - Select a suitable value for the constant α such that $\alpha > 0$ and an initial departure rate vector $h^0 \in \wedge$.

Step 1: **DNL** - Using the departure rate vector $h^K \in \wedge$, execute the dynamic network loading procedure as shown in 4.1 to compute the effective path delays $\Psi_p(t, h^K)\ \forall\ t \in [t_0, t_f]$ and $p \in P$.

Step 2: **Fixed-point update** - Solve the following equation for the dual variable v_{ij} for every O-D pair $(i,j) \in W$ using a standard root-finding algorithm:

$$\sum_{p \in P_{ij}} \int_{t_0}^{t_f} \left[h_p^K(t) - \alpha\Psi_p(t, h^K) + v_{ij}\right]_+ dt = Q_{ij} \tag{4.20}$$

where $[v_{ij}]_+ \doteq max\{0, x\}$ assures non-negativity. Compute $h_p^{K+1}(t)$ using the following equation:

$$h_p^{K+1}(t) = \left[h_p^K(t) - \alpha\Psi_p(t, h^K) + v_{ij}\right]_+ \quad \forall t \in [t_0, t_f] \text{ and } p \in P_{ij} \tag{4.21}$$

Step 3: **Convergence test** - If the following convergence criterion is satisfied

$$\frac{|| \ h^{K+1} - h^K \ ||^2}{|| \ h^K \ ||^2} \leq \epsilon \tag{4.22}$$

h^{k+1} is the DUE solution. If convergence criterion is not satisfied, adjust the value of h_p^{k+1} based on the Equation 4.23, update $k = k + 1$ and repeat step 1-3.

$$h_p^{K+1} = \beta h_p^K + (1 - \beta)h_p^{K+1} \quad \forall t \in [t_0, t_f] \text{ and } p \in P_{ij} \tag{4.23}$$

where,

$$\beta = \left(\frac{1}{1 + K}\right)^{0.9} \tag{4.24}$$

For more details on the formulation and the solution approach, the readers are recommended to read Han et al. (2019) and the references mentioned in that study.

4.2 SCF problem

The objective of a SCF problem is to form optimal SAV chains for efficiently serving service requests. A SAV chain represents the sequence of requests served by a single SAV. For a more detailed description of SAV chains, the readers are referred to Shun Su (2018). A SAV chain consists of four types of trips namely dispatch, service, relocation and collection trips. A dispatch trip is a trip from depot to the origin of a customer request and a service trip is a trip that fulfils one customer request. A trip between the destination of one customer request to the origin of another customer request is a relocation trip and a trip between destination of a customer request to depot is a collection trip. In the current formulation, each trip will be represented by a link, i.e., a dispatch trip will be represented by one dispatch link, a service trip by one service link and so on. To make required fleet size as an implicit variable of the formulation, a virtual link, which represents flow of SAVs from a depot to the same depot, with null cost is introduced. Vehicles that do not serve any customer request will use the virtual link. For more info on virtual link, the readers are referred to Ma et al. (2017). The SAV network will consist of a number of dispatch, service, relocation and collection links and one virtual link and each of these will have an associated decision variable.

4.2.1 Notations

I:	Set of trip demands in a planning horizon $[t_0, t_f]$
G(N, A):	SAV network graph

N:	Set of all nodes in the network (service and depot nodes)
o:	Origin depot node
d:	Terminal depot node
$A1$:	Set of service links with each link representing one service trip ($i \in I$)
$A2$:	Set of feasible relocation links (relocation links with travel time less than the difference between drop-off time of preceding service trip and the pick-up time of the subsequent service trip)
$A3$:	Set of dispatch links
$A4$:	Set of collection links
$A5$:	Virtual link
A:	Set of all links in the network ($A_1 \cup A_2 \cup A_3 \cup A_4 \cup A_5$)
c_{ij}:	Cost of using a link (i, j)
x_{ij}:	Number of vehicles using a link (i, j); Decision variable
m_{ij}:	Capacity of a link (i, j)
F:	Available fleet size
l_i:	Penalty for loosing a service trip
d_{ij}:	Driving cost in a relocation link; for A_2 links
p_{ij}:	Parking cost when using a relocation link; for A_2 links
f:	Fleet cost per vehicle to account SAV maintenance and refuelling at the depot
d_i:	Cost for dispatching a SAV to the first service trip; for A_3 links
d_j:	Cost for collecting a SAV from the last service trip; for A_4 links
VO_{ij}:	Vehicle occupancy in a service link; for A_1 links

4.2.2 Formulation and solution

Ma et al. (2017) formulated the SCF problem as an integer problem and then proved that the formulated problem is equivalent to a linear problem. The final linear problem from Ma et al. (2017) is presented below:

$$\min \sum_{(i,j) \in A} c_{ij} x_{ij} \tag{4.25}$$

Subject to

$$x_{ij} \leq m_{ij} \quad \forall (i,j) \in A \tag{4.26}$$

$$\sum_{j \in N \setminus \{d\}} x_{ji} = \sum_{j \in N \setminus \{o\}} x_{ij} \quad \forall i \in N \setminus \{o, d\} \tag{4.27}$$

$$\sum_{j \in N \setminus \{o\}} x_{ij} = F, i = o \tag{4.28}$$

$$\sum_{j \in N \setminus \{d\}} x_{ji} = F, i = d \tag{4.29}$$

$$x_{ij} \geq 0 \quad \forall (i,j) \in A \tag{4.30}$$

where,

$$c_{ij} = \begin{cases} -l_i, & \text{if (i,j) } \in A_1 \\ d_{ij} + p_{ij}, & \text{if (i,j) } \in A_2 \\ f + d_i, & \text{if (i,j) } \in A_3 \\ d_j, & \text{if (i,j) } \in A_4 \\ 0, & \text{if (i,j) } \in A_5 \end{cases} \tag{4.31}$$

$$m_{ij} = \begin{cases} 1, & \text{if (i,j) } \in A \setminus A_5 \\ F, & \text{if (i,j) } \in A_5 \end{cases} \tag{4.32}$$

Objective function of this problem is the total cost of the SAV service, as can be seen in Equation 4.25. While Equation 4.26 is the standard link capacity constraint, flow conservation at the intermediate nodes (nodes other than depot nodes) is satisfied by using the Equation 4.27. While the SAVs serving customer requests depart from depot through depot links and return to depot through collections links, idle SAVs depart from and return to depot through the virtual link, i.e., all the SAVs should depart from depot and return to the depot. This condition is ensured by the Equations 4.28 and 4.29. Equation 4.30 states that the value for the decision variable should be positive. In the original integer formulation, the decision variable is designated as an integer variable and in the final linear problem, though the decision variable is designated as a continuous positive variable, the value obtained will be an integer since the constraint matrix is totally unimodular. For more details on the formulation, the readers are recommended to read Ma et al. (2017). As shown in Equation 4.31, the cost associated with a dispatch link is d_i along with fleet cost f and the cost associated with a collection link is d_j. Relocation links have a sum of driving cost for relocation and a parking cost and a penalty cost, l_i, is attached to the service links. Usage of virtual link does not incur any cost. Finally, the capacity of the links are defined in Equation 4.32.

It should be noted that the above presented model is formulated only for SAV carsharing service and in order to extend it to include ridesharing, the author employs a pre-processing technique. Users with same O-D pair and expected time of arrival are considered to be eligible for ridesharing, which is usually called as O-D ridesharing. The number of people willing to share the ride, i.e., ridesharing penetration rate and the vehicle occupancy rate are taken as an input. The ridesharing demand is calculated by dividing the number of trips available for sharing (equal to the number of people willing to share the ride) by the vehicle occupancy rate. This data will be used to calculate the modified service demand. In the original formulation I will represent original demand, i.e., all the trip requests, but in the current scenario, I will represent the modified demand. For example, a total demand of 50 trips for SAV services and 10% exclusively for ridesharing services with vehicle occupancy of 5 mean a demand of $45 + (5/5) = 46$ trips. If the given vehicle occupancy is 3, then the ridesharing demand will be 2 trips with one trip consisting of 3 customers and the other with 2 customers. The modified demand in this case (given vehicle occupancy of 3) will be 45+2=47 trips.

Further, to ensure priority for servicing the high occupancy trips when the available SAVs are inadequate, the penalty for loosing a serving a trip ($-l_i$ in Equation 4.31) will be multiplied by the occupancy rate. Thus, Equation 4.31 becomes:

$$c_{ij} = \begin{cases} -VO_{ij} * l_i, & \text{if (i,j) } \in A_1 \\ d_{ij} + p_{ij}, & \text{if (i,j) } \in A_2 \\ f + d_i, & \text{if (i,j) } \in A_3 \\ d_j, & \text{if (i,j) } \in A_4 \\ 0, & \text{if (i,j) } \in A_5 \end{cases} \tag{4.33}$$

VO_{ij} can be a distribution or a constant value and based on the input, each service trip will have an associated VO_{ij}. Since vehicle occupancy is a manual input, inclusion of it in the SCF formulation does not make the formulation non-linear. On the other hand, inclusion of it forces the model to assign vehicles for the high occupancy trips first, because of high penalty for loosing such trips, and then the single occupancy car sharing trips. With regards to solution for this formulation, any linear program can be used.

4.3 DUESCF problem

4.3.1 Notations

r:	Departure rate which captures both departure time choice and path choice of the road users (h^* in DUE model)
R:	Feasible set of departure rate ($\wedge$ in DUE model)
ω:	Vector of SAV chains (x_{ij} in SCF model)
Ω:	Feasible set of SAV chain vector
$Fp(R, F)$:	DUE problem formulated as a fixed-point system (Equation 4.1)
$F(r)$:	Cost function, based on the DNL model used (Equation 4.19)
C:	Cost (travel time) in the network for a given r (Matrix of $D_p(t)$)
$G(\omega, C)$:	Objective function of SCF problem (Equations 4.25)
$g(\omega, C)$:	Constraints of SCF problem (Equations 4.26 - 4.30)
CG:	Cost gap
PFG:	Path flow gap
X:	Iteration count of the IOA algorithm
TC:	Total Cost from SAV chain formation model

4.3.2 Formulation

The DUESCF problem can be formulated as a game between group of road users and SAV service operator, wherein both players try to maximize their utilities by rationally making their decisions. The road users select appropriate paths and departure times to minimize their own costs (travel time) leading to dynamic user equilibrium and the SAV service operator tries to form appropriate SAV chains to optimize the system performance, i.e., to minimize the total system travel time of the SAV operation. The final objective of this formulation is to find a traffic assignment and SAV chain formation such that both road users and SAV service operator obtain their optimal solutions, thus forming a Nash equilibrium (see Fudenberg and Tirole, 1991 and Holt and Roth, 2004 for more information about game theory and Nash equilibrium).

The two players make their decisions (r for road users and ω for SAV service operator) to minimize their own costs without any knowledge about the other player's performance function, i.e., the strategy of one player is not pre-known to. This implies that no player has any advantage over the other. The road users try to obtain minimum cost while considering that the SAV chains finalized by the SAV operator might affect the traffic levels and travel time in the road network. On the other hand, the SAV service operator tries to minimize the total system cost, while taking into account that road users may change their routes or departure time.

At Nash equilibrium, no player is better off by unilaterally changing their decisions. If the road users change their path flow pattern while the SAV chains are kept the same, they may not be in equilibrium. On the other hand, if the SAV service operator alters the SAV chains while the path flow pattern of road users is unchanged, the total system cost will increase or at least be equal to the previous cost. This game can be formulated as a bilevel problem.

A multilevel program in which only two levels are present is called a bilevel program (Ben-Ayed, 1993). For information on bilevel programs, the readers are referred to Dempe (2002) and Sinha et al. (2018). A bilevel program based on game theory comprises of a leader and a follower of equal status. Each has his/her own decision variables and objective function. The leader can use his own decision variables to influence (but not dictate) the reactions of the follower. The follower optimizes his/her objective function, taking into consideration the decisions of the leader. Thus, a bilevel program based on game theory is equivalent to a DUESCF problem formulated with leader-follower strategy.

Figure 4.2 shows the combined dynamic user equilibrium and SAV chain formation problem formulated as a bilevel problem based on game theory. The goal is to find the Nash equilibrium in which no player has an incentive to change his/her decision unilaterally. For a given demand, which is based on the output (ω) from SCF model, the DUE model computes the user equilibrium departure rates and path flow (r). Based on the departure rates and path flow, the DNL model outputs the travel time values (C) for each path and time instant. Based on the departure rates (r) and travel time values (C), the SCF model forms SAV chains. The SAV service operator optimizes the total system travel time by minimizing SCF objective function $G(\omega, r)$ subject to the SCF constraints.

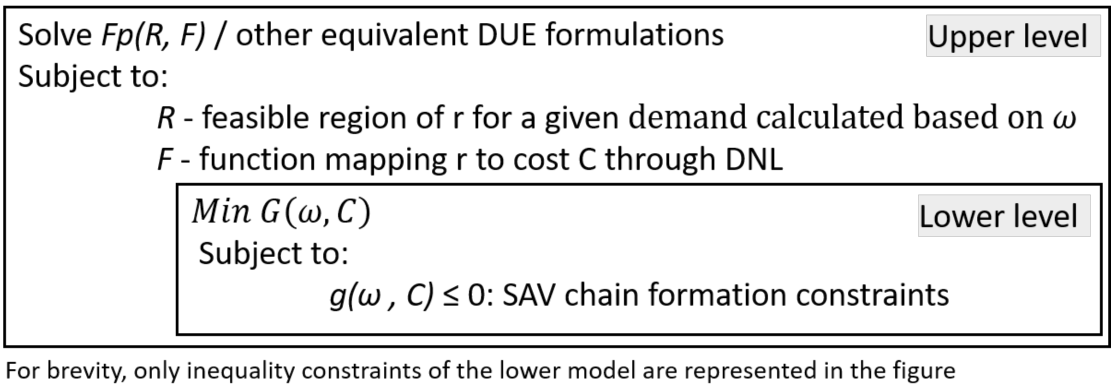


Figure 4.2: DUESCF problem formulation based on game theory

The author believes that this formulation is applicable to a combination of any type of DTA and SCF model. The formulated bilevel problem does not have a closed form and it has not been studied theoretically yet. However, a heuristic algorithm can be developed to solve this game, which will be presented in the next section.

4.3.3 Solution

In a Nash game, no player knows the other player's strategy in advance and hence, it is not possible to solve the problem in one step. The user equilibrium traffic conditions can vary significantly depending upon the SAV chains formed and formed SAV chains cannot be validated until the traffic stabilizes at user equilibrium condition. Therefore, in this section, we propose a heuristic algorithm based on the iterative optimization and assignment (IOA) procedure. IOA procedure is commonly employed for solving combined traffic assignment and signal control problems (Meneguzzer, 2000) and the approach can be adopted for solving the DUESCF problem formulated in this thesis.

The proposed algorithm breaks down the intractable problem into two solvable modules: Dynamic user equilibrium with given demand based on SAV chains and SAV chain formation module with given departure rate pattern. This algorithm includes multiple stages in which each player's decision is based on the other player's decision. If the algorithm converges, the expected optimal solution possesses the properties such that no player has any incentive to deviate unilaterally from his/her optimal strategy. The output from this heuristic algorithm represents a Nash equilibrium since no player has any advantage over the other.

In the proposed heuristic algorithm, we start with the upper level DUE problem using the initial demand, which is an exogenous input. The result (departure rates and travel times) from the DUE model is used to solve the lower level SAV chain formation problem. Based on the SAV chains formed, modified demand is calculated and fed in to the upper level DUE model. The algorithm iterates until the convergence criterion is satisfied. Figure 4.3 shows the heuristic algorithm proposed to solve the DUESCF problem.

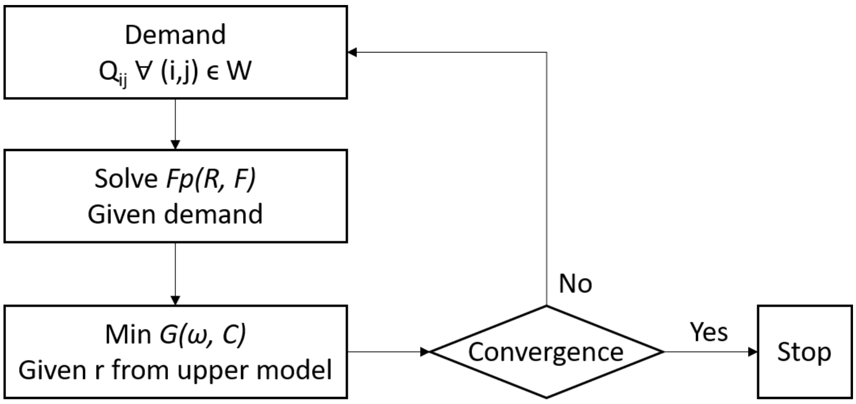


Figure 4.3: DUESCF problem solution algorithm based on IOA

The heuristic algorithm shown in Figure 4.3 can be elaborated as follows:

Step 0: Set demand = input demand.

Step 1: Solve the upper level problem, $Fp(R^X, F^X)$, using fixed-point algorithm (other relevant algorithm in case of other type of formulation) based on the demand to find departure rate (r^X) and cost (travel time; C^X).

Step 2: Given the travel times and departure rates from step 1, solve the lower level problem, $G(\omega^X, C^X)$, using an appropriate solver to obtain th vector of SAV chains (ω^X).

Step 3: Perform the convergence test. If the convergence criterion is not satisfied, recalculate the input demand based on the formed SAV chains (demand corresponding to SAV empty trips will change every iteration). Update X = X + 1 and repeat step 1-3.

The convergence criteria can be considered as the mutual consistency between the two consecutive solutions from both dynamic user equilibrium and SAV chain formation modules. The author proposes the following convergence criteria:

$$CG \; and \; PFG < \epsilon \tag{4.34}$$

where,

$$PFG = \frac{|| \sum\limits_{p \in P_{ijk}} h_p^X - \sum\limits_{p \in P_{ijk}} h_p^{X-1} ||^2}{|| \sum\limits_{p \in P_{ijk}} h_p^{X-1} ||^2} \tag{4.35}$$

$$CG = \left(\frac{| \, TC^X - TC^{X-1} \, |}{TC^{X-1}} \right) 100 \tag{4.36}$$

$$TC = \sum_{(i,j) \in A} c_{ij} x_{ij} \tag{4.37}$$

Chapter 5

Robustness of the proposed solution algorithm

This chapter starts with a description on the assumptions made in the computational experiments, followed by a brief on the modelling process. Later, the model outputs are enlisted and finally, results of the computation experiments on three different networks (2-Node toy, Braess bidirectional and Sioux Falls) are presented. Following research question is answered in this chapter:

- *How good the proposed solution algorithm performs with different networks of varying complexity?*

5.1 Assumptions

- Effective delay in the model, Ψ, will be a linear combination of travel time and arrival time penalties, as shown in Equation 5.1. The term $T_A - T_E$ represents the difference between actual and expected arrival time.

$$\Psi_p(t,h) = D_p(t,h) + (T_E - T_A)^{2\gamma} \tag{5.1}$$

$$\gamma = \begin{cases} 0.8, & \text{for early arrival trips} \\ 1.2, & \text{for late arrival trips} \end{cases} \tag{5.2}$$

- Only single planning horizon is considered $[t_0, t_f]$ and one expected arrival time for all the travellers travelling between an O-D pair.
- As mentioned in Section 4.1.2, vehicle characteristics do not differ within the DUE model.
- SAV service is assumed to be operating with a single depot
- A constant vehicle occupancy is defined for all the vehicle trips, i.e., $VO_{ij} = aconstant$ (e.g., 3).
- Zero fleet cost is assumed for SAV dispatch, i.e., $f = 0$, and the cost associated with the dispatch and collection link will be the travel time in the respective links.
- A value much larger than the maximum path travel time in a network is applied as penalty for loosing a customer request (l_i).
- No parking cost is considered for relocation links, i.e., $p_{ij} = 0$ and the cost associated with the relocation links will be the travel time in the respective links.

5.2 Modelling process

The model gets as input the following data: initial demand, network data, number of SAVs available (F), penetration rate of SAV services (PR) and SAV vehicle occupancy (VO). The demand data includes demand between each O-D pair (Q_{ij}) and the expected time of arrival (T_E). The network data includes network name, node coordinates, link details, path list and the node number of the depot. Required link details are capacity in veh/s, length in m, free flow travel time in s and origin and destination node. The path list should include the link numbers that make up each path. Penetration rates of SAV services in general as well as ridesharing services are required, values of which can range from 0.1 (10%) to 1 (100%). Although the SAV vehicle occupancy value can be any positive number, the model has been tested for a range of 2 to 5 customers per vehicle. The penetration rates and the vehicle occupancy values can be either a single value or a vector for scenario analysis.

The model flow chart is shown in Figure 5.1. Based on the penetration rates given as input, demand for SAV services, both ridesharing and car sharing, is determined along with the calculation of private conventional vehicle demand. For example, a total demand of 100 trips per O-D pair with 0.5 penetration rate for SAV services and 0.1 exclusively for ridesharing services mean a demand of 50 trips for SAV services with 45 trips to be served through car sharing services and 5 trips through ridesharing services. Further, if the vehicle occupancy is 5, then the ridesharing demand will be converted to 1 trip and the demand for SAV services will be 45+1=46 trips (Q_{ij2}). If the given vehicle occupancy is 3, then the ridesharing demand will be 2 trips with one trip consisting of 3 customers and the other with 2 customers. The demand for private vehicles will be 50 trips (Q_{ij1}). The modified demand in this case (given vehicle occupancy of 3) will be 50+45+2=97 trips (Q_{ij}).

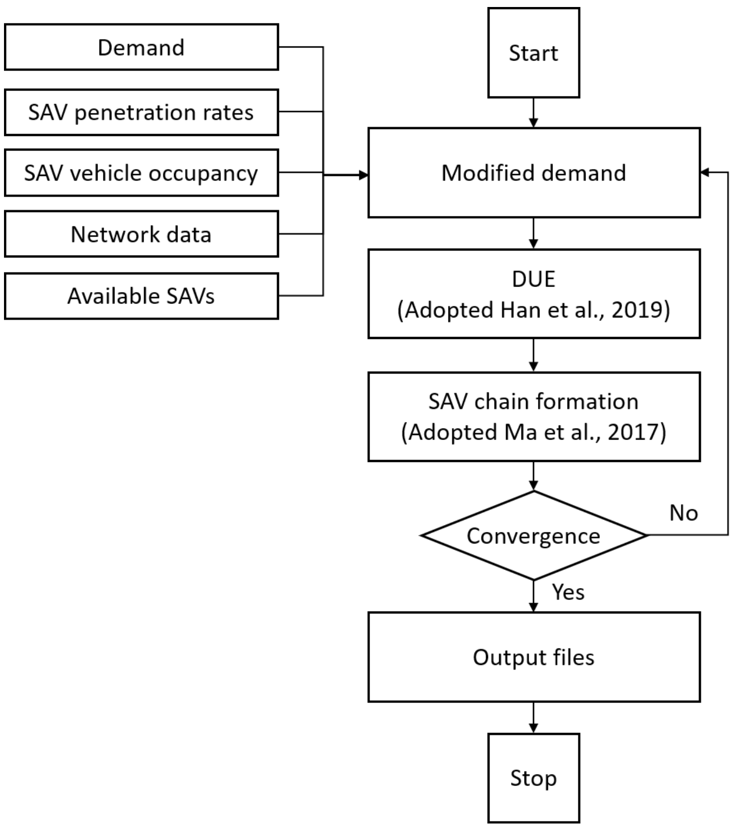


Figure 5.1: Model flow chart

The modified demand calculated as mentioned above is given as input to the DUE model. As mentioned in the previous section, each vehicle type (conventional private vehicles and SAVs) will have their own path set. The output (path departure rates h_* and travel times D) from the DUE model will be used to create requests matrix for the SAV chain formation model. The request matrix will contain details such as origin node, destination node, departure time and path to be used for each trip to be served by a SAV. It should be noted that the departure rate obtained from the DUE model will be in terms of veh/s and this has to be converted into number of trips departing in a time instant. This is achieved by multiplying the departure rate with time step size of the DUE model and then rounding off the value to the nearest decimal. During this conversion, rounding off issues might arise which would result in a difference between total trips based on original values and rounded off values. In order to negate this difference, three steps of checking are performed. In the first step, total trips within a path (Equation 5.3) are compared before and after rounding off, followed by a comparison of the values corresponding to single path set between an O-D pair (Equation 5.4). Due to the path duplication done to include different expected time of arrival (as mentioned in Section 4.1.2), each O-D pair can have multiple path sets and the final checking is done by comparing the summed values before and after rounding off from all the path sets of an O-D pair (Equation 5.5). The discrepancy will usually be one or two trips. Any discrepancy found in the first step will be assigned to the time instant with maximum departure rate. Random assignment and assignment to time instant with minimum departure rates were also tried out but the assignment based on maximum departure rate was found to yield better result for convergence of the proposed solution algorithm. Any discrepancy found in the second and third step will be assigned to the path with maximum departure rate and within the selected path, again, time instant with maximum departure rate is chosen. Next step in the process is to differentiate carsharing and ridesharing trips and this is done by randomly selecting the trips and assigning them as ridesharing trips.

$$\int_{t_0}^{t_f} h_p(t)dt \quad \forall p \in P_{ijkl}, k = 2, l \in L, (i,j) \in W \tag{5.3}$$

$$\sum_{p \in P_{ijkl}} \int_{t_0}^{t_f} h_p(t)dt \quad \forall k = 2, l \in L, (i,j) \in W \tag{5.4}$$

$$\sum_{p \in P_{ijk}} \int_{t_0}^{t_f} h_p(t)dt \quad \forall k = 2, (i,j) \in W \tag{5.5}$$

Based on the data from the request matrix, the SAV chain formation model forms the SAV chains (x_{ij}). Departure time and paths for SAV dispatch trips are chosen based on the departure time of the service trips and for the collection trips, arrival time of the service trips is considered as basis. Departure time and paths for relocation trips are decided based on the arrival time of preceding service trip and the departure time of the next service trip. After forming SAV chains, convergence is checked (Equation 4.34) and if the convergence criterion is satisfied, the model publishes the output files (described in Section 5.3). If the convergence criterion is not satisfied, then the SAV chains are converted as individual trips and modified demand (inclusion of SAV empty trips Q_{ije}) is calculated. The process is iterated until the convergence criterion is satisfied.

5.3 Model outputs

The entire solution algorithm was developed in Matlab. With regards to upper level DUE model (Han et al., 2019), the Matlab code for the model was directly available in GitHub (`https://github.com/DrKeHan/DTA`) and the same had been utilised after implementing the necessary modifications mentioned in Section 4.1.2. Concerning the lower level SCF model (Ma et al., 2017), the code for the model was not directly available and hence, has been self-coded by the author. The required modifications mentioned in Section 4.2.2 were then applied and CPLEX for Matlab (an extension to access IBM ILOG CPLEX Optimizer in Matlab) was used to solve it.

The model outputs several plots and CSV files. Following plot files are exported as images:

- Variation of convergence parameter 1 (PFG) in a single scenario
- Variation of convergence parameter 2 (CG) in a single scenario
- Elapsed time plot 1 (running time per iteration of different components of the script for a single scenario)
- Elapsed time plot 2 (total running time of different components of the script per scenario; running time of all the iterations per scenario summed up)
- Elapsed time plot 3 (mean running time of different components of the script per scenario)
- Maximum travel time in each path per iteration for a single scenario

Following data (called as *output variables*) are exported to a MAT file (native data file of Matlab) for each scenario: travel time matrix from each iteration, path flows from each iteration, O-D gap from the DUE model for each iteration, maximum travel time in the paths during each iteration, requests matrix from each iteration created by DUE to SAV chain data conversion script and route matrix of the SAVs from each iteration.

A CSV file is exported for each scenario with the following data: iteration number, SAV service total cost, total system cost (total travel time of conventional private vehicles and SAVs), number of DUE iterations, path flow gap (Equation 4.35), cost gap (Equation 4.36), DUE model elapsed time, DUE to SAV chain data conversion script elapsed time, SAV chain formation model elapsed time, SAV chain to DUE data conversion script elapsed time, time elapsed for storing variables for the MAT file mentioned above. Another CSV file is exported to store the route data of SAVs from the final iteration of each scenario.

5.4 Computational experiments

Since the DUESCF problem is not yet explored in literature, there are no benchmark instances to which the performance of the proposed solution algorithm can be compared to. Therefore, numerical tests on three networks of varying complexities were conducted to ensure the efficiency and robustness of the proposed solution algorithm. Different parameters for the proposed solution algorithm are tested in each of the three networks. The model was run in a PC with Intel core i7-8700 processor running at 3.20GHz and consisting of 16GB RAM, which can execute parallel computation with a maximum of 6 cores.

5.4.1 2-Node toy network

Test on this simple network, shown in Figure 5.2, is performed to establish the optimality of the solution, i.e., chain forming capability of the proposed algorithm along with the consideration for the required number of vehicles, trip travel time and arrival time.

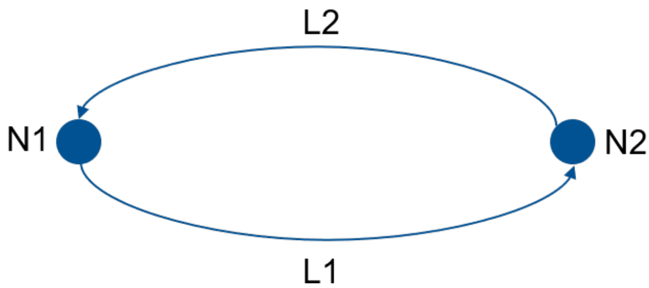


Figure 5.2: 2-Node toy network

The network consists of two nodes (N1 and N2) and two links (L1 and L2). Link L1 connects node N1 and N2 and link L2 connects node N2 and N1. Both the links have a capacity of $1800veh/h$ ($0.5veh/s$) and are of $8km$ length. The free flow travel time in the links is 12 minutes. 100 trips are assumed between N1 and N2 and another 100 trips between N2 and N1. All the 200 trips need to be served by SAVs. The expected time of arrival for the former trips is first hour and the expected time of arrival for the latter trips is fourth hour. A fleet of 200 homogeneous SAVs are available for service during the planning horizon of 300 minutes (5 hours). Depot is assumed to have the capacity to serve the available vehicles and be located at node N1. The planning horizon of 300 minutes is discretized into time intervals of 2 minutes i.e., the DUE is modelled with a time step size of 2 minutes and the convergence threshold for the DUE model is set as 0.0001.

The test result showed that the convergence value corresponding to both the upper level (4.35) and lower level (4.36) models converge to 0, thus indicating that both road users and the SAV operator do not have an incentive to change their decisions. This shows the establishment of a Nash equilibrium. The output from the model showed that the total number of vehicles required is 100, which is the optimal number of vehicles required. The travel time experienced in all the trips is 12 minutes since the total flow is well below the capacity in all the paths and time instants and this is possible because of the lower total demand. In case of higher demand, though trip departures will get distributed due to departure time choice, congestion can occur and this will be shown in Section 6.2 (scenario analysis using Sioux Falls network). Distribution of departures did not create a large gap between the actual and expected time of arrivals and as expected, the actual arrival times were close to the expected time of arrival. This was attainable because of the absence of congestion. If congestion would have occurred, the actual arrival times might have a wider distribution. The actual arrival time for the N1-N2 trips ranged from hour 0.8 (46th minute) to 1.16 (70th minute) and for N2-N1 trips, the value ranged between hour 3.8 (228th minute) to 4.16 (250th minute). These can be observed in Figure 5.3, where red colour indicates outflow from origin, cyan indicates inflow to destination, violet indicates flow in links, light grey indicates empty link and dark grey indicates empty node. At 46th minute, the first set of vehicles reaches N2 (Figure 5.3b) and the last vehicle reaches at 70th minute (Figure 5.3c). Similarly, the first set of vehicle reaches N1 at 228th minute (Figure 5.3) and the last vehicle reaches at 250th minute (Figure 5.3g).

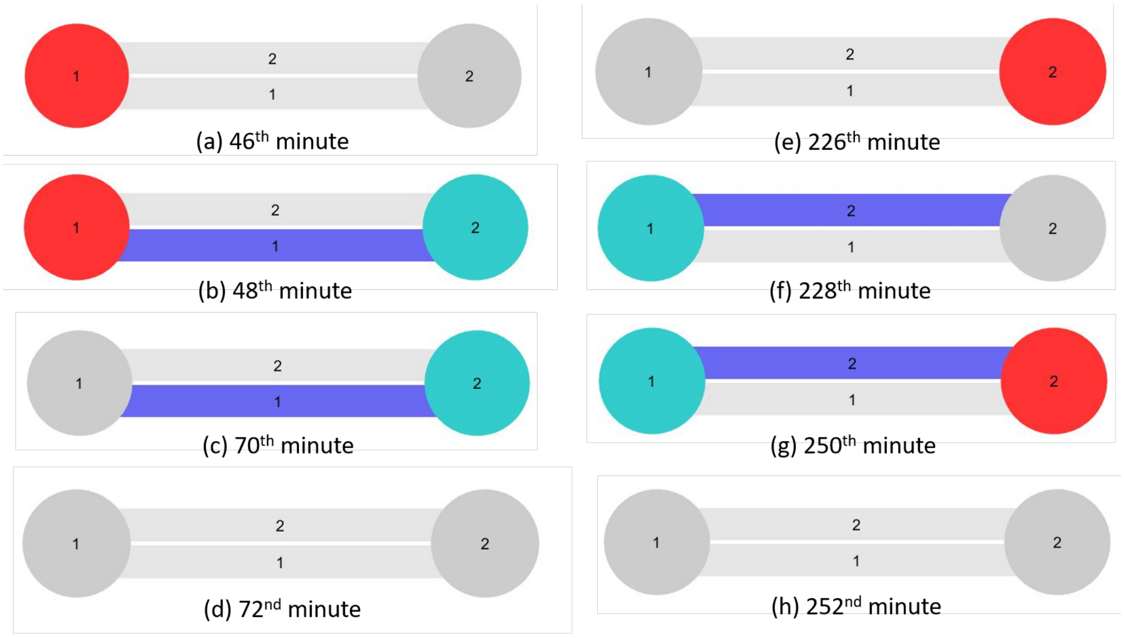


Figure 5.3: Flow in 2-Node toy network based on result from the model

Analysing the route matrix, it was found that each vehicle serves two trips, one N1-N2 trip and one N2-N1 trip. Thus, each vehicle travels from N1 to N2 to serve one N1-N2 trip, parks in N2 and then travels from N2 to N1 to serve one N2-N1 trip. There is no extra dispatch or collection trip since the vehicles start from and end at N1. Also, no relocation trip is found. The results show that an optimal solution can be obtained using the proposed bilevel model.

5.4.2 Braess bidirectional network

The famous Braess paradox network, which originally has unidirectional links between nodes, has been modified to include bidirectional links as shown in Figure 5.4. This network is used to evaluate the robustness and ensure the stability of the proposed algorithm. The robustness of the algorithm will be ascertained by its ability to model different scenarios and its stability will be ascertained based on the convergence for different scenarios. Also, the computation time will be examined.

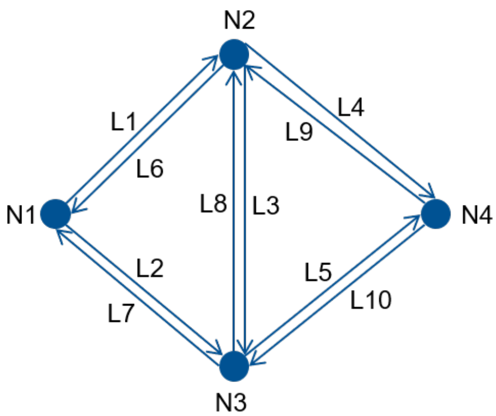
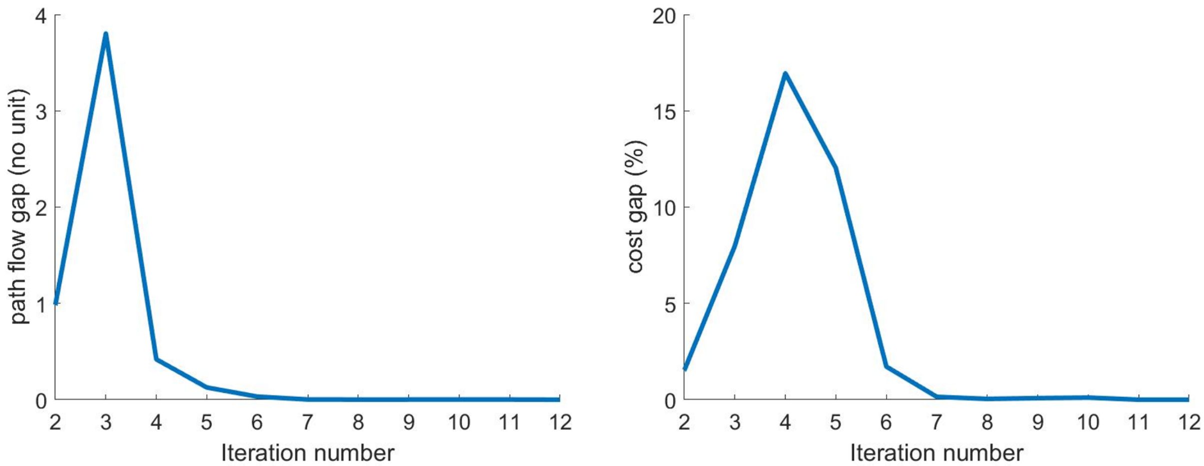


Figure 5.4: Braess bidirectional network

The bidirectional network consists of four nodes (N1 to N4) and ten links (L1 to L10). All the links have a capacity of $1800veh/h$ and are of $7.2km$ length. The free flow travel time in the links is 6 minutes. 100 trips are assumed between all the 12 possible O-D pairs. The expected time of arrival ranges from hour 2.5 to hour 4.0. A fleet of 1200 homogeneous SAVs are available for service during the planning horizon of 300 min (5 hours). Depot is assumed to have the capacity to serve the available vehicles and be located at node N1. DUE is modelled with a convergence threshold of 0.001 and a time step size of 2 minutes.

By varying the SAV service penetration rate (0% to 100% in steps of 10%), ridesharing penetration rate (0% to 100% in steps of 10%) and vehicle occupancy (2 to 5 in steps of 1), 411 scenarios were tested and the model was able to run all the scenarios without any issue. This proves the robustness of the proposed algorithm for running different scenarios. Excepting few cases, for most of the scenarios, the algorithm converged to the convergence value of 0 within 15 iterations (e.g., Figure 5.5 – carsharing only SAV system with 100% penetration rate) with majority around 5 iterations (e.g., Figure 5.6 – ridesharing only SAV system with 50% penetration rate and vehicle occupancy of 5). In few cases, the algorithm did not reach the convergence value of 0 even after 100 iterations (e.g., Figure 5.7). Looking into the convergence plots showed that the algorithm reached a convergence value greater than 0 but lesser than 0.1 within few iterations and stayed around that value thereafter. This could be due to numerical issues. A convergence threshold of 0.1 would be suitable for such cases.



(a) Path flow gap

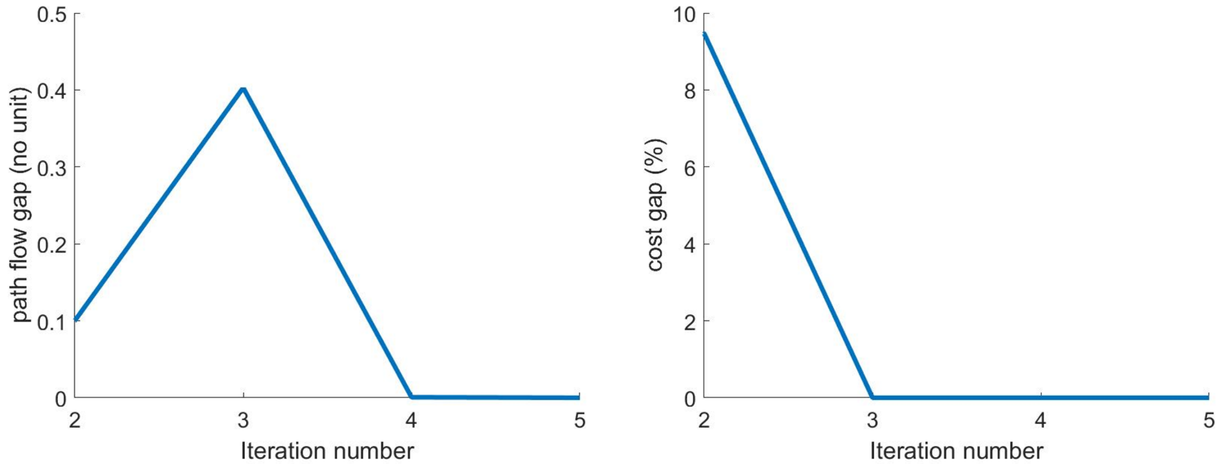
(b) Cost gap

Note: Calculation of convergence parameters involves difference between two consecutive iterations and hence, no value exists for first iteration.

Figure 5.5: Convergence for the Scenario 'Carsharing only SAV system with 100% penetration rate'

The computation time for modelling each scenario ranged from few seconds to around 10 minutes. Inspecting the running time of different parts of the algorithm per scenario showed the following:

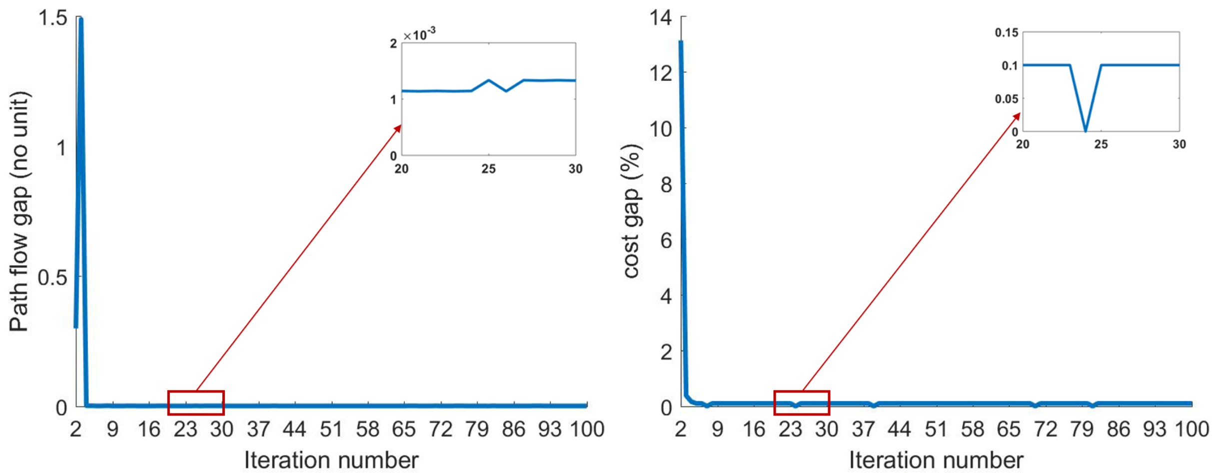
- As observed in Figure 5.8, elapsed time for DUE computation reduces steadily along the iteration of the bilevel model and this is due to the decrease in number of required DUE iterations.



(a) Path flow gap (b) Cost gap

Note: Calculation of convergence parameters involves difference between two consecutive iterations and hence, no value exists for first iteration.

Figure 5.6: Convergence for the Scenario ‘Ridesharing only SAV system with 50% penetration rate and vehicle occupancy of 5’



(a) Path flow gap (b) Cost gap

Note: Calculation of convergence parameters involves difference between two consecutive iterations and hence, no value exists for first iteration.

Figure 5.7: Convergence for the Scenario ‘SAV system with 50% penetration rate - 50% carsharing and 50% ridesharing (vehicle occupancy of 5)’

- Elapsed time for SAV chain formation stays almost constant throughout the iteration process and the same can be observed in Figure 5.8. SAV chain formation computation time depends majorly on number of SAV service requests, which is a constant throughout the bilevel iteration process, and hence, the elapsed time is almost constant.
- As SAV service penetration increases, elapsed time for SAV chain formation increases and a comparison of Figure 5.8 and Figure 5.9 clearly shows the difference in elapsed time for SAV chain formation. This increase in elapsed time is due to the time required

for forming constraints. As the number of service requests increases due to increase in penetration rate, number of possible relocations gets almost squared (n*n-1 to be exact) and this in turn increase the number of constraints. Increase in number of constraints, naturally, increase the time required for forming constraints and hence, the elapsed time for SAV chain formation is also increased.

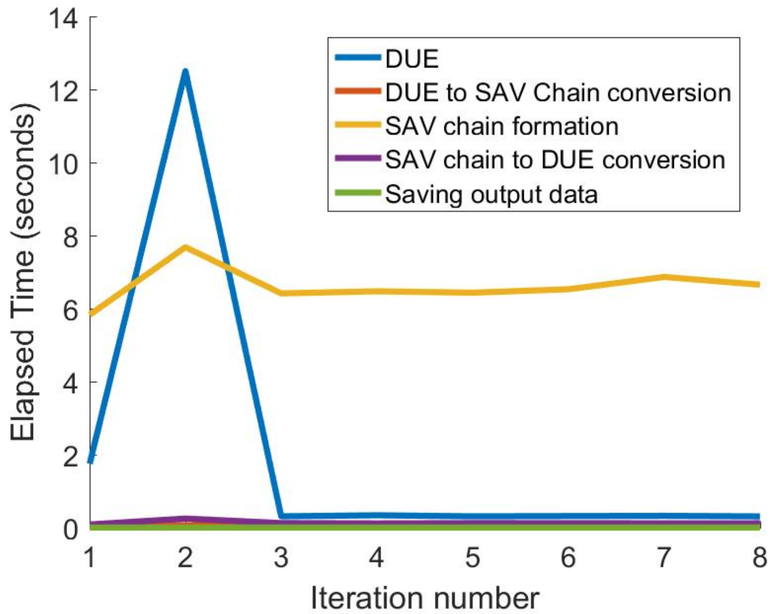


Figure 5.8: Elapsed time for the Scenario 'Carsharing only SAV system with 50% penetration rate'

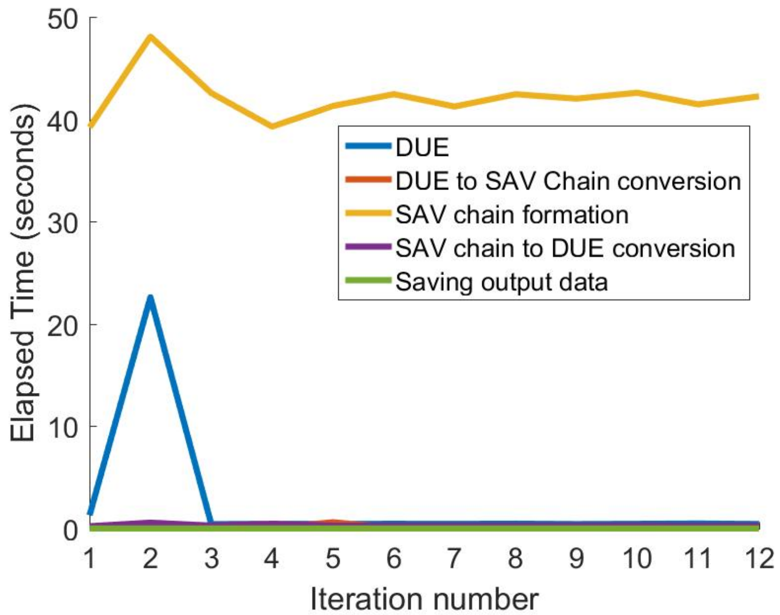


Figure 5.9: Elapsed time for the Scenario 'Carsharing only SAV system with 100% penetration rate'

5.4.3 Sioux Falls network

Last numerical test is performed on Sioux Falls network, shown in Figure 5.10, and the main aim is to evaluate the stability in terms of convergence and robustness of the solution algorithm to model larger networks with zero demand O-D pairs.

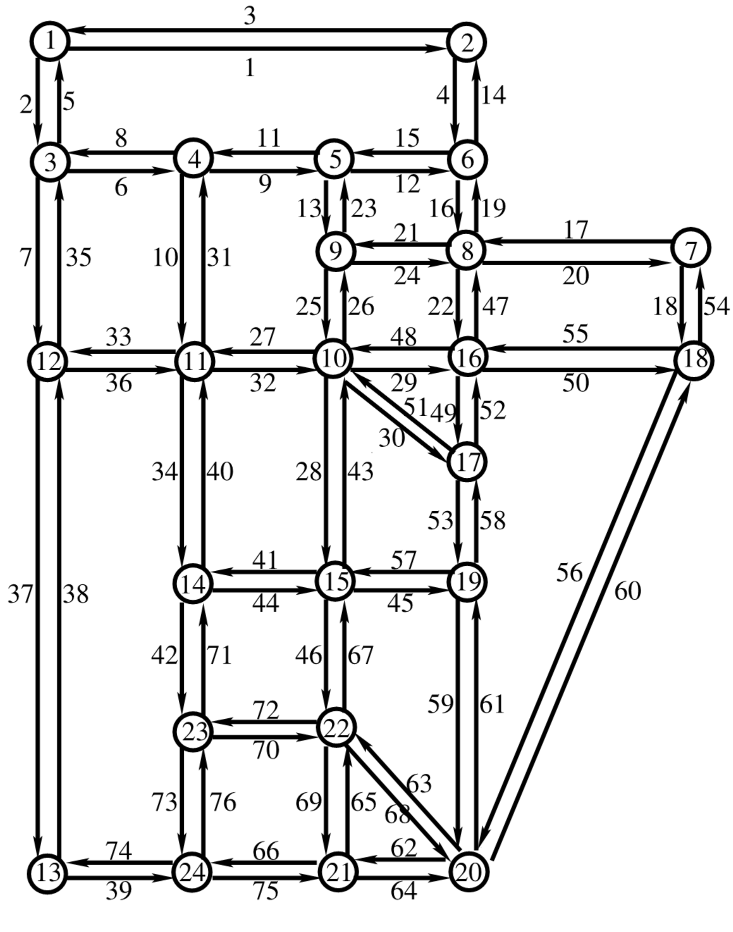


Figure 5.10: Sioux Falls network (Han et al., 2019)

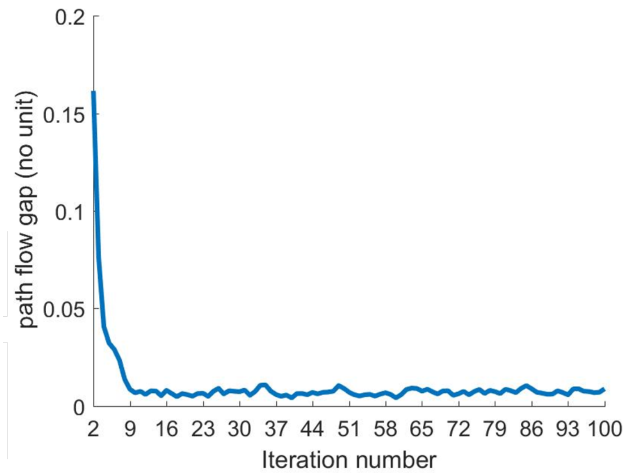
Network and demand data used here are based on the data from the study Han et al. (2019). The network consists of 24 nodes and 76 links. Paths between all the nodes were generated using K-shortest paths algorithm and the total number of paths generated is 716. The total demand in the whole network is 16,896 with majority of the O-D pairs (528 out of 552 O-D pairs) having a demand of 32 trips. Rest of the O-D pairs have a zero demand. The expected time of arrival ranges from hour 3.0 to hour 4.0. A fleet of 8400 homogeneous SAVs (about 50% of the original demand) are available for service during the planning horizon of 360 minutes (6 hours). Depot is assumed to have the capacity to serve the available vehicles and be located at node 1. DUE is modelled with a convergence threshold of 0.001 and a time step size of 2 minutes. A convergence threshold of 0.1 is selected based on the results of test on Braess bidirectional network (5.4.2).

Considering the time limit, only five scenarios will be tested. Based on the review results pertaining to the expected penetration rate of SAV services (3.5.1) and taking into account that the computation time will increase as penetration rate increases, SAV penetration rates of 10% and 20% have been chosen for evaluation. Following five scenarios, apart from the base scenario, have been tested:

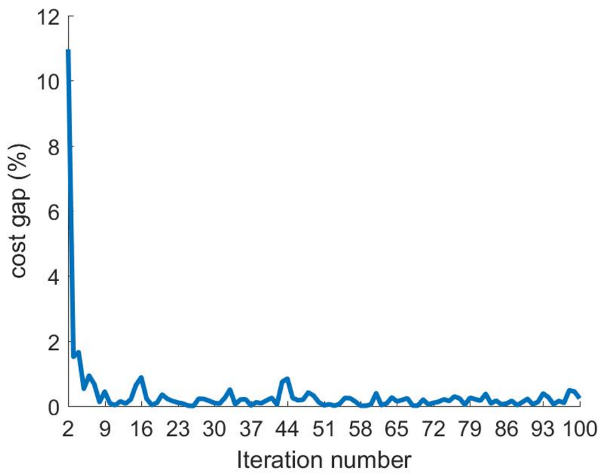
- **Base scenario**: 0% SAV penetration rate (only conventional private cars are used)
- **Scenario 1 (S1)**: Carsharing only SAV system with 10% penetration rate
- **Scenario 2 (S2)**: Ridesharing only SAV system with 10% penetration rate and vehicle occupancy of 3
- **Scenario 3 (S3)**: Ridesharing only SAV system with 20% penetration rate and vehicle occupancy of 2
- **Scenario 4 (S4)**: Ridesharing only SAV system with 20% penetration rate and vehicle occupancy of 3
- **Scenario 5 (S5)**: SAV system with 20% penetration rate - 50% carsharing and 50% ridesharing (vehicle occupancy of 3)

The scenarios have been chosen in a way to include a carsharing only SAV system, a ridesharing only SAV system with two different vehicle occupancy rates and a mixed SAV system consisting of both carsharing and ridesharing. This selection enables evaluation of the ability of the solution algorithm to model different SAV systems. Also, the selected scenarios support in finding the effect of carsharing, ridesharing and vehicle occupancy on the total system travel time, traffic congestion level and vehicle requirements, which will be reported in Chapter 6.

The model was able to run all five the scenarios without issues, ensuring the algorithm's ability to model different SAV systems and also proving its stability and robustness when modelling larger networks with zero demand O-D pairs. Concerning convergence, as can be seen in Figure 5.11 to Figure 5.15, while Scenario 2 has convergence to a constant value, convergence plots of rest of the scenarios exhibit spiky behaviour after a steep descent from a larger value. In terms of oscillations, Scenario 1 and 4 have minor oscillations, while Scenario 3 and 5 have comparatively larger oscillations. The oscillations could be due to the change of paths between the bilevel iterations for certain trips, which could have happened due to the stochasticity of the DUE algorithm.



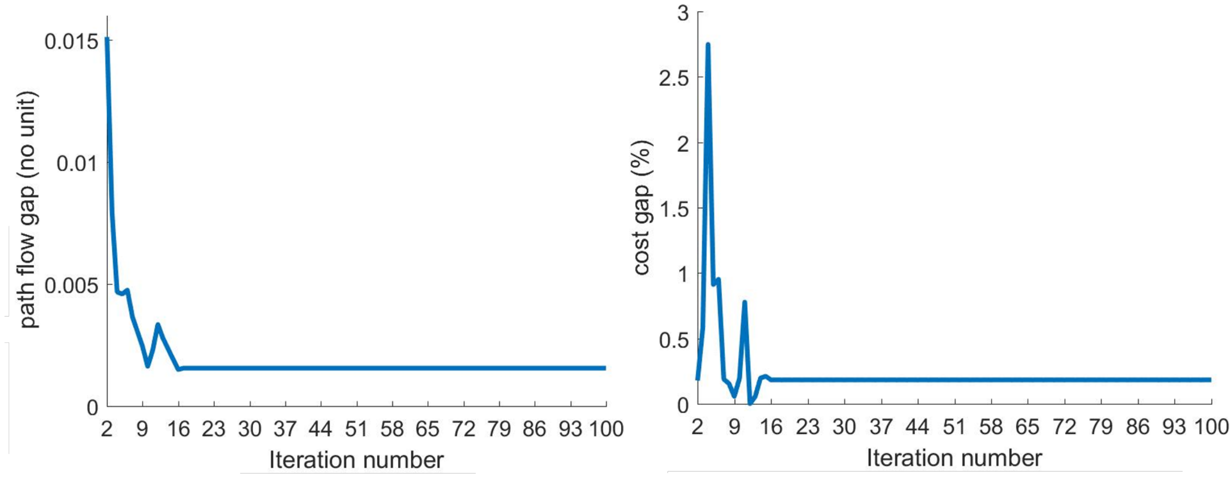
(a) Path flow gap



(b) Cost gap

Note: Calculation of convergence parameters involves difference between two consecutive iterations and hence, no value exists for first iteration.

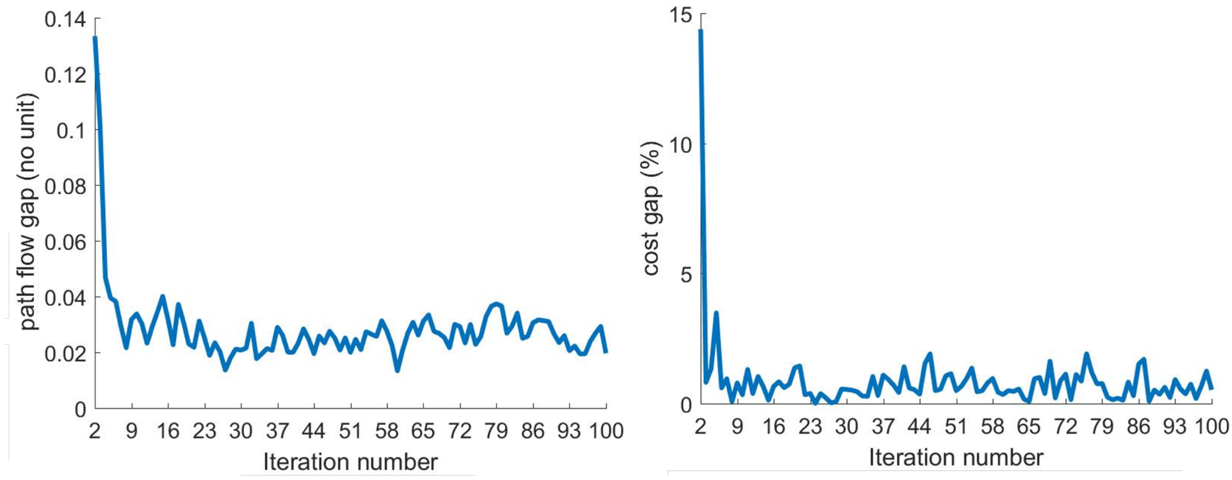
Figure 5.11: Convergence for the Sioux Falls Scenario 1



(a) Path flow gap (b) Cost gap

Note: Calculation of convergence parameters involves difference between two consecutive iterations and hence, no value exists for first iteration.

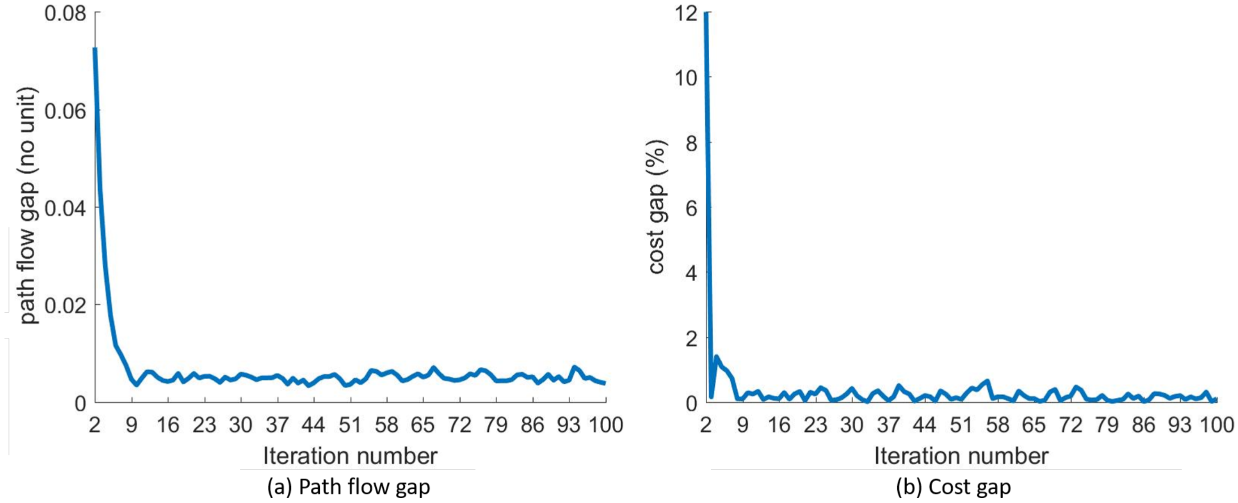
Figure 5.12: Convergence for the Sioux Falls Scenario 2



(a) Path flow gap (b) Cost gap

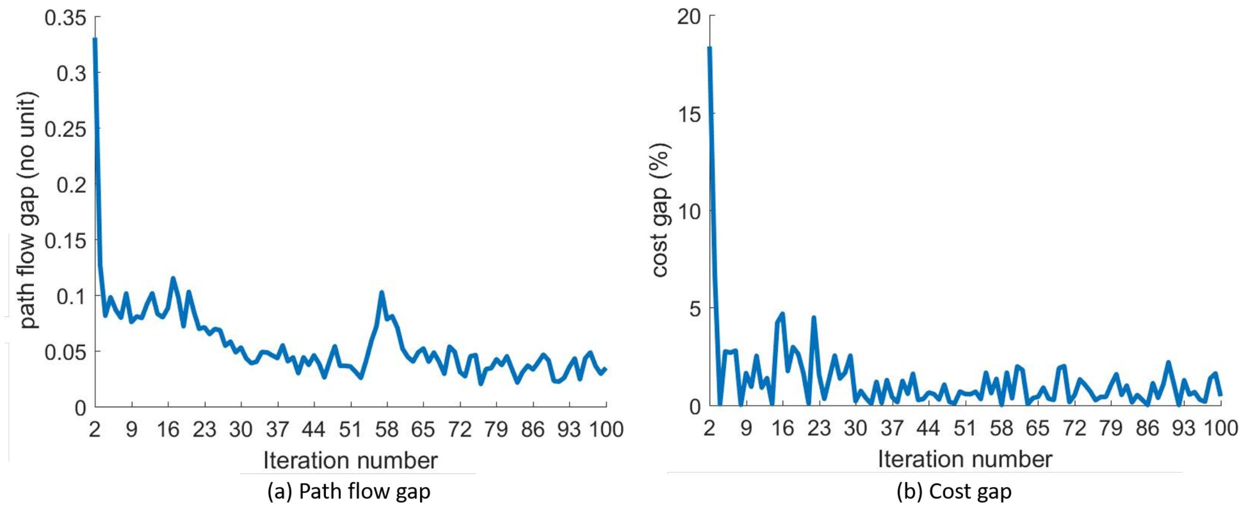
Note: Calculation of convergence parameters involves difference between two consecutive iterations and hence, no value exists for first iteration.

Figure 5.13: Convergence for the Sioux Falls Scenario 3



Note: Calculation of convergence parameters involves difference between two consecutive iterations and hence, no value exists for first iteration.

Figure 5.14: Convergence for the Sioux Falls Scenario 4



Note: Calculation of convergence parameters involves difference between two consecutive iterations and hence, no value exists for first iteration.

Figure 5.15: Convergence for the Sioux Falls Scenario 5

With regards to computation time, as can be seen in Figure 5.16, the elapsed time for DUE computation is very high because of larger total demand (16,896 trips). But the three patterns related to the computation time that are identified in the previous test, i.e., test on Braess bidirectional network, was found to exist also in this test.

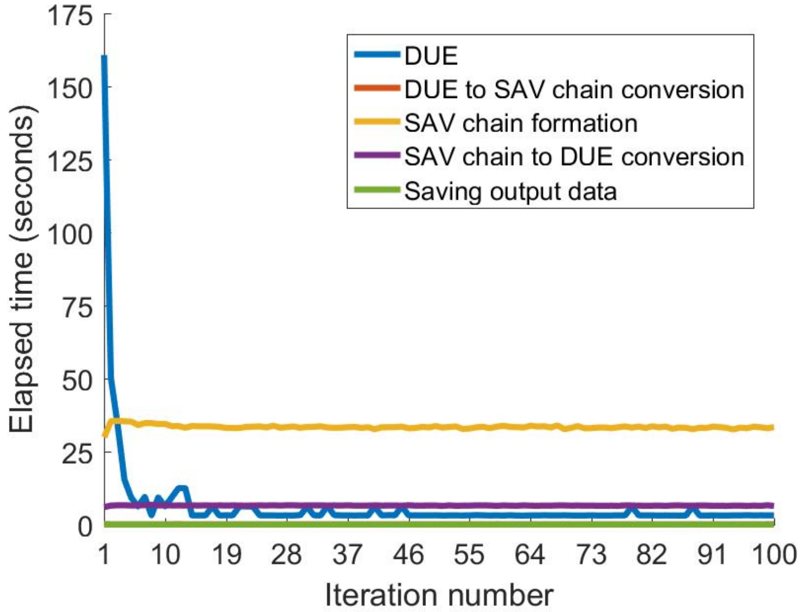


Figure 5.16: Elapsed time for the Sioux Falls Scenario 3

To conclude this chapter, based on the solution quality (Section 5.4.1), computation time (Sections 5.4.2 and 5.4.3) and convergence (Sections 5.4.2 and 5.4.3), the proposed solution algorithm for the DUESCF problem possesses the adequate capability to run multiple scenarios for different networks.

Chapter 6

Scenario analysis

Scenario analysis was carried out as part of the computation experiment on the Sioux Falls network. The results of the same is reported in this chapter and thus, the following research question is answered:

- *Based on the developed model, what will be the impact of introducing reservation based SAV services?*

Five different scenarios along with the base scenario, described in Section 5.4.3, are compared in this chapter in terms of actual trip arrival times, total system travel time, mean of individual trip times and vehicle requirements. Values of different variables from each scenario are presented in Table 6.1.

Table 6.1: Scenario analysis results

Scenarios	**Base**	**1**	**2**	**3**	**4**	**5**
Total demand	16896	16896	16896	16896	16896	16896
Demand for SAV services	-	1584	1584	3168	3168	3168
No. of private vehicle trips	16896	15312	15312	13728	13728	13728
No. of SAV service trips	-	1584	528	1584	1056	2112
Actual arrival time (planning horizon hour)	1.07 to 5.57	1.13 to 5.07	1.27 to 5.60	1.40 to 5.63	1.53 to 5.37	1.40 to 5.10
Mean of actual arrival time (planning horizon hour)	3.4	3.4	3.4	3.4	3.4	3.4
Travel time related						
Total system travel time (hr)	9434	11110	8343	9170	8001	10610
Total private vehicle travel time (hr)	9434	9210	7868	7373	7015	8037
Total SAV travel time (hr)	-	1900	475	1797	986	2573
Total SAV empty trip travel time (hr)	-	940	205	880	461	1289
Mean of individual trip time (min)	33.5	36.1	30.8	32.5	30.6	35.2
Distance related						
Total VKT (km)	191662	222634	187954	203916	186091	220199
Total private vehicle VKT (km)	191662	173782	173542	155653	155463	155768
Total SAV VKT (km)	-	48852	14412	48263	30628	64431
Total SAV empty VKT (km)	-	30892	8441	30327	18666	40489
Vehicle related						
Total No. of vehicles used	16896	16040	15509	14475	13925	14704
No. of SAVs used	-	728	197	747	197	976
No. of trips per SAV vehicle	-	1 to 5	1 to 6	1 to 5	1 to 6	1 to 6
Vehicle replacement	-	2.2	8.0	4.2	16.1	3.24

6.1 Actual arrival time

All the scenarios have an arrival time range smaller than base scenario. The reason could be distribution of trip departures in the base scenario to lower the congestion levels that would arise because of comparatively greater number of vehicles on road. It should be noted here that such a wider distribution would be obtained only if the congestion levels could be brought down substantially through distribution. Otherwise, due to penalties for arrival times, a comparatively narrower distribution would be obtained, though there might be existence of congestion, i.e., a trade-off would happen between arrival time and travel time.

Comparing Scenarios 1 and 2, the arrival time range is smaller in case of Scenario 1, showing that a carsharing system could result in better arrival times than a ridesharing system. Comparing Scenarios 3 and 4, the arrival time range is smaller in case of Scenario 4 and this is due to the lower number of service trips attainable with higher vehicle sharing rate. Scenario 5 has a range smaller than all other scenarios. Thus, when compared to other scenarios, Scenario 5 results in actual arrival time range closer to the expected arrival time and based on this, with regards to trip arrival time range, it can be concluded that a mixed system is better than a ridesharing and a carsharing SAV system. However, looking at the mean value, all the scenarios including the base scenario, resulted in an equal value of 3.4, which is close to the mean of expected arrival time (3.5).

6.2 Total system travel time and individual trip time

Total system travel time is highest in case of Scenario 1, even larger than the base scenario and this is due to greater congestion levels (indicated by the mean of individual trip times) and SAV empty rides. The total system travel time value from Scenario 5 is also higher than the base scenario. Scenario 4 has the least total travel time and this shows that a ridesharing system with higher vehicle occupancy rate is better compared to a carsharing or a mixed SAV system. In terms of percentages for change in total system travel time, as can be seen in Figure 6.1, Scenario 1 and 5 have an increase of 17.8% and 12.5% compared to base scenario, while the scenarios 2, 3 and 4 have a decrease of 11.6%, 2.8% and 15.2% respectively. SAV empty rides accounted for 2% to 12% of the total system travel time.

With regards to the mean of individual trip times, again Scenario 1 and 2 have poor performance with a value of 36 and 35 minutes respectively, around 7.7% and 5.1% more than the base scenario. Scenario 2 and 4 have lower values when compared to other scenarios and this again proves that a ridesharing system with higher vehicle occupancy rate is better than both a carsharing and a mixed SAV system. The mean of individual trip times could be considered as a representative for traffic congestion and the model results are in line with the results related to traffic congestion from the review on SAV services (3.4.1), i.e., carsharing system is found to increase congestion, while on the other hand, ridesharing system reduces congestion.

The maximum individual trip time value in all the scenarios (168 to 252 minutes) is greater than the maximum free flow path travel time value (58 minutes) in the network and this is due to the occurrence of congestion. As stated in Section 5.4.1, congestion can occur in case of higher demand and this will result in path travel time values greater than the free flow path travel times, e.g., travel time in Path 2 (6.2), which connects node 1 and 2, as shown in Figure 6.3.

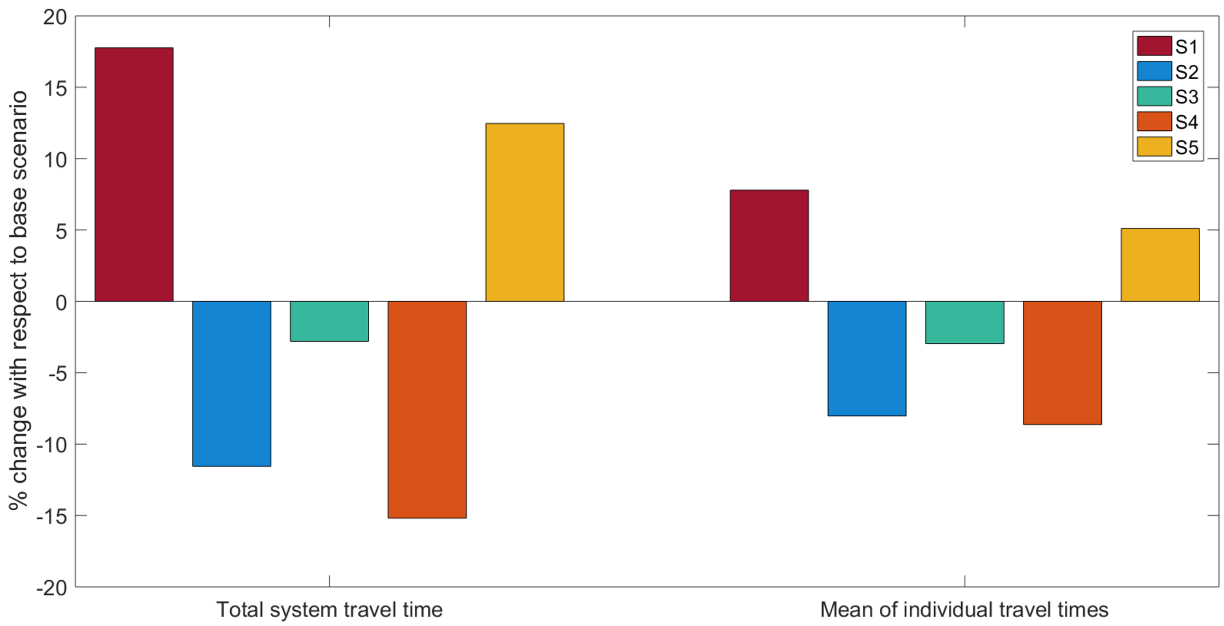


Figure 6.1: Comparison of total system travel time and mean of individual trip times

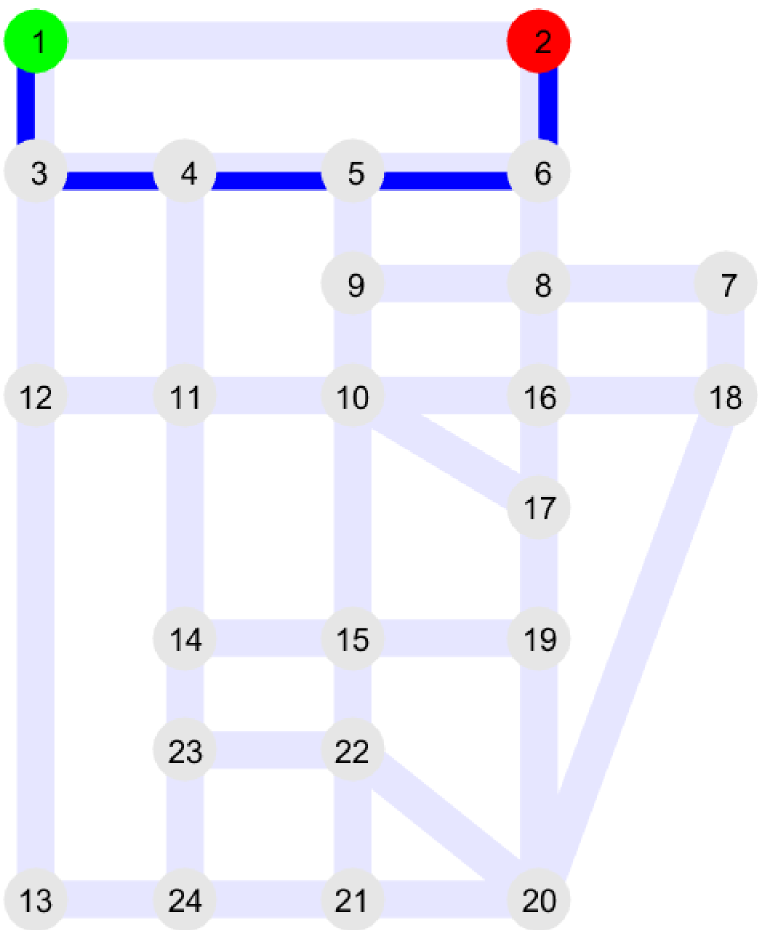


Figure 6.2: Path 2 connecting node 1 and node 2

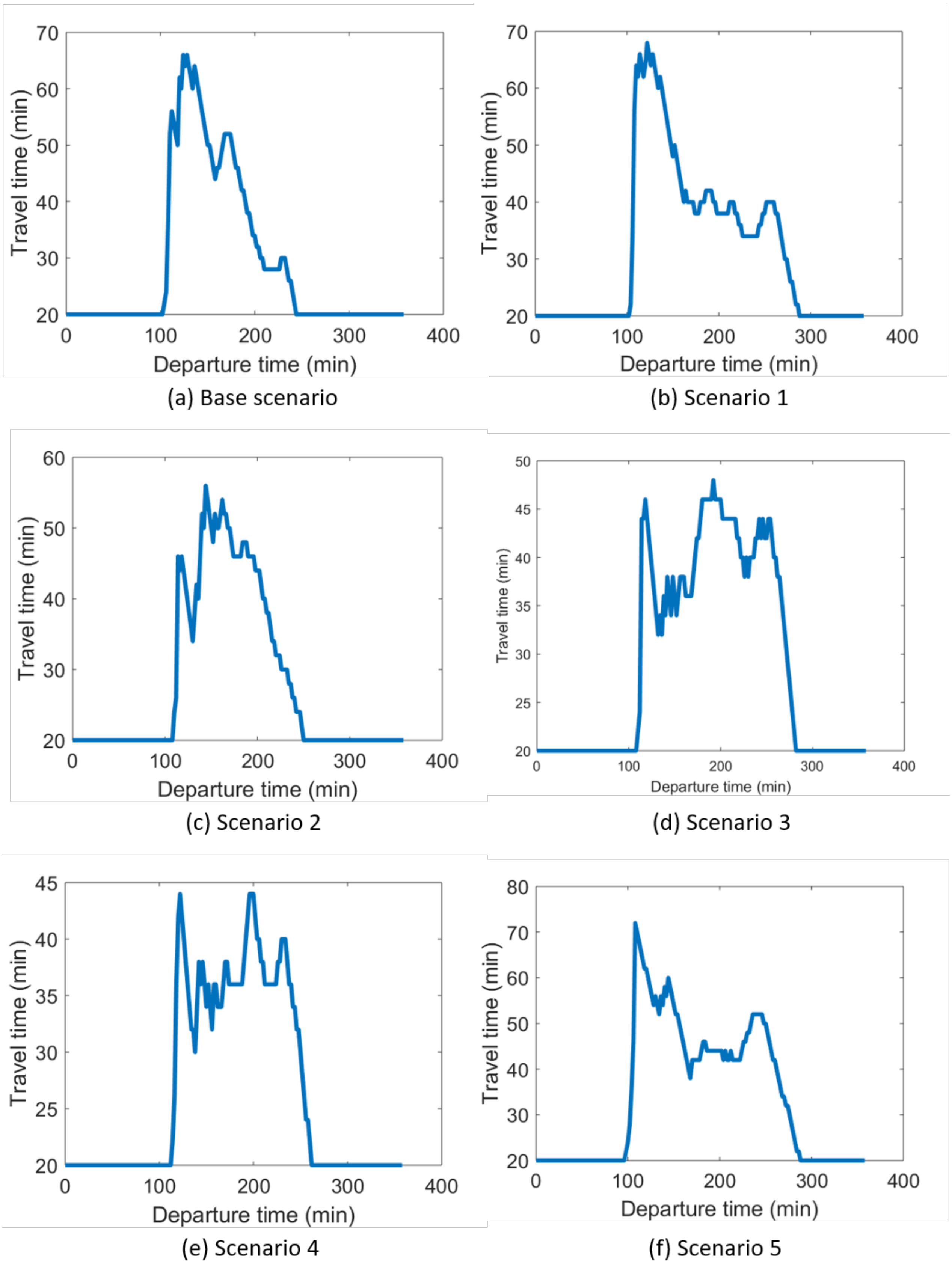


Figure 6.3: Travel time in path 2

6.3 Vehicle kilometres travelled

Scenario 4 outperformed rest of the scenarios in terms of VKT, showing a reduction in total VKT compared to the base scenario. While Scenario 2 also showed a reduction of VKT compared to the base scenario, VKT increased in rest of the scenarios, as can be seen in Figure 6.4. The carsharing and mixed SAV system (Scenarios 1 and 5) resulted in an increase of around 15% and the ridesharing system with vehicle occupancy of 2 (Scenario 3) resulted in an increase of around 6%. Thus, it can be ascertained that a ridesharing system with higher vehicle occupancy (Scenario 2 and 4 consist of trips with vehicle occupancy of 3) is required to reduce total VKT. This result has a similar pattern to the one obtained from review regarding 'VMT/VKT' (3.4.2). SAV empty rides accounted for 4% to 18% of the total VKT.

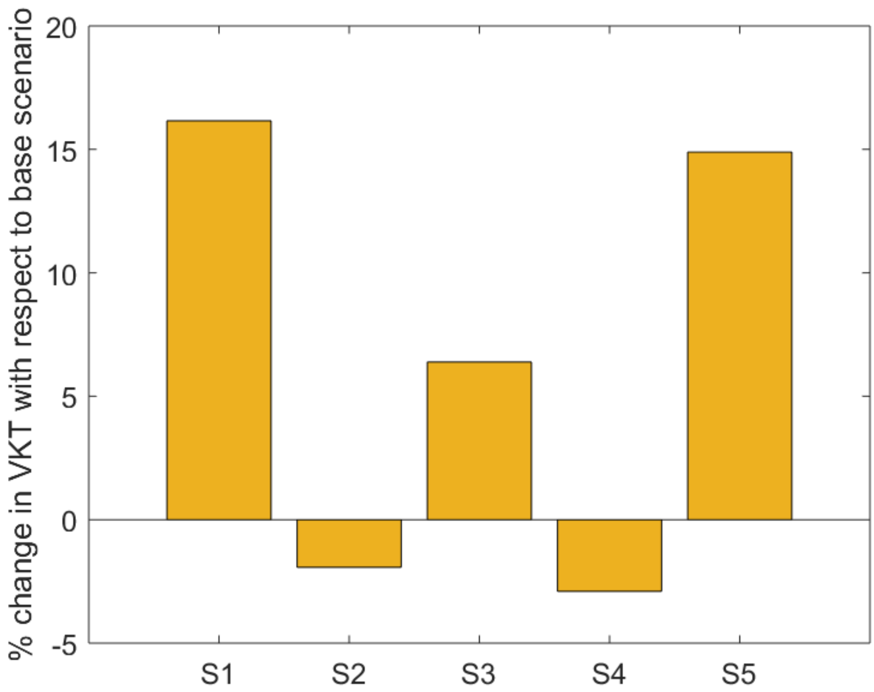


Figure 6.4: Comparison of VMT/VKT

6.4 Vehicle requirements

In case of conventional private vehicle trips, it is assumed that the number of vehicles used is equal to the number of trips. In case of SAV, the number of trips served by a single vehicle range from 1 to 6 trips in Scenarios 2, 4 and 5 and in case of Scenarios 1 and 3, the range is 1 to 5 trips. Looking into the vehicle replacement values, which refers to the ratio between trip demand served by the SAVs and the number of SAVs utilised in a scenario, it is obvious that the SAV services have the potential to reduce vehicle requirements, as can be seen in 6.5 and further, a ridesharing system has a high vehicle replacement rate compared to a carsharing system (based on Scenario 1 and 2). Based on Scenarios 3 and 4, it is certain that the vehicle replacement increases as vehicle occupancy increases. By comparing Scenarios 3, 4 and 5, one can confirm that a mixed system requires more vehicles than a ridesharing SAV system.

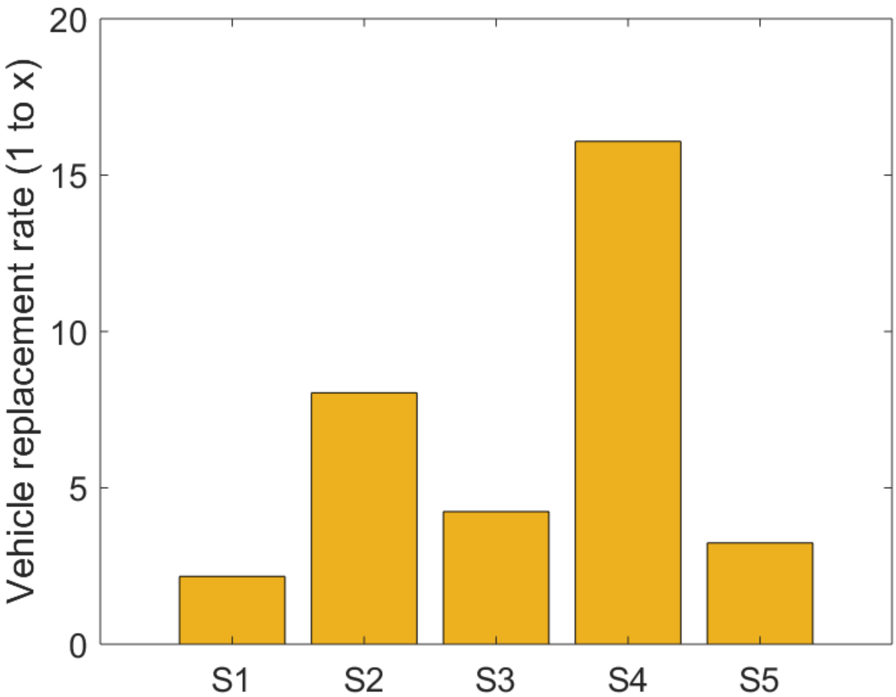


Figure 6.5: Comparison of vehicle replacement rate

Finally, based on the results from the scenario analysis, a ridesharing SAV system has lower total system travel time, traffic congestion levels, total VKT and vehicle requirements compared to the base scenario as well as other scenarios with carsharing and mixed SAV system. Further, the benefits obtained increase as vehicle occupancy increases in case of ridesharing SAV system. Scenarios with carsharing SAV system and mixed SAV system showed lower performance compared to the base scenario in terms of total system travel time and traffic congestion levels, though performed well in terms of vehicle requirements. All these show that a ridesharing SAV system is better among the three and can lead to a better future. Implementation of carsharing SAV system or mixed SAV system could lead to a less sustainable future.

Chapter 7

Conclusion

This chapter summarizes the conclusions obtained based on the review work and the development of the bilevel model along with recommendations for the future work on the bilevel model.

7.1 Summary

7.1.1 Review of SAV services and their impacts

Multiple business models currently exist in the domain of shared autonomous mobility and it is still uncertain, which service model would attain popularity. However, it is certain that the emergence of AV technology is to be streamlined by the public authorities to prevent negative growth. The current state-of-the-art on methodologies for modelling the operations and impacts of SAVs is developed on the basis of long-existing models which, due to the lack of realistic indications of operation, are impossible to verify and even more validate. The majority of the studies uses modified simulation models by including SAV services. Their results mostly point towards similar directions in terms of SAV impacts. Most studies point towards an increase of mobility (VKT, user-groups served) and an increase of efficiency for the transportation system (vehicle replacement and utilization, as well as emission reduction). Researchers and policy makers should be aware of the aspects of congestion and equity, which will inevitably arise. With regards to demand, the results presented are rather scattered with the majority of them to be less than 50% of the current trips performed (in a horizon up to 2040). However, as Vosooghi et al. (2017) state, the current tools used to estimate demand for shared services have limited capabilities. Several components are still missing in simulation systems for estimating demand and the main challenges are data detail, accessibility and reliability, high computational time, calibration and validation. In addition, as Hawkins and Nurul Habib (2018) conclude, some types of models, such as Integrated Land Use and Transport (ILUT) models do not possess the capabilities to adequately model autonomous vehicles. Hawkins and Nurul Habib (2018) suggest using stated adaption surveys instead of stated preference surveys, inclusion of cusp effects when forecasting AV usage and inclusion of a specification in the model structure to account for the inter-temporal nature of AV adoption.

From a policy perspective, SAVs should be introduced in shared mobility services and shared mobility services should be integrated with an efficient public transport system, rather than in the form of independent systems which induce risk of modal shift from public transport. Ridesharing should be encouraged and incentivised and public transport fusion is recommended. Policy makers should understand the nuances of this and carefully streamline the development of autonomous vehicles. Also, the capabilities of current tools need to be improved to enable better planning. Without these, there is a greater risk of unsustainable growth of SAV services or, in the worst case, personal cars continuing to be a major mode.

Though a vast amount of research is being published every year, a considerable number of research gaps still exist. Although it is conceivable that the introduction of autonomous vehicles is a reality, road networks are going to be filled with mixed traffic (non-, semi- and fully autonomous vehicles) at least for the next couple of decades. The actual way that AV (and consequently SAV) would work is still under investigation, resulting in most studies inevitably basing their analyses on strong assumptions. Also, the response of individuals to the introduction of autonomous vehicles has yet to be validated. Thus, the capabilities of the current modelling tools need to be improved to account for such issues by developing a set of scenarios based on plausible assumptions, e.g. inter-temporal nature of AV adoption. With regards to SAV operations, regular trips like commuting trips and pre-planned trips like trips to the airport are suitable for reservation-based service. Reservation-based operations could be one of the factors for shifting current personal car users to shared autonomous vehicles in the future. Reservation-based systems ensure vehicle availability, which could be a factor in increasing preference towards shared mobility services, influencing the mode shift of personal car users to shared operations. In addition, the mix of reservation–based and dynamic operations is believed to prevail at the end; thus, efforts should be put in understanding their impact. Changes in the available transport modes would result in a change of supply, in terms of total transport system capacity. Studies suggesting an increase in capacity do so based on just automation and the increase could be much higher when considering ride sharing and better utilization of vehicles enabled with the introduction of SAV. However, an exploration of these effects is still missing.

Finally, cities should start preparing for this new mode of transport, that is coming, in a proactive way, with the development of guidelines and strategies for the changes foreseen in terms of SAV introduction and the policies required in order to ensure sustainability and an equitable transportation system.

7.1.2 Modelling reservation based SAV services

This thesis contributes to the field of modelling reservation based SAV services by formulating the DUESCF problem as a bilevel model based on game theory and deriving an algorithm based on an iterative procedure to solve the model. In order to formulate the DUESCF model, existing DUE model and SAV chain formation models from the literature were used with some modifications. The used DUE model considers not only route choice but also departure time choice. Modifications in the DUE model enabled modelling both SAV services and conventional private vehicles and modifications in SAV chain formation model enabled inclusion of ridesharing services. The DUE model was solved using a fixed point algorithm and the SAV chain formation model using a Linear Program (LP). As mentioned before, the bilevel model is solved using an iterative optimization and assignment method, which is commonly used in solving combined traffic assignment and control problem.

In order to prove the robustness and the efficiency of the proposed algorithm, computational experiments were performed on three different networks. Computational experiment on the 2-Node toy network proved that the model converges to a Nash equilibrium. The formed SAV chains showed absence of empty trips and that each of the 100 vehicles utilised served 2 trips, forming an optimal solution. This is possible due to the fact that the lower model uses linear program which is an exact optimization method. The trip travel time obtained was the free flow time in the paths which was possible due to lower demand and distribution of departures. Looking into the actual arrival times, they were distributed close to the expected time of arrivals and this was attainable due to the absence of congestion.

Tests on Braess bidirectional network showed that the model has the capacity to evaluate multiple scenarios but some of the scenarios does not convergence to a convergence threshold of 0 but rather a value between 0 to 0.1. The author attributes this to numerical issues. With regards to computation time, the elapsed time for running the DUE model reduces steadily along the iteration of the bilevel model due to the decrease in required number of DUE iterations. However, elapsed time for forming SAV chains stays almost constant throughout the bilevel iteration process. This is due to the fact that the computation time for SAV chain formation depends majorly on number of SAV service requests which is a constant throughout the bilevel iteration process. It was also found that the elapsed time for SAV chain formation increases as the SAV service penetration increases and this is due to the increase in number of SAV service requests.

Results from the test on Sioux Falls network ensure the algorithm's ability to model different SAV systems and also prove the algorithm's stability and robustness when modelling larger networks with zero demand OD pairs. With regards to computation time, the three patterns identified in the test on Braess network was found to exist also in this test. Further, elapsed time for DUE computation was comparatively higher because of the high total demand. Concerning the convergence patterns, a spiky oscillatory behaviour was observed after a steep descent from a larger value. This could be due to the stochasticity of the DUE algorithm.

The scenario analysis results showed that a reservation based ridesharing SAV system can perform significantly better than a reservation based carsharing SAV system or a reservation based mixed SAV system, which is in line with the conclusions obtained from the review on SAV services. In fact, reservation based carsharing SAV system and mixed SAV system perform poorer than the base scenario wherein conventional private cars are used. However, the current results from the model are based on lower penetration rates for SAV services and scenarios with higher SAV penetration rates, wherein empty SAV rides might be significantly higher, are to be tested to ensure that the direction of impact is not altered.

To conclude, the proposed model can be used by policy makers to evaluate the impacts caused by reservation based SAV services and by SAV service operators to maximise their service performance by forming efficient SAV chains.

7.2 Future research on the proposed bilevel model

- As observed in computational experiments, elapsed time for SAV chain formation stays almost constant throughout the bilevel model iteration process. Clustering trips before forming SAV chains and parallelly solving the SAV chain formation problem, as done in Shun Su (2018), could reduce time for forming SAV chains and the work here is to find the most suitable clustering technique. Alternatively, time for formation of relocation links and constraints could be reduced by keeping track of the changes that occurs in these two variables over iterations and modifying only those updated data instead of forming them from scratch in each iteration. This technique is implemented in Himpe (2016) for modelling of DUE.

- Only one expected time of arrival can be given for service trips between an OD pair and this could be updated with ability to have multiple expected time of arrivals. Again, this could be done by duplicating the path set. However, care should be taken that the stability of model is not affected due to too much path duplications.
- Inclusion of dynamic SAV services. As demand for reservation-based service will be known beforehand, SAV chains are first formed and then by applying iteration for the time instants, demand for dynamic services can be dynamically fed in to the model based on the time instant and vehicles can be assigned based on a heuristic technique. Extra vehicles available after allotting vehicles for the reservation-based services could be used for dynamic services.
- In case of ride sharing, only OD based ridesharing is possible and the model could be updated to include ridesharing en-route.
- Road pricing could be added to the effective delay operator in the DUE model. Currently, effective delay operator is a linear combination of path travel time and arrival penalty.
- The DUE model could be updated to model vehicles with different characteristics (multiclass DNL).
- SAV operation can be modelled with multiple depots instead of one.
- Maintenance, service, parking and other similar costs could be added to the link costs in the SAV chain formation model.
- Parking and charging (in case of electric vehicles) constraints can be included in the SAV chain formation model.
- Application of the model for more complex networks.
- Scenario analysis with higher SAV service penetration rates.
- The solution approach for the bilevel problem tested in this study is based on Iterative Optimization and Assignment (IOA) method. Other solution approaches currently seen in literature for solving bilevel models could be tested.
- Usage of a route choice DUE model or other DTA models instead of simultaneous route and departure time choice DUE model.

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