

Impact of Autonomous Vehicles and Ride-Sharing on Urban Transportation

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Abstract

This thesis investigates how autonomous vehicles and ride-sharing influence urban transportation, using the SATURN mesoscopic modelling suite to quantify effects on capacity, delay, routing, and network efficiency. The study updates core SATURN inputs to represent AV behaviour, including saturation flow, gap acceptance, stacking capacity, speed–flow relationships, and generalised cost, and frames the analysis within a static user-equilibrium assignment to isolate supply-side effects of automation.

The methodology progresses from controlled junction tests to a toy network and then a city-scale application for York. Nine scenarios examine unopposed and opposed movements at priority junctions, turning at signals, and network-wide impacts under different AV penetration shares, with a parallel comparison between a flow-theory approach and a PCU-based treatment of AVs. An automated workflow iteratively recalculates node-level LSAT and GAP and link-level STACK from the assigned AV share, using SATDB and re-assignment until stability is reached.

Results show substantial capacity gains. In all-AV conditions, unopposed turns increase by about 95 percent and signalised turning capacity rises by about 42 percent, which aligns with but slightly exceeds prior benchmarks because the modelling also reduces safety distance. In the toy network, these capacity changes cut total travel time and queues markedly, with large reductions in over-capacity delay. In the City of York model, increasing AV penetration improves city-wide performance: total travel time falls by roughly 4 percent at 25 percent AV and about 12 percent at 100 percent AV, average speed rises by about 4 to 12 percent, and average queues fall by about 16 to 50 percent, while total distance changes little. Benefits concentrate on inner-city signalised corridors where shorter headways reduce lost time, while strategic corridors that run near free flow change little. The flow-theory outcomes closely match a PCU factor of about 0.7 for AVs across both toy and city networks, supporting use of either approach for planning analysis when calibrated appropriately. Varying AV values of time and operating cost produces only minor network-wide differences under the tested settings.

Finally, the thesis develops a fast, non-integer ride-matching algorithm that aggregates paths by zone sequence and matches rides within a model hour. It integrates with multi-path assignments, estimates impacts on delay and capacity at city scale, and offers a base for future Shared AV modelling.

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Chapter 1 Introduction

1.1 Background

Autonomous Vehicles (AVs), also referred to as self-driving or automated vehicles, are expected to transform the transportation system in the coming years. Rapid advancements in AV technology have led to testing and deployment in various global locations. Companies such as Waymo, Tesla, GM, BMW, and Ford aim to introduce fully automated vehicles within the next few years. Waymo, Alphabet's self-driving unit, aims to launch its fully autonomous ride-hailing service in Washington, D.C. in 2026 (Shepardson, 2025). Tesla has pushed for self-driving vehicles on EU roads by early 2025 (Pinsent Mason, 2024). Chiao *et al.* (2024) predicts that by 2030, autonomous vehicles equipped with 'Full Automation' will be capable of operating anywhere, anytime. According to a 2022 report by the Department for Transport (DfT), it is projected that by 2035, 40% of new cars sold in the UK will be equipped with self-driving capabilities (DfT, 2022). Governments are also preparing for widespread adoption; for instance, the Automated Vehicles Act Implementation Programme was launched in 2024 to secure the safe deployment of automated vehicles on roads in Great Britain and is responsible for implementing the Automated Vehicles Act 2024 in 2027 (CCAV, 2025).

AVs promise a fundamental shift in mobility, alleviating the need for human driving and reducing associated stress. Beyond convenience, they offer solutions to persistent traffic challenges, e.g., traffic congestion. The traditional solution to mitigate traffic congestion is capacity expansion. However, building more roads is not a feasible solution, as there is little space available for roads in urban areas (Park *et al.*, 2021). But AVs can drive more accurately and sense their surroundings better than human. Specifically, they require a much smaller gap, or shorter headway, than human-driven vehicles, since they have more information about the surrounding driving environment and a shorter reaction time delay (Fernandez *et al.*, 2012; Arnaout and Bowling, 2014). AVs can also communicate with each other to form groups (Fernandez *et al.*, 2012; Hu *et al.*, 2021). These technological advances will be able to increase traffic flow efficiency and road capacity. Studies suggest AVs could improve traffic flow by up to 50% under uninterrupted conditions, though benefits may be marginal below a 40% penetration rate (Fernandez *et al.*, 2012; Arnaout and Bowling, 2014; Park *et al.*, 2015).

The impact of AVs on traffic efficiency and congestion varies significantly depending on the type of road they are operating on. On highways, AVs can achieve substantial efficiency gains. This is primarily because highways typically have fewer complex interactions, such as traffic signals and pedestrian crossings. AVs can maintain consistent speeds and form platoons, which reduces the need for frequent braking and acceleration. This leads to smoother traffic flow, reduced fuel consumption, and lower emissions (FHWA, 2020). In contrast, urban roads present a more complex environment for AVs. These roads are characterised by numerous interactions, including traffic signals, roundabouts, pedestrian crossings, and close-proximity junctions. The presence of various road users, such as cyclists and pedestrians, adds to the complexity. AVs must navigate these interactions safely and efficiently, which requires advanced sensing and decision-making capabilities. While AVs have the potential to improve traffic flow and reduce congestion in urban areas, further studies are needed to fully understand their impact and optimise their performance in urban road network (Makahleh *et al.*, 2024).

The capability of self-parking and increased vehicle sharing services due to AVs could reduce demand for on-street and off-street parking (Anderson *et al.*, 2016). Modelling empty AV trips is crucial as these unoccupied journeys could increase vehicle mileage travelled (VMT) and exacerbate congestion in already congested urban road networks.

The introduction of fully Autonomous Vehicles, also referred AV, could facilitate the development of ride- and vehicle-sharing services. AVs could significantly reduce operational costs (e.g., no driver costs) of shared autonomous vehicles (SAVs) for the ride-sharing benefits. Such schemes could effectively meet individuals' travel demand needs with lower cost and higher flexibility than what today's bus and taxi systems offer to passengers. Subsequently, urban residents could reduce the number of cars they own or even live car-free, avoiding the fixed costs associated with car ownership.

System-wide coordination of SAVs could mitigate congestion and facilitate the integration of advanced propulsion systems (Burns *et al.*, 2013). Furthermore, SAVs could substantially reduce private car ownership levels (Fagnant *et al.*, 2015; Fagnant and Kockelman, 2014), and dynamic ride-sharing (DRS) schemes could be implemented. Several studies have investigated consumer perception of the AV technology (Bansal *et al.*, 2016) dealing with the adoption of SAVs. Furthermore, Bansal *et al.* (2016) analyse individuals' stated frequencies to use SAVs under different pricing scenarios and identify the characteristics of potential SAV adopters.

The concept of SAVs combines elements of conventional carsharing and taxi services with AVs (Fagnant *et al.*, 2015). SAVs could provide inexpensive and convenient mobility-on-demand services (Burns *et al.*, 2013), described as driverless taxis (Fagnant *et al.*, 2015). Carsharing is generally considered a flexible mobility option that complements public and slow modes by offering the flexibility of the private car without the obligations associated with private car ownership. As such, carsharing could potentially foster more sustainable mobility by facilitating multi-modal travel behaviour, and in the longer run, carsharing could potentially reduce private car ownership levels.

Recent surveys suggest a diverse pattern of public opinions on AVs where people have high expectations of the benefits of AVs such as crash reduction but are highly concerned about equipment failure and hacking issues (Schoettle and Sivak; 2014; Kyriakidis *et al.*, 2015; Bansal *et al.*, 2016). Apparently, it will take time for AVs to achieve a major market share. Litman (2017) used the adoption patterns of previous vehicle technologies to estimate that AVs will represent 10%-20% and then 20%-40% of the vehicle fleet by 2030 and 2040 respectively. Using a survey about preferences for connected and automated vehicle technologies in the US, Bansal and Kockelman (2017) predicted that the share of fully AVs in 2045 would vary between 25% and 87%, depending on willingness to pay and technology prices. Given these projections, it is crucial to monitor the impact of AVs on the road network at varying penetration rates. Higher penetration rates of AVs generally improve traffic flow and fuel efficiency, but there can be instances where the opposite trend is observed (Kavas-Torris, 2020). Therefore, understanding and preparing for these changes is essential for optimising the benefits of AV technology.

1.2 Definition of “AV” – Level of Automation

With the goal of providing common terminology for automated driving, SAE International’s new standard J3016 delivers a harmonised classification system and supporting definitions that identified six levels of driving automation from “no automation” to “full automation” (SAE, 2014):

- **Level 0: No Automation:** The driver controls all aspects of the vehicle, with no automated assistance.
- **Level 1: Driver Assistance:** The vehicle can assist with either steering, acceleration, or braking, but not both simultaneously.

- **Level 2: Partial Automation:** The vehicle can control both steering and acceleration/deceleration, but the driver must remain attentive and be ready to take control.
- **Level 3: Conditional Automation:** The vehicle can handle most driving tasks under specific conditions, but the driver must be ready to take over if needed.
- **Level 4: High Automation:** The vehicle can handle all driving tasks under specific conditions, and the driver is not required to be attentive.
- **Level 5: Full Automation:** The vehicle can handle all driving tasks in all conditions, and the driver is not required to be present or attentive.

However, Department for Transportation (DfT), UK uses two definitions to describe different levels of automated or driverless vehicles (DfT, 2015):

- **High Automation:** a vehicle in which a driver is required to be present and may need to take manual control for some parts of the journey. Under certain traffic, road or weather conditions, the vehicle's automation systems may request the driver to take control. Early highly automated vehicles may only offer an automated mode under certain very specific driving conditions such as highway cruising or in low speed conditions. As the technology develops, the vehicle will be able to undertake driving duties autonomously for a greater and greater proportion of the time.
- **Full Automation:** a vehicle in which a driver is not necessary. The vehicle is designed to be capable of safely completing journeys without the need for a driver in all normally encountered traffic, road and weather conditions. Occupants of fully automated vehicles will be able to engage in tasks other than driving for the entire journey. Fully automated vehicles may still offer a full set of controls to allow a driver to resume manual control if they so wish, but this would be entirely optional.

The recent advances in the fields of mobile broadband and vehicular communication systems have contributed to the development of vehicles endowed with communication capabilities: connected vehicles. Connected vehicles use any of a number of different communication technologies to communicate with the driver, other cars on the road (vehicle-to-vehicle [V2V]), roadside infrastructure (vehicle-to-infrastructure [V2I]), and the "Cloud." This technology can be used to not only improve vehicle safety, but also to improve vehicle efficiency and commute times.

Autonomous Vehicle (AV) referred in this study is assumed to have all the features of ‘full automation’ and ‘connected’ vehicle technologies.

1.3 Research Context

Traffic modelling for AVs primarily utilises microsimulation and macrosimulation techniques. **Microsimulation** models simulate the behaviour of individual vehicles within a predefined road network. These models are highly detailed and can capture interactions between vehicles, including AVs, such as lane changes and gap acceptance at intersections (Berkin, 2012). Microsimulation is particularly used for operational assessment; however, due to its limited network extent, it struggles with capturing the broader impacts of traffic reassignment and is not typically used in scheme appraisal processes. It also requires significant data and computational resources, making it unrealistic to model a city-scale network. These limitations highlight the importance of choosing the right modelling approach based on the specific traffic analysis needs.

Macrosimulation modelling deals with aggregate traffic flow and uses simplified representations of traffic dynamic (DfT, 2024). These models are less detailed but can efficiently handle large networks and provide insights into overall traffic patterns and congestion levels. However, they lack the junction modelling required for urban networks.

Mesoscopic models, on the other hand, bridge the gap between microsimulation and macrosimulation (AIMSUN, 2012). They combine elements of both approaches by representing individual driver choices at a probabilistic level while limiting the detail on driving behaviours. Mesoscopic models are particularly useful for scenarios that require both network-wide analysis and detailed junction modelling.

Any modelling that covers the strategic road network but also includes junction modelling and delay can be defined as mesoscopic. This dual capability can make the mesoscopic approach suitable for modelling urban road network, where understanding the impact of AVs on road capacity is crucial. Traffic assignment at the mesoscopic level can be either dynamic, accounting for time-varying traffic conditions, or static, assuming constant traffic patterns (DfT, 2018).

To effectively model AVs, it is important to subdivide the modelling elements:

- **Road Capacity:** Assessing how AVs influence overall road capacity and traffic flow.
- **Ride-Sharing:** Evaluating ride-sharing element for Shared Autonomous Vehicles (SAVs) to optimise their integration into the urban network.

The impact of SAVs on urban networks is significant. To break down the modelling elements, it is crucial to first understand the impact of AVs without ride-sharing on urban road capacity. Separately modelling unoccupied AVs or empty vehicles running on urban networks helps isolate their impact. Lastly, ride-sharing modelling methods for the same platform are useful before integrating all the modelling elements in SAVs.

Current research is limited to assessing modelling methods in isolation. However, combining these approaches can provide a more holistic understanding of AVs' impact on urban traffic networks. Mesoscopic models, with their ability to cover both network-wide and junction-specific dynamics, offer a potential tool for modelling AVs in the urban road network.

The SATURN modelling tool is considered a mesoscopic model because it operates at a level of detail that lies between macroscopic and microscopic models. SATURN is a well-established tool, extensively utilised by local authorities and government bodies for various traffic modelling projects. SATURN's flexibility allows it to be used for both local network changes and large-scale strategic assessments. There are many regions and major cities in the UK that have been modelled in SATURN and used for various transport planning projects (RTM, 2019; WYTM, 2024; PRISM, 2018). However, there has been limited research specifically focusing on modelling AVs in detail using SATURN. This presents an opportunity for further exploration and development in this area.

1.4 Aims and Objectives

The aim of the research is defined as:

- **Assess the impact of autonomous vehicles and ride-sharing on urban network using SATURN modelling tool.**

The primary aim of this research is to evaluate how autonomous vehicles and ride-sharing impact urban transportation networks. By employing SATURN mesoscopic modelling, the study aims to understand the

implications of integrating self-driving cars and ride-sharing behaviour into existing traffic systems. The modelling of self-parking behaviour of unoccupied AVs is also included to understand its impact in urban road network. This assessment considers factors such as traffic flow, congestion, route optimisation and overall network efficiency. Ultimately, the goal is to provide robust evidence that modelling AVs in SATURN can yield comprehensive and reliable analyses.

The proposed objectives of the research include:

A. Designing and testing suitable parameters in SATURN to model AV behaviour.

The primary objective of this research is to design various scenarios and test suitable network parameters in SATURN modelling to model the behaviour of autonomous vehicles (AVs). This modelling approach enables the assessment of the impact of AVs on road capacity within urban transportation networks. The modelling of AV behaviour considers factors influencing interaction with other vehicles in different types of junctions based on traffic flow dynamics. By incorporating AV-specific parameters, the research examines the impact of AV on road capacity.

B. Modelling Ride-Sharing in SATURN modelling.

The research provides a behavioural regime for shared mobility to understand the behavioural rules and patterns specific to ride-sharing. This step is crucial for accurately modelling ride-sharing dynamics to design and test. By incorporating ride-sharing specific parameters for SATURN modelling tool, the research examines the impact of ride-sharing on road capacity.

1.5 Scope

This research utilises the SATURN modelling tool to assess the first-order impacts of autonomous vehicles (AVs) and ride-sharing on urban transportation networks. Given that SATURN is a simulation and assignment model, the primary aim is to establish a robust modelling methodology for integrating AVs and ride-sharing.

1.6 Thesis Outline

The remainder of the chapters of the thesis are outlined as:

- **Chapter 2: Literature Review**

A comprehensive review of existing research on modelling AV to assess the impact of road capacity, modelling unoccupied AV and ride-sharing for SAV. This chapter identifies gaps in the current knowledge, research gaps and establishes the foundation for the study.

- **Chapter 3: Overview of SATURN**

This chapter provides an introduction to the SATURN mesoscopic modelling tool, detailing its features, capabilities, and relevance to the study. It explains the rationale behind choosing SATURN for the research and is placed before the methodology chapter to ensure that key terms and parameters are clearly understood and referenced later.

- **Chapter 4: Study Design and Methodology**

Details the research design, data collection methods, and analytical techniques used in the study. The SATURN input parameters that are required to be modified for modelling AVs are identified here. This chapter ensures the research is methodologically sound and replicable.

- **Chapter 5: Modelling Autonomous Vehicles**

This chapter focuses on the development and implementation of models for autonomous vehicles within the SATURN framework. It examines how AVs in mixed traffic conditions and varying AV penetration impact traffic flow and road capacity. The test scenarios are exercised in the “Toy” Saturn network.

- **Chapter 6: Modelling Autonomous Vehicles in a City Network**

This chapter explores the integration of AV modelling methods established in the previous chapter, assessing their effects on congestion, route optimisation, and overall network efficiency within a “city-scale network”.

- **Chapter 7: Future Work to Continue to the Research**

This chapter demonstrates the methodology to model ride-sharing in a mesoscopic platform and is tested in a “toy network”.

- **Chapter 8: General Discussions**

This chapter summarises the findings, discusses their implications, and provides recommendations for future research. This chapter also reflects on the study's limitations and potential areas for further investigation.

Chapter 2

Literature Review

2.1 Introduction

This literature review aims to explore various modelling methods and their implications for AVs, focusing on two key areas: road capacity and ride-sharing with shared autonomous vehicles (SAVs). Each section will delve into the current state of research, highlighting significant findings and identifying gaps that warrant further investigation.

To conduct this literature review, a comprehensive search of scholarly articles, conference papers, and industry reports was performed. The review process involved evaluating the methodologies, findings, and limitations of each study. By synthesising the insights from these sources, this review aims to provide a holistic understanding of the current state of AV research and identify areas for future exploration.

2.2 Studies on Modelling Autonomous Vehicles

2.2.1 Modelling Road Capacity

The efficiency of the transport system depends on the capacity of a transport infrastructure. When a transport infrastructure is used by autonomous vehicles (AVs), the capacity will differ from that of a transport infrastructure used by human drivers. Either the capacity of the route sections or the intersections define the traffic flow. While the capacities of the intersections and the traffic signals are relevant to the performance of urban road networks, on highways the capacities of open stretches of road are of principal importance.

Building on literature reviews of first-order efficiency impacts in traffic flow (Diakaki *et al.*, 2015; Hoogendoorn *et al.*, 2014; Hounsell *et al.*, 2009; Scarinci and Heydecker, 2014; Milakis *et al.*, 2017), recent studies provide new analytical headway and fundamental-diagram results for mixed AVs, platoon-centric capacity metrics, and network-equilibrium models (Mohajerpoor and Ramezani, 2019; Sun *et al.*, 2024; Zhao, 2025; Wang *et al.*, 2023).

Modelling methods to assess the impact of AV on network efficiency in the previous studies involved both microscopic and macroscopic activity-based and flow-based modelling.

2.2.1.1 Microscopic Approach

The microscopic model describes the relevant characteristics of a single vehicle: temporal headway, spatial separation, speed etc. Most of the microsimulation models are based on car following models (Wiedemann 1974 & 1999, Intelligent driver model 1999, Gipps 1981).

Arem, Driel, and Visser (2006), Hoogendoorn, Arem and Hoogendoorn (2014), Arnaout and Bowling (2014), Shladover *et al.* (2012), Lioris *et al.* (2017), Milanés *et al.* (2014), Alam and Habib (2018) have explored traffic impacts of longitudinal automation [i.e., Adaptive Cruise Control (ACC), Cooperative Adaptive Cruise Control (CACC)] in existing car following model in either exogenously or endogenously. Recent analytical and string-stability results for mixed traffic consisting of CACC, ACC, and human vehicles clarify how the share of CACC vehicles and controller gains trade off stability and saturation throughput, and they suggest dynamic activation of CACC on arterials where appropriate (Qin and Wang, 2021).

Lioris *et al.* (2017) concluded that CACC platoon in urban intersection could achieve a saturation flow rate of 4800 vph per movement with 0.75s headway at 45 mph or 0.7s headway at 30 mph. Ploeg *et al.* (2011) report a 6-vehicle CACC platoon, with a 0.5s headway; and Milanés *et al.* (2014) describe a 4-vehicle CACC platoon, with a 0.8s headway, capable of cut-in, cut-out and other manoeuvres. On signalised arterials, CACC controllers tailored to signal phase variability outperform ACC and human drivers on spacing error and energy use, and the better controller can depend on the pattern of phase changes. These findings inform saturation-flow adjustments at urban junctions (Mu *et al.*, 2021; Chen and Rakha, 2020).

Early Japanese AHS work demonstrated that automated longitudinal control could safely support short headways in mixed traffic, for example 0.5 s with platoons and 0.9 s without, improving efficiency (Yokota *et al.*, 1998; MLIT, 1998). Recent studies reaffirm that cooperative automation (CACC and platooning) stabilizes flow and boosts capacity at moderate penetration, particularly when platoons are structured appropriately (Oriol *et al.*, 2024; Zhang *et al.*, 2024). Ongoing corridor programs show that V2V-enabled platoons can operate at reduced gaps while maintaining safety, although human-factors and operational constraints remain central (FHWA, 2024; Caltrans, 2023). Robust controller designs and learning-based policies now adapt time headway to traffic conditions, which further enhances performance near bottlenecks (Liu and Wang, 2021; Veksler *et al.*, 2025). In

parallel, vehicle-infrastructure cooperation via variable speed limits has reduced speed variability and improved safety and efficiency in mixed traffic (Nice *et al.*, 2023; Yuan *et al.*, 2022, ITS JPO, 2019).

2.2.1.2 Macroscopic Approach

Ngoduy (2013) and Nikolos *et al.* (2015) used analytical macroscopic approach on Gas Kinetic Model to confirm better performance of CACC over ACC with respect to both traffic stability and capacity. However, the macroscopic descriptive model takes into consideration many vehicles and the relevant properties of a traffic flow: traffic volume (vehicle/hour), traffic density (vehicle/km), average speed (kph).

Exogenous approach. Childress *et al.* (2015) used Seattle region's activity-based travel demand model to explore impacts of automated vehicles on travel demand. They simulated four different scenarios with respect to AV penetration rate and changes the capacity exogenously on a macroscopic network. Klooststra *et al.* (2017) assumed that AVs would change road capacity and exogenously modified road links capacities in EMME to simulate theoretical increase in throughput enabled by AV driving behaviour. Gukwa (2014) also used exogenous approach to apply the effect of increase road capacity on CUBE platform. Kim *et al.* (2015) analysed the availability of AVs across the Atlanta, Georgia region, using the MPO's (ARC's) existing activity-based model and assumed increases in roadway capacity and 100-percent market penetration of the new technology. Zhao and Kockelman (2018) used macroscopic flow-based model to model AV in TransCAD and assumed the changes of network capacity exogenously in various scenarios.

PCU based approach. Macroscopic route choice and assignment models apply volume-delay (or speed-flow) relationship to determine travel time in the road network. For links, the travel time is computed by multiplying the free flow travel time by a factor that is determined by a speed-flow relationship. The relationship between volume and capacity assumes a constant capacity and a volume, which considers the vehicle composition. The vehicle composition is described by passenger car units (PCU). Each vehicle type has a specific PCU factor converting the vehicle volume into a volume equivalent to passenger cars. This concept of PCU is a common concept in macroscopic assignment models. It is mainly used to convert Heavy Goods vehicle (HGV) / Bus into PCU.

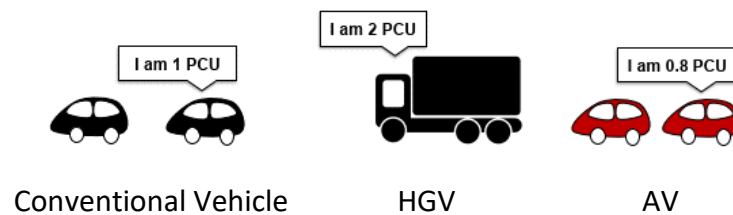
Sonnleitner J. and Friedrich M. (2020a) proposes extending the PCU concept to AV. This extension comes in two forms making different assumptions:

- Assumption 1: The performance of a network element changes proportionally to the share of AV

This assumption implies a linear relationship between vehicle-type and performance. The impact of one single AV depends on the type of road facility, but not on the penetration rate. The PCU-factor must be extended to distinguish road and intersection types (motorway / urban road, grade separated / at-grade intersections, signalised / unsignalised intersections). The PCU factor is a constant value, which remains fixed during an assignment.

Based on this concept, PCU factors for AV cars will be less than 1.0 compared to conventional vehicles, as AV will have less reaction time thus less headway (Figure 2.1).

Figure 2.1 Example of PCU factors by vehicles



Sonnleitner J. and Friedrich M. (2020a) assumed different PCU factors for AV by road types (Motorway 0.73, Arterial 0.76, Urban Street 0.85) and applied in VISUM macroscopic flow-based model (Sonnleitner J. and Friedrich M., 2020b).

- Assumption 2: The performance of a network element changes disproportionately to the share of AV

This assumption includes a nonlinear relationship between vehicle-type and performance. The impact of one single AV depends on the type of road facility and on the penetration rate. In case of a low penetration rate the impact of a single AV is smaller than in cases with a higher one. The PCU-factor must be extended to distinguish road and intersection types, but also the share of AV. This leads to a dynamic PCU-factor, which is adapted during an assignment.

Link-level PCUs respond to lane count, section length, control type, transit presence, and lane flow, which advances beyond fixed PCU factors (Gasparinatou *et al.*, 2022).

VISUM or Aimsun implementations that adjust reaction times and effective vehicle lengths by vehicle class and by leader-follower pairing show improvements at many penetrations, but also show that overly cautious AV logic on motorways can reduce performance, which highlights the need for careful behaviour calibration (PTV , 2024; Desta and Tóth, 2022; Obaid and Török, 2021).

Flow theory based approach. Yokota *et al.* (1998) described the functionality and the effect of longitudinal control (acceleration and deceleration) in the Advanced Cruise-Assist Highway Systems (AHS) for the mixed traffic of Autonomous Highway System (AHS) and non-AHS vehicles and presents quantitative analysis of the effect of AHS on traffic efficiency improvement. In this study, headway for the AHS movement with and without platoon used were 0.5 and 0.9 seconds. Friedrich B. (2016) proposed a theoretical approach to model AV using fundamental of traffic flow theory in macroscopic framework. Wagner (2016) introduced an approach to incorporate effects of AV on performance by adapting the capacities of road facilities. In macroscopic four-step settings, researchers link capacities by facility type, AV capability, and penetration; results show that cautious first-generation AV behaviour can decrease performance at low penetrations, with improvements emerging as capabilities and shares rise (Sonnleitner, Friedrich, and Richter, 2022). Planning-horizon analyses indicate mid-term capacity dips followed by long-term gains as penetration increases, reinforcing the headway-based capacity narrative (Saha and Motuba, 2023). These studies determine road capacity depending on vehicle headways, vehicle lengths, share of AV and speed.

2.2.1.3 Junction Modelling Approach

Junction modelling for AV extends classic signal coordination by embedding automation-aware parameters into established tools and analytical frameworks. TRANSYT remains foundational for coordinated signals, using Robertson's platoon-dispersion recurrence to predict arrivals and optimize splits and offsets (Robertson, 1974), with subsequent work confirming that the dispersion model is central to TRANSYT and detailing calibration sensitivity (Axhausen and Körling, 1987; Salter, 1989). Current practice guidance incorporates AV adjustments directly into junction capacity calculations. The Highway Capacity Manual (7th Edition) provides supplemental procedures to adjust saturation flow and capacity at

signalised intersections and roundabouts as a function of CAV market penetration and cooperative control assumptions, enabling planning-level junction analyses without changing core methods (TRB, 2022). State guidance similarly outlines when and how to apply these factors in future-year junction assessments, emphasising dependence on CACC behaviour and penetration levels (ODOT, 2022). Beyond conventional signals, analytical junction-management studies compare signalised control with reservation or priority policies under AV settings and derive capacity-delay relationships that can inform model structures for intersections and roundabouts (Bilal and Giglio, 2023; Wu and Zhu, 2021). Recent reviews synthesise trajectory-planning and joint intersection-vehicle control methods for AVs, highlighting model categories, assumptions, and gaps relevant to junction modelling in mixed traffic (Wu and Qu, 2022; Wu and Zhu, 2021; Fan and Liu, 2020).

2.2.1.4 Mesoscopic Approach

Mesoscopic models bridge microscopic and macroscopic coverage by simulating packetised flows with queue dynamics on links and explicit junction mechanisms providing tractable, city-scale evaluation while retaining node-level realism (FHWA, 2022). Recent mesoscopic AV studies combine junction and network modelling in one framework: bi-level methods choose where to install AV-dedicated lanes, while a mesoscopic lower-level assignment captures mixed headways and junction saturation; city-scale tests show how these scales to dense downtown grids (Kamjoo *et al.*, 2024). Related network-design works quantifies system benefits and equity effects as AV market share changes (Long *et al.*, 2025; Zhang *et al.*, 2024). Together, these studies show that mesoscopic models can encode AV affected headways, saturation flow and lost time at nodes while also capturing route choice across the network, and that multiresolution guidance supports switching between mesoscopic, microscopic and macroscopic views for validation and hotspot checks (FHWA, 2022).

2.2.2 Route Choice and Traffic Assignment of Autonomous Vehicles

The foundations of route choice in congested networks come from Wardrop's principles, which separate user equilibrium (UE) from system optimum (SO). Under UE, all used routes between an origin and a destination have the same lowest perceived travel cost, so no traveller can do better by switching routes. Under SO, flows are arranged to minimise total travel time for the whole network (Wardrop, 1952). Beckmann, McGuire and Winsten (1956) set out the mathematical form of UE and showed that it can be solved as a convex optimisation problem. These works form the core of classical traffic assignment and remain the main

benchmarks for realistic behaviour and for evaluating efficiency. Clear overviews are provided by Sheffi (1985) and Patriksson (1994).

In deterministic static models, UE is usually solved with variants of the Frank-Wolfe algorithm, which makes use of the convex Beckmann formulation (Sheffi, 1985; Patriksson, 1994). When travellers have imperfect information or different perceptions, stochastic user equilibrium (SUE) treats route choice as probabilistic and extends Wardrop's first principle. Early work set out the foundations of stochastic assignment and questioned standard logit assumptions (Daganzo and Sheffi, 1977). Later studies increased behavioural realism and improved network loading, for example with probit-based SUE and stochastic network models (Watling, 2006). More recent research introduces bounded-error formulations that relax assumptions on the distribution of perception errors (Kitthamkesorn and Chen, 2024).

Temporal dynamics introduce further complexity. Dynamic user equilibrium (DUE) and wider dynamic traffic assignment (DTA) allow travel times to change over time and represent how queues form and dissipate. These dynamics can overturn static insights, including how we interpret Braess's paradox, once dynamic queuing is modelled explicitly (Lin and Lo, 2009). Within DTA, connected vehicle information and responsive control lead to dynamic system optimal (DSO) models and real-time routing methods (Boyles *et al.*, 2015; Chen *et al.*, 2017).

Algorithmic progress follows these modelling choices. Besides link-based Frank-Wolfe methods, origin-based algorithms and conjugate-direction schemes have been proposed to improve convergence and computational efficiency on large networks (Sheffi, 1985; Patriksson, 1994). These methods support deterministic and stochastic assignments, as well as dynamic variants, in practical planning workflows.

The emergence of AVs challenges the behavioural basis of classical assignment. Human drivers make decentralised decisions, focus on their own travel time and cost, which aligns with UE (Wardrop, 1952; Sheffi, 1985). AVs can access network-wide, real-time information and can be routed by centralised or fleet-level controllers. Coordinated AV routing can internalise congestion effects and move outcomes towards SO, often called system equilibrium (SE) in this context (Levin and Boyles, 2015; Xu *et al.*, 2020). Simulations and analytical studies show that cooperative or centrally managed AV fleets can reduce the price of anarchy compared with purely decentralised behaviour (Fagnant and Kockelman, 2018;

Levin *et al.*, 2017). Studies on connected AVs also shows that cooperative strategies often differ from standard UE predictions (Mehr and Horowitz, 2019; Sorani and Bekhor, 2018).

The behaviour of AVs affect headways, stability, and effective capacity. This motivates multiclass models that distinguish AVs and human-driven vehicles (HVs) through different volume-delay functions (Talebpour and Mahmassani, 2016). Empirical and modelling studies show how AV penetration changes performance and equilibrium patterns, including non-linear capacity effects in mixed traffic (Carrone *et al.*, 2021; Tani *et al.*, 2024). As a result, mixed-AV assignment combines UE behaviour for HVs with cooperative or SO-oriented routing for AVs, often in bilevel or multiclass forms with explicit coupling between classes (Lo and Szeto, 2002; Wang *et al.*, 2019). Dynamic mixed-equilibrium models further integrate pricing or control policies that steer AVs toward SO while HVs continue to follow UE, enabling richer scenario analysis for transition pathways (Mansourianfar *et al.*, 2020; Wang *et al.*, 2023).

From a modelling perspective, this literature suggests a structured classification. First, behavioural objectives range from UE (individual optimality) to SO/SE (network optimality), with hybrid schemes that trade off fairness and efficiency, which is increasingly relevant as connected and autonomous technologies becomes prominent (Morandi, 2024; Tani *et al.*, 2024). Second, uncertainty is represented by deterministic UE, logit-based and probit-based SUE, and bounded-error variants, with the caveat that AVs with near-perfect information may not require the same stochastic assumptions that remain appropriate for human drivers (Daganzo and Sheffi, 1977; Kitthamkesorn and Chen, 2024). Third, temporal scope spans static assignment to DUE/DSO, where dynamic queuing and control materially influence outcomes (Lin and Lo, 2009; Chen *et al.*, 2017). Fourth, algorithmic structures include link-based, origin-based and conjugate-direction methods tailored to the chosen behavioural and temporal setting (Sheffi, 1985; Patriksson, 1994).

In summary, UE remains the behavioural baseline for networks dominated by human drivers (Wardrop, 1952; Sheffi, 1985). AVs add demand-side coordination and supply-side capacity changes that can shift equilibria towards SO, especially with centralised or cooperative routing (Levin *et al.*, 2017; Fagnant and Kockelman, 2018). Although the literature calls for clear separation between UE and SO regimes, focus should be given to the immediate system effect of AV adoption such as higher capacity efficiency from reduced headways. To keep attribution clear,

behaviour is held constant via a common UE rule for both AVs and HVs, and AV benefits are represented through multiclass junction modelling and volume-delay functions within a mesoscopic, non-integer flow framework. This design highlights technology-driven supply gains, while leaving cooperative routing or SO-oriented coordination to future extensions (Wardrop, 1952; Sheffi, 1985; Talebpour and Mahmassani, 2016).

2.2.3 Literature Gap

Review study on the policy and societal implication of AV by Milakhis D. (2016) as accumulated from number of studies indicates that impact of AV on network capacities will be significant. Also, early macroscopic studies often scaled link capacities exogenously to represent AV effects in activity-based or four-step models; while useful for screening, such adjustments do not capture feedback between route choice and junction operations and can bias performance forecasts when intersection delays drive corridor outcomes. Multiresolution practice emphasises integrated feedback across resolutions to avoid these pitfalls.

Compared to this, PCU-based approach explained above will assess the network capacity more incisively. But this concept only considers the efficiency of AV in PCU factor and penetration rate to calculate capacity of link and intersections. Also, PCU-based approaches extend the conventional PCU concept to AVs across roadway and control types, with CoEXist delivering public guidance and tool extensions to apply AV PCUs in VISUM and to assess network-wide implications in multiple EU cities. More recent work shows PCU values are not constant: at the network level, CAV PCU varies nonlinearly (often polynomially) with penetration; at the link level, it varies with lane flow, section length, control type, road type, lane count and transit presence, supporting dynamic PCU over fixed factors.

However, one of the fundamental elements of the speed-flow relationship used in the macroscopic traffic assignment model is density, which can be estimated from headway. The mean net time headway over all vehicles can be based on the probability of specific vehicle types succeeding others, which in turn can be depended on the proportion of vehicle types (e.g., car, HGV) and the penetration rate of AV of this type. This analytical approach is applied in the network and used for behavioural (shared mobility) assessment of AV.

At the mesoscopic resolution, there is clear evidence that frameworks can combine junction modelling and network assignment, and also shows that headway-driven

discharge and saturation-flow/lost-time mechanics can be embedded directly in mesoscopic DTA or in static UE.

While PCU-based scaling and headway-based flow theory have been applied at macro and, increasingly, within mesoscopic tools, there is still a distinct gap for a mesoscopic framework that simultaneously: (i) simulates junction operations, (ii) performs network assignment, and (iii) uses a unified flow-theory approach to endogenously change capacity at both links and junctions for mixed AV/HV traffic, moving beyond fixed PCUs or purely exogenous link-capacity scaling.

Table 2.1 shows the studies that used PCU-based and flow theory-based approaches.

Table 2.1 Researches on modelling concept of macroscopic assignment

Concept	Resolution	Link	Junction	Network	Assignment	Study
PCU based	Macro	✓	✓	✓	Static UE	Sonnleitner J. and Friedrich M. (2020a)
		✓	(✓)	✓		Sonnleitner <i>et al.</i> (2022)
PCU based dynamic	Macro→Meso	✓	(✓)	✓		Gasparinatou <i>et al.</i> (2022)
Flow theory based	Macro	✓	(✓)	-	Static UE	Friedrich (2016)
		✓	-	✓		Bilal and Giglio (2023)
	Meso	✓	✓	✓	DTA	Kamjoo <i>et al.</i> (2024)
		✓	✓	✓	Static UE	Research Gap

(✓) Partial

However, a distinct research gap has been identified in mesoscopic modelling, particularly in the simultaneous modelling of both junction simulation and network assignment based on static user equilibrium approach to assess the impact of autonomous vehicles (AVs).

2.3 Studies on Modelling Shared Mobility

2.3.1 Context

The concept of Shared Autonomous Vehicles (SAV) can be divided into two main categories:

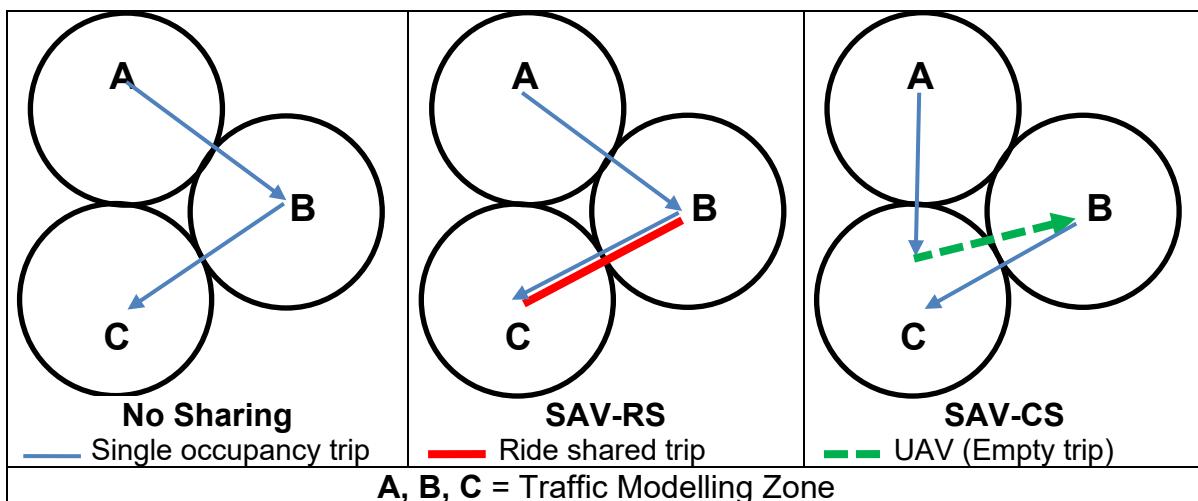
SAV Ride-sharing (SAV-RS). Ride-sharing is a joint-trip of at least two ride-sharing participants that share a vehicle. Successful ride-sharing requires coordination with respect to itineraries that include the specification of a pick-up and drop-off of a passenger. Ride-sharing can be broadly divided into two types:

- unorganised ride-sharing that involves family, colleagues, neighbours, and friends has a long history; and
- Organised ride-sharing is operated by ride-sourcing agencies that provide ride-matching opportunities for participants without regard to any previous historical involvements.

In this study we only consider the impact of morning commuting trips thus the modelling assumption involves AV-enabled organised ride-sharing behaviour.

SAV Car-Sharing (SAV-CS). Car sharing, also referred as ride hailing in some of the literatures, encompasses a range of companies and services, including traditional taxis and car services. The case for SAV-CS, after dropping off the passenger to his or her destination the unoccupied autonomous vehicle (UAV) will travel to pick-up location of the next passenger. SAV-CS could involve SAV-RS described above. Figure 2.2 shows the schematic diagram of SAV-RS and SAV-CS.

Figure 2.2 Schematic diagram of shared mobility



Transportation system models that include SAV are inherently complex and a series of modelling element are involved. These elements dictate the actual implementation of the evaluation of SAV systems as well as the required assumptions. The reviewed studies focusing on the modelling of SAV are discussed in four main modelling components: (a) Travel Demand, (b) Traffic Assignment, (c) SAV Distribution, and (d) other components (pricing, charging and parking).

2.3.2 Traffic Demand

The component demand involves estimation of demand in the study area and mode share for SAV services. With regards to the former, trips are generated based on travel survey data (Chen *et al.*, 2016; Dia and Javanshour, 2017; Fagnant and Kockelman, 2014; Fagnant and Kockelman, 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; Jäger *et al.*, 2017; Meyer *et al.*, 2017; Moreno *et al.*, 2018; Zhao and Kockelman, 2018; Iacobucci *et al.*, 2019), 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 distribution (e.g. a Poisson distribution) is 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 and the rest use mode choice models or simple rules to estimate demand. 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) assume 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.

2.3.3 SAV Distribution

Rule-based approach. Vehicle distribution component assigns SAVs 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 was implemented by Chen *et al.* (2016), Fagnant and Kockelman (2018), Gurusurthy and Kockelman (2018), Hörl (2017), Jäger *et al.* (2017), Mendes *et al.* (2017) and 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 seldom used because of their complexity and required computation power. 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). Alam and Habib (2018) uses rule based approach for the ride request using MATLAB and applied the distribution in VISSIM microsimulation model.

Vehicle rebalancing or repositioning is used to redistribute excess vehicles from low demand areas to high demand areas when modelling on-demand SAV services (Alonso-Mora *et al.*, 2017; Babicheva *et al.*, 2018; Fagnant and Kockelman, 2014; Rossi *et al.*, 2018; Zhang and Pavone, 2016). Vosooghi *et al.* (2019) conclude that redistributing vehicles has a significant effect on service performance, such as modal share and fleet usage. However, empty VMT/VKT increases significantly. We would like to opine here that the extent of change in empty VMT/VKT depends on the algorithm used for redistribution. 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, 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) propose a congestion-aware algorithm that shows good performance in terms of network congestion and customer service times. The algorithm selectively redistributes vehicles through routes that do not increase congestion. Babicheva *et al.* (2018) evaluate six different methods to apply redistribution and their results show that the combination of simple nearest neighbours and index-based redistribution method provide 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.

Friedrich, M., Hartl, M., Magg, C. (2018) presents a rule-based ride matching algorithm, which can be integrated in existing travel demand models. The study analysed the impacts of large ridesharing systems with AV on the number of required vehicles and the vehicle distance travelled. An algorithm working with integer demand was applied to determine the number of vehicles and the empty trips between drop-off and pick-up locations. Similar to a study for Lisbon (OECD 2015), the study (Friedrich 2016; Friedrich *et al.* 2017) estimated that the entire travel demand of all motorized modes in the Stuttgart Region could be transported by 7% of the current car fleet with 65% of the current vehicle distance travelled, if all travellers were willing to either use ridesharing vehicles with 6 seats or traditional rail. Estimating the number of cars for such a system requires a vehicle-blocking algorithm, which assigns every ridesharing trip to one specific car.

Sharing mode choice. Kröger and Kickhöfer (2017) used mode choice between conventional car, SAV-RS, SAV-CS to distribute SAV and modify the travel demand. This study assumed fleet size before the mode choice application. Zhao and Kockelman (2018) also used mode choice to distribute conventional car, CAV, SAV and Bus in multinomial logit framework.

2.3.4 Overview of Modelling Approaches

Many modelling studies have investigated the possibility of using SAVs to reduce reliance on personal vehicles and improve mobility. Jäger *et al.* (2018) used fixed travel time as referred as static assignment where free flow travel time multiplied by a factor to represent congestion. Chen *et al.* (2016), Fagnant and Kockelman (2014) and Zhang *et al.* (2015) considered average travel time of off-peak and peak hour in the traffic assignment. An hour-based value, either extracted from Google Maps (Bauer *et al.*, 2018) or obtained from the transport department of the city where the analysis is carried out (Kondor *et al.*, 2018). Ma *et al.* (2017) used the travel time mentioned in the taxi dataset along with a correction factor, when designing a reservation-based system.

However, dynamic traffic assignment models are closer to reality and can be divided into two categories: simulation-based (microsimulation and agent based) and analytical models. For modelling on-demand SAV services, majority of the studies use simulation systems. Bischoff and Maciejewski (2016), Bösch *et al.* (2016), Liu *et al.* (2017), Lokhandwala and Cai (2018) and Moreno *et al.* (2018) used agent-based simulation model to model SAV but did not consider dynamic SAV assignment. Fagnant and Kockelman (2018) and Hörl (2017) applied traffic assignment with dynamic SAV in agent-based model.

A major limitation of previous studies is that many relied on custom software packages with unspecified or unrealistic congestion models (Burns *et al.*, 2013; Fagnant and Kockelman, 2014; Fagnant and Kockelman, 2016) and/or grid networks (Fagnant and Kockelman, 2014; Fagnant and Kockelman, 2016). Although these were important studies for technology demonstration purposes, they lacked realistic flow models. Many studies even assumed that link travel times were constant. This has yielded over-optimistic results, such as one SAV replacing eleven personal vehicles (Fagnant and Kockelman, 2014). This limitation prevents prevent accurate predictions of the benefits of SAVs.

The most sophisticated SAV modelling approach should include micro-simulation simulation-based approach. However, inclusion of sharing choice of SAV-RS in combination with ride matching algorithm can improve the integrity of SAV modelling framework. Micro-simulation modelling approaches by Alam and Habib (2018) using VISSIM microsimulation and by Alazzawi *et al.* (2018) using SUMO considered constant demand. But these studies would require external demand model to deal with mode choice and SAV assignment to match the ride share. They are not often suitable for modelling larger network and does not provide strategic decision for any transport intervention.

To evaluate the performance of SAV, Fagnant and Kockelman (2018), Hörl (2017), Bischoff and Maciejewski (2016), Bösch *et al.* (2016), Lokhandwala and Cai (2018), Liu *et al.* (2017), Moreno *et al.* (2018) considered agent-based models (ABMs) with either constant or mode choice component of the traffic demand and dynamic SAV allocation. The agent-based model has other benefits, such as a disaggregate level of travel behaviour, compared with the trip-based model. Despite the numerous benefits of agent-based modelling as a research tool, there are several challenges associated with creating ABMs. One of the common difficulties such as the integration of too many features and the choice of the parameters. The results of models are often criticised for being either trivial or, on the other hand, too complex

and therefore probably wrong because of their surprising results (Waldherr and Wijermans, 2013).

The ABMs require time-use survey (travel diary) data for analysis and estimation. However, the constraint of data availability has made the use of ABM unpopular specially in the UK. In many cases, development of such resource demanding modelling method will not be suitable to assess the impact of transport intervention with and without SAV scenario for the future. Thus, more aggregate approach such as trip-based (origin-destination) modelling with in-depth SAV demand modelling will be useful if they provide same level of assessment for various SAV regime and modelling components. Only two studies: Zhao and Kockelman (2018) and Friedrich *et al.* (2018) used macroscopic flow-based modelling in modelling SAV. Although, other scenario-based studies included macroscopic flow based modelling but used SAV modelling input exogenously to the trip distribution and assignment model.

Zhao and Kockelman (2018) used mode choice model in flow-based macroscopic model to assess the impact of SAV. SAV with and without sharing was considered as a new mode and the exogenous travel cost was used as the mode choice parameters. However, this study did not consider the trip matching problem of ride sharing at the trip assignment stage.

Friedrich *et al.* (2018) used origin-destination based macroscopic model to assess the impact of ride sharing applied on human-driven vehicle. But he did not consider shared AV in his study. Also, in this study trip assignment process included shortest path assignment assuming one origin-destination trip only used one route.

2.3.5 Characteristics of Ride Sharing

The term ride sharing is defined as an automated system that facilitates drivers and riders to share one-time trips close to their desired departure times. Concept of the ride sharing is characterised by the following features, which are addressed in developing the methodology of modelling ride sharing.

- **Dynamic:** The ride share request can be accomplished on a short notice, which can range from a few minutes to an hours before departure time. The growing use of Internet-enabled mobile phones allows people to offer and request trips whenever they want, wherever they are. Thus, communication technology is a key enabler to dynamic, on-demand ride sharing.

- **Independent:** The drivers which provide the rides are independent private entities. This is different from most traditional forms of passenger transportation where a central organisation owns vehicles and/or employs drivers.
- **Cost-sharing:** The variable trip-related costs are reallocated among the ride share participants in a way that makes it beneficial for them to participate from the perspective of cost reduction. The variable trip cost minimally includes fuel expense but may also consider wear and tear on vehicles, parking costs or road fees such as tolls.
- **Non-recurring trips:** Dynamic ride sharing focuses on single, non-recurring trips. This distinguishes it from traditional carpooling, which require a long-term commitment among two or more people to travel together on recurring trips for a particular purpose, often for traveling to work. Single trip ride sharing is more flexible because it does not require rigid time schedules or itineraries over time.
- **Automated matching:** To establish ride shares in a way that requires minimal effort from the participants, ride matching should be automated in a dynamic setting. This means that a system helps riders and drivers to find suitable matches and facilitates the communication between participants. We do not include in our definition simple (online) notice boards where riders and drivers can post desired or planned trips and choose to contact potential ride share partners themselves.

2.3.6 Ride Matching Process

The ride sharing process now a days can be established by the internet-enabled mobile phones' app. Most of the ride sharing apps e.g., Uber, Lyft, Trees for cars etc. achieve the generic goal where users can offer a ride as a driver or a request for transportation as a rider. To facilitate easy trip specification, the app lets users store and select pre-defined locations such as home, work, and the grocery store. With a Location (GPS)-enabled phone, users can set their current location as the origin of their trip, or en-route. If a ride share match is established, the app program proposes the arrangement to the participants. If the driver and the rider agree on the proposed arrangement, the driver picks up the rider at the agreed time and location. The app will guide the driver to an appropriate pickup location and from

thereon to the rider's destination via the incorporated navigation system. When the driver is in range for the pickup, the application will notify the rider in real-time. The program automatically assesses a trip fee to the rider, of which the application company receives a fixed percentage.

Basic principle of trip matching process of ride sharing is mostly same for SAV and human-driven vehicle. The core of a ridesharing system is the trip matching process. The complexity of the matching problem depends on the number of trips. With an increasing number of trips, the number of possible matches increases. The challenge is to find reasonable solutions within a short computational time to run the system as an online real-time application.

2.3.7 Ride Sharing Objectives

Ride sharing allows participants with cars to save on travel-related expenses by sharing trip costs and enhance the mobility of system users. A ride share provider helps people to establish ride shares on short-notice by automatically matching up drivers and riders. If the system is private and operated for profit, the provider may generate revenues by commissions or advertisement. For example, a ride share provider may charge a commission per successful ride share, either a fixed fee or proportional to the trip cost. Public systems may have a societal objective, such as the reduction of pollution and congestion. The objectives of the ride share provider and ride share users are mostly in line. Given these overall system objectives, review study on ride share by Agatz *et al.* (2012) considered one (or a combination) of the following specific objectives when determining ride share matches:

- **Minimise total travel distance (D).** This objective is an important consideration for the participating drivers and riders and the revenues of the ride share provider. This objective is important from a societal point of view since it helps to reduce pollution (emissions) and congestion.
- **Minimise total travel time (T).** The travel time is the time spent in the vehicle while travelling between origin and destination. From a societal perspective, this is an important measure since vehicle emissions not only relate to vehicle-kilometres but also to vehicle speeds. Obviously, time is also an important convenience consideration for the participants.
- **Maximise the number of riders (R).** This objective maximises the number of satisfied drivers and riders in the system. This objective is beneficial for a

private ride share provider whose revenues are linked to the number of successful rides share arrangements. Moreover, the matching success-rate may also be an important performance indicator for users of a ride share service.

Baldacci *et al.* (2004), Calvo *et al.* (2004), Winter and Nittel (2006), Amey (2011), Kleiner *et al.* (2011), Ghoseiri *et al.* (2011), and Agatz *et al.* (2011) are the most acknowledged research that deals with optimisation aspects of ride matching problems.

The literature on ride sharing typically considers variable travel costs that are roughly proportional to vehicle-kilometres (Baldacci *et al.*, 2004; Calvo *et al.*, 2004; Agatz *et al.*, 2011; Amey, 2011). If the cost of ride share trip is less than the sum of the costs of individual trips of its participants, it is always feasible to allocate the cost savings among the participants such that everyone receives cost savings. Note that a complete ride share trip should be defined as all travel required to move each participant from his origin to his destination. For example, in the case where a driver shares a ride with a single rider this would include travel from the driver's origin to the rider's origin, then onto to the rider's destination, and finally onto the driver's destination.

Kleiner *et al.* (2011), on the other hand, develop the optimisation aspect as an adaptive dynamic ridesharing system that is capable to consider individual preferences of participants while matching the trips. Ghoseiri *et al.* (2011) formulated a dynamic rideshare matching optimisation model by maximising the number of participants. In Winter and Nittel (2006) and Agatz *et al.* (2011) study, the optimisation process were dynamic in nature where participant specify an earliest possible departure time and latest possible arrival time.

Only Agatz *et al.* (2011) among these studies implemented the ride matching optimisation in a network model, but none of these considered shared autonomous vehicle in their framework.

In travel demand modelling so far, the ride matching problem for shared autonomous vehicle is addressed exclusively in the context of microscopic and agent-based demand modelling in which the negotiation process of the transport users (agents) is modelled. Example of such studies (also mentioned in Section 3.2) are Lokhandwala and Cai (2018), Moreno *et al.* (2018), Fagnant and Kockelman (2018), Loeb and Kockelman (2019), Yan *et al.* (2020), Hörl (2017),

Hörl *et al.* (2029a), Hörl *et al.* (2019b), Alam and Habib (2018) and Alazzawi *et al.* (2018). Objective of the ride matching and network modelling approach for these studies are summaries in Table 2.2.

However, the matching algorithm used in these studies are suitable for integer demand only, which is suitable for microscopic and ABM, and not compatible for matching non-integer demand, as it occurs in demand matrices of an origin-destination based macroscopic travel model.

Also, the ABMs require time-use survey (travel diary) data for analysis and estimation. However, the constraint of data availability has made the use of ABM unpopular specially in the UK. In many cases, development of such resource demanding modelling method will not be suitable to assess the impact of transport intervention with and without SAV scenario for the future. Thus, more aggregate approach such as trip-based modelling with in-depth SAV demand modelling will be useful if they provide same level of assessment for various SAV regime and modelling components.

Friedrich *et al.* (2018) proposed a rule-based ride matching algorithm on an origin-destination based macroscopic model that compares two path sets of suppliers and demanders. The representation of a path in the road network is reduced from a sequence of links to a sequence of zones. The zones act as a buffer along the path, where demanders can be picked up. Estimating the number of cars for such a system establishes an algorithm that assigns every non-integer ridesharing trip to one specific car. In a subsequent study by Richter *et al.* (2019), the same algorithm was applied in a macroscopic travel demand model to allow mode choice for shared AVs.

In both studies, trips were assigned based on the shortest path assignment. Each link was included in one path only. Also, the matching algorithm in this study did not consider the fee (or revenue) of the ride-sharing trip to match the ride; thus, the effect of the cost of the ride on the travel demand and network assignment is absent in this research. Thus, partial ride matching is established between the ride supplier and demander based on priority of the longest distance only.

Table 2.2 Summary of the literature gap analysis of shared mobility on macroscopic modelling

Study	Ride Matching Objective	Dynamics	Network Modelling Approach	AV
Baldacci <i>et al.</i> (2004)	D, R	No	No	No
Calvo et al, (2004)	D, R	No	GIS Network	No
Winter and Nittel (2006)	T, R	Yes	No	No
Amey (2011)	D	No	No	No
Kleiner <i>et al.</i> (2011)	D, R	Yes	Journey Planner	No
Ghoseiri et al (2011)	R	Yes	No	No
Agatz <i>et al.</i> (2011)	D	Yes	Microsim	No
Bischoff and Maciejewski (2016)	P	No	ABM	Yes
Bösch <i>et al.</i> (2016)	T, R	No	ABM	Yes
Liu <i>et al.</i> (2017)	T	No	ABM	Yes
Lokhandwala and Cai (2018)	T	No	ABM	Yes
Moreno <i>et al.</i> (2018)	P	No	ABM	Yes
Fagnant and Kockelman (2018), Loeb and Kockelman (2019), Yan and Kockelman (2020)	T, R	Yes	ABM	Yes
Zhao and Kockelman (2018)	D	No	No	Yes
Hörl (2017), Hörl <i>et al.</i> (2019b)	D	Yes	ABM	Yes
Alam and Habib (2018)	T	Yes	Microsim	Yes
Alazzawi <i>et al.</i> (2018)	T	Yes	Microsim	Yes
Freidrich <i>et al.</i> (2018)	D	No	Flow-based	No
Ritchter <i>et al.</i> (2019)	D	No	Flow-based	Yes

D = Minimise Travel Distance, T = Minimise Travel Time, P = Maximise Riders

2.4 Summary, Research Gap and Contribution

The literature reviewed in this chapter provides the theoretical and methodological foundation for modelling autonomous vehicles (AVs) and shared mobility within transport networks and establishes the context for the modelling framework developed in this research. The review examined existing work on AV traffic flow characteristics, network assignment modelling, and shared mobility, and the findings presented in Table 2.1 and Table 2.2 identified the key gaps that motivate the study.

The literature gap analysis presented in Table 2.1 identifies a clear absence of studies that model AVs within mesoscopic network assignment models based on static user equilibrium principles. Existing studies such as Obaid and Török (2021), Desta and Tóth (2022), Sonnleitner *et al.* (2022), and Saha and Motuba (2023) focus primarily on macroscopic modelling approaches and do not provide procedures for incorporating AV behaviour within operational network assignment models. Similarly, network-level studies such as Kamjoo *et al.* (2024), Zhang *et al.* (2024), and Long *et al.* (2025) rely on simulation-based approaches rather than equilibrium-based assignment methods. As a result, there is limited research on representing AV behaviour within mesoscopic network assignment models using a static user equilibrium framework.

A second key gap identified in Tables 2.1 and 2.2 is the lack of modelling approaches that represent AV behaviour using traffic flow theory within network assignment models. Existing studies typically represent AV impacts through simplified capacity adjustments or behavioural assumptions, but do not provide a systematic method for linking headway and saturation flow to AV penetration within an assignment model. This limitation motivates the development of the flow-theory-based modelling approach presented in Chapters 4 and 5.

A further gap identified in the literature is the absence of studies that compare flow-theory-based and PCU-based approaches for modelling autonomous vehicles within the same assignment framework. PCU-based approaches are widely used in transport planning practice to represent different vehicle classes, but existing research does not provide a consistent comparison between PCU-based and flow-theory-based modelling approaches for AVs. The comparative analysis undertaken in Chapters 5 and 6 therefore addresses an important methodological gap identified in the literature.

The literature gap analysis indicates limited research on integrating shared mobility within equilibrium-based assignment models. While Agatz et al. (2012), Alam and Habib (2018), and Alazzawi et al. (2018) demonstrate the potential of shared autonomous vehicles, these studies do not incorporate ride-matching procedures within conventional origin-destination based assignment models. This limitation motivates the ride-sharing framework developed in Chapter 7.

The key research works that contributed to this research are referenced in in Chapters 4-8 in developing methodology and benchmarking. Chapter 4 translates the flow-theory insight that capacity depends on speed, time headway, and effective vehicle length into SATURN inputs that vary with AV penetration, drawing on the mixed-traffic formulations in Friedrich (2016) and Wagner (2016) and on short-headway evidence from the AHS/CACC lineage (Yokota *et al.*, 1998). Chapters 5-6 benchmark the flow-theory results against a PCU-based AV class in standard planning practice, aligning closely with the 0.6-0.8 range reported in the literature (Sonnleitner & Friedrich, 2020a/b). Literature review on ride-sharing literature, Agatz *et al.*, (2012), Friedrich et al. (2018), Zhao and Kockelman (2016), Fagnant and Kockelman (2014), Alam and Habib (2020), and Alazzawi *et al.* (2020), establishes the optimisation objectives, behavioural assumptions, and highlights the gap in macroscopic, non-integer matching within assignment. Chapter 7 builds directly on this by segmenting demand into suppliers and riders, assigning both under UE to generate feasible paths, and then applying a path-sequence, zone-buffer matching algorithm that handles non-integer flows and prioritises generalised cost and revenue, extending Friedrich et al. (2018) to a mesoscopic context.

Overall, the literature reviewed in this chapter establishes the context and justification for the research. The modelling framework developed in this study addresses the absence of mesoscopic network assignment models for AVs based on static user equilibrium principles, introduces a flow-theory-based method for representing AV behaviour, and provides a comparison with PCU-based modelling approaches. These contributions form the central methodological advances of the research.

Chapter 3

Overview of SATURN

3.1 Introduction

SATURN, Simulation and Assignment of Traffic to Urban Road Networks, is a comprehensive traffic modelling suite designed to simulate and predict traffic patterns in urban areas, helping planners and engineers to analyse the effectiveness of various traffic management strategies. The software can model the flow of individual vehicles through road networks, taking into account factors such as traffic signals, congestion etc. This allows for a detailed understanding of traffic behaviour and the potential impact of changes to the road system (SATURN, 2024 Section 1).

In the context of traditional 4-step travel demand modelling, which includes trip generation, trip distribution, mode choice, and route assignment, SATURN is primarily involved in the last step. While it can be used to inform decisions about trip distributions and mode choices indirectly, its strength lies in simulating route choices and assignments based on the current traffic conditions. This is crucial for understanding how traffic moves through an urban network and for planning improvements to reduce congestion and enhance mobility.

SATURN is considered a mesoscopic model because it operates at a level of detail that is between macroscopic and microscopic models (Abudayyeh, 2018; Tranhuu *et al.*, 2007). Unlike macroscopic models that treat traffic flows in a more generalised way, and microscopic models that simulate the behaviour of each individual vehicle, mesoscopic models like SATURN capture the essential characteristics of both. It models groups of vehicles and their interactions with the network, providing a balance of detail and computational efficiency. This makes SATURN particularly useful for studying urban traffic where individual vehicle movements are less predictable, but the overall patterns can still be understood and influenced through planning and management (SATURN, 2024).

3.2 SATURN Modelling Components

SATURN can be considered a highly advanced traffic assignment model. Like most models of this nature, it operates on the premise that the underlying traffic pattern, as represented by an Origin-Destination (O-D) trip matrix, remains fixed (though external techniques may account for changes in modal split and distribution). The model is structured with two integral phases: a detailed simulation of intersection

delays and an assignment phase that determines the routes taken by the aforementioned O-D trips (Hall, Vliet and Willumsen, 1980). Before outlining the manner in which these phases are interconnected, a brief overview of the model's components is discussed in this section.

3.2.1 The Simulation Model

The primary objective of the simulation is to determine junction delays resulting from a given pattern of traffic. Two fundamental assumptions are made for this purpose (SATURN, 2024; Chapter 8):

- The pattern of traffic flows is assumed to be constant over time periods equivalent to the length of the simulated time period, which is typically the model hour e.g., 60 minutes.
- For simulation purposes, a cyclical behaviour is imposed on the flows by traffic signals, which are operated with a common cycle time (typically in the range of 60-120 seconds).

The first assumption is shared by virtually all models in this area and allows reliance on a fixed trip matrix. It also restricts the investigation to the average behaviour of the system within the given time period.

The second assumption enables the simulation to concentrate on a single cycle, making a detailed simulation possible while avoiding many of the overheads normally associated with simulation. Within each cycle, traffic is represented by semi-continuous 'flow profiles,' as opposed to modelling individual vehicles or packets of vehicles.

These features, together with the use of traffic flow dispersion along links, are techniques that have been used successfully in the conventional signal optimisation programme.

Given that junction delays significantly influence urban travel times, accurate modelling of these delays holds great importance in SATURN. The software distinguishes and models the following junction types separately: traffic signals, pelican crossings, priority junctions (including merges and diverges), and roundabouts.

Unlike the majority of assignment models, SATURN takes into account variations in delays at intersections for different turning movements. A crucial aspect of this process involves the detailed calculation of the pattern of traffic which can actually make the turn, demanding considerable computational effort. Specific purpose-built routines are employed for each type of turning movement at an intersection. For instance, separate routines are used to calculate flows conflicting with left turns, right turns, or straight-on movements at stop-lines of priority junctions. Turn markers are employed to identify the type of turn under consideration.

Innovative techniques incorporated into the simulation include the adoption of a gap acceptance formulation to calculate merging and crossing capacities, as well as the classification of junction approaches based on lane markings. The former ensures that the merging flow's level varies throughout the cycle, reacting to the instantaneous strength of opposing flows. The latter enables the calculation of turning flow distributions between available lanes, providing a better understanding of interactions between distinct movements.

By using these techniques in conjunction with information on turn and link capacities, SATURN effectively accounts for various factors, including:

- Delays caused by opposing flows, such as those affecting right-turning traffic;
- Delays resulting from vehicles on the same link, such as the impact on straight-ahead traffic caused by impeded right-turners in a shared lane;
- The shape of arriving flows;
- The influence of phase structure and offsets at traffic signals; and
- Individual lane capacities.

When handling roundabouts, SATURN employs an iterative procedure that aims to replicate the intricate conflicts that occur in real-world scenarios. Although developed independently, the roundabout sub-model seems to adopt an approach similar to TRL (1979).

3.2.2 The Assignment Model

The objective of the assignment phase is to select minimum-time routes through the network for each element in the trip matrix, considering the relationship between travel time and flows. The model uses an 'equilibrium technique,' which optimally combines a series of all-or-nothing assignments, resulting in a flow pattern that

satisfies Wardrop's first principle of user equilibrium. The concept of focusing solely on fastest routes may face objections in large networks, where exceptions are frequently observed. However, it holds more validity for small networks, where potential routes available to each O-D pair are relatively distinct (SATURN, 2024; Chapter 7).

The model assumes two key factors:

- The travel time of each link remains fixed regardless of flow, and
- The delay to each turning movement at an intersection is a function of the turning volume.

The simulation model is utilised to model 'flow-delay' curves by calculating delays for each turning movement at zero flow, current flow, and capacity, while keeping all other flows (i.e., opposing traffic) constant. A curve is then fitted based on these three points.

$$t = AV^n + t_0 \quad V < C \quad (a)$$

$$t = AC^n + t_0 + B*(V - C)/C \quad V \geq C \quad (b) \quad \dots 3.1$$

where:

t : the simulated travel time (seconds)

t_0 : the free-flow travel time (seconds)

C : the turn capacity (pcu/hr)

V : the turn flow (pcu/hr)

A, B, n : constants worked out by the programme

For turning movements A and n are calculated by the program simulating three different delays: that at zero flow, that at the current assignment flow and that at capacity. If the current flow is either too high (over capacity) or too low (near zero) then a suitable arbitrary flow is used to determine the middle point (20% or 80% of capacity).

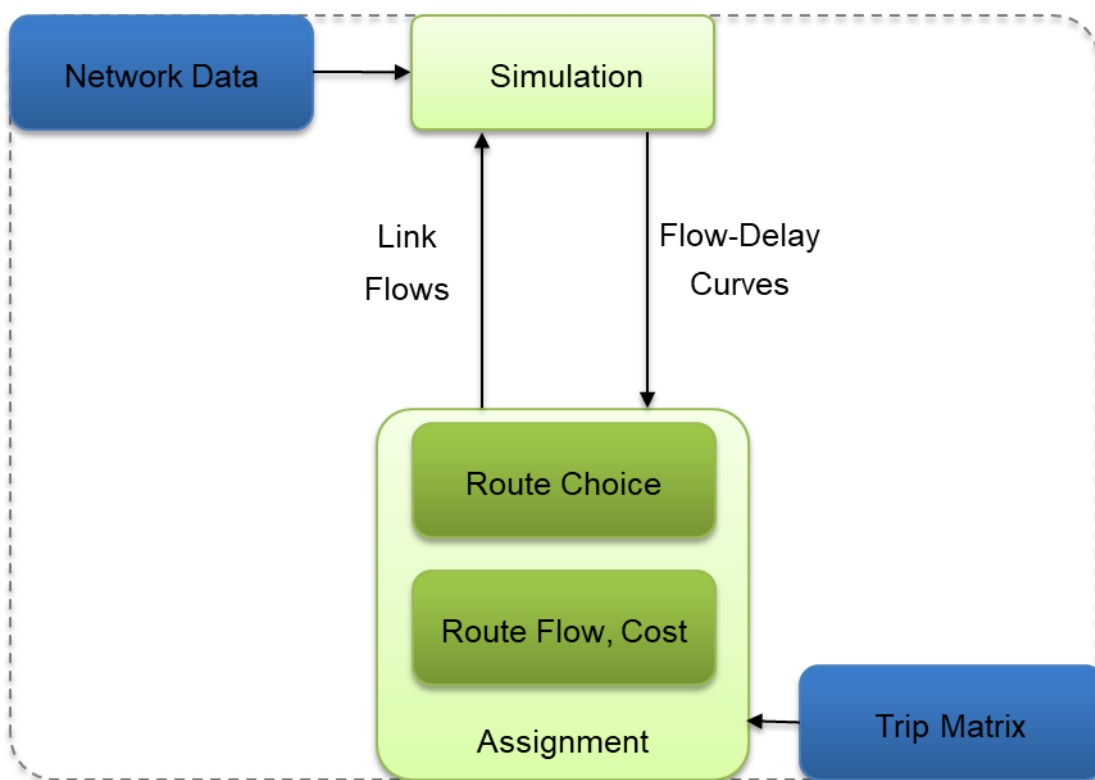
B is a constant worked out by the program equal to one half the time period being modelled.

The linear section of the curve corresponds to queues building up at a uniform rate throughout the simulation period.

3.2.3 The Complete Model

The complete model entails an iterative loop between the assignment and simulation phases (Figure 3.1). The simulation determines flow-delay curves based on a given set of turning movements and feeds them to the assignment. The assignment phase, in turn, uses these curves to determine route choices and subsequently updates turning movements. These iterations continue until reasonably stable values for the turning movements are achieved.

Figure 3.1 The Simulation and Assignment Phases of SATURN



The need for this 'outer' iteration stems from the fact that the delay curves used by the assignment are based on fixed values of opposing traffic at each intersection. As each assignment produces different opposing flows, the simulation yields different delay curves, leading to varied assignments. Therefore, the dependence of delay, t , on flow V is incorporated within the assignment phase via equation 3.1, while the broader dependence on opposing flows is addressed by the 'outer' loop.

Although SATURN consists of two separate phases, it appears as a single program to the user. The simulation and assignment stages run automatically without user intervention until convergence is achieved or a specified number of iterations is completed.

Incorporating both simulation-based and conventional network representations, SATURN provides a comprehensive suite of assignment options that includes generalised cost assignment, all-or-nothing assignment, Wardrop user equilibrium assignment, Burrell multiple-route stochastic user equilibrium assignment, and demand-responsive elastic assignment for the representation of induced traffic effects. These approaches are grounded in established theoretical frameworks and employ algorithms designed to achieve stable convergence, reflecting SATURN's development upon a strong academic and methodological foundation.

Within SATURN's standard configuration, route-choice decisions are modelled as independent, decentralised choices made by individual users, consistent with Wardrop's first principle of user equilibrium (UE). This representation reflects conventional assumptions about human driver behaviour and forms the default behavioural basis of SATURN's assignment procedures.

Although SATURN does not apply system-optimal routing by default, it is important to acknowledge that the software can represent a System Optimal (SO) assignment internally through the SOWHAT and WHATHO parameters, as documented in Section 7.11.9 of the SATURN Manual. These options enable SATURN to minimise total system travel cost by substituting marginal costs for actual costs within the Frank-Wolfe algorithm. However, SO assignment is described in the Manual as a research-focused capability, with recognised issues such as potential discontinuities in marginal cost curves, convergence difficulties, and limited behavioural realism.

Given these considerations, together with the additional configuration, calibration, and computational effort required, the application of SO-based assignment fell beyond the scope and resources of the present study. Accordingly, all network assignments in this research were undertaken using the standard UE framework.

3.3 Data Requirements

Two distinct forms of data input are required in SATURN. The first is an Origin-Destination (O-D) trip demand matrix T_{ij} , which represents the number of trips from

origin zone i to destination zone j . To convert this demand into traffic flow, the O-D matrix in number of vehicles is multiplied by the PCU factors. The resulting matrix units are in PCUs (e.g., PCUs per hour). The PCU factors account for the different space requirements of various vehicle types. For example:

- A passenger car (sedan) is assigned a PCU value of 1.0.
- Light-duty vehicles (such as SUVs) receive a PCU value of 1.5.
- Heavy-duty vehicles (trucks, buses) have a PCU value of 2.0.

The second input is 'network' data. As usual the road network is described graphically as a set of nodes and connecting links. Additional information is essentially node-based, with the exact details varying with the junction type. In general data refer to junction type, to entry links to the node (free run times, lengths, lane structure, etc.) and to turns (saturation flows and types). The saturation flows represent unopposed values and can often be taken as functions of the road geometry. In addition, stage descriptions and offsets are required for traffic signals; and centroid connectors for the assignment phase.

Simulation network data requirements may be summarised as follows:

- Universal parameters such as minimum gap acceptance, etc;
- Junction data - type of junction (signals/priority/roundabout); co-ordinates;
- Link data - distance, time or speed, number of lanes, stacking capacity (optional);
- Turn data - a saturation flow, lanes available, a priority marker indicating give ways, etc;
- Traffic signal data - stage lengths; offsets; cycle time

These inputs may be construed as the "demand" and "supply" components, respectively, and it is incumbent upon the user to furnish these crucial parameters.

3.4 Other Key Features

Other key features and components of the SATURN modelling suite includes:

- **Matrix Manipulation:** SATURN includes a matrix manipulation system that allows for adjustments and estimations of trip matrices, which are essential for understanding traffic demand and distribution (SATURN, 2024; Chapter 10).

- **Network Editor and Database:** A network editor and database system are part of SATURN, providing the tools necessary to create, edit, and manage the traffic network data (SATURN, 2024; Chapter 10, 18).
- **Deriving O-D Matrices from Traffic Count:** The use of the program SATME2 in conjunction with the supplementary program SATPIJA to estimate trip matrices from traffic counts. It is based on the theoretical procedure generally referred to as ME2, Matrix Estimation from Maximum Entropy (SATURN, 2024; Chapter 13).
- **Data Collaboration:** The software can input and output data at the matrix, link, and junction level in various formats, facilitating collaboration and data sharing between different transportation software platforms (SATURN, 2024; Chapter 10).
- **Performance Evaluation:** The suite provides tools to evaluate the performance of the transportation system, such as travel times, congestion levels, queue lengths, and delay at intersections.
- **Scenario Analysis:** SATURN allows users to test different scenarios, such as changes to the road network, traffic management strategies, or land-use developments, to assess their impact on traffic flow and identify optimal solutions.
- **Calibration and Validation:** Before using the model for decision-making, it's essential to calibrate and validate the SATURN model to ensure its accuracy and reliability. This involves comparing the model's output to real-world traffic data and making adjustments as necessary.

3.5 SATURN Module

SATURN includes a variety of modules, each serving a specific function within the overall modelling process. The key modules utilised in this research are discussed here.

3.5.1 SATWIN

SATWIN is the user-friendly interface for the SATURN traffic modelling suite, designed to streamline the user experience by providing a centralised platform for managing various SATURN projects. It facilitates the selection and operation of different SATURN versions, manages working directories, sets local and environmental settings, and offers access to all SATURN modules, including network editing and matrix manipulation. Additionally, SATWIN integrates with tools like SATVIEW and SATCODER for enhanced visualisation and coding capabilities,

while also managing batch files and error logs, ensuring efficient management of the model and troubleshooting within the SATURN modelling environment.

3.5.2 SATVIEW

SATVIEW is a graphical interface module designed to display and analyse traffic assignment results over a GIS platform. It allows users to quickly visualize and delve into the data created by SATURN assignments, presenting model outputs on Bing mapping data for easy interpretation. With SATVIEW, users can compare different network scenarios, assess the impact of proposed schemes on traffic flows and travel times, and export the data to standard GIS formats, making it an invaluable tool for transport analysts and planners seeking to gain deeper insights from their traffic studies.

3.5.3 SATCODER

SATCODER is a specialised module within the SATURN traffic modelling suite that streamlines the process of coding junctions in a traffic network. It provides a user-friendly graphical interface that overlays the network on mapping data, allowing for interactive and visual coding of junctions. This ensures accurate representation of junctions' physical and operational characteristics, which is essential for the reliability of traffic simulations. SATCODER's features support template-controlled coding, quality control, interactive editing, collaborative efforts, and scenario management, making it an indispensable tool for transport planners and engineers working on detailed traffic models.

3.5.4 SATNET

The SATNET module is a key component of the SATURN traffic modelling suite. Its primary function is to manage the network data, which includes defining and editing the road network's topology, such as links, nodes, zones, and junctions. SATNET allows users to input and modify the geometric and traffic control details of the network, which are essential for accurate traffic simulation and assignment. It ensures that the traffic network is accurately represented before any traffic demand or assignment simulations are performed. Input of SATNET is the traffic network data and output is the UFN file.

3.5.5 SATALL

SATALL is the assignment procedure within SATURN, taking in a trip matrix in UFM format and a network in UFN format. It then assigns these trips to routes across the network, guided by the prevailing cost-flow relationships, which may be provided by the user or derived from simulations. Its essential outputs are flows per link, including turns in the simulation network. The same procedures are included within the stand-alone assignment program SATEASY as well as within the combination program SATALL.

3.5.6 SATURN

This module is designed to execute the functions of both SATNET and SATALL in a sequential manner. It starts with the network data file and the trip matrix in UFM format as inputs. By running these two modules consecutively, SATURN provides a streamlined process that encompasses both the management of network data and the assignment of trips to the network.

3.5.7 P1X

The SATURN network analysis program P1X has powerful graphical display capabilities for network, junction, and matrix-based data. It allows for the visualisation of junction details, including link and turn data, at both individual junction and network-wide levels. The P1X module combines together the functionality of four original analysis programs, P1, SATLOOK, SATDB and SATED, plus extra functions such as network cordoning (SATCH), signal optimisation (SATOFF) and network building (SATNET) into a single multi-purpose network analysis program.

In brief SATLOOK caters for alpha-numeric output and analysis of UFS files, P1 provides graphical analysis and network editing, SATED edits simulation nodes and SATDB provides spreadsheet-like facilities. Since the four basic functions are relatively distinct it is often useful to refer to them by separate program names. SATLOOK and SATDB exist as separate programs although they may also be accessed directly through the top menu in P1X.

3.5.8 SATDB

This module is a database tool that facilitates the storage and management of traffic data. Its functions include:

- **Data Storage:** SATDB serves as a repository for various types of traffic data, including flow, speed, vehicle counts, and other relevant metrics.
- **Data Management:** It provides tools for organising, updating, and maintaining the accuracy of the traffic data stored within the system.
- **Data Export:** SATDB allows users to export traffic data into different formats, such as Excel, for further analysis or reporting.
- **Data Analysis:** The module may offer basic analysis capabilities, enabling users to perform preliminary evaluations of the traffic data directly within the system.

Overall, SATDB is an essential component of the SATURN suite, supporting the effective handling of traffic data which is crucial for accurate traffic modelling and analysis.

3.5.9 MX

The MX module in the SATURN traffic modelling suite deals with matrix operations, typically for tasks such as creating, manipulating, and analysing O-D matrices. This module provides tools for various matrix operations, which includes scaling, factoring, sectoring, and converting matrices to the appropriate format for use within SATURN. For precise functionalities and instructions on using the MX module, please refer to the SATURN manual's Chapter 10 (SATURN, 2024).

3.5.10 SATSTAT

SATSTAT is a tool used to automatically extract and summarise convergence and summary performance statistics for each network(s) into a CSV file. The resulting CSV files may be then be readily imported into the associated MS Excel spreadsheet and comparisons undertaken between different networks. SATSTAT consists of two parts: (i) a Fortran 32-bit program to extract the summary statistics, called through the batch file SATSTAT.BAT; and (ii) an MS Excel spreadsheet to undertake the comparisons. Detail of the use of SATSTAT is discussed in the section 15.49 of the SATURN Manual (SATURN, 2024).

3.5.11 SIGOPT

A “batch procedure” SIGOPT is available to optimise stage times and/or offsets in a UFS model file and to create a new output file(s). It effectively supersedes both P1X in terms of stage times and SATOFF in terms of offsets. Output files may be either (a) .UFS, (b) .DAT and/or (c) .RGS

SIGOPT makes use of existing routines within P1X but runs in a non-graphical non-interactive mode such that it resembles any other batch-mode program.

3.5.12 SATOFF

SATOFF focuses on optimising signal offsets at junctions. The primary function of SATOFF is to minimise the total vehicle delay at junctions by adjusting the timing of traffic signals. This optimisation is based on the hypothesis that the best offsets are relatively independent of traffic flows and are mainly determined by factors such as link length and travel time. By optimising signal offsets, SATOFF aims to improve traffic flow and reduce congestion, which can lead to more efficient traffic management and planning within urban road networks. For a detailed explanation of SATOFF and its functionalities, please refer to Chapter 12.2 of the SATURN manual (SATURN, 2024).

3.5.13 SATPIG

SATPIG is a relatively ad hoc program designed to produce a file of O-D route flows from a SATURN assignment, in particular to facilitate interfaces with micro-simulation network analysis programs such as DRACULA which require as input a file describing the number of trips per distinct route as opposed to a trip matrix which gives total trips independent of route. SATPIG currently only operate with a UFC file to define OD routes, not a UFO file. The use of SATPG is discussed in Section 12.6 of the SATURN manual (SATURN, 2024).

3.6 SATURN File Formats

Files in SATURN modelling suite are classified in a number of different ways; e.g. by their computer-based characteristics

- Input/output files,
- “Unformatted binary” vrs. “text” or “ascii”,
- Scratch/permanent or by function-based characteristics such as
- Network data,
- Trip matrices

All unformatted binary files have extensions beginning with UF. In particular:

- UFN: An unformatted file output (only) by SATNET which contains all the basic network structural data

- UFS: An unformatted file produced by SATSIM or SATALL, which adds full assigned flows and simulation data to the basic .UFN file
- UFA: An unformatted file produced by SATEASY for use as input to SATSIM (Effectively a .UFA file is a .UFS file which has not been through a final simulation)
- UFM: An unformatted matrix file
- UFC: An unformatted file of costs used to re construct routes
- UFO: An unformatted file containing OBA-based route information by origin

“Text” files used as control or data files:

- DAT: All basic data or control files created by the user, e.g., using a text editor such as Notepad or Wordpad (not MS Word) and used as input
- KP: A “card punch” file output by a program.
- LOG: A file containing a list of all terminal input commands from the run of an interactive program; see 14.5.1 in SATURN Manual (SATURN, 2024)
- KEY: A “dummy” terminal file used to run an interactive program; see 14.5.1 in SATURN Manual (SATURN, 2024)
- XY: A supplementary node coordinates file.
- GIS: A supplementary “Geographical Data” file; see 5.7 in SATURN Manual (SATURN, 2024),

3.7 Key Definitions and Parameters

There are several parameter specifications in SATURN, and the key features of SATURN outputs relevant to this research are briefly explained below.

3.7.1 Free Flow Time (FTIME) / Free Flow Speed (FSPEED)

The link time (in seconds) or speed (in kph) under free-flow conditions. The “free-flow” time on all links within the assignment network. For simulation turns (which have zero distance by definition) this represents the delay for arrival flows approaching zero but with all other flows (opposing or lane sharing) at their current value.

3.7.2 Cruise Time / Cruise Speed

Stoptime to stoptime time allowing (if appropriate) for speeds to decrease according to a link capacity-restraint curve. For buffer links it is the congested travel time. Cruise Speed (kph) is speed based on cruise time.

3.7.3 Link Distance (IDIST)

Link distances in metres is calculated from the centre of one junction to the centre of the next (but coding them as entry to exit lines would make virtually no difference). It is zero for all simulation turns.

3.7.4 Saturation Flow (LSAT)

Turn saturation flow represents the maximum number of vehicles per hour that can navigate a turn, considering only physical junction characteristics such as lane numbers, widths, and turn radii, while accounting for the impact of other factors on turn capacities. Factors to consider when setting saturation flows include the number and widths of lanes, junction type (e.g., roundabout or priority), major/minor arms at priority junctions, inclination on hills, visibility, and turning angles. This process requires a balance of art and science, tailored to the specific circumstances of the modelled area.

3.7.5 GAP

Gap acceptance is used in SATURN to represent the manner in which “minor” vehicles give way to “major” flows, e.g. at priority junctions or roundabouts. The approach is based on the probabilities of there being a gap at any point in time in all of the opposing flows where, the opposing flows are those which are either crossed or share the same exit as determined by the junction geometry.

The same principles apply to the choice of GAPR (minimum acceptable gap for roundabout) and GAPM (Minimum acceptable gap for merging). This input parameters are used to over-ride the parameters of the same name set as, in effect, “global” parameters under &PARAM. All gaps are input as integers representing tenths of seconds so that if 15 were input this would be interpreted as 1.5 seconds. The default values for GAPM and GAPR were set at the more realistic values of 1.0 and 1.5 respectively.

3.7.6 ALEX

Average Length of a vehicle (externally) in a queue; used to estimate the actual length of a queue from the number of vehicles. Primarily used to model blocking back.

3.7.7 Stacking Capacity (STACK)

The Link stacking capacity refers to the number of pcus that would lead to a queue extending into the previous junction. It is typically calculated by dividing the total road area (number of lanes x link distance) by the head-to-head vehicle distance. In SATURN, the stacking capacity is utilised solely to model blocking back and estimate queue overflow in congested sections of a road, primarily focusing on the junction upstream.

$$\text{STACK} = \text{LANES} \times \text{IDIST} / \text{ALEX}$$

3.7.8 Mid-Link Capacity

The mid-link capacity typically refers to the capacity of a specific link or segment within a network. This capacity represents the maximum data rate or throughput that can be achieved on that particular link. The mid-link capacity in pcus/hr is set by a link speed-flow curve.

3.7.9 Speed-Flow Curve / Flow-Delay Curve

Simulation links have fixed travel times, assumed equal to their free flow or cruise travel times and, in effect, infinite capacities. However it is possible to define link speed-flow curves for simulation links in the same way that one may define link speed-flow curves for buffer links. Equally, explicit capacities may be defined on simulation links themselves (as opposed to capacities set by downstream junctions).

This facility is extremely useful for modelling long motorway-style links where delays tend to be dictated by conditions on the link itself as opposed to junction properties. Indeed speed-flow curves may be the only way to adequately model such links. It may also be useful in urban conditions where, e.g., on-link parking or width restrictions may severely restrict the flow of traffic mid-link such that it becomes lower than that at the stop-line. The speed-flow curve records includes the following.

- the free flow travel time (t_0) in seconds / free flow speed in kph / free flow delays in seconds
- the time at capacity (t_C) in seconds / capacity speed in kph / delays at capacity
- the mid-link capacity (C)

- An 'S', 'T' or 'D' to indicate speeds, times or delays above, and a "power" n
- A "link index" or "capacity index"

The speed-flow relationship can be denoted Equation 6.2 of the SATURN Manual (SATURN, 2024).

$$t(V) = t_0 + AV^n, \text{ where } V < C$$

where the parameter A is chosen such that $t(C) = t_C$. For $V < C$ the time is constant, t_C .

This data has two effects: (1) it determines the flow-dependent (cruise) travel time/speed on the link itself; and (2) it may reduce the turn capacities at the downstream junction. The use of the single characters S or T to denote "Speeds" or "Times".

3.7.10 Generalised Cost Parameters

All assignment techniques within SATURN assume that individual drivers seek to minimise their travel cost, with "travel cost" being defined in one of three different ways under normal usage:

- i. As pure time, or
- ii. As pure distance, or (most commonly)
- iii. As "generalised cost" which is a linear combination of time, distance and monetary charges (e.g., tolls) defined by:

Equation 7.41 in SATURN Manual (SATURN, 2024) shows the generalised cost formula.

$$C = PPM * T + PPK * D + M$$

Where:

C is the cost in units of pence,

T is time in units of minutes (including any 44444 time penalties),

D is distance in kilometres,

M is monetary charge in pence,

PPM is a user-defined parameter specifying "Pence Per Minute",

PPK specifies "Pence Per Kilometre".

The “type” of cost desired is specified by the user’s choice of PPM and PPK, the default values being 1.0 and 0.0 respectively which therefore equate cost to time. Although the parameters are specified as “per minute” and “per kilometre” the actual units used by SATURN for time and distance are seconds and metres; appropriate conversion is handled by the program.

In fact, when generalised cost is requested, the assignment actually works in terms of “generalised time”, defined by adding terms proportional to the link distance and/or monetary charge to the link travel time as expressed in the Equation 7.42 in the SATURN Manual (SATURN, 2024)

$$C_t = T + (PPK/PPM) * D + (M/PPM)$$

Hence all assignment convergence statistics are always expressed in terms of time with units of seconds (so that additional factors to correct for units are added to the ratio PPK/PPM and to PPM above).

Links representing turning movements in the simulation network are assumed to have zero length so that their times are unchanged by the definition of generalised cost.

Note that “penalties” (e.g., tolls) on restricted links may be expressed either in time units as seconds and added directly onto the link generalised times used in the assignment or as monetary costs which are, for assignment purposes, converted to seconds.

3.7.11 Turn Priority Markers (TPM) and Modifiers

These describe which traffic flows oppose a turning movement. The main TPM must be one of the following as discussed in Section 6.4.2, SATURN Manual (SATURN, 2024):

- G: A turn which must give way (from a minor road) at a priority junction.
- X: Opposed right turn from a major road at a priority junction which needs to cross the major flow in the opposite direction, OR an opposed right turn at traffic signals which must cross the major flow from opposite arms.
- M: A turn which “merges” with another turning movement at a priority junction.

- F: A permanent filter at traffic signals with 100% green (generally to the left but occasionally to the right).
- W: A weaving movement between traffic entering and leaving (typically) a motorway.
- Q: A downstream motorway merge for modelling the merge delay at motorways.
- BLANK: No opposing flow.

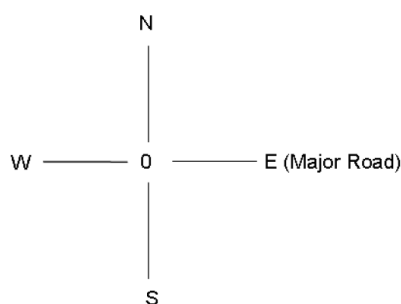
While the modifiers (which are used relatively infrequently) must be one of:

- C: To denote a “Clear” or reserved exit lane used after G or X;
- D: A “Diamond Cross”, i.e., to convert hooked into non-hooked or vice-versa; used after G or X;
- E: Both C and D apply.

The main two TPMs used in this research are discussed in more detail below.

3.7.11.1 Giveways (G)

The ‘G’ priority marker indicates either a ‘give-way’ or a ‘sharing’ manoeuvre. When a turn is marked as ‘G,’ it gives way to all ‘major’ turning movements (those without any priority marker or an ‘X’), but it also ‘shares’ with other give-way movements. SATURN determines which movements affect a ‘G’-turn based on the geometry of the junction-either those it crosses or those with which it shares an exit.



For example, in the figure above, if the turn S-O-E were coded as ‘G,’ it would give way to the major road flows W-O-E and E-O-W. Simultaneously, it would ‘share’ with movements N-O-S (crossing) and N-O-E (shared exit). However, it remains unaffected by the turn W-O-N, as it neither crosses nor shares an exit with it.

When movement 1 'gives way' to movement 2, the capacity for movement 1 decreases from its maximum value to zero as the flow on movement 2 increases from 0 to its capacity. Movement 2, in contrast, remains unaffected by movement 1.

However, when movements 'share,' the capacity for movement 1 decreases to only 50% of its maximum as movement 2 increases. Simultaneously, movement 2's capacity also decreases from 100% to 50% as movement 1 increases. In essence, sharing implies that both movements are guaranteed 50% of their capacity, plus an additional 50% depending on the shared partner.

3.7.11.2 Opposed Right Turn (X)

At priority junctions, movements coded as 'X' must give-way to opposing major movements. For instance, consider the W-O-S movement (which turns right from a major arm); it would give way to the opposing straight-ahead flow E-O-W.

The same rule applies to 'X'-turns at signalised intersections, with an additional condition: they are only opposed by flows that share the same green times, not by movements occurring during other signal phases.

3.7.12 Traffic Signal Parameters

The operation of signals is described by a series of stage times, inter-green times and the movements that are green during each stage.

Stage time is a period of time during which there is no change to any traffic signals and at least one movement has a green signal. The inter-green period is the time period between the end of one stage (i.e., when one green movement ceases) and the start of the next (i.e., when another green movement begins).

The input values for stage and inter-green durations need not add up to the total cycle time (LCY). If they do not, stage times will be factored by the program so that the sum = LCY. Inter-green times, however, remain as input on the assumption that they represent safety margins between successive signals.

The offset refers to the time at which the first coded stage for a particular node begins relative to some absolute zero point for all signals in the system assuming some form of signal co-ordination (e.g., to produce "green waves"). If there is no co-ordination the offset is essentially arbitrary and should probably be set to zero.

3.7.13 Centroids and Centroid Connectors

In addition to network nodes and links, users must define centroids (zones) in SATURN. Centroids are often referred to as zones, and the terms are interchangeable.

To distinguish zones from nodes in input files, SATURN typically includes the character “C” as the first input field for zones. SATURN assumes a one-to-one correspondence between zone sets when using both network and trip matrix data.

Simulation centroid connectors are used to link centroids (zones) within the simulation network. They allow traffic flow between different zones, ensuring continuity and accurate representation of travel patterns.

Buffer connectors serve a similar purpose but operate within the buffer network. Like simulation connectors, they link centroids, facilitating traffic movement.

3.7.14 Other Parameters

There are other parameters in SATURN that are mentioned throughout this research and are also briefly discussed.

- CAPMIN. Minimum capacity to be expected for any (give-way) turn; any junction with lower capacities will be factored up to CAPMIN (pcu/hr). The default is 30.0 pcu/hr.
- TAX. Default number of X-coded pcus that can stack in the middle of a signalised junction and clear after the end of the green. The default is 2.0 pcus.
- FLAREF. The default number of PCUs which, by default, are able to queue in an extra near-side (Filter) flared lane at either signals or priority junctions if an F is coded in the lane field. The default 2.0 pcus.
- FLAREX. The default number of PCUs which, by default, are able to queue in an extra off-side flared (X-) lane at either signals or priority junctions if an F is coded in the lane field. The default 2.0 pcus.

3.8 Conclusion

In this chapter, the basic understanding of the SATURN modelling suite is discussed. Key definitions and parameters that are mentioned throughout the research are briefly discussed here. Refer to the SATURN Manual (SATURN,

2024) for further understanding of the modelling concepts, structure, decisions, and parameters. The next chapter will address the study methodology, focusing on SATURN-specific parameters and their input and output.

Chapter 4

Study Design and Methodology

4.1 Introduction

In this chapter, a traffic modelling methodology is explored, specifically designed to assess the impact of autonomous vehicles (AVs) and shared mobility within urban networks. The research objectives discussed in Chapter 1 serve as the foundation for this chapter, which focuses on the methodology required to achieve those objectives. Additionally, insights from the literature review presented in Chapter 2 are incorporated, and specific parameters in SATURN modelling are discussed in Chapter 3.

4.2 Approach

The proposed study is designed to integrate AV characteristics into SATURN traffic modelling, specifically addressing the requirement to update SATURN parameters for AVs and ride-sharing. Table 4.1 presents the methods to achieve the objectives set in section 1.3.

Table 4.1 Study Methodology

Objectives	Methods to achieve the objectives
<i>1. Designing and testing suitable parameters in SATURN to model AV behaviour</i>	
<i>SATURN parameters and design scenarios</i>	• Identify the SATURN parameters that are required to update for AV modelling; • Design network and demand scenarios to test SATURN parameters in mixed traffic conditions;
<i>AV Modelling</i>	• Develop a flow-theory based approach by establishing a relationship between headway and capacity based on traffic flow fundamentals; • Include AV as new vehicle classes in the model using literature-suggested value of time and vehicle operating cost; • Develop an algorithm to modify the network capacity by the types of roads and intersections; • Test the AV behaviour using PCU-based approach and compare the results against the flow-theory based approach;

<i>Assess the impact of AV on capacity and delay.</i>	- Establish impact indicator for the analysis of the result of various scenarios (total vehicle travelled, total vehicle time, capacity and delay parameters etc.) in a toy network and city network; - Conduct scenario analysis with different AV market shares (e.g., 25%, 50%, 75% and 100%) for the future year to explore the impact of shared mobility network characteristics for each of the above scenarios.
2. Modelling Ride-Sharing in SATURN modelling	
<i>Define shared mobility</i>	Define behavioural regime for shared autonomous vehicle and develop scenarios for shared mobility;
<i>Modelling shared mobility and ride matching algorithm</i>	- Establish rules for the Shared Autonomous Vehicles – Ride Sharing (SAV-RS) in a trip matching algorithm to obtain generalised cost in the trip assignment process; - Develop a ride-matching algorithm for non-integer demand values, considering that the trips follow the shortest path by time and every pickup location belongs to a zone. Thus, a series of zones for each path is produced; - Sharing capacity of each path is calculated based on the ride match, supply and demand; - Ride matching is established by minimising cost for the ride supplier and demander by maximising the revenue of the supplier for each path.
<i>Assess the impact of ride sharing on congestion, vehicle occupancy, capacity and delay.</i>	- Establish impact indicator for the analysis of the result of various scenarios (total vehicle travelled, total vehicle demand, vehicle occupancy, capacity and delay parameters) in a toy network. - Conduct scenario analysis with different AV market shares (e.g., 25%, 50%, 75% and 100%) for the future year to explore the impact of shared mobility network characteristics for each of the above scenarios.

4.3 Modelling Autonomous Vehicles

4.3.1 Modelling Approach

This section introduces the modelling framework by integrating characteristics of AV in conventional macroscopic modelling to address road capacity and route choice processes of vehicles in AV environment. The traditional macroscopic traffic models typically provide an aggregated representation of traffic flow, expressed in terms of total flows per time period and averaged travel time per time period (May A.D. 1990). The geometric capacity, often referred as the maximum capacity, of a road section or a junction is reduced by the total flows per time period and averaged travel time per time period. As discussed in section 3.2, SATURN is considered as mesoscopic modelling tool, which model individual junction in addition to it macroscopic modelling of road sections. The turn capacity of a junction, referred as turn saturation flow, including gap acceptance at junctions are considered as the mesoscopic model parameters of SATURN. The routes choice parameters involving generalised travel costs are also considered for modelling AV.

Thus, the scope of the impact of the AV modelling in SATURN includes:

- Link and Turn Capacity;
- GAP Acceptance; and
- Generalised Travel cost.
- PCU for AV as a separate vehicle class (for PCU-based approach only)

4.3.1.1 Capacity

Road capacity is the maximum sustainable hourly flow rate at which persons or vehicles reasonably can be expected to traverse a point or a uniform section of a lane or roadway during a given time period under prevailing roadway, environmental, traffic and control conditions (TRB, 2010). This definition treats capacity more or less as a constant value. Brilon *et al.* (2007) indicate that this assumption is not appropriate as observed traffic flow as the maximum traffic throughput varies even under constant external conditions.

The capacity of the mixed traffic of AV and human driven vehicles is given by equation 4.1 suggested by Yokota *et al.* (1998). In a simplified case where the mean net time headway differs from the normal headway only in the case of two consecutive AV, equation 4.3 is applied to calculate the mean net time headway over all vehicles. It is simply based on the probability of specific vehicle types

succeeding others, which in turn depends on the penetration rate of AV. Then the mean gross space headway required by an average vehicle is determined from the net time headway, the speed and the mean vehicle length of the vehicle composition on the considered supply element.

$$Q_d = 3600 \cdot k_d \quad \text{..... (4.1)}$$

$$k_d = \frac{1}{h_d} \quad \text{..... (4.2)}$$

$$h_d = h_{AV}d + h(1 - d) \quad \text{..... (4.3)}$$

Where,

h_d : mean headway time of the mixed traffic with AV share (d)

h_{AV} : target headway of AV in seconds

h : average headway of human driven car in seconds

d : Market share of AV

Wagner (2016) assessed the effects of AV on performance to adapt the capacities of road facilities by modifying equation 4.1. It determines capacity depending on vehicle headways, vehicle lengths, share of AV and speed. This leads to the vehicle density shown in equation 4.4. Multiplying the vehicle density with the speed determines the capacity as shown in equation 4.5. Since the capacity depends on the share of AV, it must be updated during an assignment.

$$k_d = \frac{1}{v \cdot h_d + l} \quad \text{..... (4.4)}$$

$$Q_d = 3600 \cdot v \cdot k_d \quad \text{..... (4.5)}$$

Where,

v : speed limit of the road

l : mean vehicle length

Headway of the human driven vehicle can be calculated from the input capacity with all human driven cars in equation 4.1.

$$Q = 3600 \cdot v \cdot k = \frac{3600 \cdot v}{v \cdot h + l}$$
$$h = \frac{3600}{Q} - \frac{l}{v} \quad \text{..... (4.6)}$$

Where,

Q : capacity of road with all human driven cars

4.3.1.2 Gap Acceptance

Gap acceptance represents the manner in which “minor” vehicles give way to “major” flows, e.g. at priority junctions or roundabouts and some cases for oppose right turns at signalised junctions. The approach is based on the probabilities of there being a gap at any point in time in all the opposing flows. The opposing flows are those which are either crossed or share the same exit as determined by the junction geometry. The basic equation may be written as:

$$Q_m = S_m \cdot P_i \cdot P_{i+1} \quad \text{..... (4.7)}$$

where:

Q_m : entry capacity of minor arm

S_m : (minor) saturation flow (with zero cross traffic)

P_i : probability of a gap acceptance in opposing stream i .

The individual probabilities P_i are calculated from formulae such as:

$$P_i = \left(1 - \frac{V_i}{S_i}\right)^{G \cdot S_i} \quad \text{..... (4.8)}$$

where:

V_i : opposing major flow

S_i : saturation flow for the major movement

G : gap acceptance

Hence, P_i goes from a maximum of 1 at $V_i = 0$ down to $P_i = 0$ at $V_i = S_i$ with a power defined by GS_i . This will be applied in the case of an “absolute” give way, e.g. for minor arm traffic at a priority junction giving way to major flows.

4.3.1.3 Generalised Cost

To introduce AV as new user classes, network parameters of Value of Time (VoT) and Vehicle Operating Cost (VoC) figures are calculated based on literatures. Literature review suggests 40% reduction of value of travel time savings across all the trip purposes (Wadud, 2017). However, following the DfT (2025) Databook, the ppm and ppk values for AV were provided by National Highways and these values are utilised for this research. It is reasonable to assume that VoT component of empty AV is insignificant, thus to be used zero in this study. A 5% reduction of VoC applied considering improvement in fuel efficiency (Wadud, 2017). Table 4.2 shows the VoT and VoC values to be used in the model with AV and Empty AV as new user classes.

Table 4.2 VoT and VoC for AV by Trip Purposes

Generalised Cost Parameters	Car	AV	Empty AV
VoT (pence per minute)			
Business	33.98	36.77	-
Commuting	22.79	24.62	-
Other	15.72	11.24	0
VoC (pence per kilometre), includes non-fuel cost			
Business	10.45	9.93	-
Commuting	4.49	4.27	-
Other	4.49	4.27	4.27

Note: All figures are calculated for model forecast year of 2031, VoT calculated for morning commuting period; Source: DfT (2025), Own calculations

4.3.2 SATURN Parameters for AV Modelling

This section focuses on adjusting SATURN input parameters to reflect AV behaviour based on the principles of traffic flow theory, specifically in relation to speed, flow, and density. It aims to vary the SAURN input parameters, providing enhanced insights into the effects of AV adoption on transportation networks.

The modelling framework includes various key input parameters, such as AV behaviour profiles, interaction with conventional vehicles, and AV market penetration rates. These parameters are essential for representing AVs' influence on traffic patterns. Table 4.3 provides a list of specific input parameters and their modifications needed to incorporate AVs as a new vehicle class in SATURN.

Table 4.3 SATURN Input Parameters for AV Modelling – Flow Theory Based Approach

Network Type	Key Input Parameters	SATURN Key	AV-Modified Input	Definition (Chapter 3)
Road Section (Link) and Junction (Node)	Link Cruise Speed	CrSpeed	No	3.7.2
	Link Distance	IDIST	No	3.7.3
	Saturation Flow	LSAT	Yes	3.7.4
	GAP Acceptance	GAP	Yes	3.7.5
	Stacking Capacity	STACK	Yes	3.7.7
	Speed-Flow Relationship	SFC	Yes	3.7.9
	Traffic Signal Data (Cycle Time, Offset, Stage Length, Inter-green)	LCY, OFFSET, STAGL, INTG	No	3.7.2
Centroid Connector		-	No	3.7.13
Trip Matrix	New Vehicle Class Different PCU Factor	-	Yes	3.3
			No	
Generalised Cost Parameters	Value of Time Vehicle Operating Cost	ppm ppk	Yes	3.7.10
Universal or Global Parameters	GAP acceptance for priority and traffic signal, roundabouts and merging turns;	GAP GAPM GAPR	No No No	3.7.14
	Average Length of a vehicle (Externally) in a queue;	ALEX	No	
Other link based Parameters	Traffic queue in PCU in an extra near-side (Filter) or off-side flared lane at either signals or priority junctions.	FLAREF, FLAREX	Yes Yes	3.7.14

4.3.2.1 Link Cruise Speed and Distance

Network physical characteristics, such as link cruise speed and link distance, serve as the key input parameters for a SATURN network. It is important to note that these parameters remain unchanged with the inclusion of AV in traffic network.

4.3.2.2 Turn Saturation Flow

As discussed in chapter 3, Turn Saturation Flow (LSAT) represents the maximum number of vehicles per hour that can navigate a turn, considering only physical junction characteristics such as lane numbers, widths, and turn radii, while accounting for the impact of other factors on turn capacities.

Equations 4.4 and 4.5 suggest that the capacity of a lane relies on factors such as headway (time gap), link speed, and the average vehicle length externally in a queue (or the head-to-head distance when vehicles are at a standstill), which is also referred as ALEX in SATURN. Using these considerations, it becomes possible to derive the turn saturation flow turns for all human-driven vehicle scenario, as outlined below:

$$LSAT = 3600 \cdot \frac{v}{v \cdot h + L} \quad \text{..... (4.9)}$$

Where,

- v : link cruise speed
- h : average headway
- L : mean vehicle length (externally) in a queue

Empirical studies suggest a reasonable value for the mean headway at high traffic volumes falls within the range of $h = 1.15\text{s}$ to 1.4s without AV situation (Friedrich, 2016; Wagner, 2016). For instance, considering a saturation flow of 2000 pcu per hour for straight ahead movement on a standard urban road, a cruise speed of 48 kph, and a mean vehicle length of 7.5m, the calculated headway amounts to 1.24s.

Similar to equation 4.9, the $LSAT_a$ is defined within a saturation flow composed entirely of AV using the subsequent function, wherein h_a and L_a denote the preferred time headway and mean vehicle length externally in a queue adopted by AV. As discussed in literature review in Chapter 2, AV will have a reduced headway due to enhanced reaction time, consistent and predictable behaviour, improved

communication and coordination and platooning capability (Section 2.2.1.1). For the change in saturation flow for autonomous driving, the changed time headway h_a for the following vehicle is the deciding factor.

$$LSAT_a = 3600 \cdot \frac{v}{v \cdot h_a + L_a}$$

The ratio of the two saturation flow values and hence the change in the saturation flow is determined by the relation below:

$$LSAT_a / LSAT = (v \cdot h + L) / (v \cdot h_a + L_a) \quad \text{..... (4.10)}$$

The decisive factor in determining the change in capacity for autonomous driving is the altered headway, denoted as h_a , which pertains to the following vehicle. An appropriate and technically feasible value that also maintains acceptability from the road users' perspective is $h_a=0.5s$ (Friedrich, 2016; Wagner, 2016). As a result, the headway for mixed traffic, represented as h_d , incorporating various levels of AV penetration (% d), is estimated using equation 4.3 by Chen et al (2022) and Friedrich (2016), which is also shown below.

$$h_d = h_a d + h(1 - d) \quad \text{..... (4.11)}$$

On the other hand, the mean vehicle length (L) serves as an input parameter for estimating the saturation flow in equation 4.9. For standard passenger cars, the broadly accepted mean vehicle length is 4.5m, with a minimum safety distance to the vehicle ahead set at 3.0m, resulting in $L=7.5m$ as used by Freidrich (2014) in his study. However, in the case of AVs, the safety distance can be reduced to 1.5m (Friedrich, 2016; Wagner, 2016; Sonnleitner J. and Friedrich M., 2020a), effectively reducing the mean vehicle length to $L_a=6.0m$ for all AV traffic conditions.

The mean vehicle length for mixed traffic, represented as L_d , incorporating various levels of AV penetration (% d) changes linearly similar to equation 4.11, can be estimated as below:

$$L_d = L_a d + L(1 - d) \quad \text{..... (4.12)}$$

By incorporating h_d and L_d in equation 4.12, it becomes possible to calculate the saturation flow for mixed traffic as the modified SATURN input.

$$LSAT_d = LSAT \times \frac{(v \cdot h + L)}{(v \cdot h_d + L_d)} \quad \text{..... (4.13)}$$

4.3.2.3 Gap Acceptance

As discussed in section 3.7.5, gap acceptance (GAP) is used in SATURN to represent the manner in which “minor” vehicles give way to “major” flows, e.g. at priority junctions or roundabouts. The approach is based on the probabilities of there being a gap at any point in time in all of the opposing flows where, the opposing flows are those which are either crossed or share the same exit as determined by the junction geometry.

In a study conducted by Peng *et al.* (2023), gap acceptance at an uncontrolled intersection in the baseline condition, involving all human-driven cars, was found to be $GAP=2.57s$. However, when the traffic mix included 50% AVs, the gap acceptance reduced by 11% to $GAP=2.3s$. For AVs alone, the gap acceptance further decreased by 20.7% to $GAP_a=2.13s$. In the context of a typical priority junction in the SATURN network in the UK, the assumed gap acceptance for all human-driven cars is $GAP=2.5s$. Accordingly, a reduction by 20% to $GAP_a=2.0s$ is proposed for AVs in this study.

4.3.2.4 Stacking Capacity

The link stacking capacity (STACK) refers to the number of pcus that would lead to a queue extending into the previous junction. It is typically calculated by dividing the total road area (number of lanes x link distance) by the head-to-head vehicle distance, also referred mean vehicle length (L), externally in a queue. The mean vehicle length can be globally modified in SATURN using the parameter denoted as ALEX. In SATURN, the stacking capacity is utilised solely to model blocking back and estimate queue overflow in congested sections of a road, primarily focusing on the junction upstream. Thus, when AV is considered, the mean vehicle length will vary linearly, as a result the stacking capacity will also vary linearly. In a 100% AV scenario, ALEX can be updated in the global parameter; however, for a mixed AV scenario, STACK will be updated as a modified as an input in SATURN AV modelling. It is important to note that STACK needs to be adjusted for the SATURN network where blocking back is modelled.

4.3.2.5 Speed-Flow Curve

Speed-flow curves (SFC) serve as a way to depict delay on links caused by the volume of traffic passing through a given route, independent of delays caused by individual junctions. In SATURN, SFCs are not used to represent 'junction' delay and are therefore applied mainly on longer links.

In SATURN, a SFC is applied when the majority of delay along a link is attributed to the link itself rather than the junction at its downstream end. If most of the delay is due to the junction at the end of the link, a fixed-speed is applied on the link, with any delays being accounted for through junction coding.

SFCs are utilised on rural links that exceed 500 meters in continuous link characteristics, including motorways. The SFC parameters, such as the power of the curve, is specific to the road type and mid-link capacity. However, with the change of mid-link capacity due to AVs, there may be a requirement for additional speed-flow relationship curves to be introduced for these longer links. Nonetheless, in urban traffic networks, where delays primarily originate from junctions and the links are typically below 500 meters, they are not used in SATURN network.

4.3.2.6 Traffic Signal Data

Traffic signal data, such as stage lengths, offsets, cycle time, inter-green etc are essential input parameters for coding a signalised junction in SATURN. By incorporating AVs, turn capacity is expected to increase, allowing for the optimisation of traffic signals with reduced stage length and cycle time. The specific signal controller at each junction plays a crucial role in this optimisation process, making it dependent on the signal management authority's strategy. However, in SATURN modelling, signalised junction is coded with a fixed stage lengths, inter-green, offset and cycle time from primary e.g., field data or secondary sources e.g., signal management authority. Thus, the requirement of signal optimisation is often decided by the signal management authority. In this study, signal optimisation has not been taken into consideration in the AV modelling.

In SATURN, an automated signal timing and offset optimisation process is available through SIGOPT and SATOFF, discussed in Section 3.5.11 and 3.5.12 respectively.

4.3.2.7 Centroid Connector

AVs do not have any significant impact on centroid or zone connectors in SATURN, regardless of whether they are connected to links or nodes. These connectors, which used as the traffic loading into the network in a SATURN model, remain unaffected by the presence of AVs.

4.3.2.8 Trip Matrix

Modifying the trip matrix, which includes the origin and destination of trips, becomes essential when integrating AVs as a new vehicle class in SATURN. After performing network assignment, it becomes crucial to estimate both AV and non-AV flows on specific links or turns. This is why the trip matrix needs to be subdivided into an AV matrix and a non-AV matrix. The separate AV-matrix will help to calculate essential input parameters like saturation flow, gap acceptance, and headway distribution. Additionally, the trip matrix can be further divided based on trip purposes, such as commuting, business, shopping, education, etc. Similarly, the AV matrix elements can be subdivided into the same trip purposes. However, for the test scenarios in this chapter vehicle user classes are not sub-divided by trip purposes.

When defining the trip matrix, it is essential to distinguish the Passenger Car Unit (PCU) within the matrices according to vehicle classes. The modelling of AV, based on the traffic flow theory principles, introduces alterations in time head, saturation flow, stacking capacity, and mean vehicle length, primarily. However, in this approach, the PCU for AVs is considered the same as the PCU for conventional vehicles, which is set at 1.0. This means that, despite the unique characteristics of AVs, their impact on the trip matrix is standardised in terms of PCU, aligning with the representation used for traditional vehicles in the modelling process.

For this study, the traffic demand for AV is considered fixed. Although for comprehensive estimation, AV demand can be evaluated using demand model integrated with like land use and car ownership model considering the secondary impact of AV, which is not considered for this study. For this study, the traffic demand for AV is considered fixed. However, for this study, various AV market shares, ranging from 0% to 100% is assumed, while keeping the total number of trips constant across the test model scenarios.

4.3.2.9 Generalised Cost Parameters

The generalised cost parameters within SATURN define the route choice decisions for specific origin-destination (O-D) journeys. When incorporating AVs as a novel user class into the trip matrix, certain network parameters related to the Value of Time (VoT), denoted as ppm, and the Vehicle Operating Cost (VoC), referred to as ppk, are required to be updated. However, DfT (2025) proposed a specific ppm and ppk values that are mentioned in Table 4.2.

A review of the literature indicates a potential 40% reduction in ppm across all trip purposes when comparing AVs to human-driven cars (Wadud, 2017). Additionally, there is a 5% reduction in ppk that can be applied, attributed to the enhancement in fuel efficiency resulting from the utilisation of AV technology (Wadud, 2017).

These calculated adjustments in the ppm and ppk parameters reflect the anticipated effects of AV integration on travel costs, thereby enabling a more accurate representation of AV-influenced route choice behaviours within the SATURN model.

4.3.2.10 Universal Parameters

Universal parameters that need to be modified with AVs are proposed to be adjusted at the node level, as they are influenced by the AV traffic flow at that particular junction. By making changes at the node level, it can be ensured that the effects of AVs on the overall traffic network are appropriately captured. These modifications will allow for a more accurate representation of AV behaviour and its impact on traffic operations at junction level.

Thus, the global parameters of GAP, GAPM and GAPR is superseded by the node specific GAP as discussed in section 4.3.2.3. The ALEX is used to calculate the stacking capacity, which is also superseded by the link based input value STACK as discussed in section 4.3.2.4.

However, when considering a scenario involving 100% adoption of AVs, there arises no necessity for differentiation these parameters among distinct nodes. However, when dealing with penetration rates ranging from 0% to 100%, each node may encompass a varied mixture of vehicles owing to distinct route cost factors. Consequently, the adjustment of parameters at the individual node level becomes imperative. It is important to note that in the context of SATURN, an iterative procedure is required to facilitate this process.

By considering these modifications and assumptions, we can analyse the potential impact of AVs on the transportation network using SATURN and gain valuable insights into how AV adoption might affect travel patterns, congestion levels, and other critical factors in the model area.

4.3.3 PCU-Based Modelling Approach

In SATURN, PCU factors are used to account for the varying space requirements of different vehicle types. The total traffic flow in PCUs is estimated by multiplying the traffic volume by the corresponding PCU factors.

Traffic demand finds representation through an origin-destination (O-D) matrix in SATURN. By multiplying the O-D matrix by PCU factors, the demand transforms into equivalent traffic flow in PCUs. SATURN subsequently allocates vehicles to specific routes, taking congestion and travel times into account. PCU factors play a crucial role in determining link capacity and assessing congestion levels. These factors accommodate the varying space requirements of different vehicle types. For instance, a manually driven passenger car is assigned a PCU value of 1.0.

In the literature review (Sonnleitner J. and Friedrich M., 2020a; Sonnleitner J. and Friedrich M., 2020b), discussions highlight the possibility of reducing the PCU factor for AVs based on their space requirements such as headway, and efficiency in following preceding vehicles. While a reasonable PCU factor for AVs can be readily applied in SATURN's modelling setup, a comparative assessment of the impact of this reduced PCU factor with other approach such as flow-theory based AV modelling remains necessary. Based on these literatures, the PCU factor for AVs can range between 0.6 and 0.8, depending on the level of automation. To compare the flow-theory-based modelling method for AVs, PCU values of 0.7, 0.8, and 0.9 are used for modelling AVs in this research. This range is derived from the existing research and provides a basis for assessing the impact of AVs on traffic flow and network efficiency.

In the PCU-based approach, all other AV-modified input parameters in SATURN, as mentioned in Table 4.3, are not required to be altered.

4.4 Traffic Assignment Approach for AV

In this research, AVs are assigned using SATURN's standard static user-equilibrium (UE) framework, which reflects the decentralised route-choice mechanism applied to all vehicle classes within the model. Although AVs have the

potential to support coordinated routing and system-level optimisation, current empirical travel behaviour remains dominated by human-driven vehicles, and UE continues to provide the accepted benchmark for evaluating network performance (Wardrop, 1952; Sheffi, 1985). Applying a common UE rule to both AVs and human-driven vehicles ensures that the analysis isolates the supply-side effects of AV technology, such as reduced headways and increased effective capacity without introducing behavioural assumptions that presuppose fleet-level cooperation or system-optimal control (Talebpour and Mahmassani, 2016).

As discussed in section 3.2.3, SATURN is capable of performing a System Optimal (SO) assignment through the SOWHAT and WHATHO parameters (SATURN Manual, Section 7.11.9), which replace actual costs with marginal costs to minimise total system travel time. However, SO assignment is presented in the Manual as a specialised research tool with limitations, including potential discontinuities in marginal cost curves, sensitivity to convergence, and reduced behavioural realism. The additional configuration and testing required to apply SO assignment therefore placed it outside the scope of this study. For these reasons, and for consistency with SATURN's conventional decision structure, the UE approach was adopted throughout.

4.5 Modelling Ride-Sharing

4.5.1 Modelling Approach

Mesoscopic flow-based trip assignment modelling is used in this study to model the sharing behaviour of AV. The general structure of traffic assignment is illustrated in Figure 4.1. Thus, there are two general inputs - the "trip matrix" T_{ij} , which specifies the number of trips from zone i to zone j ; and the "network" which specifies the physical structure of the roads, etc. upon which trips take place. These may be thought of as the "demand" and "supply" inputs.

Both the matrix and network are input to a "route choice" model which allocates trips to "routes" through the network, as a result of which total flows along links in the network may be summed and the corresponding network "costs" (e.g., times) calculated.

However, modelling SAV requires separate demand input of the ride provider (supplier) and rider (demander), which are a subset of original "trip matrix". In this research, a certain portion of demand is considered separately as ride provider and rider, which are exogenous parameters and considered as an user input. The

supply and demand matrices are assigned to the transport network using Wardrop Equilibrium path assignment (Vliet, 1987), which can generate multiple paths for an origin-destination pair. Thus, the ride matching process will apply on the multiple supplier and demander path to establish ride. Following this process, the route flow of the original assignment is adjusted by estimating the occupancy factors with ride share. This is referred as the adjusted route flow in the modelling process. The adjusted route flow is then assigned to the network using fixed assignment taking from the original traffic assignment.

Network parameters affecting capacity, gap acceptance and generalised travel cost are unchanged with and without sharing behaviour.

Schematic Diagram of the traffic assignment process for ride sharing modelling is presented in Figure 4.1.

4.5.2 Ride Matching Process

In this study we only consider the impact of morning commuting trips thus the modelling assumption involves AV-enabled organised ride-sharing behaviour. However, ride sharing algorithm for AV and No AV is same thus in this section of the study one vehicle class (no AV) is considered to model ride share.

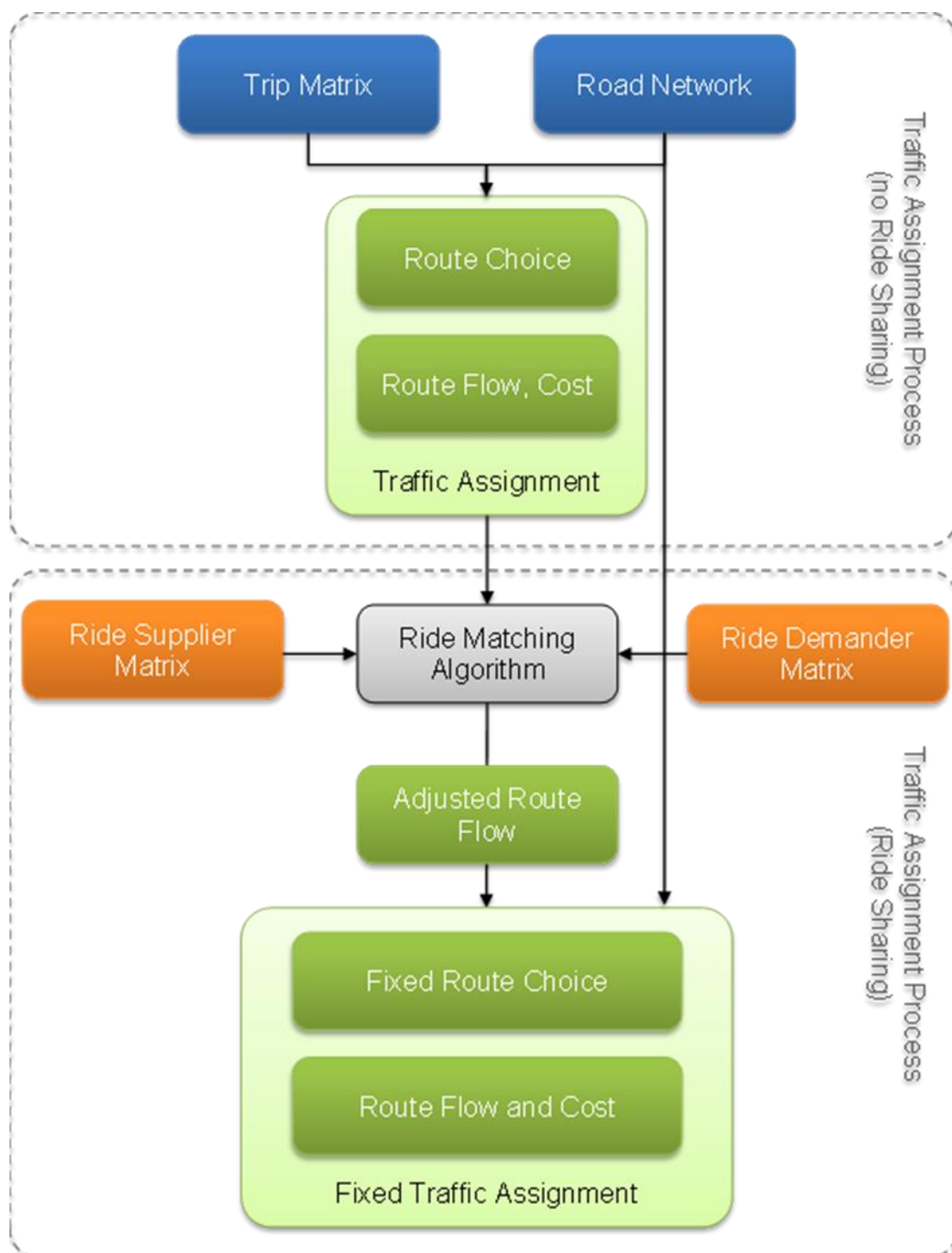
In this study, ride-matching algorithm follows the combination of the objectives that minimise total travel cost of both the driver and riders as well as maximise the number of riders based on priority rules. Riders choose to participate in ride sharing primarily for potential cost-savings; trip-related expenses, such as fuel and tolls, are shared.

However, in this study the time schedules to establish ride match is not considered, assuming that ride sharing is accomplished within the model hour in the traffic assignment. Other feasibility considerations for example, age, gender, smoking etc. are also not included in matching rides in the proposed ride-matching process.

As trip matrix in this type of modelling framework includes non-integer demand, the calculation of sharing capacity is based on the proportion non-integer trip numbers as suggested by Friedrich, M., Hartl, M., Magg, C. (2018).

The proposed study introduces ridesharing fee in prioritising ride match with new sets of rules to develop ride sharing modelling framework.

Figure 4.1 Traffic Assignment Process – Ride Sharing



Chapter 5

Modelling Autonomous Vehicles

5.1 Introduction

This chapter presents the application of the modelling framework, extensively discussed in section 4.2, with a primary focus on seamlessly integrating the unique characteristics of AV into a mesoscopic traffic assignment system like SATURN. SATURN Modelling suite is utilised to assess the impact of AVs on network capacity based on the principles of traffic flow theory. Integrating AV characteristics into SATURN enables to showcase realistic and insightful simulations that offer valuable insights into the role of AVs in traffic assignment.

This chapter focuses on adjusting SATURN input parameters to reflect AV behaviour based on the principles of traffic flow theory, specifically in relation to speed, flow, and density. It aims to vary the SAURN input parameters, providing enhanced insights into the effects of AV adoption on transportation networks.

The subsequent sections of this chapter describe a modelling setup for AVs using a two-level network approach. The first level analyses AV impacts on capacity and delay at junctions, and the second level tests the AV framework on a toy network for understanding AV effects on network capacity, traffic assignment, and route choice. It presents nine test scenarios involving various junction types and parameters adjustments to assess AV influences on traffic flow, capacity, and network behaviour.

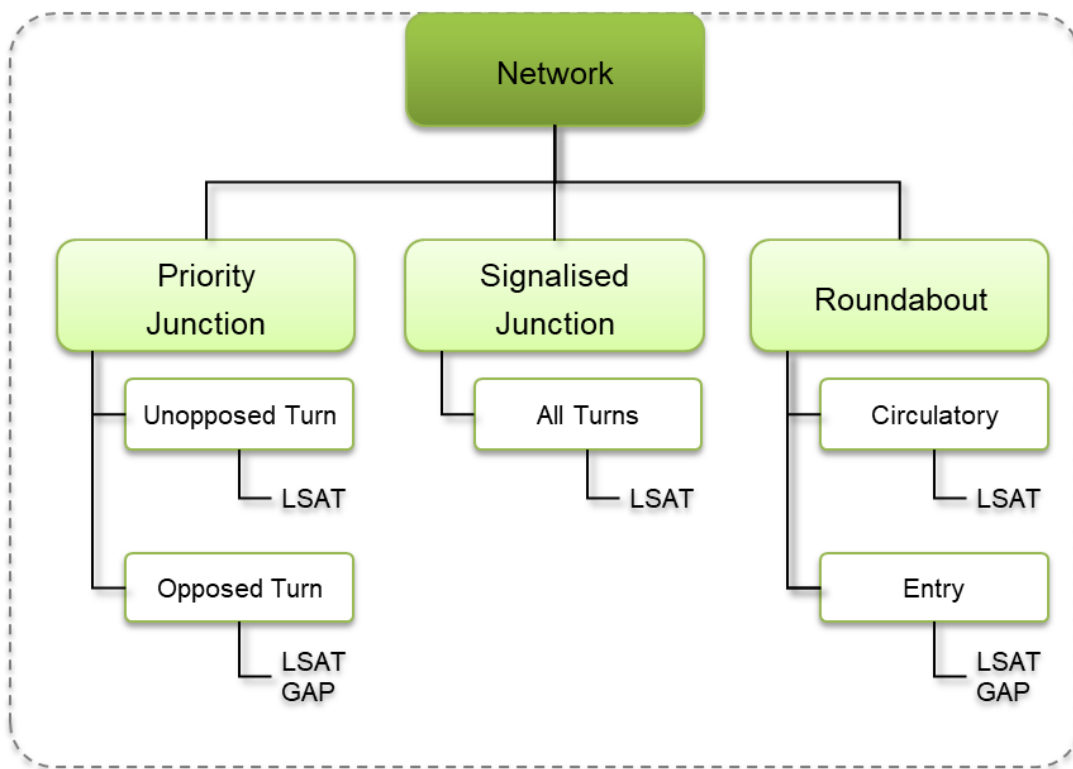
5.2 Model Setup

The modelling setup for AVs is based on three levels of networks. Firstly, the impact of various AV penetration rates on capacity and delay is estimated at the **junction** level. A three-arm junction with three one-lane links and three centroids is created to achieve this. This assessment helps to understand the influence of AVs and establish the modelling framework while varying different parameters. This enables a simplified understanding of the changes caused by AVs at priority junctions, signalised junctions, and roundabouts. Each case assesses all types of turn movements, such as opposed turns, unopposed right turns, and circulatory and entry movements in the case of roundabouts. For each type of turning movement, the modified input required for AV, as identified in section 4.3.2 LSAT and GAP were updated.

Next, the AV modelling framework is tested on a **toy network** to gain insights into its impact on network capacity and traffic assignment. This toy network involves priority, signalised and roundabouts type junctions. This step would help evaluating the performance of AVs in a controlled environment before implementing them on larger and more complex real-world networks. Based on the parameters testing in toy network, the AV modelling is tested at a **city network** level. This provides the impact of AV on road capacity in real network.

By adopting this three-level approach as discussed in Figure 5.1, the research aims to better understand how AVs affect transportation systems at both the junction and network levels.

Figure 5.1 Test Scenario Junction Type and Input Parameters



5.2.1 Test Scenarios Toy Junction

Nine test scenarios have been formulated to understand the impact on turning movements across the types of junctions mentioned in Figure 5.1 and to explore the factors that affect capacity, as listed in Table 5.1.

Table 5.1 List of Test Scenarios

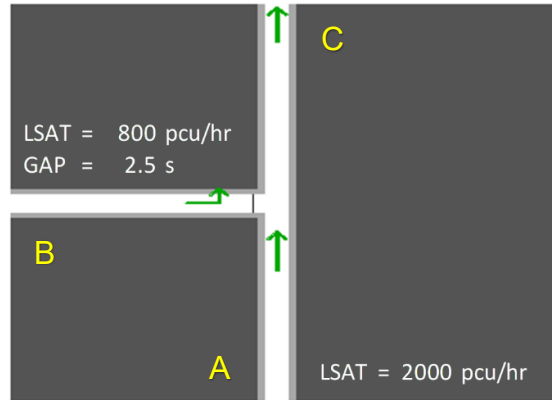
Test Scenario	Network Type	Network Element Modelled	Modelling Measure
1	Toy Junction (Priority)	Unopposed turning movement	Headways
2			Headways and mean vehicle lengths
3		Opposed turning movement	Headways
4			Headways and GAP
5			Headways, GAP and mean vehicle lengths
6	Toy Junction (Signalised)	Turning movement	Headways and mean vehicle lengths
7	Toy Network	Signalised junction, priority junctions, roundabouts, traffic assignment	Headways, GAP and mean vehicle lengths
8			Headways, GAP, mean vehicle lengths and generalised cost
9			Headways, GAP, mean vehicle lengths and generalised cost with iterative

5.2.1.1 Unopposed Turn at Priority Junction

Test Scenario 1

This test scenario has been designed to simulate an unopposed turning movement (A-C) within a priority junction. Figure 5.2 portrays a three-arm priority junction, which serves as the designated test network for this particular scenario. In this configuration, the unopposed saturation flow rate at the major arm (A-C) is set at 2000 pcu/hr, while for the minor arm (B-C), the saturation flow rate at the give-way turn is established as 800 pcu/hr, accompanied by a GAP value of 2.5 seconds.

Figure 5.2 Toy Junction (Priority)



In this particular scenario, alterations in saturation flow are ascertained through the analysis of headway distribution resulting from varying levels of AV penetration. Utilising equation 5.2, where $h = 1.24\text{s}$, $h_{100} = 0.5\text{s}$ for an AV penetration level of $d = 100\%$, $v = 48\text{ kph}$ (13.33 m/s) and $L = L_{100} = 7.5\text{m}$, and for a given $LSAT = 2000\text{ pcu/hr}$, $LSAT_{100}$ can be estimated as:

$$LSAT_{100} = LSAT \cdot \frac{v \cdot h + L}{v \cdot h_{100} + L_{100}} \quad \dots\dots\dots (5.1)$$

$$LSAT_{100} = 2000 \times \frac{13.33 \times 1.24 + 7.5}{13.33 \times 0.5 + 7.5} = 3388$$

By incorporating adjustments to the $LSAT_d$ values, and considering unopposed traffic flow at the major arm with a value of $Q_M = 2400\text{ pcu/hr}$, capacity and delay are estimated in SATURN across a range of $d = 0\%$ to 100% .

In this test scenario, alterations in saturation flow resulting from variations in the mean vehicle length (L) are not taken into account. And also, for unopposed turn movements, the concept of gap acceptance is not applicable and therefore not subjected to variation within the simulation.

Test Scenario 2

In addition to Test Scenario 1, this test scenario incorporates considerations for changes in saturation flow due to fluctuations in the mean vehicle length (L). While keeping all other parameters constant, except for $L_{100} = 6.0$, $LSAT_{100}$ can be estimated to:

$$LSAT_{100} = 2000 \times \frac{13.33 \times 1.24 + 7.5}{13.33 \times 0.5 + 6.0} = 3789$$

Similar to Test Scenario 1, the $LSAT_d$ values are updated for this scenario, and considering unopposed traffic flow at the major arm (A-C) with a value of $Q_M = 2400$ pcu/hr, capacity and delay are estimated in SATURN across a range of $d = 0\%$ to 100% .

5.2.1.2 Opposed Turn at Priority Junction

Test Scenario 3

This test scenario has been formulated to replicate an opposed turning movement (B-C) scenario within a priority junction. The same toy network employed in Scenarios 1 and 2, depicted in Figure 5.2, is utilised for this test scenario.

In this specific scenario, changes in saturation flow are determined by analysing the distribution of headways resulting from different levels of AV penetration. However, in the case of an opposed turning movement (B-C) at a give-way (or stop-line) junction, traffic initiates motion from a nearly standstill position or from a very low speed. The plausible values for the average speed at the give-way of a priority junction to be $v = 22.5$ kph (6.25 m/s) (Friedrich 2014).

Utilising equation 5.3, where $h = 1.24$ s, $h_{100} = 0.5$ s for an AV penetration level of $d = 100\%$, $v = 22.5$ kph (6.25 m/s) and $L = L_{100} = 7.5$ m, and for a given $LSAT = 800$ pcu/hr, $LSAT_{100}$ can be estimated as:

$$LSAT_{100} = 800 \times \frac{6.25 \times 1.24 + 7.5}{6.25 \times 0.5 + 7.5} = 1147$$

By incorporating adjustments to the $LSAT_d$ values, and considering unopposed traffic flow at the major arm (A-C) with a value of $Q_M = 1200$ pcu/hr, opposed traffic flow at the minor arm (B-C) with a value of $Q_m = 400$ pcu/hr, capacity and delay are estimated in SATURN across a range of $d = 0\%$ to 100% .

In this test scenario, alterations in saturation flow resulting from variations in the mean vehicle length (L) and GAP are not taken into account.

Test Scenario 4

In addition to Test Scenario 3, the gap acceptance for all human-driven cars is $GAP=2.5s$, and a reduction by 20% to $GAP_{100}=2.0s$ is used for an AV penetration level of $d = 100\%$ as discussed in Section 4.2.2.3.

The GAP_d values are updated for this scenario, and considering unopposed traffic flow at the major arm (A-C) with a value of $Q_M = 1200$ pcu/hr, opposed traffic flow at the minor arm (B-C) with a value of $Q_m = 400$ pcu/hr, capacity and delay are estimated in SATURN across a range of $d = 0\%$ to 100% .

In this scenario, alterations in saturation flow resulting from variations in the mean vehicle length (L) is not tested.

Test Scenario 5

In addition to Test Scenario 4, this test scenario incorporates considerations for changes in saturation flow due to fluctuations in the mean vehicle length (L). While keeping all other parameters constant, except for $L_{100} = 6.0$, $LSAT_{100}$ for opposed turn can be estimated to:

$$LSAT_{100} = 800 \times \frac{6.25 \times 1.24 + 7.5}{6.25 \times 0.5 + 6.0} = 1336$$

Similar to Test Scenario 3 and 4, the $LSAT_d$ and GAP_d values are updated for this scenario, and considering unopposed traffic flow at the major arm (A-C) with a value of $Q_M = 1200$ pcu/hr, opposed traffic flow at the minor arm (B-C) with a value of $Q_m = 400$ pcu/hr, capacity and delay are estimated in SATURN across a range of $d = 0\%$ to 100% .

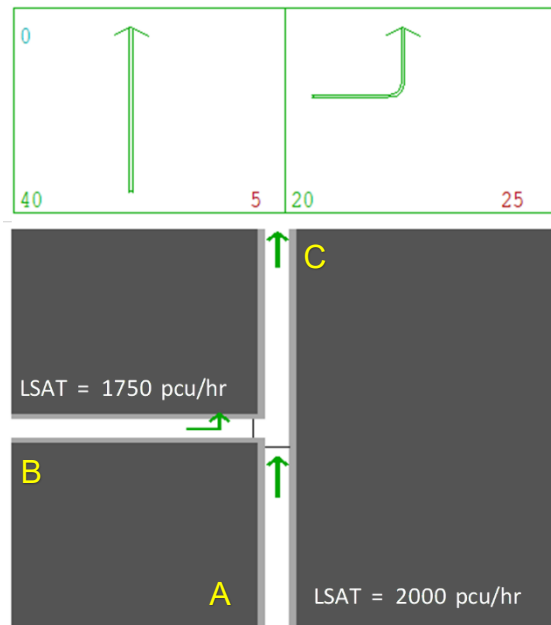
5.2.1.3 Turn at Signalised Junction

Test Scenario 6

This test scenario has been created to simulate turning flow at a signalised junction. Figure 5.3 shows a simple signal-controlled junction with three arms, specifically chosen as the testing ground for this scenario. In this arrangement, the saturation flow rate for vehicles moving straight through the main arm (A-C) is set at 2000 pcu/hr, whereas for the minor arm (B-C), the saturation flow rate for turning is

determined as 1750 pcu/hr based on road geometry (RTM, 2022). Two phase signal control with each phase with one stage is considered. The total cycle time is chosen 90s with 40s and 25s for the stage times and 5s and 25s inter-green respectively. A all red phase of approximately 20s is included in the inter-green of the 2nd phase.

Figure 5.3 Toy Junction (Signalised)



In this particular scenario, alterations in saturation flow are estimated through the analysis of headway distribution resulting from varying levels of AV penetration. However, in the case of a signalised junction at a stop-line, traffic initiates motion from a nearly standstill position from start of green stage. Due to this, the term 'headway' is most accurately replaced as a response time for calculating saturation flow for a signalised junction. Additionally, for the same underlying rationale, a clearance speed is considered rather than the mean speed for estimating saturation flow.

At the start of the column of traffic, the time at which departure occurs can be anticipated from the movement of vehicles ahead. Thus, the response time to the departure of the driver directly in front is reduced. Friedrich (2014) considered the reaction time or the safety margin of $h = 0.6s$ and $h_{100} = 0.3s$ for non-AV and pure AV environment respectively. These values are adopted for this research to model

Utilising equation 5.2, where $h = 0.6\text{s}$, $h_{100} = 0.3\text{s}$ for an AV penetration level of $d = 100\%$, clearance speed of $v = 22\text{ kph}$ (6.25 m/s) and $L_{100} = 6.0\text{m}$, and for a given $LSAT = 2000\text{ pcu/hr}$, $LSAT_{100}$ can be estimated as:

$$LSAT_{100} = 2000 \times \frac{6.25 \times 0.6 + 7.5}{6.25 \times 0.3 + 6.0} = 2857$$

By incorporating adjustments to the $LSAT_d$ values, and considering traffic flow at the major arm with a value of $Q_M = 1200\text{ pcu/hr}$, traffic flow at the minor arm with a value of $Q_m = 400\text{ pcu/hr}$, capacity and delay are estimated in SATURN across a range of $d = 0\%$ to 100% .

5.2.1.4 Circulatory and Entry at Roundabout

Within the SATURN, saturation flows at roundabouts are implemented at an entry level rather than being specific to individual turns. The entry saturation flow remains consistent for each turn originating from a given arm. The simulation attributes of entry saturation flow bear resemblance to the yield-based turn capacity observed at priority junctions. Likewise, the circulatory capacity is estimated in a manner similar to calculating the unopposed turn saturation flow at a priority junction. Thus, the modelling method to address AV is same as the priority junction with opposed movement shown in scenarios 3 to 5. Hence, there is no need for separate scenarios to be developed in order to simulate turning movements at roundabouts due to the presence of AV.

However, gap acceptance at a roundabout, denoted as GAPR in SATURN, tends to be slightly lower compared to the GAP observed at priority junctions. The GAPR values are typically computed by the circulatory capacity dividing 3,600 (RTM, 2022).

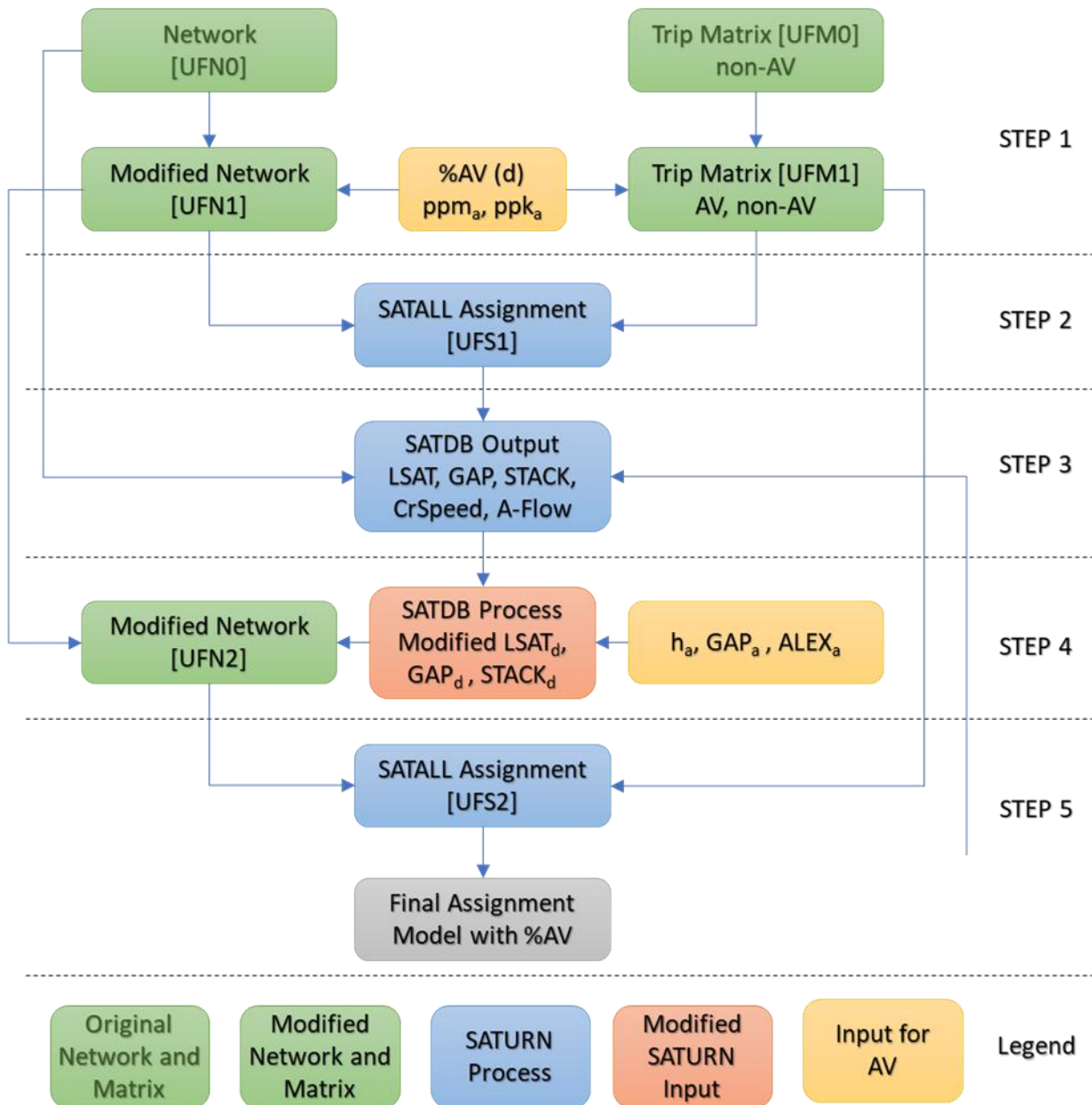
5.2.2 Test Scenarios Toy Network

5.2.2.1 Model Setting

The modelling parameters for the AV network have been established in the previous section and are documented in Table 5-1. These parameters serve as the foundation for the AV-modified input in the toy network modelling. However, it's crucial to note that the network level comprises numerous junctions and links, necessitating an automated procedure to update SATURN network based on the modified input to accommodate varying levels of AV traffic on each individual link.

The steps involved in this process for creating the AV-modified network and the subsequent assignment steps are presented in Figure 5.4 and will be discussed in detail in the following sections.

Figure 5.4 Model Process for AV Network Modification and Assignment



Step 1 Modify SATURN network and Trip Matrix with % AV

The initial step involves modifying the existing SATURN network (UFN0) with no AV environment. This modification will require a specified AV share (%d) across all links to create the AV-modified network (UFN1). In this preliminary step, the gap

acceptance (GAP) and turn saturation flow (LSAT) for all links are uniformly adjusted before any traffic assignment occurs.

Simultaneously, the existing trip matrix (UFM0), encompassing origin and destination data for all human-driven vehicles environment, is divided into two separate matrices: one for non-AV trips and another for AV trips, based on the specified AV share. As previously discussed in Section 4.3.2.8, AV trips are introduced as a distinct vehicle class within the SATURN framework. Furthermore, the AV trip matrix is categorised by trip purposes, such as commuting, business, and other activities like shopping and education, according to the specified %AV share.

In line with the modelling requirements for AV, outlined in toy network scenarios regarding the concept of generalised cost in Section 4.3.2.9, the parameters ppm_a and ppk_a are required for the AV user classes by trip purposes

Input : UFN0, UFM0, %AV (d), ppm_a , ppk_a

Output: UFN1, UFM1

Step 2 SATURN Traffic Assignment - UFN1, UFM1

This step entails traffic assignment utilising the SATALL module within SATURN, which utilises the modified SATURN network and trip matrices that includes AV as a new user class. The output of this step results as the traffic assignment model (UFS1), which is executed and converged using user defined traffic assignment principle, such as Wardrop equilibrium.

Input : UFN1, UFM1

Output: UFS1

Step 3 SATDB Output – Turn and Link Attributes and Assigned Flow

This step involves the extraction of turn and link attributes, such as LSAT, GAP, STACK, and CrSpeed for each turn and link. These attributes are necessary for modification based on the proportion of AVs at each specific turn. The SATDB module within SATURN is utilised to extract the actual flow for each turning movement for both AV and non-AV user classes. This information is required for estimating the proportion of AVs at each turn.

Input : UFN0, UFS1

Output: LSAT, GAP, STACK, CrSpeed, A-FLOW_a, A-FLOW_h

Step 4 SATDB Process – Modified SATURN Input

This step involves obtaining user input parameters for AVs, such as time headways (h_a), mean vehicle length in an external queue ($ALEX_a$), and GAP_a . These input parameters are essential for estimating the modified SATURN input parameters for an assigned proportion of AVs and non-AVs at the individual node level. This includes parameters like $LSAT_d$, GAP_d , and stacking capacity ($STACK_d$).

As per the equation provided in Section 4.3.2.2 (equation 4.13), $LSAT_d$ for each turning movement can be expressed as follows:

$$\frac{LSAT_d}{LSAT} = \frac{CrSpeed \cdot h + L}{CrSpeed \cdot h_d + L_d}$$

$$d = AFLOW_a / (AFLOW_a + AFLOW_h) \quad \dots\dots\dots (5.2)$$

$$h_d = h_a d + h(1 - d)$$

GAP_d is estimated linearly with the proportion of AVs and non-AVs at the individual node level, as discussed in Section 4.3.2.3.

In contrast, $STACK$ is estimated by considering the proportion of $ALEX$ for non-AVs and AVs at the individual link level, as expressed in equation 4.12.

$$ALEX_d = ALEX_a d + ALEX(1 - d) \quad \dots\dots\dots (5.3)$$

The SATDB module within SATURN is utilised to calculate the modified SATURN inputs for each turn and link. These calculated values are then imported into the modified SATURN network (UFN2).

Input : $LSAT$, GAP , $STACK$, $CrSpeed$, $ALEX$, $A-FLOW_a$, $A-FLOW_h$, h_a , GAP_a , $ALEX_a$, UFN1

Modified Input: $LSAT_d$, GAP_d , $STACK_d$

Output: UFN2

Step 5 SATURN Traffic Assignment and Convergence - UFN2, UFM1

Similar to Step 2, this step also involves traffic assignment using the SATALL module within SATURN, which utilises the modified SATURN network (UFN2) and trip matrix that includes AV as a new user class (UFM1). The outcome of this step is the traffic assignment model (UFS2).

Following the assignment, traffic flow by vehicle classes can undergo changes, potentially resulting in different AV proportions for each turning movements.

Input : UFN2, UFM1

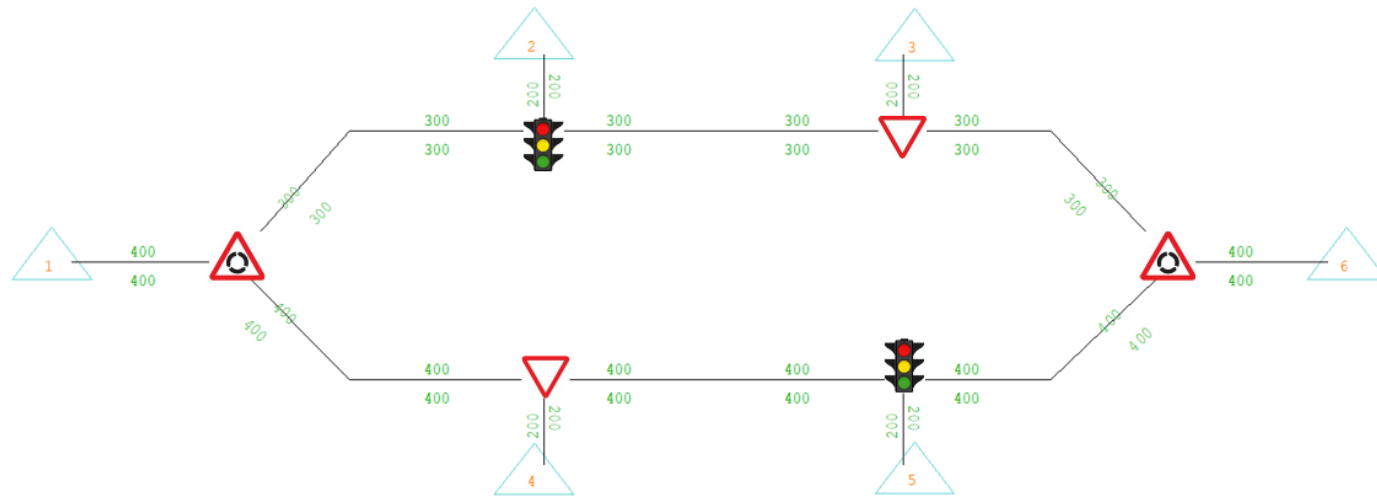
Output: UFS2

Test Scenario 7

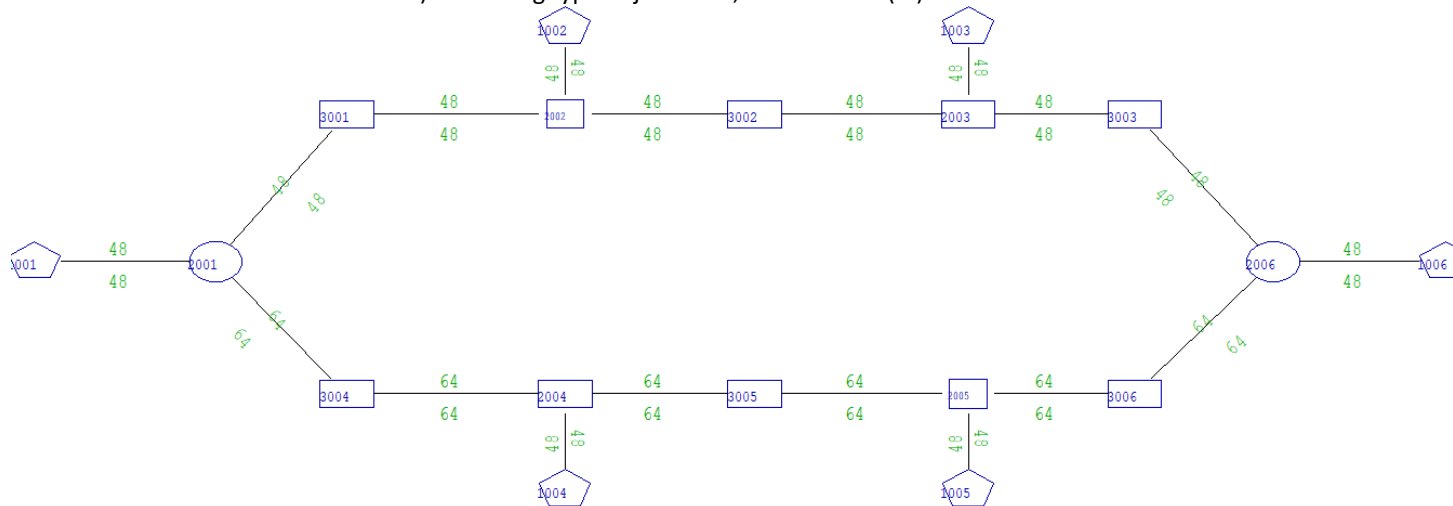
This test scenario has been designed for the simulation and assignment of AV trips in a toy network. Figure 5.5 presents the structure of the toy network that comprised of 2 priority junctions, 2 signalised junctions and 2 roundabouts; and 6 centroids (zones) connected with 6 external nodes. The network is created in simulation coding.

In Figure 5.5a, the location of the junctions by their respective types, accompanied by the measurement of link distances expressed in meters. Figure 5.5b, shows the node numbers with the representation of link speed (kph). Subsequently, Figure 5.5c illustrates the distribution of demand flow as allocated within the context of the scenario at 0% AV penetration level.

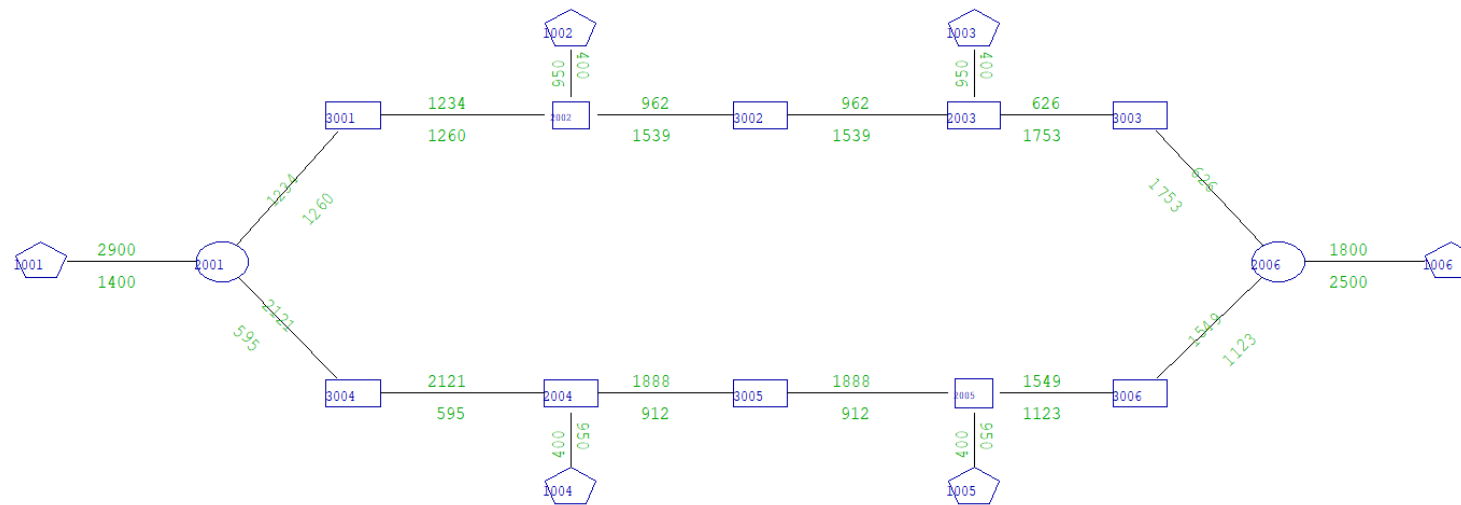
Figure 5.5 Toy Network



a) showing type of junctions, link distance (m) and zone number



b) showing cruise speed (kph) and node numbers



c) showing demand flow (pcu/hr) at 0% AV

The model network uses two vehicle classes: human driven car and AV, the PCU factor for both used is 1.0. Model time period is 60 minutes. Figure 5.6 illustrates the trip matrix under the baseline condition, characterised by 0% AV penetration. The matrix encompasses a total size of 7000 PCU and spans a time period of LTP = 60 minutes. The allocation and distribution of trips are established with the premise that all junctions would encounter some level of delays at a 0% AV penetration rate.

Figure 5.6 Toy Network Tri Matrix (0% AV)

O\D	1	2	3	4	5	6	Total
1	0	300	400	300	400	1500	2900
2	50	0	100	50	100	100	400
3	50	100	0	100	50	100	400
4	100	50	100	0	100	50	400
5	100	100	50	100	0	50	400
6	1100	400	300	400	300	0	2500
Total	1400	950	950	950	950	1800	7000

In Test Scenario 7, changes to the saturation flow are implemented by examining parameters such as headway (including response time), GAP, and safety distance (derived from the mean vehicle length). This analysis is conducted across both 0% and 100% AV penetration scenarios. The SATURN parameters for the toy network are then adjusted using the approach employed in Scenarios 1 through 6 and listed in Table 5.2.

Table 5.2 SATURN Input Parameters for Toy Network

Input Calculation	Modified/Direct Input Parameter	0% AV	100% AV
Headway	LSAT	$h = 1.24s$	$h_{100} = 0.5s$
Response time	LSAT	$h = 0.6s$	$h_{100} = 0.3s$
Mean vehicle speed	LSAT	$v = 48 \text{ kph}, 64 \text{ kph}$	
Clearance speed	LSAT	$v = 22.5 \text{ kph}$	
Mean vehicle length	LSAT	$L = 7.5m$	$L_{100} = 6.0m$
GAP Priority Junction	GAP	$GAP = 2.5s$	$GAP_{100} = 2.0s$
GAP Roundabout	GAPR	$GAPR = 1.0s$	$GAPR_{100} = 0.8s$
LSAT Priority - Unopposed - Opposed-left - Opposed-right		2000 pcu/hr 800 pcu/hr 700 pcu/hr	3789 pcu/hr 1336 pcu/hr 1169 pcu/hr
LSAT Signalised - Straight Ahead - Left - Right		2000 pcu/hr 1750 pcu/hr 1800 pcu/hr	2857 pcu/hr 2500 pcu/hr 2571 pcu/hr
LSAT Roundabout - Circulatory - Entry		4000 / 3000 pcu/hr 2200 / 1600 pcu/hr	7579 / 5684 pcu/hr 3673 / 2671 pcu/hr

By incorporating adjustments to the $LSAT_d$, GAP and $GAPR_d$ values in the toy network, capacity, delay, volume over capacity (V/C) and global network statistics like total travel cost (TTC), total travel time (TTT) etc are in SATURN for $d = 100\%$.

Test Scenario 8

In addition to Test Scenario 7, this particular test scenario integrates generalised cost parameters to assess the impact of AV on route choice. The selected values for $ppm = 30.0$, $ppk = 6.0$ are complemented by $ppm_a = 18.0$, $ppk_a = 5.7$, which are adopted for AV.

Table 5.3 summarises the model settings that include AV behaviour, input, and output of the SATURN test model, along with a brief description of the scenario.

Table 5.3 AV-Model Scenario Setup

Test Scenario	Network Type	Network Element Modelled	Modelling Measure	Demand and Network Variation	%AV (d)	Modified Input	Output
1	Toy Junction (Priority)	Unopposed turning movement	h	Three-arm priority junction Q _M =2400 pcu/hr Q _m =100 pcu/hr h _a =0.5s, L _a =6.0m, GAP _a =2.0s	0%, 25%, 50%, 75%, 100%	LSAT _d	Capacity Delay
2			h, L			LSAT _d	
3		Opposed turning movement	h	Three-arm priority junction Q _M =1200 pcu/hr Q _m =400 pcu/hr h _a =0.5s, L _a =6.0m, GAP _a =2.0s	0%, 25%, 50%, 75%, 100%	LSAT _d	
4			h, GAP			LSAT _d , GAP _d	
5			h, GAP, L			LSAT _d , GAP _d	
6	Toy Junction (Signalised)	Turning movement	h, L	Three-arm signalised junction Q _M =1200 pcu/hr Q _m =400 pcu/hr h _a =0.5s, L _a =6.0m	0%, 25%, 50%, 75%, 100%	LSAT _d	Capacity Delay
7	Toy Network	Signalised junction, priority junctions, roundabouts	h, GAP, L	Q=7000 pcu h _a =0.5s, L _a =6.0m, GAP _a =2.0s	0%, 100%	LSAT _d , GAP _d	Flow Delay V/C TTT TTD Speed
8			h, GAP, L, GC	Q=7000 pcu h _a =0.5s, L _a =6.0m, GAP _a =2.0s ppm=30.0, ppk=6.0 ppm _a =18.0, ppk _a =5.7	0%, 100%	LSAT _d , GAP _d ppm _a , ppk _a	
9					0%, 25%, 50%, 75%, 100%		

Note: LSAT = saturation flow, GAP = gap acceptance, h = headway, L = mean vehicle length, Q = Traffic Flow, GC = generalised cost

d = %AV, M = Major Arm, m = minor arm, a = AV, aa = AV-AV interaction, ah = AV-human car interaction

V/C = volume over capacity, TTT = total travel time, TTC = total travel distance

All scenarios involve modification of trip matrices for a new vehicle class by %AV penetration while keeping the matrix total unchanged

5.3 Result and Analysis

All the altered trip matrices are assigned to their respective test scenario networks in SATURN version 1.5.05N. Due to the small size of the network, the runtime for model assignment is negligible. The model results are analysed and discussed in the following sections.

5.3.1 Test Result – Priority Junction Unopposed

5.3.1.1 Test Scenario 1 – Change in Headway

This test scenario involves variations in saturation flow due to the percentage of AVs in the network for unopposed turn movement at a priority junction. The changes in saturation flow are determined using the distribution of headway. Table 5.4 and Figure 5.7 show model output for Test Scenario 1.

Table 5.4 Model Output – Test Scenario 1

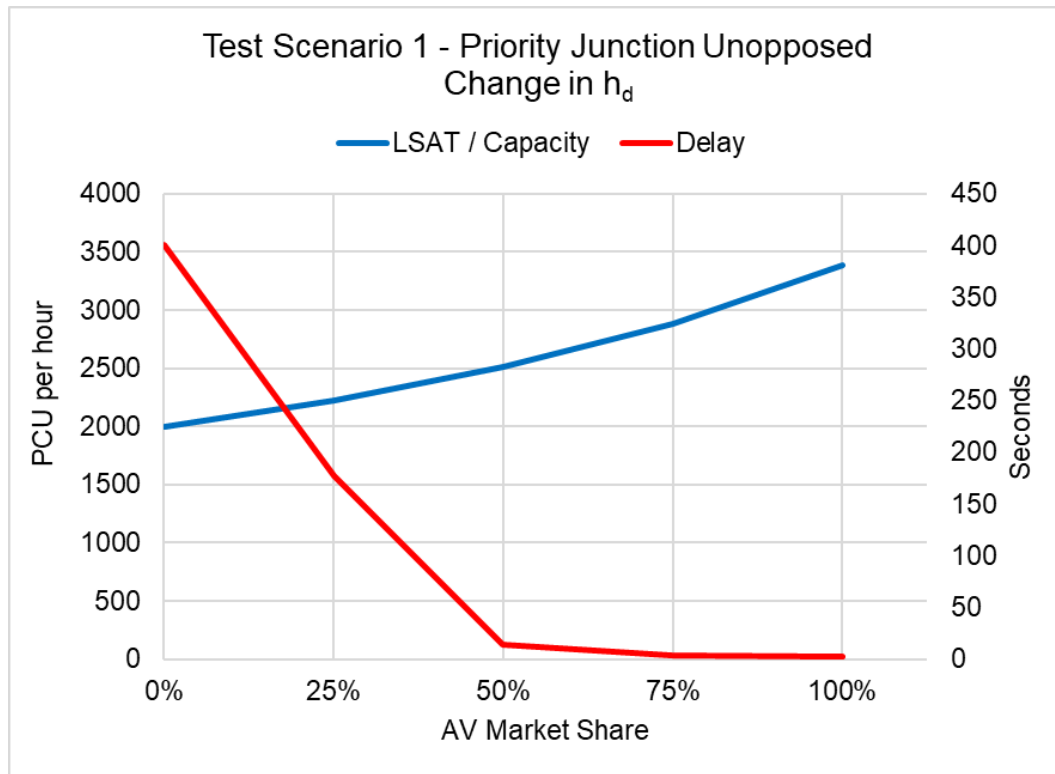
%AV	Headway		Modified Input Saturation Flow		Output			
	h_d		LSAT _d (M)		Capacity _d (M)		Delay _d (M)	
	Seconds		pcu/hour		pcu/hour		Seconds	
0%	1.2	-	2000	-	2000	-	400	-
25%	1.1	-15%	2228	11%	2228	11%	177	-56%
50%	0.9	-30%	2515	26%	2515	26%	14	-97%
75%	0.7	-45%	2887	44%	2887	44%	4	-99%
100%	0.5	-60%	3388	69%	3388	69%	2	-100%

In the baseline condition (0% AV), an observed delay of approximately 400 seconds occurs in the unopposed turn due to a demand flow of 2400 PCU/hr, contrasting with the saturation flow of 2000 PCU/hour. This situation leads to a queued flow of 400 PCU/hr, translating to a 1-second delay per queued vehicle.

With a 50% AV share, there is a notable 26% increase in saturation flow and capacity attributed to a 30% reduction in headway. This reduction in headway results in a 97% reduction in delays, reducing them to 14 seconds.

Upon achieving a 100% AV share, the 30% reduction in headway to 0.5 seconds shows 69% capacity increase, reaching 3388 pcu/hr. This leads to a considerable delay reduction, bringing it down to just 2 seconds.

Figure 5.7 Model Output – Test Scenario 1



5.3.1.2 Test Scenario 2 – Change in Headway and Safety Distance

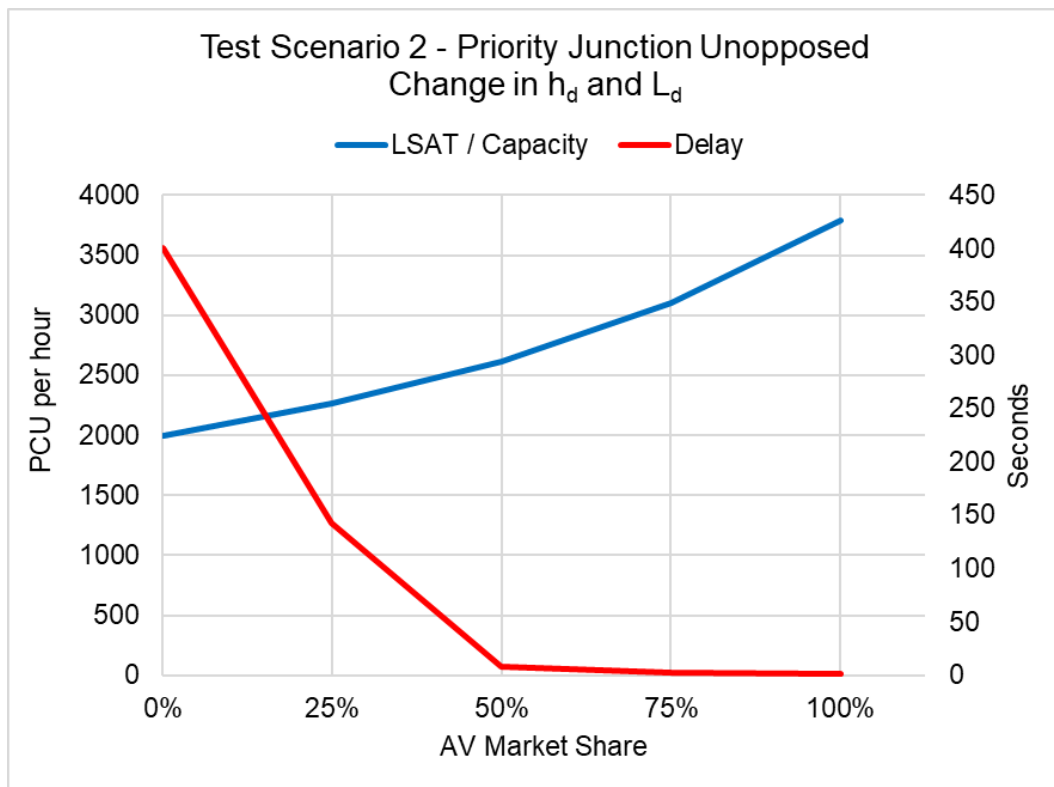
Similar to Test Scenario 1, this specific scenario is designed to explore the impact of altering the saturation flow on the major arm under congested conditions, where the traffic flow on the major arm exceeds the saturation flow at pure human driven car environment. This test scenario involves variations in saturation flow and mean vehicle length due to the percentage of AVs in the network. Table 5.5 and Figure 5.8 shows modelled output for Test Scenario 2.

In addition to Scenario 1, an additional AV behaviour model focused on safety efficiency, which integrates safety distance within the context of mean vehicle length, is modelled. With 100% AV penetration rate, the reduction of headway by 30% to 0.5 seconds, combined with a 20% decrease in mean vehicle length to 6 metres, results in an 89% surge in capacity, reaching to 3789 pcu/hr.

Table 5.5 Model Output – Test Scenario 2

%AV	Headway		Vehicle length		Modified Input Saturation Flow		Output			
	h_d		L_d		$LSAT_d$ (M)		$Capacity_d$ (M)		$Delay_d$ (M)	
	Seconds		metres		pcu/hour		pcu/hour		Seconds	
0%	1.2	-	7.5	-	2000	-	2000	-	400	-
25%	1.1	-15%	7.1	-5%	2268	13%	2268	30%	143	-64%
50%	0.9	-30%	6.8	-10%	2618	31%	2618	70%	8	-98%
75%	0.7	-45%	6.4	-15%	3097	55%	3097	133%	3	-99%
100%	0.5	-60%	6.0	-20%	3789	89%	3789	214%	1	-100%

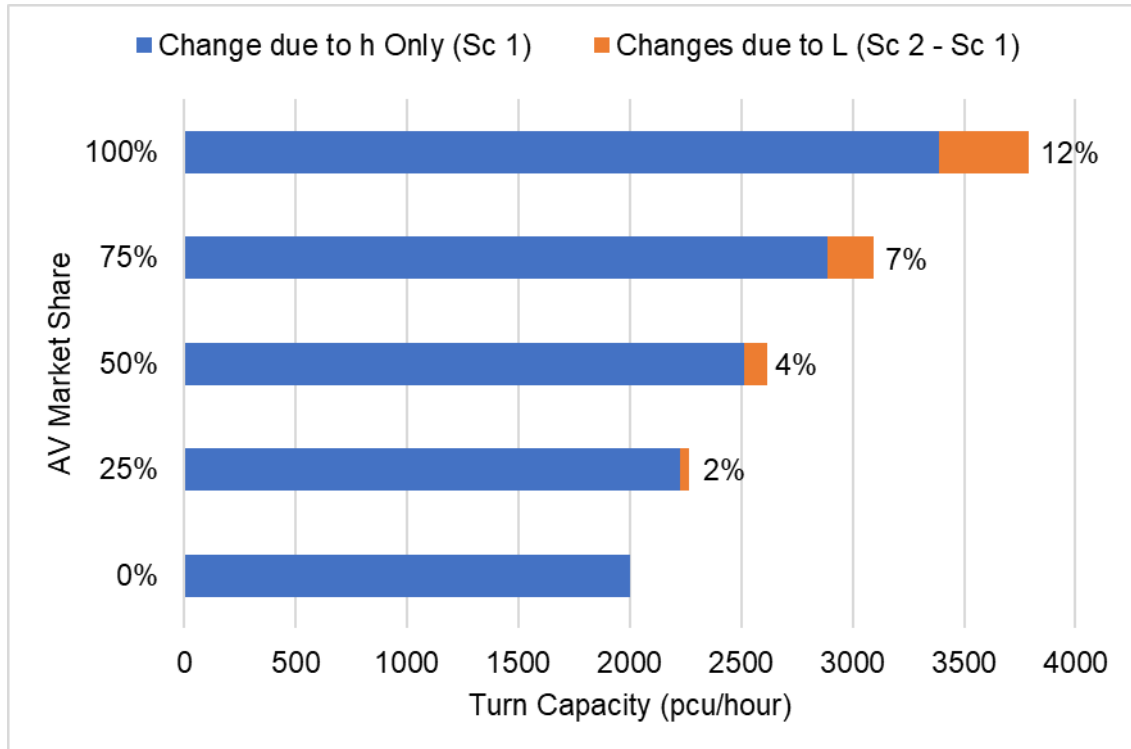
Figure 5.8 Model Output – Test Scenario 2



The primary objective of test scenarios 1 and 2 is to investigate the relationship between the capacity of the unopposed turn and various influencing factors. These factors include saturation flow, mean vehicle length, and the interplay with varying AV flow rates within priority junctions. In Scenario 2, a comparison with Scenario 1 reveals that a modification in mean vehicle length attributed to enhanced safety distance efficiency results in an increased saturation flow. This alteration, introduced as an input into the SATURN model, generates a notable 4% capacity

increase at 50% AV penetration. Notably, at a complete 100% AV penetration, this impact becomes more pronounced, estimating 12% capacity increase, as shown in Figure 5.9.

Figure 5.9 Comparing Scenarios 1 and 2 – Unopposed Turn Capacity



5.3.2 Test Result – Priority Junction Opposed

5.3.2.1 Test Scenario 3 – Change in Headway

This test scenario involves variations in saturation flow due to the percentage of AVs in a priority junction. The changes in saturation flow are determined using the distribution of headway. Table 5.6 and Figure 5.10 show the model output for test scenario 3.

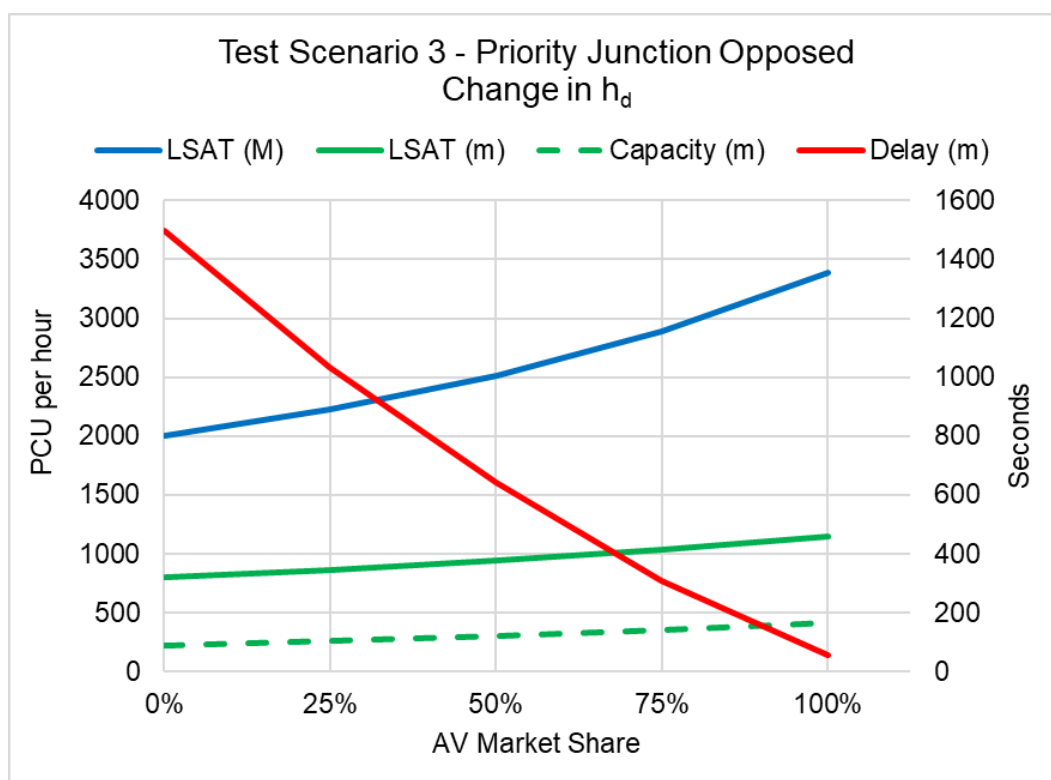
The analysis suggests that at 50% AV penetration, there is a 26% increase in saturation flow on the unopposed movement at a priority junction, corresponding to a 69% increase from the baseline in an all-AV environment. Similarly, the saturation flow at the minor arm increases by 18% and 43% at 50% and 100% AV penetration, respectively. The rate of increase in saturation flow at the minor arm is slightly lower than that of the major arm. This disparity primarily arises from the fact that AVs effectively initiate their movement from a standstill position at the yield point on the

minor arm, starting with lower speeds. In contrast, the major arm's movement follows a mean speed pattern.

Table 5.6 Model Output – Test Scenario 3

%AV	Headway		Modified Input - Saturation Flow				Output			
	h _d		LSAT _d (M)		LSAT _d (m)		Capacity _d (m)		Delay _d (m)	
	Seconds		pcu/hour				pcu/hour		Seconds	
0%	1.2	-	2000	-	800	-	224	-	1498	-
25%	1.1	-15%	2228	11%	865	8%	261	17%	1032	-31%
50%	0.9	-30%	2515	26%	943	18%	304	36%	641	-57%
75%	0.7	-45%	2887	44%	1035	29%	352	57%	308	-79%
100%	0.5	-60%	3388	69%	1147	43%	410	83%	56	-96%

Figure 5.10 Model Output – Test Scenario 3



The capacity of the minor arm is the function of the saturation flow of both the major and minor arms. A higher saturation flow on the unopposed movement leads to a reduced probability of finding gap acceptance for the minor arm traffic. However, this issue is effectively mitigated by increasing the saturation flow for the minor arm,

resulting in a substantial 36% capacity gain in a 50% AV share. Furthermore, this capacity gain further increases to an impressive 83% in a pure AV environment.

In this test model, considerable delays are observed on the minor arm in the baseline situation, as the traffic flow on the minor arm amounts to 400 pcu/hour, exceeding its capacity of 224 pcu/hour. Despite achieving a 47% increase in capacity, which results in a 57% reduction in delay, some congestion persists. However, it is worth noting that complete congestion alleviation is achieved only when the flow reaches 100% AV penetration with 83% gain in capacity.

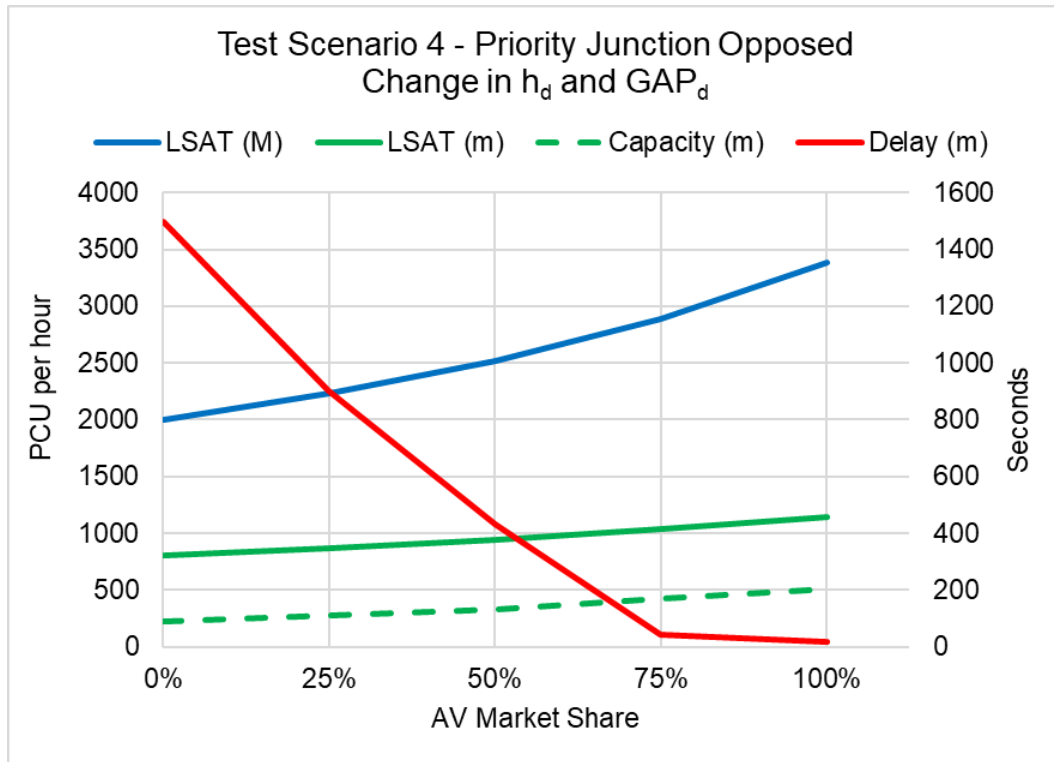
5.3.2.2 Test Scenario 2 – Change in Headway and GAP

This test scenario involves variations in saturation flow and GAP due to the percentage of AVs in a priority junction. The changes in saturation flow are determined using the distribution of headway. The choice of GAP parameters for AVs assumes a value of 2.0 seconds compared to human cars, which is set at 2.5 seconds. Consequently, the variation in the GAP distribution by AV market share is applied. Table 5.7 and Figure 5.11 show the model output for test scenario 4.

Table 5.7 Model Output – Test Scenario 4

%AV	Gap Acceptance		Modified Input - Saturation Flow				Output			
	GAP _d		LSAT _d (M)		LSAT _d (m)		Capacity _d (m)		Delay _d (m)	
	Seconds		pcu/hour				pcu/hour		Seconds	
0%	2.5	-	2000	-	800	-	224	-	1498	-
25%	2.4	-4%	2228	11%	865	8%	274	22%	901	-40%
50%	2.3	-8%	2515	26%	943	18%	333	48%	431	-71%
75%	2.1	-16%	2887	44%	1035	29%	419	87%	43	-97%
100%	2.0	-20%	3388	69%	1147	43%	504	125%	18	-99%

Figure 5.11 Model Output – Test Scenario 4



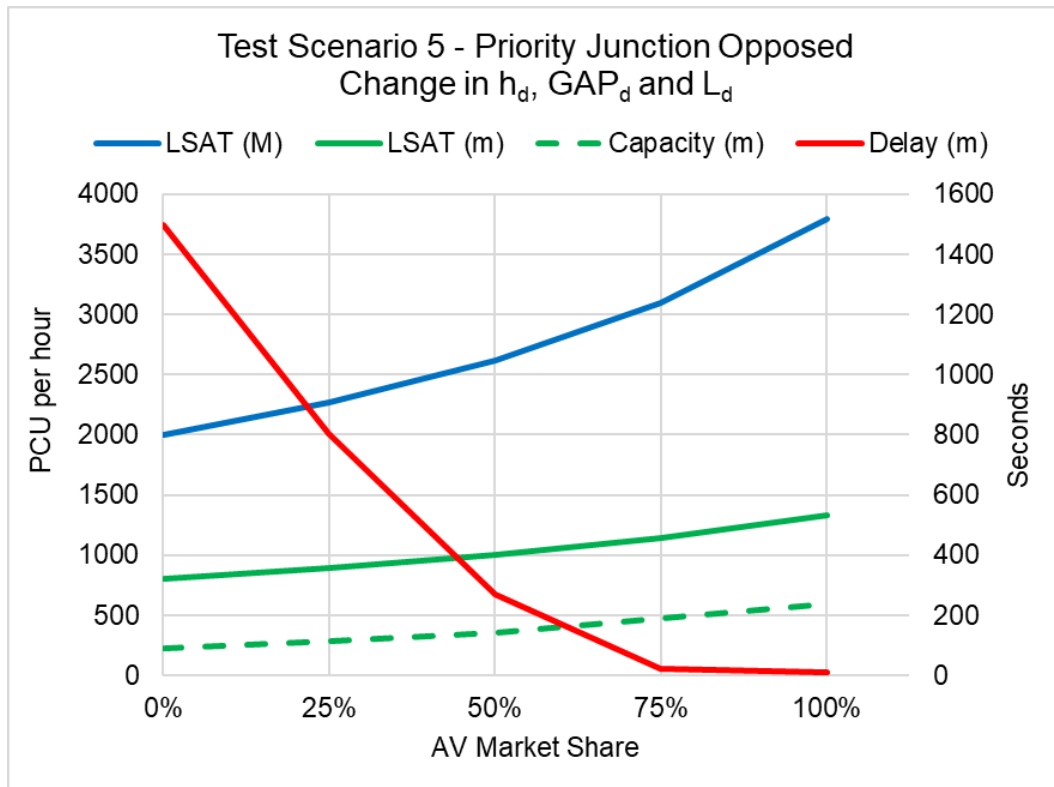
5.3.2.3 Test Scenario 5 – Change in Headway, GAP and Safety Distance

This test scenario involves variations in saturation flow, GAP and safety distance in mean vehicle length due to the percentage of AVs in a priority junction. The changes in saturation flow are determined using the distribution of headway and mean vehicle length. The choice of GAP parameters for AVs assumes a value of 2.0 seconds compared to human cars, which is set at 2.5 seconds. Consequently, the variation in the GAP distribution by AV market share is applied. Table 5.8 and Figure 5.12 show the model output for test scenario 5.

Table 5.8 Model Output – Test Scenario 5

%AV	Mean Vehicle Length		Modified Input - Saturation Flow				Output			
	L _d		LSAT _d (M)		LSAT _d (m)		Capacity _d (m)		Delay _d (m)	
	metres		pcu/hour				pcu/hour		Seconds	
0%	7.5	-	2000	-	800	-	224	-	1498	-
25%	7.1	-5%	2268	13%	889	11%	285	27%	802	-46%
50%	6.8	-10%	2618	31%	1001	25%	359	60%	270	-82%
75%	6.4	-15%	3097	55%	1144	43%	472	111%	23	-98%
100%	6.0	-20%	3789	89%	1336	67%	599	167%	12	-99%

Figure 5.12 Model Output – Test Scenario 5

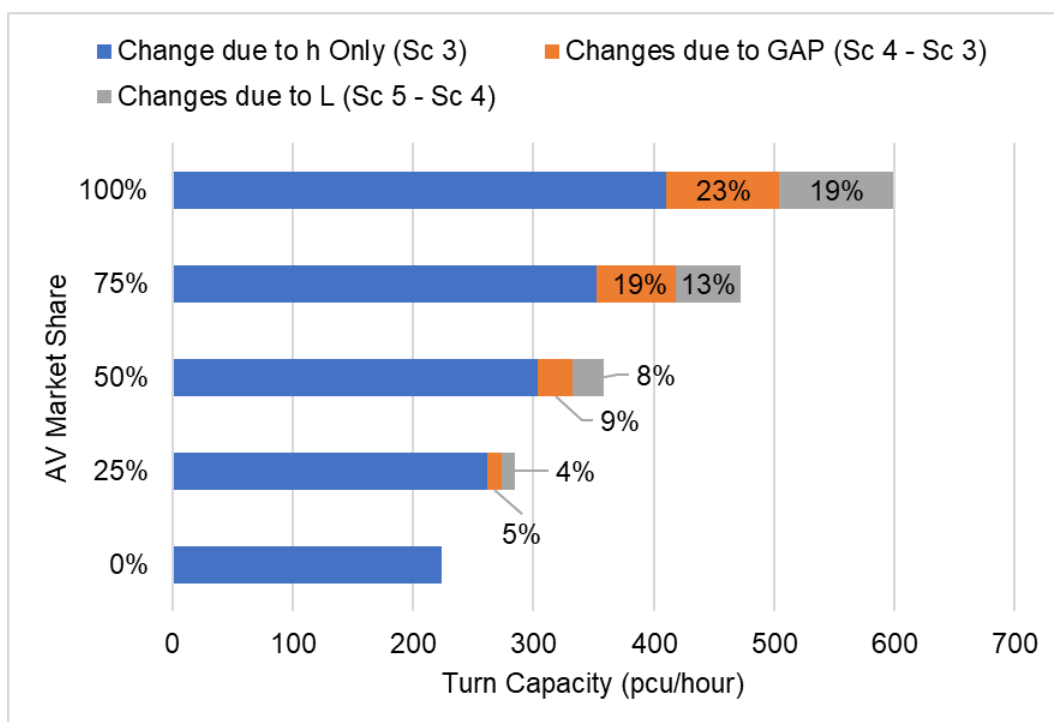


The primary objective of test scenarios 3 to 5 is to investigate the relationship between the capacity of the give-way turn and several factors, including saturation flow, GAP, and safety distance, in response to varying AV flow in a priority junction. In Scenario 2, a comparison with Scenario 1 reveals that a change in GAP, introduced as an input in the SATURN model, leads to a 9% increase in the give-way turn capacity at 50% AV penetration and a substantial 23% increase at 100% AV penetration. The analysis is summarised in shown in Figure 5.13.

Building on this, Scenario 3 explores the impact of reducing the safety distance at the give-way line for AVs. As a result, a further 8% increase in capacity is observed at 50% AV penetration, and this capacity improvement reaches up to 19% with 100% AV penetration.

Importantly, it should be noted that while changes in gap acceptance significantly influence the capacity of the give-way turn in scenarios with AVs, this factor has no impact on the capacity of unopposed traffic movement.

Figure 5.13 Comparing Scenarios 3 to 5 – Opposed Turn Capacity



These findings carry significant implications for optimising junction performance in the context of AV integration. By understanding the interplay between AV demand, saturation flow, GAP, and safety distance, traffic engineers can make informed decisions to enhance traffic flow efficiency and safety at junctions with AVs.

5.3.3 Test Result – Signalised Junction

5.3.3.1 Test Scenario 6 – Change in Headway and Safety Distance

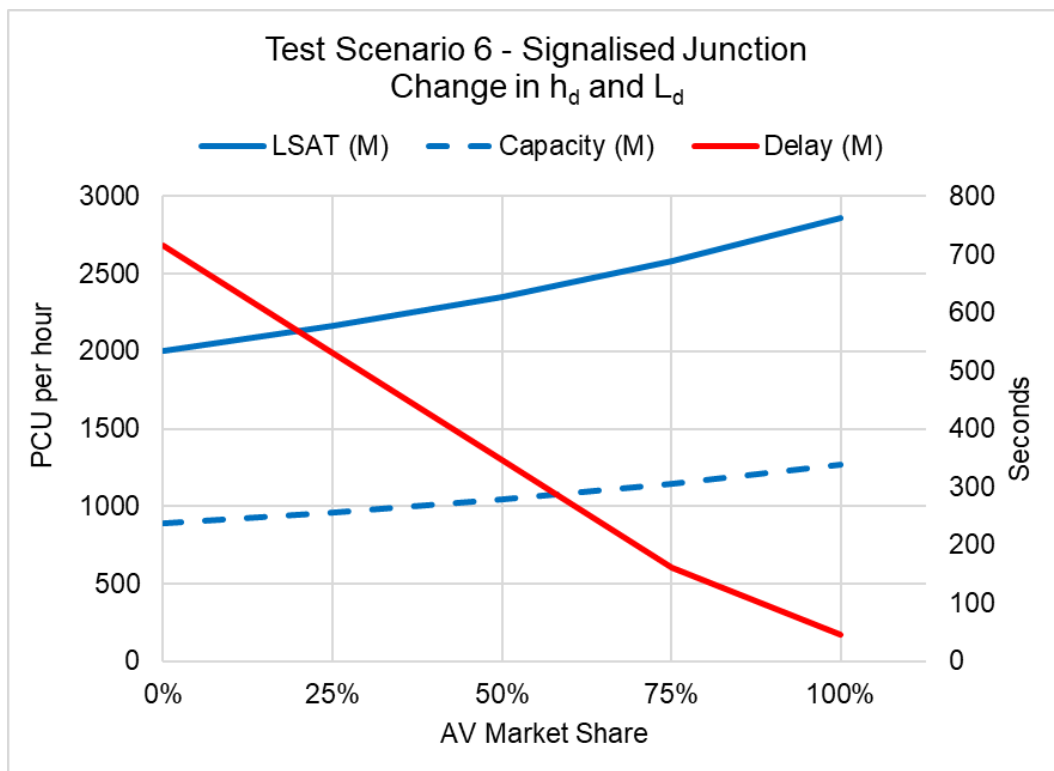
This test scenario involves variations in saturation flow due to the percentage of AVs in a signalised junction. The changes in saturation flow are determined using the distribution of headway and safety distance in mean vehicle length. Table 5.9 and Figure 5.14 show the model output for test scenario 6.

In the baseline condition (0% AV), an observed delay of approximately 715s occurs in the major arm due to the due to a demand flow of 1200 pcu/hr, contrasting with the saturation flow of 2000 pcu/hour. With a cycle time of 90 seconds, an effective green time of 40 seconds is designated to facilitate this specific movement. Consequently, the capacity of this movement is reduced to 889 pcu/hr as a direct consequence of these factors.

Table 5.9 Model Output – Test Scenario 6

%AV	Headway		Vehicle length		Modified Input Satuation Flow		Output			
	h_d		L_d		LSAT _d (M)		Capacity _d (M)		Delay _d (M)	
	Seconds		metres		pcu/hour		pcu/hour		Seconds	
0%	1.2	-	7.5	-	2000	-	889	-	715	-
25%	1.1	-15%	7.1	-5%	2162	8%	961	8%	531	-26%
50%	0.9	-30%	6.8	-10%	2353	18%	1046	18%	346	-52%
75%	0.7	-45%	6.4	-15%	2581	29%	1147	29%	161	-77%
100%	0.5	-60%	6.0	-20%	2857	43%	1270	43%	45	-94%

Figure 5.14 Model Output – Test Scenario 6



With a 50% AV share, there is a notable 18% increase in saturation flow and capacity attributed to a 30% reduction in headway. This reduction in headway results in a 52% reduction in delays, reducing them to 346 seconds.

Upon achieving a 100% AV share, the 30% reduction in headway to 0.5 seconds shows 43% capacity increase, reaching 2857 pcu/hr. This leads to a considerable delay reduction, bringing it down to just 45 seconds.

5.3.4 Test Result – Toy Network

5.3.4.1 Test Scenario 7 – Change in Headway, GAP and Safety Distance

This particular test scenario has been developed to simulate and assign AV trips within a toy network. The saturation flow is established by considering alterations in headway, mean vehicle length, and GAP parameters. These settings are configured to represent a scenario where 100% AV penetration is achieved. Table 5.10 shows the global network statistics for the toy network.

Table 5.10 Global Network Statistics – Test Scenario 7

Global Network Statistics	0% AV	100% AV	% Change
Total Travel Time (pcu.hrs)	1944	350	-82%
Total Travel Distance (pcu.kms)	15500	15137	-2%
Average Speed (km/h)	8	43	440%
Avg Queues (pcu/h)	1074	44	-96%
Transient Queues (pcu.hrs)	197	68	-66%
Over Capacity Queues (pcu.hrs)	1458	0	-100%
Total Trips Loaded (pcu)	7000	7000	0%

The table presents data indicating that in the baseline scenario (0% AV), the primary portion of the total travel time, amounting to 1944 pcu-hrs, can be attributed to overcapacity and transient queues.

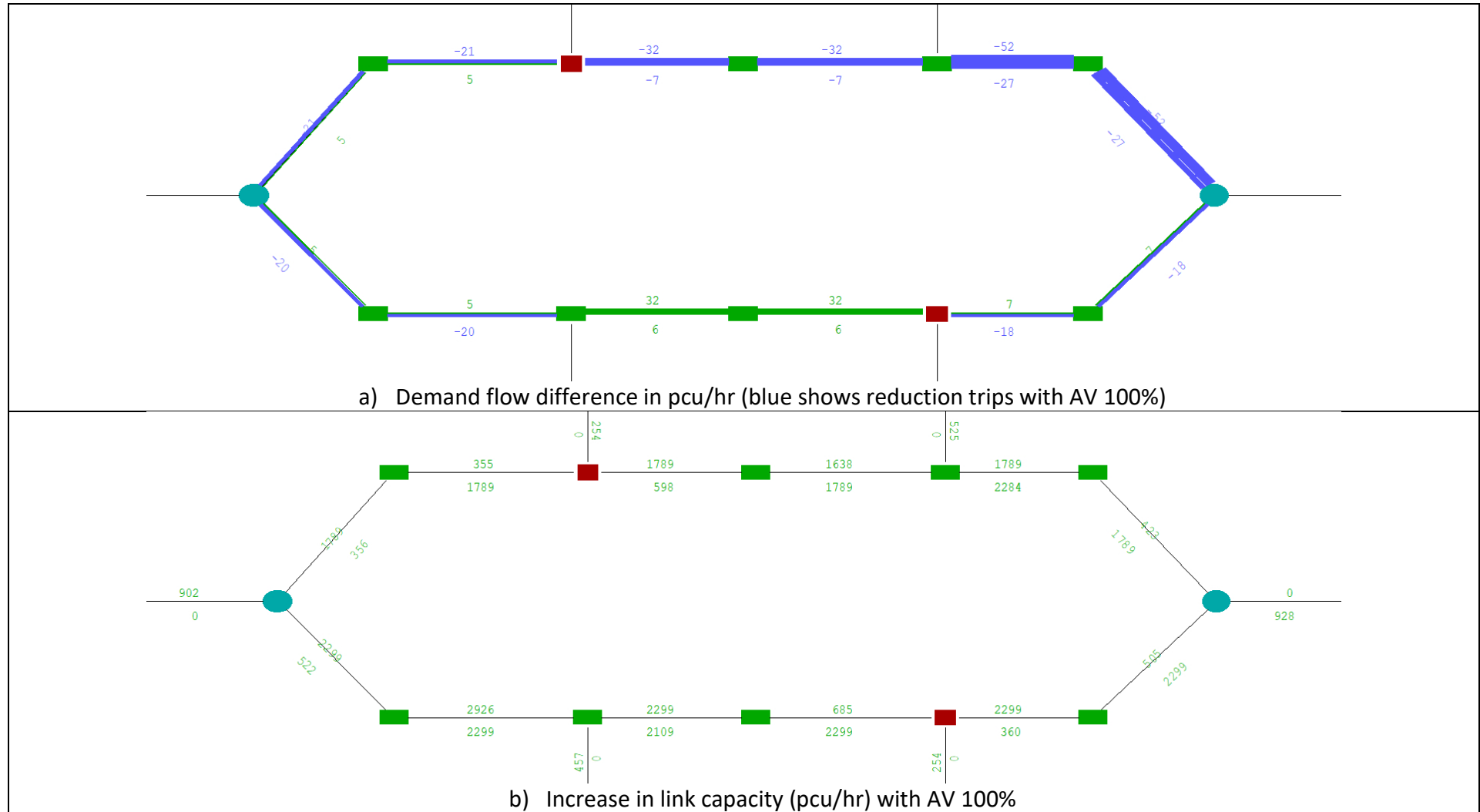
Notably, an 82% reduction is achieved in the overall travel time resulting from 100% AV penetration, and this is primarily due to the reduction in overcapacity queues. The transient queue at signalised junctions is also significantly decreased by 66%.

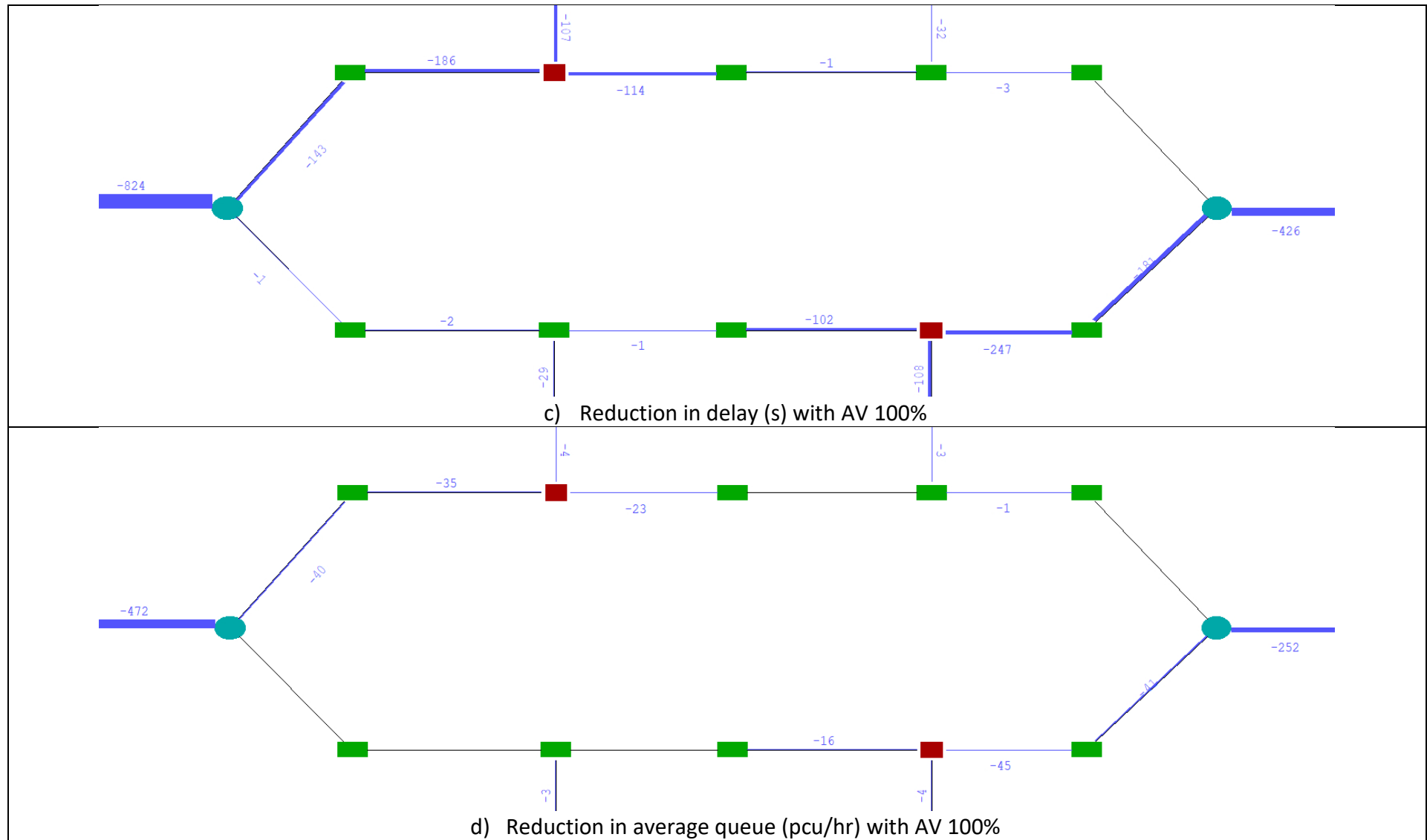
Taken together, there is a 96% reduction observed in the average queue due to the implementation of full automation. This substantial reduction serves as a clear testament to the effectiveness of complete automation in alleviating congestion.

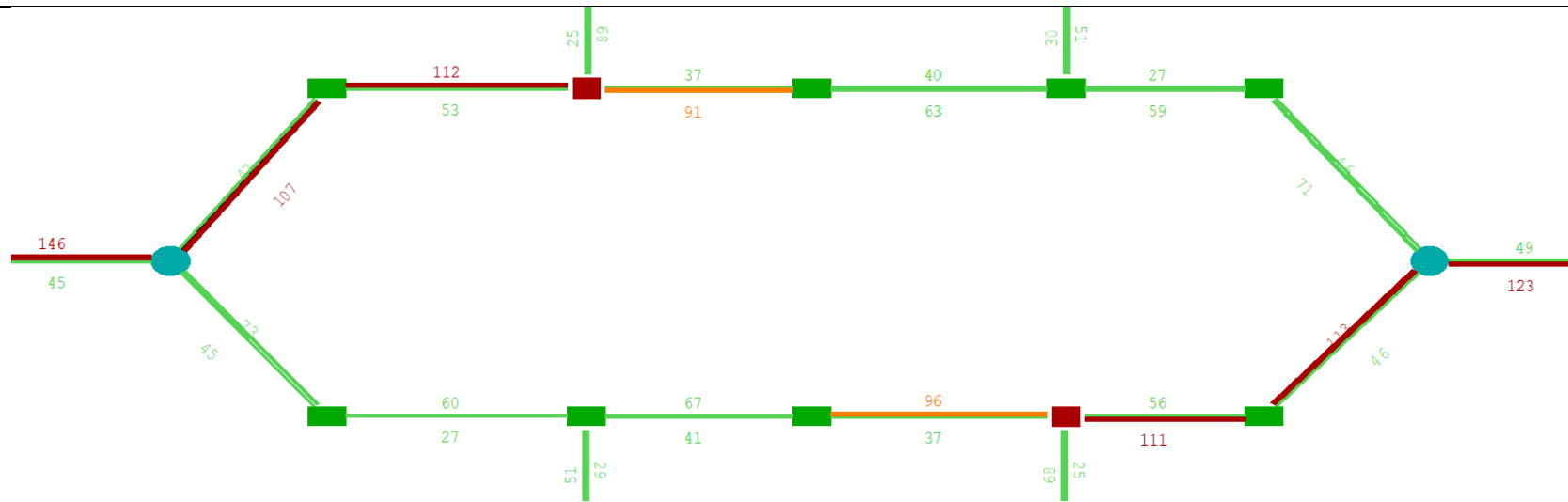
Moreover, the reduction in travel distance signifies that, with increased capacity available, vehicles that previously opted for longer routes due to congestion are now inclined to select shorter routes. This shift in behaviour underscores how enhanced capacity can prompt more efficient route choices, a crucial advantage brought about by the adoption of AVs.

Figure 5.15 displays SATURN screenshots for Test Scenarios, illustrating the model outcomes at links in the toy network. This includes parameters such as flow differences, capacity changes, variations in delays, queue reductions, and the volume-over-capacity ratio. These screenshots effectively showcase the extent of impact resulting from a 100% AV market share.

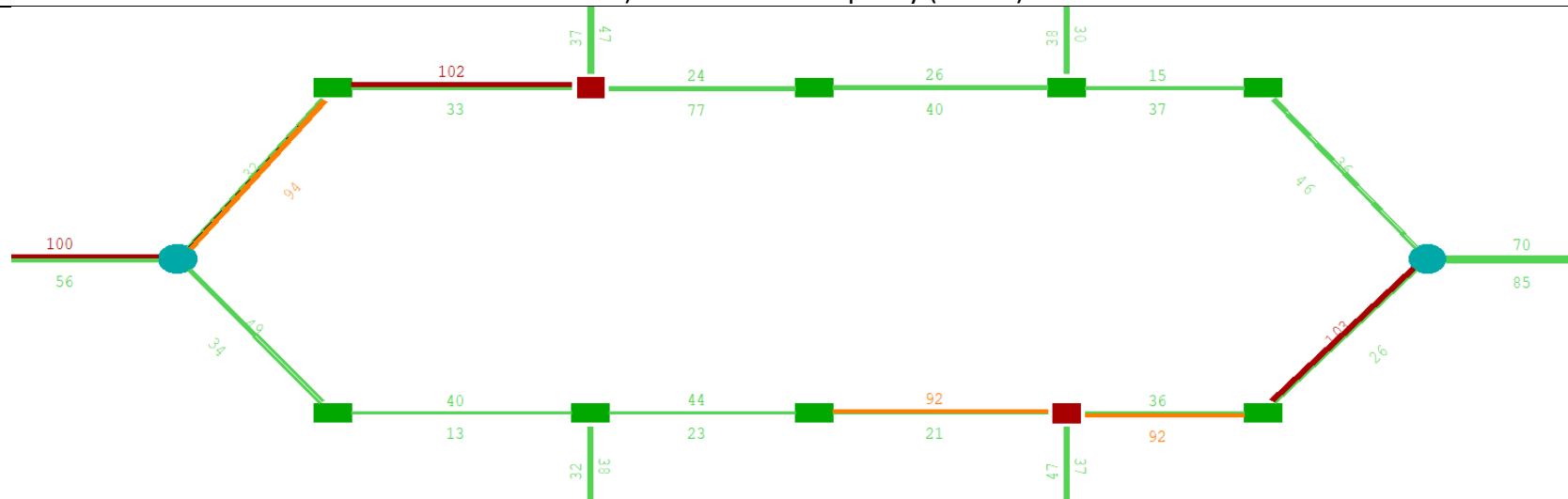
Figure 5.15 Model Output – Test Scenario 7







e) Volume over Capacity (0% AV)



f) Volume over Capacity (100% AV)

5.3.4.2 Test Scenario 8 – Change in Headway, GAP, Safety Distance and Generalised Cost

In addition to Test Scenario 7, this particular test scenario integrates generalised cost parameters to assess the impact of AV on route choice. As stated in the section, the selected values for $ppm = 30.0$, $ppk = 6.0$ are complemented by $ppm_a = 18.0$, $ppk_a = 5.7$, which are adopted for AV. This AV was assigned in the model as a separate user class.

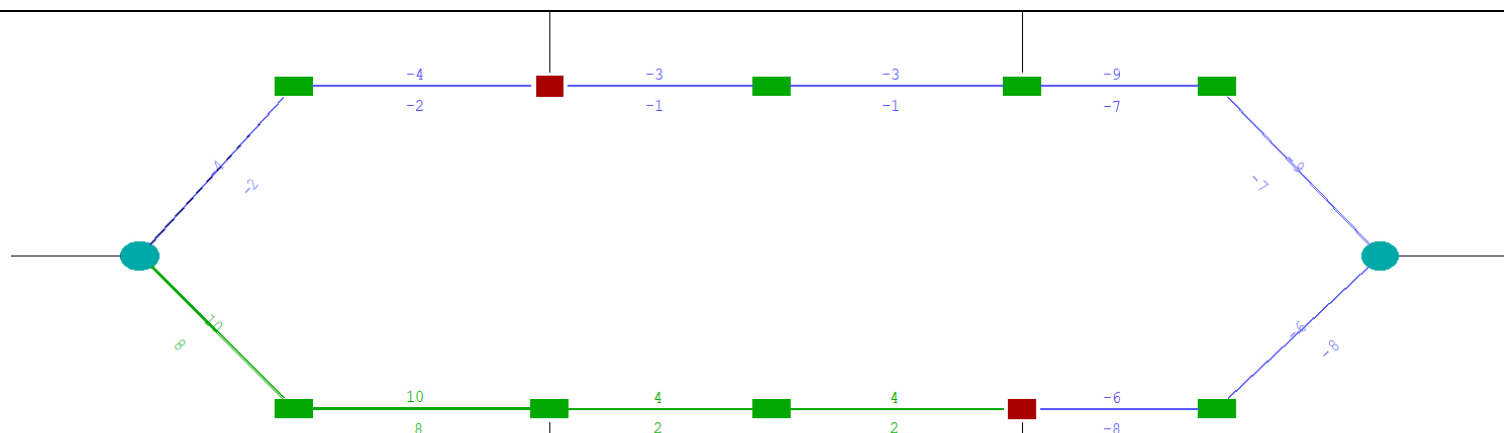
Table 5.11 provides a comparison of global network statistics for the toy network between Scenarios 7 and 8. The table reveals that there is no significant impact on network-wide characteristics due to the variation in value of time and vehicle operating cost associated with AVs.

Table 5.11 Global Network Statistics – Test Scenario 8

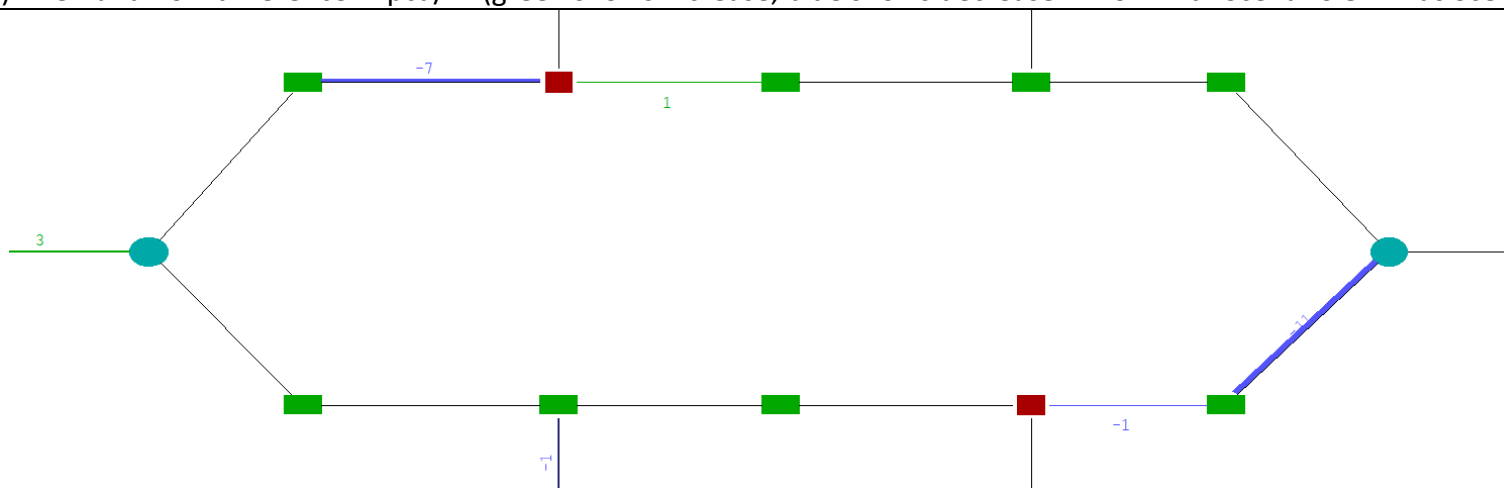
Global Network Statistics	Sc 7 AV 100%	Sc 8 AV 100%	% Change
Total Travel Time (pcu.hr)	350	355	1%
Total Travel Distance (pcu.kms)	15,137	15,100	0%
Average Speed (km/h)	43	43	-1%
Avg Queues (pcu/h)	44	44	-1%
Total Trips Loaded (pcu)	7,000	7,000	0%

Figure 5.16 presents the variation in traffic flow when the values of ppm and ppk are decreased for AVs. This observation indicates that, under specific generalised cost parameters, AVs are inclined to follow routes with lower speeds in a free flow condition.

Figure 5.16 Model Output – Test Scenario 8 against Scenario 7 (AV 100%)



a) Demand flow difference in pcu/hr (green shows increase, blue shows decrease in flow with Scenario 8 minus Scenario 7)



b) Delay difference in seconds (Scenario 8 minus Scenario 7)

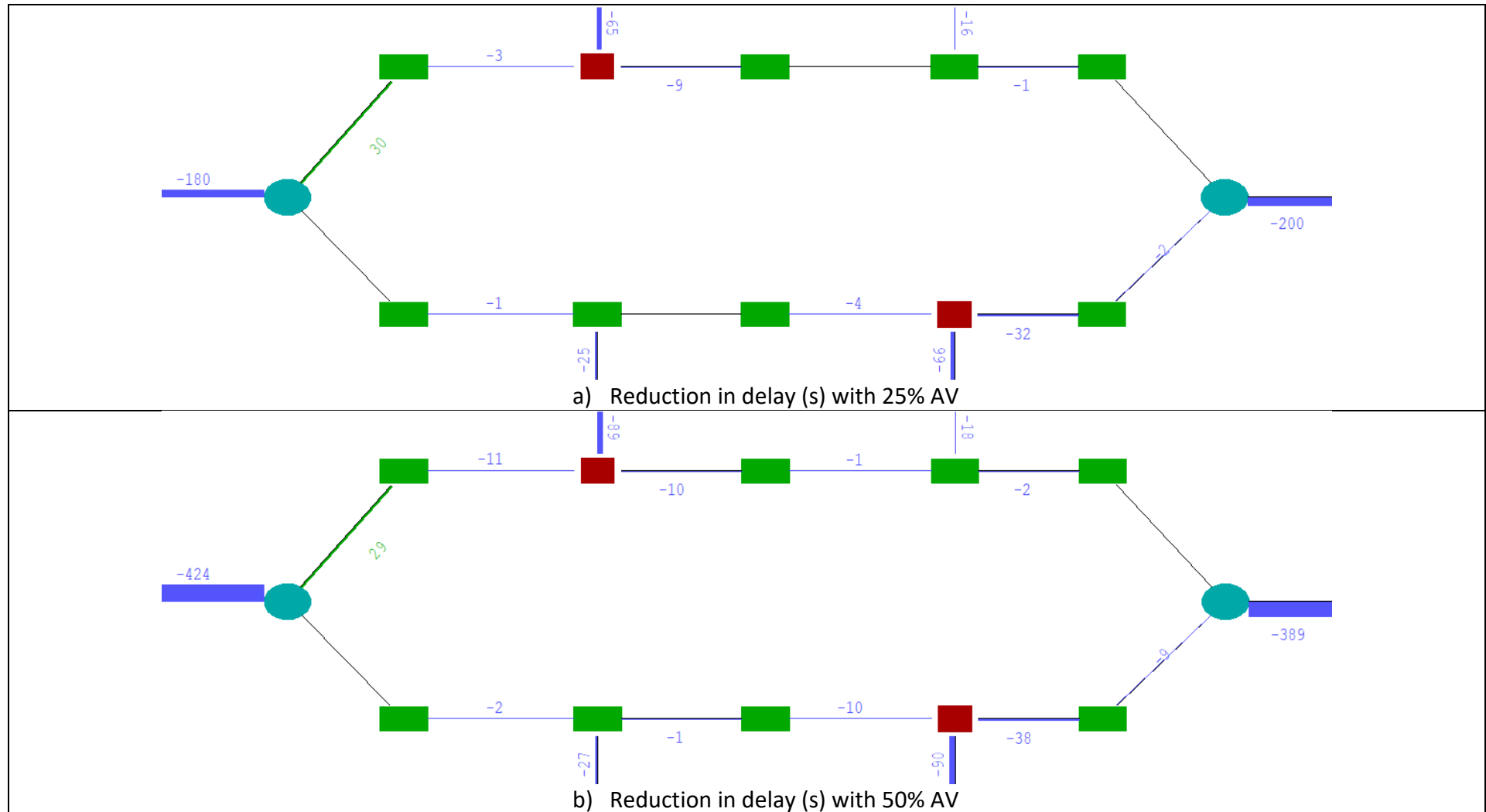
5.3.4.3 Test Scenario 9 – Change in Headway, GAP, Safety Distance and Generalised Cost for Mixed Traffic Scenario

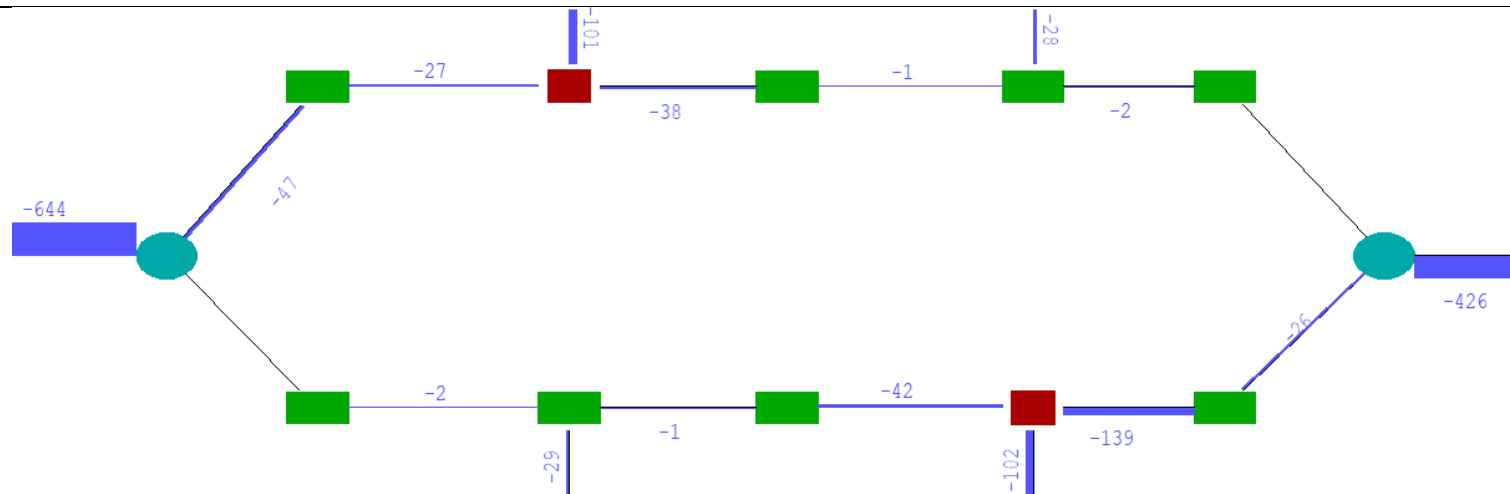
When considering a scenario involving 100% adoption of AVs in Scenarios 7 and 8, there is no necessity for differentiation of these parameters among distinct nodes. Scenario 8, when AV penetration rates varied, ranging from 0% to 100% with mixed conditions 25%, 50% and 75%, each node encompassed a varied mixture of vehicles owing to different route cost factors for AV and non-AV. The adjustment of parameters at the individual node level is applied based on the input variation applied in the toy junction scenarios 1 to 6. To adjust these parameters in SATURN, an iterative procedure involving SATDB and a customised BATCH script is coded for this scenario as illustrated in Figure 5.4 and discussed in section 5.2.2.1. The steps for performing this iterative parameter update process, along with the resulting changes in global network performance, are summarised in Table 5.12.

Table 5.12 Global Network Statistics – Test Scenario 9

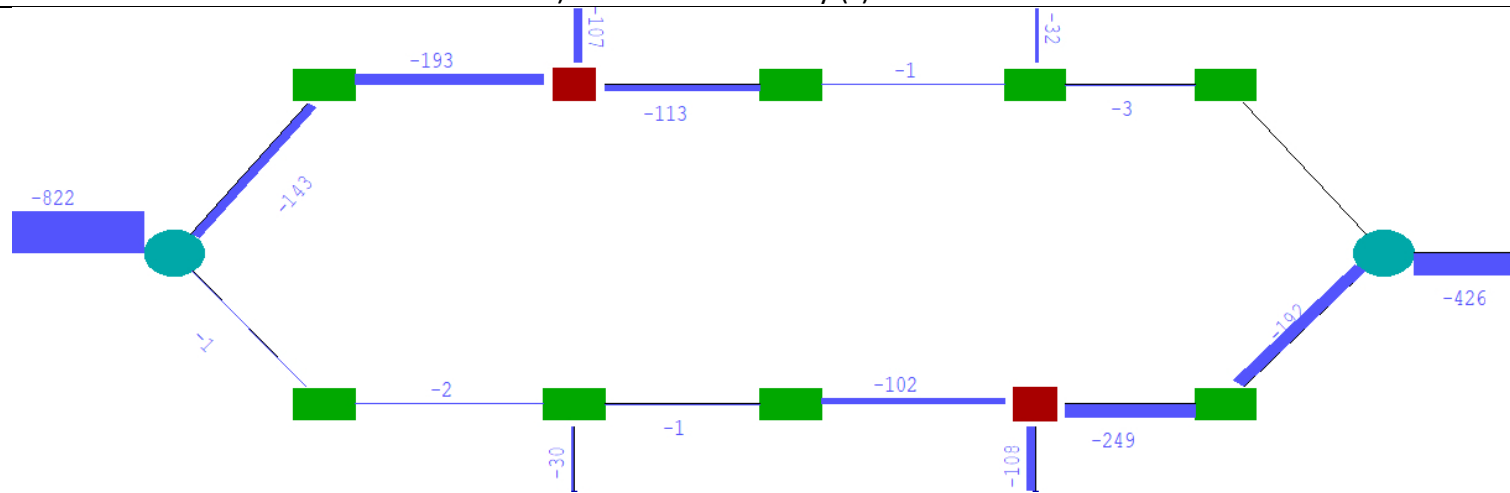
Global Network Statistics	AV 0%	AV 25%	AV 50%	AV 75%	AV 100%
Total Travel Time (pcu.hr)	1,944	1,606 [-17%]	1,230 [-37%]	900 [-54%]	480 [-75%]
Total Travel Distance (pcu.kms)	15,500	15,386 [-1%]	15,376 [-1%]	15,368 [-1%]	15,423 [0%]
Average Speed (kph)	8	10 [20%]	13 [56%]	17 [114%]	32 [301%]
Average Queues (pcu/hr)	1,074	900 [-16%]	680 [-37%]	460 [-57%]	129 [-88%]

Figure 5.17 Model Output Delay Difference – Test Scenario 9





c) Reduction in delay (s) with 75% AV



d) Reduction in delay (s) with 100% AV

5.3.5 Test Result – PCU Based Approach

As discussed in Section 4.3.3, the PCU factors for AVs used in this research are 0.6, 0.7, and 0.8. Various model runs were conducted with different AV penetration rates to assess their impact. In these models, AVs were treated as a separate user class, and the demand matrix was adjusted with different PCU factors.

Figure 5.18 shows the changes in total travel time, distances, average speed, and average queue in comparison with flow-theory-based AV models tested in Scenario 9. The results from the various model runs indicate several key trends.

As AV penetration increases, total travel time decreases significantly. Notably, the flow-theory-based results are close to those obtained with a PCU of 0.7, particularly between the PCU values of 0.7 and 0.8. For instance, at 100% AV penetration, the flow-theory model shows a total travel time of 480 veh.hr, while the PCU 0.7 and 0.8 models show 485 veh.hr and 1,004 veh.hr, respectively.

The total travel distance remains relatively stable across different PCU values and AV penetration rates, with minor fluctuations. The flow-theory-based results are consistent with those of PCU 0.7 and 0.8, indicating similar travel patterns.

Average network speed increases with higher AV penetration. The flow-theory-based results align closely with the PCU 0.7 model, especially between the PCU values of 0.7 and 0.8. For example, at 100% AV penetration, the flow-theory model shows an average speed of 32 kph, while the PCU 0.7 and 0.8 models show 35 kph and 16 kph, respectively.

Average queues decrease significantly with higher AV penetration. The flow-theory-based results are similar to those of the PCU 0.7 model, particularly between the PCU values of 0.7 and 0.8. At 100% AV penetration, the flow-theory model shows average queues of 129 veh/hr, while the PCU 0.7 and 0.8 models show 85 veh/hr and 505 veh/hr, respectively.

These findings suggest that the flow-theory-based results are most comparable to the PCU 0.7 model, providing a reliable benchmark for assessing the impact of AV integration on urban transportation networks.

Model outputs for PCU based test are also presented in Figure 5.18.

Figure 5.18 Model Output Global Statistics – Comparison of Flow-Theory and PCU-Based Approach

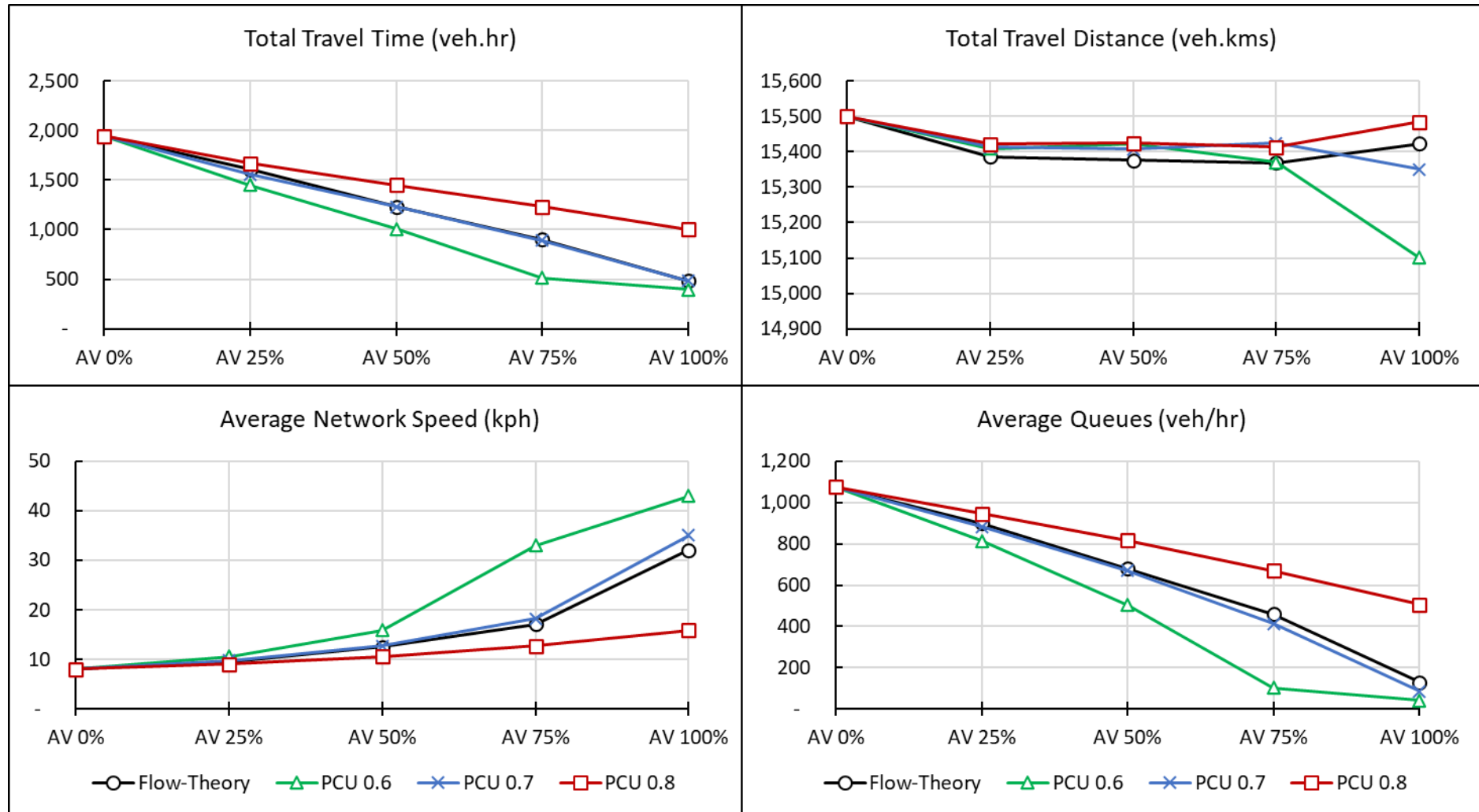
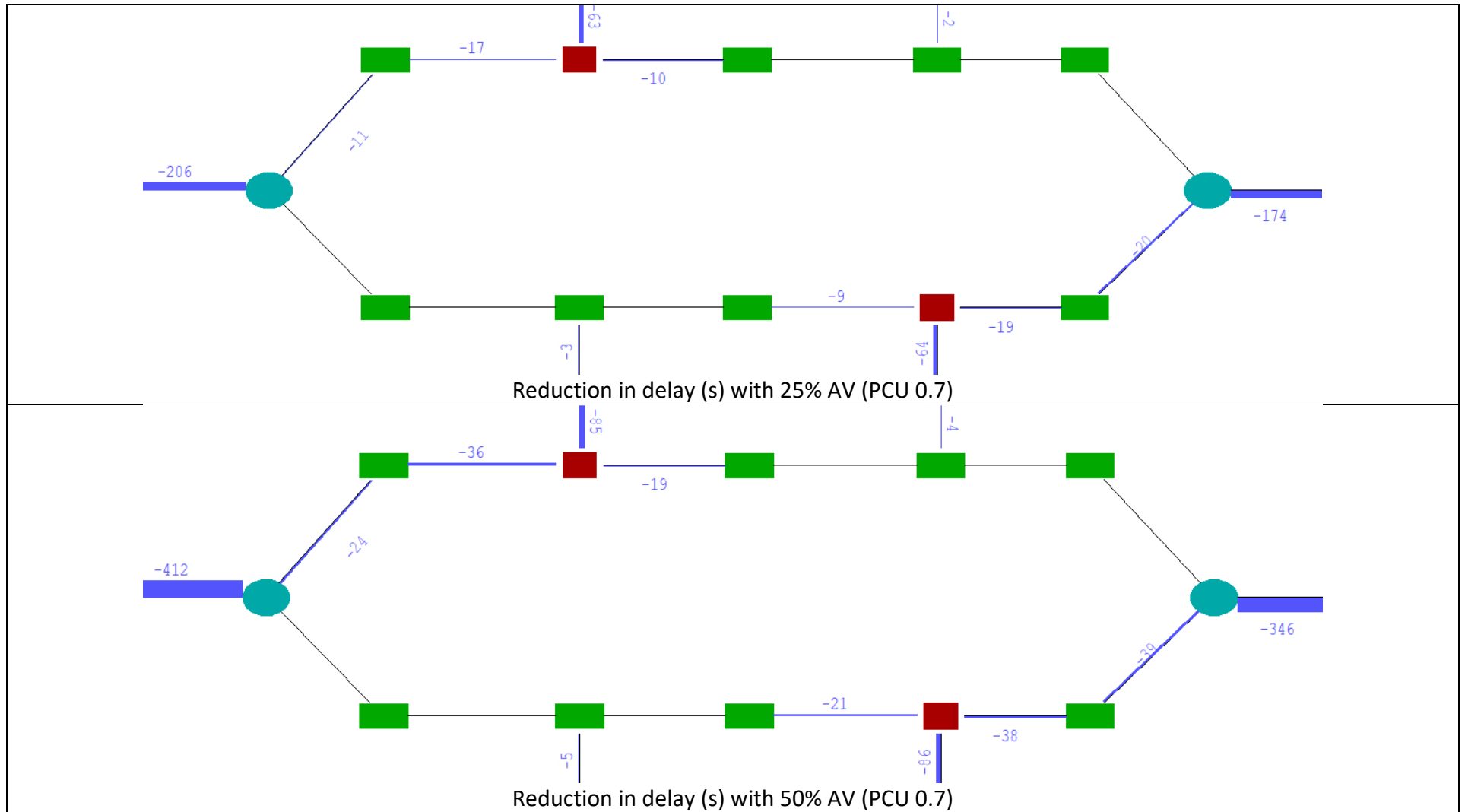
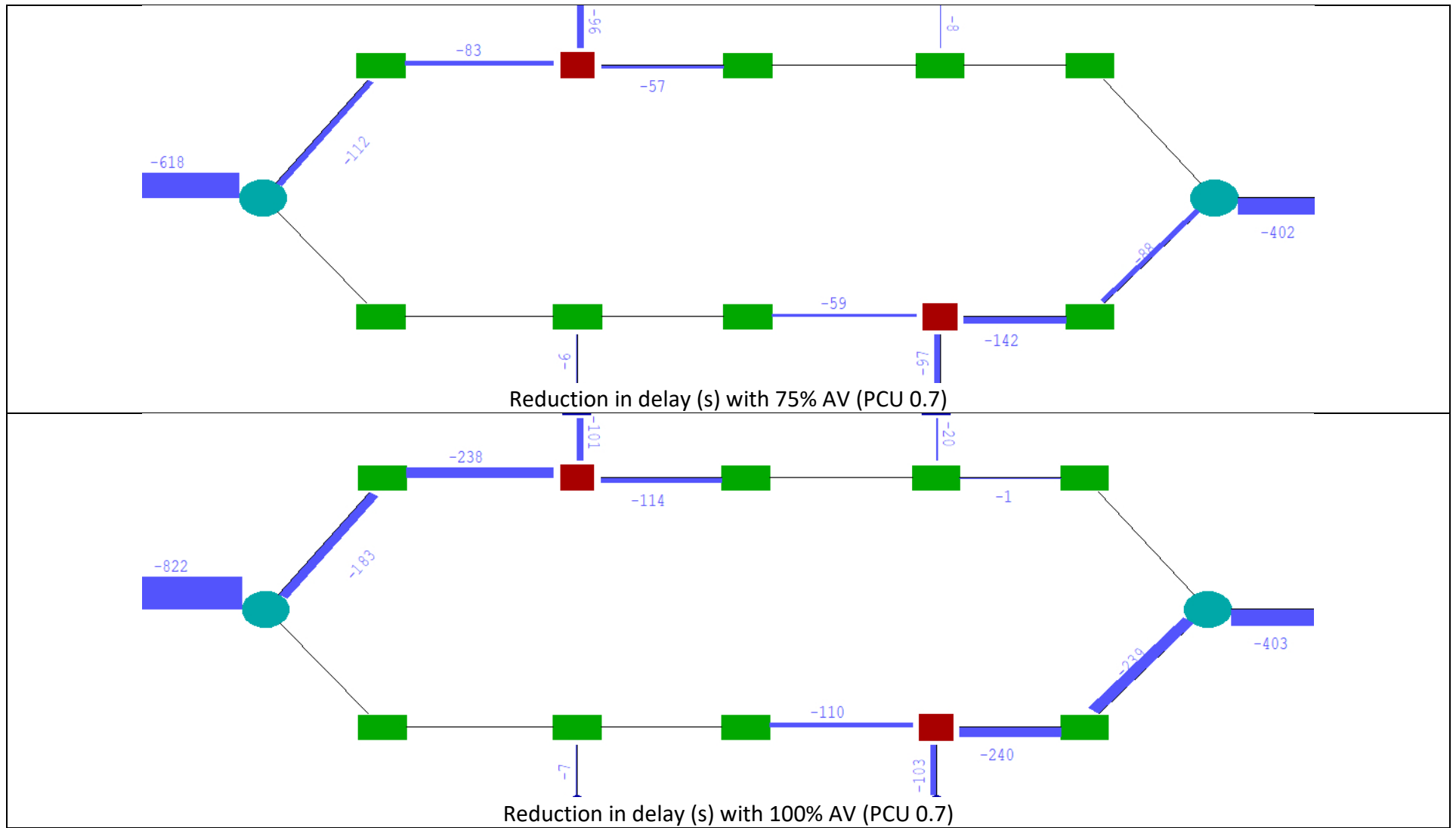


Figure 5.19 Model Output Delay Difference – Test Scenario 10





5.4 Conclusions

In summary, this chapter has extensively examined the integration of AV characteristics into the SATURN Modelling. The objective was to test the modelling framework and evaluate the impact of AVs on network capacity, traffic flow patterns, and the overall efficiency of transportation systems.

Our investigation proceeded systematically, commencing with the modification of SATURN input parameters mainly saturation flow, GAP and generalised cost parameters to reflect the influence of AVs. This preparatory step laid the foundation for a series of comprehensive test scenarios. These scenarios encompassed diverse traffic situations, ranging from unopposed and opposed turning movements at priority junctions to a typical signalised junctions. The thorough analysis of each scenario considered crucial factors like headway, safety distance, GAP, and the broader perspective of generalised cost.

The influence of AVs on capacity aligns with findings from prior literature (Friedrich, 2016; Wagner, 2016), which indicated an approximately 80% increase in capacity when fully integrated with AVs. In contrast, our study reveals that the capacity of unopposed turns can experience a substantial enhancement of 95% with full AV implementation. Notably, the inclusion of model behaviour accounting for safety distance, which was not considered in the those, indicates a slight more capacity increase in this study.

Likewise, Friedrich's work (2014, 2016) demonstrated a 40% increase in turn capacity within a signalised junction. In contrast, our study reveals an approximate 42% increase in capacity within an all-AV environment.

Additionally, the PCU-based findings indicate that the flow-theory-based results are closely aligned with those obtained using a PCU of 0.7, particularly between the PCU values of 0.7 and 0.8. This alignment suggests that the flow-theory model provides a reliable benchmark for assessing the impact of AV integration on urban transportation networks.

Looking ahead, the lessons gleaned from this chapter offer a robust foundation for the AV-enabled macroscopic traffic assignment modelling in SATURN. The next chapter presents the modelling of Scenario 9 assumptions in a city network and compares against the PCU-based approach, varying PCU values from 0.6 to 0.8.

This comparison will provide insights into the effectiveness of different PCU values in modelling AV impacts on urban transportation networks.

Chapter 6

Modelling Autonomous Vehicles in a City Network

6.1 Introduction

This chapter presents a comprehensive analysis of the impact of AVs on road capacity within a city network model constructed using SATURN. The modelling methodologies and approaches are elaborated upon in Chapter 5, where the performance of modified SATURN inputs across diverse types of toy junctions and a simplified toy network is evaluated while also varying the penetration of AVs.

In this chapter, we shift our focus to the city network model for the City of York developed in SATURN. The chapter presents the description of the existing City of York Model, model setups, modified SATURN input parameters, and discusses the underlying assumptions that form the basis of our analysis. To provide a comprehensive overview, various scenarios aimed at assessing the impact of AVs on network capacity are defined. These scenarios encompass a wide range of SATURN inputs, which were tested within toy junctions and toy network scenarios presented earlier in Chapter 5. This chapter thus serves as a bridge between the theoretical framework of macroscopic and mesoscopic modelling for AV outlined in Chapter 5 and the practical implementation within the network model of the City of York.

6.2 City of York SATURN Network

6.2.1 Why the City of York

City of York is located in North Yorkshire, UK (Figure 6.1). The total population of the city is about 206,900 (2015) with 687/sq.km density. Like a typical city in the UK, centre of the city is surrounded by an inner ring road and the entire city is surrounded by outer ring road (A1237 and A64). Eight radial road corridors connect the ring roads and the city centre. Six park and ride sites along with the bus routes on major corridors are an integral part of the City of York transport network. Relatively flat terrain of the city is suitable for sustainable mode of travel (e.g., bike and walking).

Figure 6.1 City of York



Coupled with road congestion, parking demand is one of the known transport challenges during the morning commuting hour as the city centre is highly attracted by the city dwellers and other cities within the regions. Approximately 2000 trips end at city centre car parks during the morning peak and occupies almost 100% of all the car parks.

Over the next 20 years, local changes such as employment and population growth, together with other regional and national changes will place considerable pressures on York's transport network. The council believes in the sustainable growth of the city and also promotes sustainable mode of transport, whereas one of the revenue generated sources of the council is the city centre parking sites. City of York region is selected as the test network in this research as it resembles the common transport issues and challenges like many other cities in the UK have. The size of the model is reasonable compare to the network extent that covers whole UK by buffer network and city and surrounding growth centres in simulation network. The

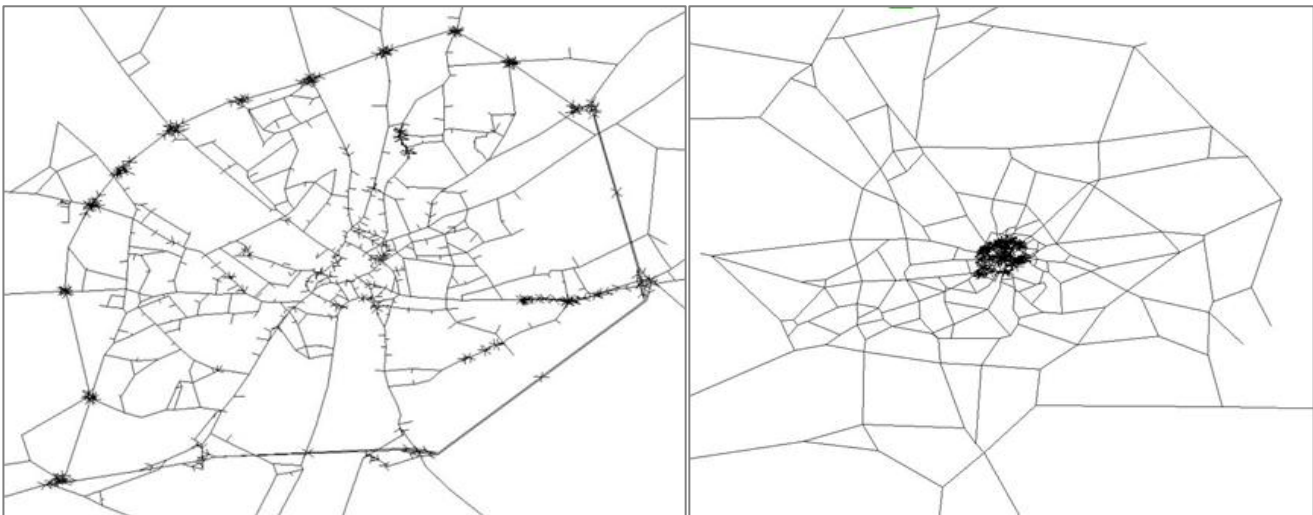
model runtime takes not more than 15 minutes with very tight convergence. This is one of the advantages to consider the City of York Transport model to have reasonable number of feedback loops with modified network changes for AV.

6.2.2 York Transport Model

Figure 6.2 shows the model simulation model area and network extent of York Transport Model in SATURN. Generic features of the York Transport Model are:

- Base model validated in 2014, updated in 2019;
- Model forecast year used for this research is 2031;
- Five model user classes – Car Business, Car Commuting, Car Others, Light Goods Vehicles (LGVs) and Heavy Goods Vehicles (HGVs);
- Length of time period – 60 minutes;
- Number of zones – 352;
- Number of parking zones – 27 (city centre), 6 (park & rides);
- Simulation junctions – 1042; Simulation links – 2296; and Bus routes (fixed demand) – 80.

Figure 6.2: City of York SATURN Model

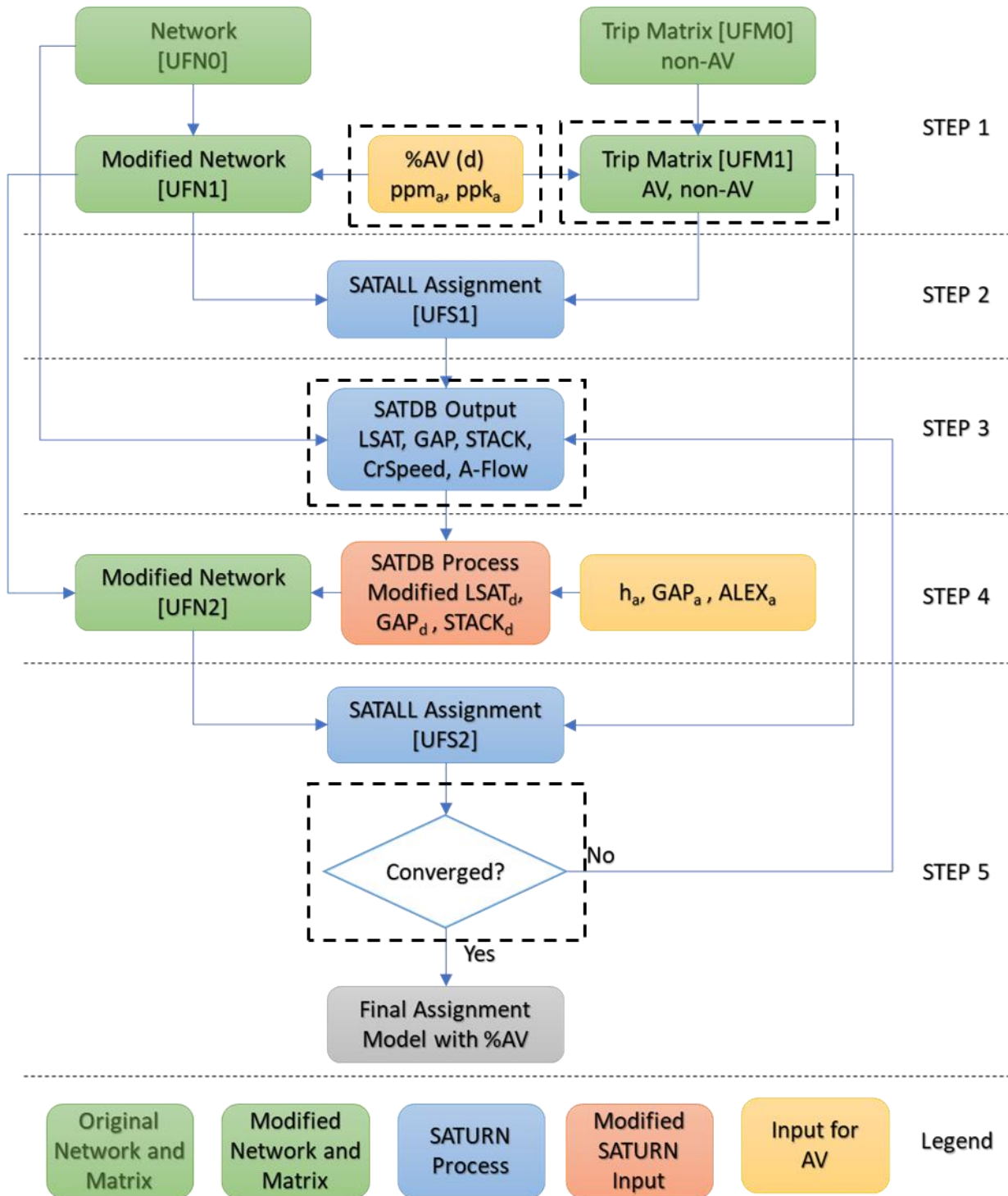


6.3 Model Setting

The modelling parameters for the AV have been established in Chapter 5 and are documented in Table 4.3. These parameters are required to be modified based on the AV market share in the city-scale SATURN network in the flow-theory based approach of AV modelling. However, it's crucial to note that the city-level network comprises numerous junctions and links, necessitating an automated procedure to

update the SATURN network based on the modified input to accommodate varying levels of AV traffic on each individual link. The steps involved in creating the AV-modified network and the subsequent assignment steps are presented in Figure 6.3 and will be discussed in detail in the following sections.

Figure 6.3 Model Process for AV – Flow-Theory Based



Step 1 Modify SATURN network and Trip Matrix with given % AV

Simialar to the setup of toy network modelling, this step involves modifying the existing SATURN network (UFN0) with no AV environment. For City of York SATURN network, various model elements are expanded with mor vehicle classes (Car, goods) and trip purposes car business, car commuter and car other.

In line with the modelling requirements for AV, outlined in city network regarding the concept of generalised cost in Section 4.3.2.9, the parameters ppm_a and ppk_a are required for the AV user classes by trip purposes.

Input : UFN0, UFM0, %AV (d), ppm_a , ppk_a

Output: UFN1, UFM1

Step 2 SATURN Traffic Assignment - UFN1, UFM1

This step entails traffic assignment utilising the SATALL module within SATURN, which utilises the modified SATURN network and trip matrices that includes AV as a new user class. The output of this step results as the traffic assignment model (UFS1), which is executed and converged using user defined traffic assignment principle, such as Wardrop equilibrium. This step is unchanged for the city network model test.

Input : UFN1, UFM1

Output: UFS1

Step 3 SATDB Output – Turn and Link Attributes and Assigned Flow

This step involves the extraction of turn and link attributes, such as LSAT, GAP, STACK, and CrSpeed for each turn and link, similar to the toy network test. However, with more vehicle types, traffic flow output needs to be extracted differently with an update of BATCH scripts. These attributes are necessary for modification based on the proportion of AVs at each specific turn. The SATDB module within SATURN is utilised to extract the actual flow for each turning movement for both AV and non-AV user classes. This information is required for estimating the proportion of AVs at each turn.

Input : UFN0, UFS1

Output: LSAT, GAP, STACK, CrSpeed, A-FLOW_a, A-FLOW_h

Step 4 SATDB Process – Modified SATURN Input

The modified SATDB process was tested in the toy network as it is easier to investigate the results. Following successful tests, this process is readily applicable to any type of SATURN model with varying complexity.

This step involves obtaining user input parameters for AVs, such as time headways (h_a), mean vehicle length in an external queue ($ALEX_a$), and GAP_a . These input parameters are essential for estimating the modified SATURN input parameters for an assigned proportion of AVs and non-AVs at the individual node level. This includes parameters like $LSAT_d$, GAP_d , and stacking capacity ($STACK_d$).

GAP_d is estimated linearly with the proportion of AVs and non-AVs at the individual node level, as discussed in Section 4.3.2.3. In contrast, $STACK$ is estimated by considering the proportion of $ALEX$ for non-AVs and AVs at the individual link level.

The SATDB module within SATURN is utilised to calculate the modified SATURN inputs for each turn and link. These calculated values are then imported into the modified SATURN network (UFN2).

Input : $LSAT$, GAP , $STACK$, $CrSpeed$, $ALEX$, $A-FLOW_a$, $A-FLOW_h$, h_a , GAP_a ,
 $ALEX_a$, UFN1

Modified Input: $LSAT_d$, GAP_d , $STACK_d$

Output: UFN2

Step 5 SATURN Traffic Assignment and Convergence - UFN2, UFM1

Similar to Step 2, this step also involves traffic assignment using the SATALL module within SATURN, which utilises the modified SATURN network (UFN2) and trip matrix that includes AV as a new user class (UFM1). The outcome of this step is the traffic assignment model (UFS2).

Following the assignment, traffic flow by vehicle classes can undergo changes, potentially resulting in different AV proportions for each turning movements. These varying AV proportions necessitate updates to the modified SATURN inputs, starting an iterative process that continues until it meets predefined user-defined convergence criteria to achieve a stable AV assigned traffic model.

In this iterative process, the examination of $LSAT$ for all turning flows between consecutive iterations is crucial. This process continues from Step 3 onwards until it aligns with the user-defined convergence criteria.

The default convergence criteria in SATURN are discussed in Chapter 3. Nevertheless, the specific convergence criteria for achieving stability in the AV model are discussed in the subsequent section.

Input : UFN2, UFM1

Output: UFS2

6.4 Model Scenarios

The City of York Model in SATURN is used to assess the impact of various AV input parameters to define model scenarios. These model scenarios are defined below.

- Flow-theory based approach: Scenario 9 tested in toy network is adopted for the City of York model. This scenario involves following parameters for AV.

Q=7000 pcu
 $h_a=0.5s$, $L_a=6.0m$, $GAP_a=2.0s$
ppm and ppk value as per Table 4.2
AV share %d = 25, 50, 75 and 100

- Modified PCU Factor for AV

As discussed in Chapter 4 (Section 4.3.3), considering PCU-based approach AV is considered with a reduced PCU factor suggesting 0.6 to 0.8 by Sonnleitner J. and Friedrich M. (2020a). With implementing PCU-Factor for AV, other parameters except ALEX should not be modified.

PCU-Factor AV = 0.6, 0.7 and 0.8, with AV share %d = 25, 50, 75 and 100.

6.5 Result and Analysis

6.5.1 Flow theory based modelling result

This section presents a high-level analysis of the global network statistics, focusing on the impact of varying AV penetration rates on key traffic metrics. Table 6.1 summarises the changes in total travel time, total travel distance, average speed, and average queues as AV penetration increases from 0% to 100%.

As the AV penetration rate increases from 0% to 100%, total travel time decreases significantly. At 25% AV penetration, there is a 4% reduction in travel time, which further decreases to 12% at 100% AV penetration. This indicates that higher AV penetration can substantially reduce travel time across the city.

Table 6.1 Global Network Statistics – City of York Model Scenario 1 Flow Theory Based Approach

Global Network Statistics	AV 0%	AV 25%	AV 50%	AV 75%	AV 100%
Total Travel Time (pcu.hr)	20,832	20,029 [-4%]	19,368 [-7%]	18,768 [-10%]	18,311 [-12%]
Total Travel Distance (pcu.kms)	1,005,756	1,000,712 [-1%]	996,249 [-1%]	991,594 [-1%]	987,528 [-2%]
Average Speed (kph)	48	50 [4%]	51 [6%]	53 [9%]	54 [12%]
Average Queues (pcu/hr)	2,758	2,316 [-16%]	1,917 [-30%]	1,605 [-42%]	1,380 [-50%]

The total travel distance shows a slight decrease as AV penetration increases. The reduction is minimal, with a 1% decrease at 25%, 50%, and 75% AV penetration, and a 2% decrease at 100% AV penetration. This suggests that AVs have a relatively small impact on the total distance travelled.

Average speed increases with higher AV penetration. At 25% AV penetration, there is a 4% increase in average speed, which rises to 12% at 100% AV penetration. This improvement in average speed indicates that AVs can enhance traffic flow efficiency.

Average queues decrease significantly with higher AV penetration. At 25% AV penetration, there is a 16% reduction in average queues, which further decreases

to 50% at 100% AV penetration. This substantial reduction in queues highlights the potential of AVs to alleviate congestion.

The findings demonstrate that increasing AV penetration can lead to significant improvements in travel time, average speed, and congestion, with only a minimal impact on total travel distance.

6.5.2 Comparison of flow-theory and PCU-based result

Figure 6.4 summarises the changes in total travel time, total travel distance, average speed, and average queues as AV penetration increases from 0% to 100% and compares flow-theory-based results with PCU-based results. By default, SATURN's global totals for distance and time are reported in veh·kms and veh·hr. However, when link flows are expressed in PCUs, these global totals are effectively PCU-weighted. As a result, they under-report true vehicle totals whenever the AV class uses a PCU factor < 1 . In the model setup, the PCU factor is applied to the AV class only; all non-AV classes are treated with PCU = 1 except the HGV. This means the AV share in PCU terms can be smaller than in vehicle terms at higher AV penetrations, which depresses the global veh·kms and veh·hr if left unadjusted. To ensure a like-for-like comparison with the flow-theory method, we convert each link's flow from PCU to vehicles and then recompute the system totals.

As AV penetration increases, total travel time decreases significantly across all models. The flow-theory results are closely aligned with the PCU 0.7 results, particularly between the PCU values of 0.7 and 0.8. For instance, at 100% AV penetration, the flow-theory model shows a total travel time of 18,311 veh.hr, while the PCU 0.7 and 0.8 models show 18,897 veh.hr and 19,413 veh.hr, respectively. This indicates that the flow-theory model provides a reliable benchmark for assessing AV impacts.

The total travel distance shows a slight decrease as AV penetration increases. The flow-theory results are consistent with those of PCU 0.7 and 0.8, indicating similar travel patterns. For example, at 100% AV penetration, the flow-theory model shows a total travel distance of 987,528 veh.kms, while the PCU 0.7 and 0.8 models show 981,373 veh.kms and 982,115 veh.kms, respectively.

Average speed increases with higher AV penetration. The flow-theory results align closely with the PCU 0.7 model, especially between the PCU values of 0.7 and 0.8. At 100% AV penetration, the flow-theory model shows an average speed of 54 kph,

while the PCU 0.7 and 0.8 models show 55 kph and 53 kph, respectively. This improvement in average speed indicates that AVs can enhance traffic flow efficiency.

Average queues decrease significantly with higher AV penetration. The flow-theory results are similar to those of the PCU 0.7 model, particularly between the PCU values of 0.7 and 0.8. At 100% AV penetration, the flow-theory model shows average queues of 1,380 veh/hr, while the PCU 0.7 and 0.8 models show 1,316 veh/hr and 1,655 veh/hr, respectively. This substantial reduction in queues highlights the potential of AVs to alleviate congestion.

The findings demonstrate that the flow-theory-based results are most comparable to the PCU 0.7 model, providing a reliable benchmark for assessing the impact of AV integration on urban transportation networks. These results are consistent with the findings from the toy network tests, reinforcing the validity of the modelling approach.

Figure 6.4 Model Output Global Statistics – City of York Model Comparison of Flow-Theory and PCU-Based Approach

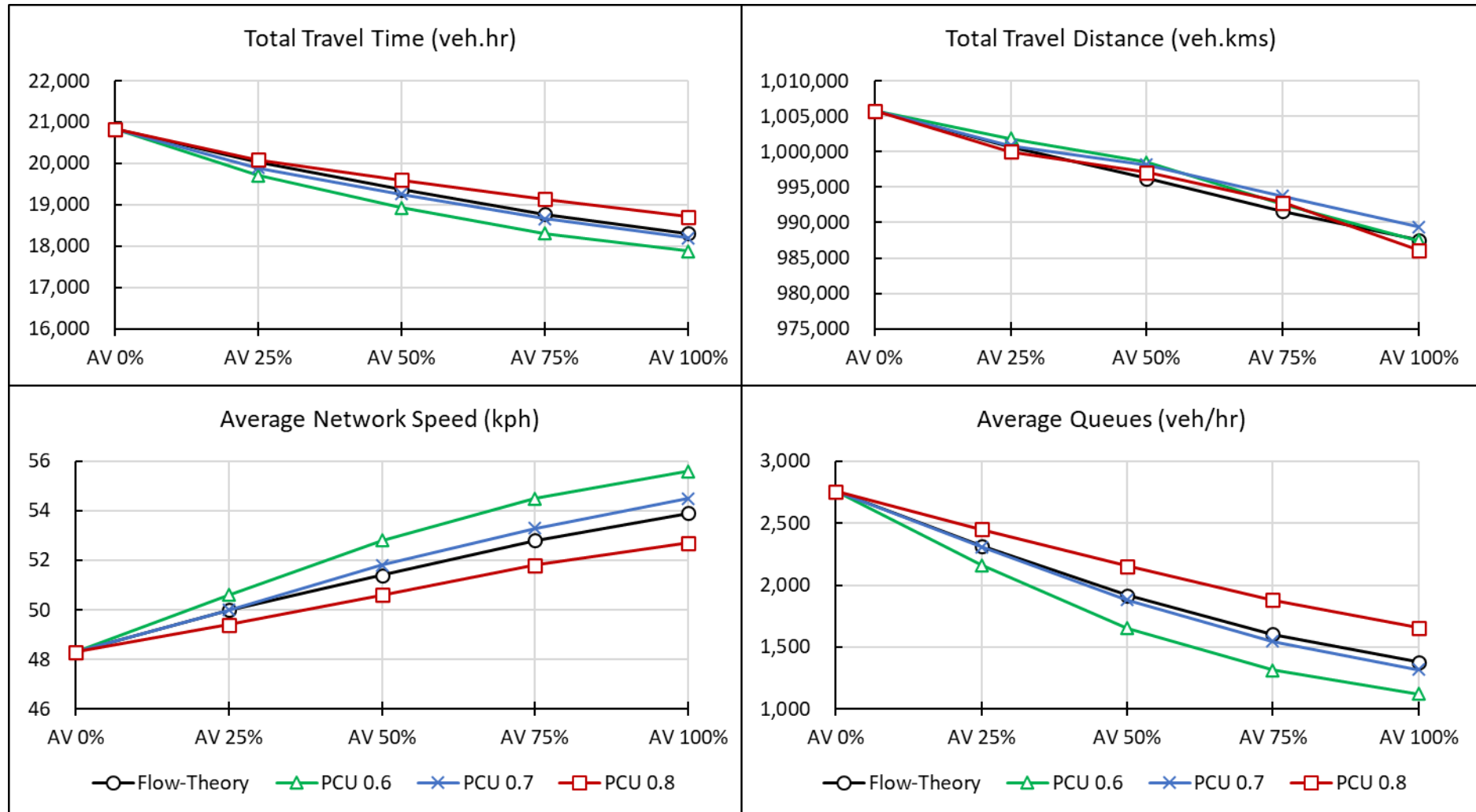


Figure 6.5 illustrates the delay differences in the flow-theory-based approach, showing a reduction in link delays compared to no-AV scenario across the City of York network with an increase in AV market share. Only delay difference greater than 30s is shown at the link level. Figure 6.6 presents the model output in terms of Volume over Capacity (V/C) ratio, indicating that the number of links with higher V/C ratios decreases as AV penetration increases.

The maps in Figure 6.5 show changes in AM peak delay for AV penetrations of 25%, 50%, 75%, and 100% relative to a 0% AV base. Four reference links are highlighted, with flows and mean travel times extracted from SATURN (SATDB) output.

- Section 1: Outer Ring Road shows limited change in time from 56 s at 0% AV to 55 s at 100% AV, with flow changing from 1521 to 1453 veh/h.
- Section 2: Holgate Road shows a substantial time reduction from 551 s to 234 s and a flow increase from 474 to 523 veh/h.
- Section 3: Tadcaster Road shows time reducing from 299 s to 170 s and flow increasing from 683 to 895 veh/h.
- Section 4: A64 shows minimal time change from 108 s to 106–107 s with flows varying slightly around 3050 to 2977–3082 veh/h.

Across the network, delay decreases consistently as AV penetration increases. The largest benefits are concentrated on the two inner-city, signalised links that already experience peak-hour delay. At Holgate Road, average time falls by about 58% between 0% and 100% AV, alongside an 11% increase in flow. At Tadcaster Road average time falls by about 43% with a flow increase of roughly 16%. By contrast, the strategic links show little change in time despite small flow adjustments. On the Outer Ring Road between Haxby and Wigginton roundabouts, time reduces by about 1–3% with a small reduction in flow. On the A64 section, time changes are within about 0–2% with flows moving by only a few percentage points. These results suggest that AV benefits are realised where signal control and close-up interactions constrain capacity, while longer, higher-standard corridors operate close to free flow and therefore exhibit limited time savings. The modest increase in inner-city flows indicates some re-routing toward shorter urban paths as AV market share rises, without imposing notable delay on the strategic network.

Figure 6.5 Delay Difference > 30 seconds - Flow-Theory Based

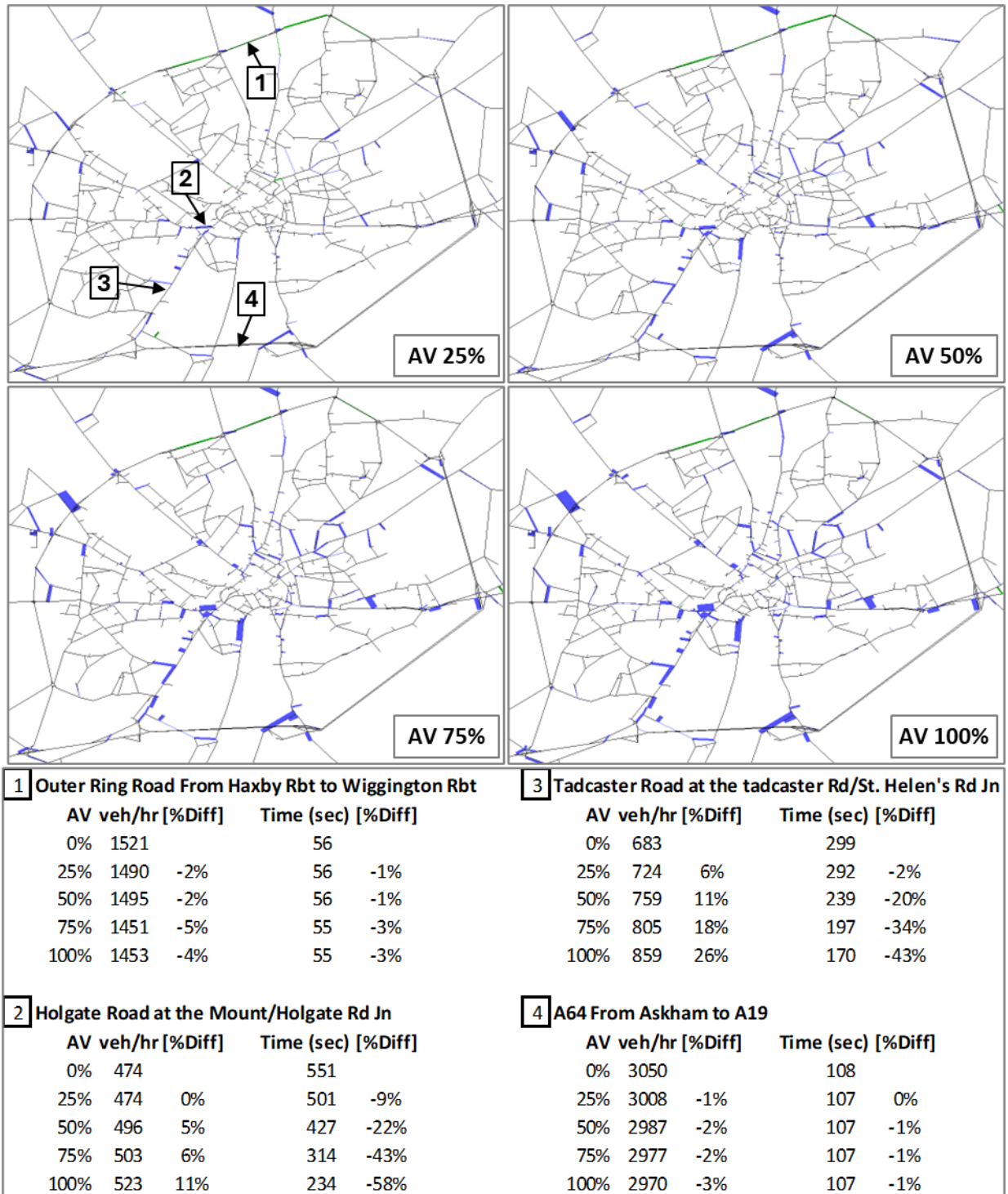


Figure 6.6 Volume over Capacity - Flow-Theory Based

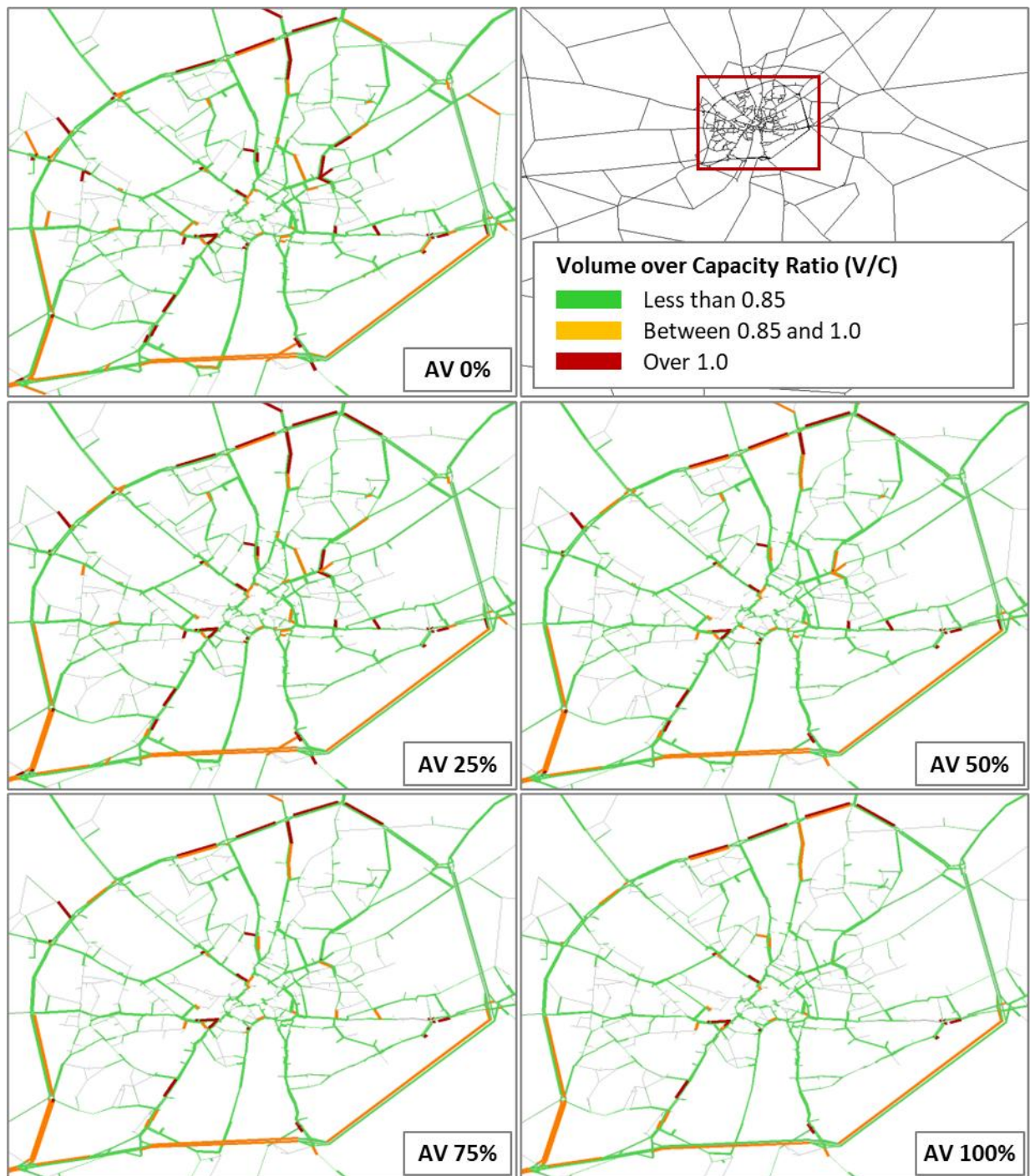


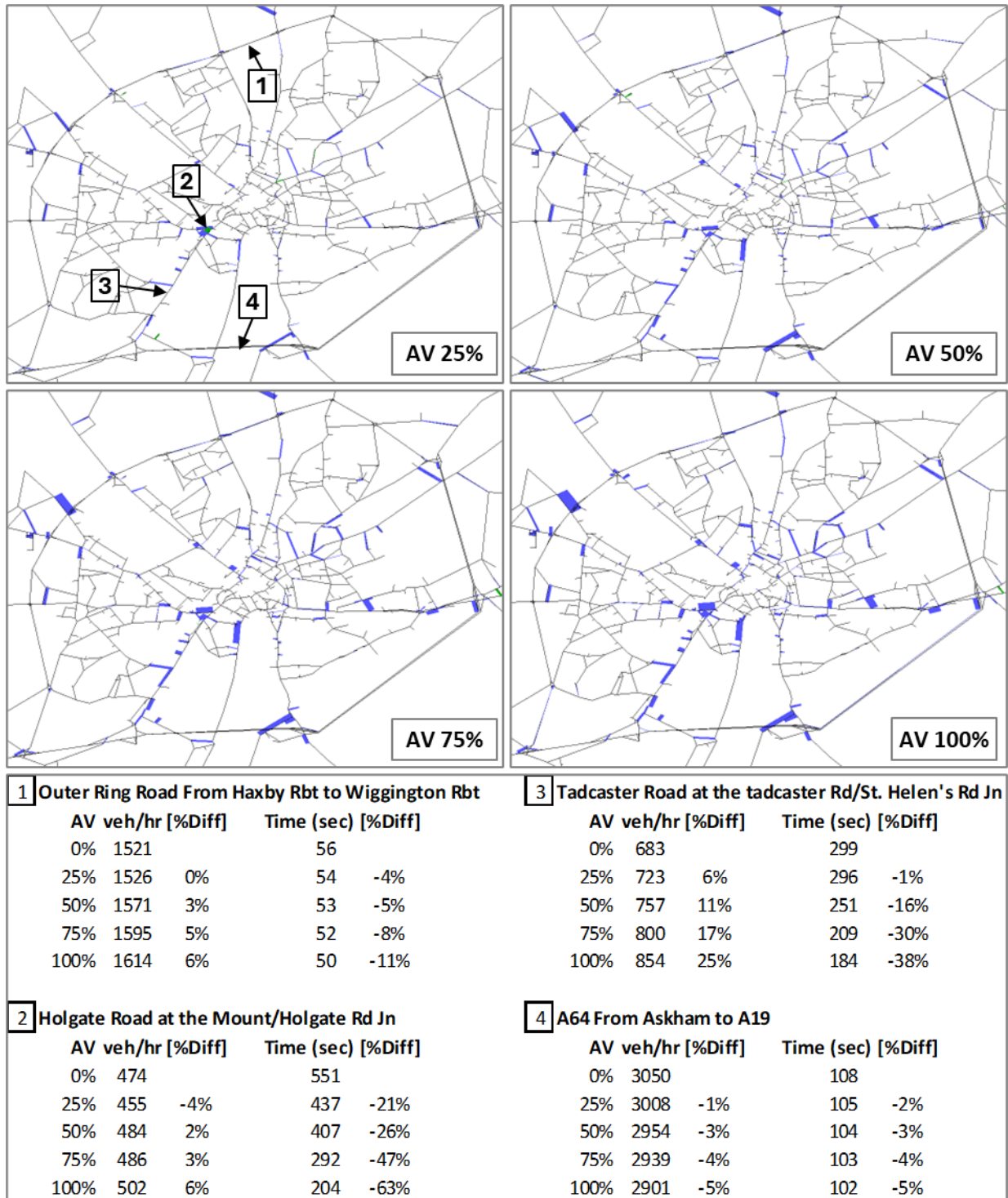
Figure 6.7 illustrates the delay differences in the flow-theory-based approach, showing a reduction in link delays compared to no-AV scenario across the City of York network with an increase in AV market share. Only delay difference greater than 30s is shown at the link level.

The maps in Figure 6.7 show changes in AM peak delay for AV penetrations of 25%, 50%, 75%, and 100% relative to a 0% AV base. Four reference links are highlighted, with flows and mean travel times extracted from SATURN (SATDB) output.

- Section 1: Outer Ring Road shows limited change in time from 56 s at 0% AV to 50 s at 100% AV, with flow changing from 1521 to 1521 veh/h.
- Section 2: Holgate Road shows a substantial time reduction from 551 s to 204 s and a flow increase from 474 to 502 veh/h.
- Section 3: Tadcaster Road shows time reducing from 299 s to 184 s and flow increasing from 683 to 854 veh/h.
- Section 4: A64 shows minimal time change from 108 s to 102 s with flows varying slightly around 3050 to 2901 veh/h.

Similar to flow theory based result, delay declines steadily as AV market share increases across the network. The strongest effects are on the two inner-city, signalised links that already experience peak-hour queuing. At Holgate Road, average travel time drops by about 63% between 0% and 100% AV, with a 6% rise in flow. At Tadcaster Road, average time falls by about 38% and flow increases by roughly 25%. The two strategic links show smaller changes. However, on the Outer Ring Road between Haxby and Wigginton roundabouts, time reduces by about 11% alongside a 6% increase in flow. On the A64 section, time reductions are within about 5% and flows move only a few percentage points, with a slight decline overall. These patterns indicate that AV benefits are realised where signal control and close-up interactions constrain capacity, while longer, higher-standard corridors operate near free-flow conditions and therefore gain little in terms of time savings. The modest increase in inner-city flows points to some re-routing toward shorter urban paths as AV share rises, without imposing noticeable delay on the strategic network.

Figure 6.7 Delay Difference > 30 seconds – PCU (0.7) - Based



Comparing the V/C ratio plots against the flow-theory and PCU 0.7 approaches in Figure 6.8 reveals that the PCU-based results show a more significant reduction in links with higher V/C ratios compared to the flow-theory-based approach in scenarios with 100% AV penetration. This suggests that the PCU-based approach is showing more change in capacity compared to flow-theory-based specially on the strategic roads like Outer Ring Road and A64.

Figure 6.8 Volume over Capacity – Comparison of Flow-Theory and PCU-based for AV 100%

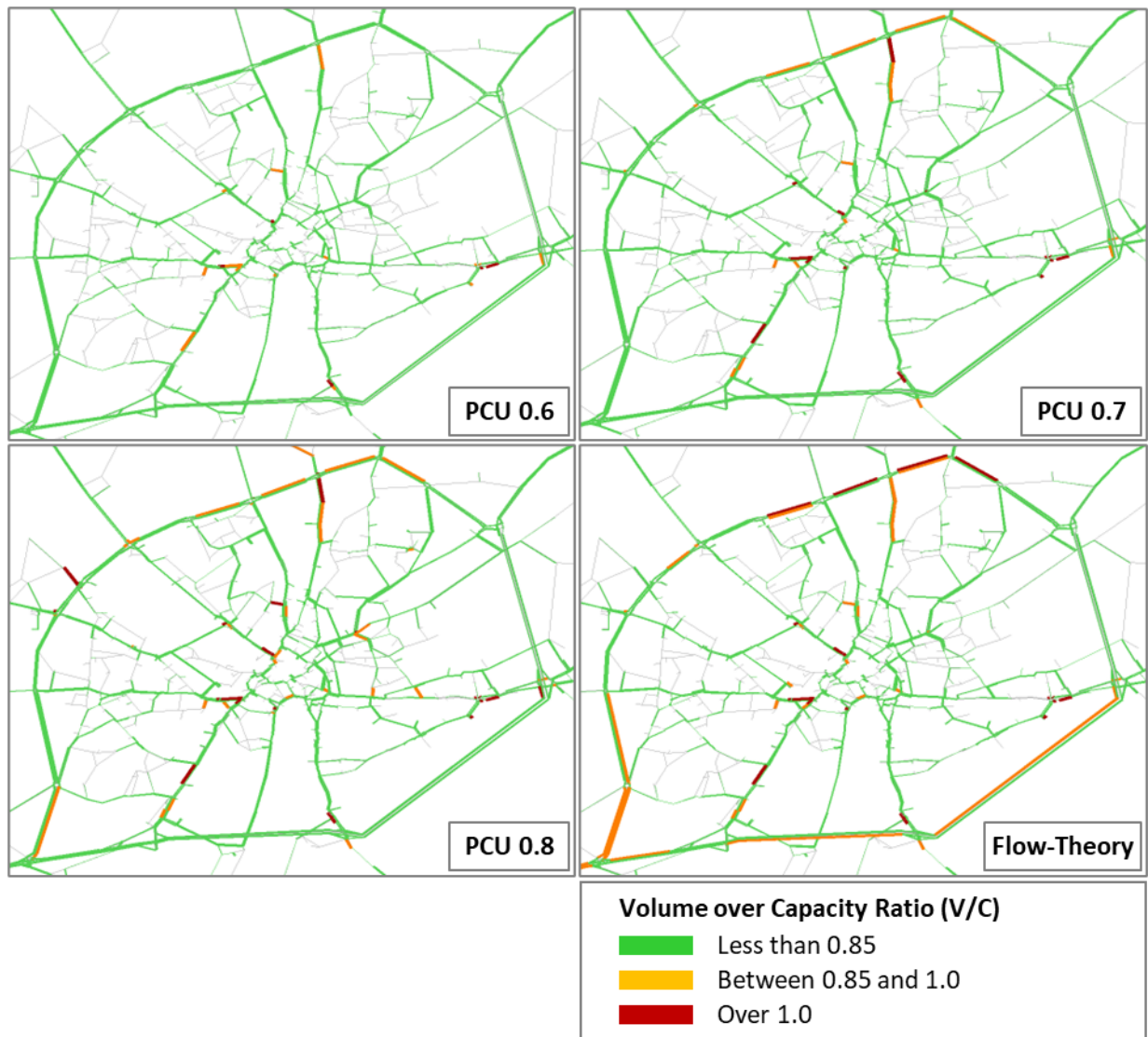


Table 6.2 summarises the key observation on impact of AVs and compares the flow-theory-based with PCU 0.7 based model output. Both approaches agree on the location and nature of benefits. Signalised urban sections gain the most because shorter headways and smoother interactions reduce lost time and queues. Strategic corridors that operate closer to free flow see limited savings in either approach. Magnitudes differ by link. The PCU method often shows slightly larger benefits on strategic links and very similar or slightly larger benefits on one of the inner-city links, while the flow-theory method is slightly stronger on the other inner-city link. The V/C results corroborate this pattern, with the PCU treatment producing a larger reduction in the proportion of high V/C links at 100 percent AV.

Table 6.2 Key Observation - Impacts of AV Penetration: Flow-theory Assignment versus PCU-based Assignment

Road Type	Indicator	Flow-theory (0%→100% AV)	PCU 0.7 (0%→100% AV)	Key observation
Urban (inner city)	Delay	-43% to -58%	-38% to -63%	Both methods reduction delay with increase in flow. PCU 0.7 gives change slightly larger overall.
	Flow	+11% to +16%	+6% to +25%	
Strategic (outer)	Delay	-1% to -3% or 2%	-11% to -5%	Flow-theory shows little change on strategic roads. PCU 0.7 has small but clearer time savings, most evident on the Outer Ring Road, while the A64 remains close to free flow.
	Flow	Flow small variation	Moderate change based on the road use	
Network	V/C	Fewer high V/C links as AV increases	Larger reduction in high V/C links at 100 percent AV	PCU based indicates greater effective capacity gains, especially on strategic corridors.

The PCU-based approach lowers the effective demand that enters capacity calculations. This explains the clearer reductions in travel time and V/C on the Outer Ring Road and the modest improvement on the A64 in the PCU runs. From a planning perspective, inner-city links are the priority locations for realising operational benefits from AVs, while strategic links may require complementary measures, such as signal coordination at key junctions or targeted geometric changes, to convert capacity headroom into meaningful travel time savings.

The flow-theory case provides a reliable benchmark because it directly represents operational changes without altering vehicle equivalence. The PCU-based case offers a useful sensitivity, but it implicitly assumes that AVs impose lower equivalent demand. This assumption can amplify capacity on corridors and at junctions and should be interpreted alongside signal timing and saturation flow.

To further understand the impact of AVs on different road types, the following actions are recommended.

- Conduct a junction-level review at principal signalised locations to check saturation flows, effective green splits, lane utilisation, and intergreens under both methods.
- Test additional PCU values for AVs as a sensitivity, and consider a hybrid setup that applies small PCU adjustments only where junctions are demonstrably saturation constrained.
- Extend the V/C analysis to distributional metrics, for example the share of vehicle-hours exposed to links above selected V/C thresholds, to support appraisal.

Because the flow-theory-based approach in this study is focused on urban, signalised operation, strategic roads that are governed by speed-flow relationships may not fully capture AV-related changes to mid-link capacity. The PCU-based approach, by design, affects the speed-flow relationship through the PCU discount. To ensure a consistent comparison, the flow-theory-based approach should be supplemented with AV-adjusted speed-flow curves on strategic links, for example by revising speed-density parameters to reflect higher mid-link capacity at higher AV shares.

Overall, both modelling treatments point to the same qualitative conclusion. AVs reduce network delay most strongly at signalised urban bottlenecks, while strategic corridors experience small improvements. The PCU-based approach indicates a larger network-wide reduction in high V/C links at 100% AV, which is consistent with an increase in effective capacity, especially on strategic roads.

6.6 Conclusion

This chapter connects the modelling principles developed in Chapter 5 with their practical application in the City of York network. The scenario tests show that higher levels of AV penetration lead to clear system-wide benefits, particularly through reductions in travel time, increases in average speed and noticeable decreases in congestion. The overall travel distance remains largely unchanged, which indicates that the improvements come primarily from increased junction and link capacity rather than changes in route choice behaviour.

These findings reinforce the earlier conclusion that the flow-theory approach provides a dependable basis for representing AV behaviour in a mesoscopic assignment environment. The close agreement between the flow-theory results and the PCU 0.7 models strengthens this position, since both methods capture the

capacity effects associated with reduced headway and shorter effective vehicle length identified in Chapter 2 and Chapter 4. The analysis also highlights the potential for AVs to enhance the operational performance of urban networks, particularly in locations where junction control and turning movements currently limit capacity. Further investigation would be beneficial to refine the representation of AV interactions at individual junctions and to improve understanding of how different AV market shares influence city-scale network performance.

Chapter 7

Future Work to Continue to the Research

7.1 Introduction

As the original research has focused primarily on modelling autonomous vehicles (AVs) within a conventional mesoscopic framework, an important avenue for future work lies in extending this capability to represent shared-ride operations more explicitly. Ride-sharing introduces additional layers of behavioural complexity, including dynamic matching between passengers, flexible routing, and interdependencies between individual trip-makers that are not captured in traditional origin-destination modelling. Incorporating these features into a mesoscopic model such as SATURN would enable more realistic evaluation of shared-mobility scenarios by allowing AVs to serve multiple passengers along optimised routes while accounting for changes in demand patterns, vehicle occupancy, and network performance. This chapter therefore begins to explore that direction by developing and testing a ride-matching formulation that can be integrated within the SATURN environment as a basis for future, more comprehensive modelling of shared AV services.

As discussed in section 3.3, there are two general inputs - the “trip matrix” T_{ij} which specifies the number of trips from zone i to zone j ; and the “network” which specifies the physical structure of the roads, etc. upon which trips take place. These may be thought of as the “demand” and “supply” inputs;

Both the matrix and network are input to a “route choice” model which allocates trips to “routes” through the network, as a result of which total flows along links in the network may be summed and the corresponding network “costs” (e.g., times) calculated.

The ride sharing model is based on a ride matching algorithm to solve the matching problem with an aim to minimise the travel cost of both the driver and riders and by maximising the number of riders.

7.2 Model Framework

The ride matching algorithm involves supply and demand data as input. Supply data contains road networks that includes links (as road sections), nodes (junctions, pick-up or drop off point) and traffic analysis zone (z) with a defined boundary. z

should be of an appropriate size assuming intra-zonal travel time is negligible compared to the average trip travel time. Demand data are defined as:

- Full demand matrix (M) that includes origin and destination of all trips without ride sharing.
- Demand matrix of ride providers referred as drivers (D), which is a sub-set of M, more specifically these are the car-drivers or SAV who are willing to provide a ride to unacquainted travellers not belonging to the family.
- The demand matrix of the riders (R), which is a subset of the matrices for car-self driver and car-passenger users, who consider using a ridesharing service.

D_t = supply matrix of ride providers at time interval t ; and

R_t = demand matrix of rider at time interval t .

The ride matching algorithm assumes that routes of the trips follow a shortest path by time and cost, and that every pick-up location belongs to exactly one traffic zone. With this assumption, the algorithm for matching the trips of one-time interval consists of the following steps:

- Step 1. Each zone z has one pick-up and drop-off locations. Every link l is assigned to a zone z . A link, which has no access or stopping point may not be assigned a zone number (e.g., section of a high-speed motorway). To assign z to l , an intersect operation using Geographic Information Systems is used.
- Step 2. For every time interval t , the two supply and demand matrices, D_t and R_t , respectively are assigned to the transport network using Wardrop Equilibrium path assignment (Vliet, 1987). The result is one path set for the suppliers (driver) P_t^D and one path set for the demanders (riders) P_t^R for the same time interval t . Each set contains one or multiple path $p_{n_t}^{od}$ for each origin-destination pair with the corresponding supplier and demanders.
- Step 3. Each path $p_{n_t}^{od}$ is disaggregated into a sequence of links $l_1, l_2, \dots, l_n$ thus as each link l is connected to a zone z , the path can be expressed as $z_{l_1}, z_{l_2}, \dots, z_{l_n}$. The sequence of zone objects is stored as a string attribute of a path. It describes the sequence of traversed traffic zones

where demanders can be collected. The sequence of zone objects often contains the same zone object several times. In this case, duplicate zone objects are removed. As a result, each path is reduced to a sequence of zones containing considerably less elements than the sequence of links.

- Step 4. Each path of the supplier path set P_t^D obtains a capacity resulting from the demand volume of the supplier and the average vehicle capacity (for instance a 4-seater vehicle). As suppliers may travel with car passengers, e.g. family members, the capacity needs to be reduced appropriately. Equation (1) shows how to compute the available capacity for ridesharing for one path demand on origin-destination level using an average occupancy rate (Friedrich, M., Hartl, M., Mägg, C., 2018):

$$c_{p_t^D,t}^{od} = (c^{veh} - o^{veh}) \cdot d_{p_t^D,t}^{od} \quad \dots(1)$$

where $c_{p_t^D,t}^{od}$ capacity for ridesharing provided by supplier on path $p_{n_t}^{od}$ in time interval t . In the case of a path match, path capacity is equal to the capacity $c_{p_t^D,t}^{od}$ from zone o to zone d ; c^{veh} average vehicle capacity including driver; $d_{p_t^D,t}^{od}$ travel demand of suppliers from zone o to zone d in time interval t ; o^{veh} average occupancy rate of a private car: $o^{veh} = (d^D + d^{CarPass}) / d^{CarPass}$.

- Step 5. The matching of the two path sets P_t^D and P_t^R compares the reduced paths of zone sequences. A full match occurs, if the origin and destination zones of are identical. A partial match occurs if path P_t^R is covered by P_t^D . Path P_t^R is covered by path P_t^D if origin o and destination d of path P_t^R occur in the right order (o before d) in the zone sequence of path P_t^D . This can be implemented as a string comparison.
- Step 6. To establish the priority rule for the ride match, for each path $p_{n_t}^{od}$ the generalised cost that includes travel time and travel distance cost, for both supply and demand paths are calculated.

$$G(p_{n_t}^{od}) = tt^{od} \cdot VOT + td^{od} \cdot VOC$$

where, VOT = value of time;

VOC = vehicle operating cost (fuel and non-fuel cost)

tt^{od} = travel time

td^{od} = travel distance between o and d on path $p_{n_t}^{od}$

Thus, by introducing service fee for ride share $f(td^{od})$, which is a function of td^{od} that is shared among the ride sharing participants based on the distance, the total generalised cost for the supplier (driver) and demander (rider) path can be denoted as:

$$G_{Driver}(p_{n_t}^{od}) = tt^{od} \cdot d_{p^D,t}^{od} \cdot VOT + td^{od} \cdot d_{p^D,t}^{od} \cdot VOC - f(td^{od}) \cdot s_{p^R,t}^{od}$$

$$G_{Rider}(p_{n_t}^{od}) = tt^{od} \cdot d_{p^R,t}^{od} \cdot VOT + f(td^{od}) \cdot d_{p^R,t}^{od} / s_{p^R,t}^{od}$$

Where, $s_{p^R,t}^{od}$ is the satisfied ride.

Considering a fixed pickup time t^p , the above equations can be expressed as:

$$G_{Driver}(p_{n_t}^{od}) = (tt^{od} \cdot d_{p^D,t}^{od} + t^p \cdot d_{p^R,t}^{od}) \cdot VOT + td^{od} \cdot d_{p^D,t}^{od} \cdot VOC - f(td^{od}) \cdot s_{p^R,t}^{od} \dots(2)$$

$$G_{Rider}(p_{n_t}^{od}) = (tt^{od} \cdot d_{p^R,t}^{od} + t^p \cdot d_{p^R,t}^{od}) \cdot VOT + f(td^{od}) \cdot d_{p^R,t}^{od} / s_{p^R,t}^{od} \dots(3)$$

Ride match is prioritised for the driver with minimum cost path (eq. 2) to take on the rider with minimum cost path (eq. 3). Thus, maximising the $s_{p^R,t}^{od}$ will provide minimum cost path for both supplier and demander.

Step 7. After every match, the sharing capacity $c_{p^D,t}^{od}$ of path P_t^D is reduced by the demand of ride sharers moving along the same path until the entire capacity is utilised. At the same time the unsatisfied ridesharing demand is reduced as below:

$$c_{p^D,t}^{od} = \begin{cases} c_{p^D,t}^{od} - d_{p^R,t}^{od} & \text{if demand} \leq \text{capacity} \\ 0 & \text{if demand} > \text{capacity} \end{cases} \dots(4)$$

$$d_{p^R,t}^{od} = \begin{cases} 0 & \text{if demand} \leq \text{capacity} \\ d_{p^R,t}^{od} - c_{p^D,t}^{od} & \text{if demand} > \text{capacity} \end{cases} \dots(5)$$

7.3 Model Setting

The ride matching algorithm mentioned above is implemented in SATURN modelling suite. SATURN contains all data structures of the transport supply (nodes and links) and of the travel demand (traffic zones, demand matrices). Model input used in SATURN are:

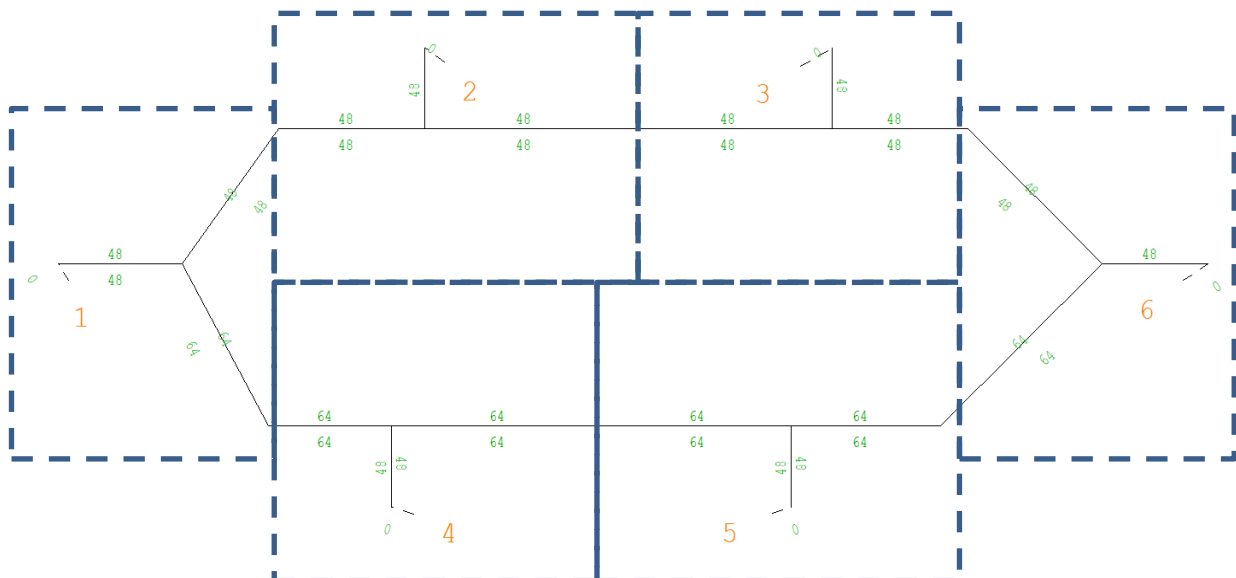
7.3.1 Model Input

- **Network Structure.** A toy network is designed with 6 traffic model zones ($z = 6$). From zone 1 to 6, two alternate paths are considered so that multi-path assignment can be obtained to test the proposed ride matching algorithm. Figure 7.1 shows the network diagram in SATURN P1X module showing the link speed in km/hour.

The network consists of number of road nodes and links. Zones are linked with the network using centroid connectors. The links are coded with simulation nodes that include distance, speed, capacity (saturation flow) parameters.

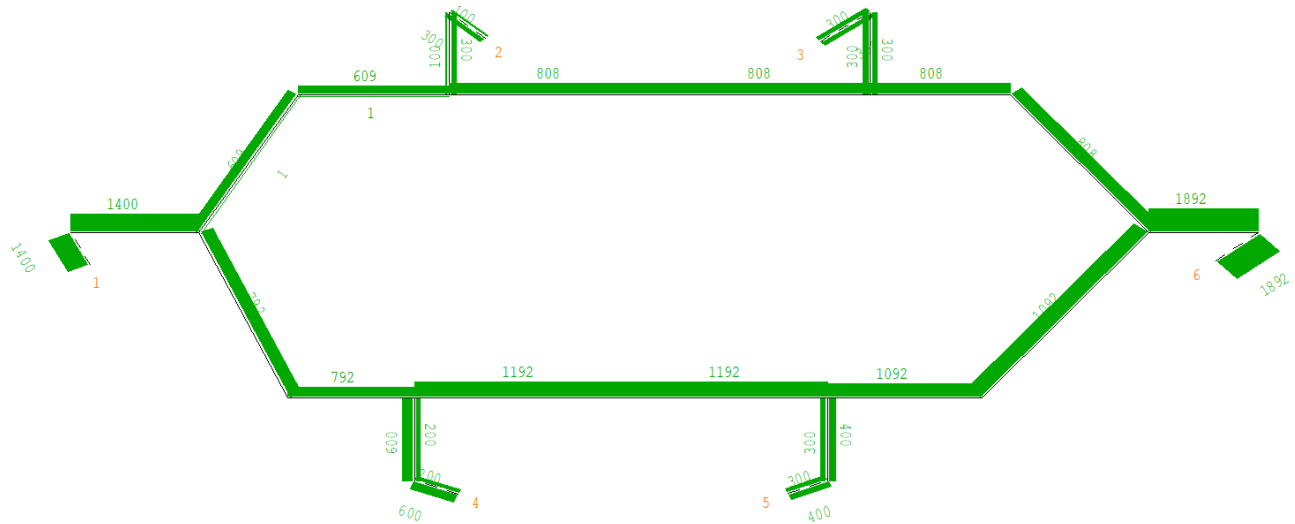
The model network uses one vehicle class – Car. The PCU factor for car used is 1.0. Model time period is 60 minutes

Figure 7.1 Road network with zone boundary



- **Origin-destination trip matrix.** A 6x6 demand matrix ($M = 2900$ pcu) is designed in such a way that trips are distributed from zones left to right (e.g., 1 to 6). This simplified trip distribution is considered to monitor each step of the ride matching process. Figure 7.2 shows the assigned demand (M) on the road network without ride sharing.

Figure 7.2 Traffic assignment without ride sharing

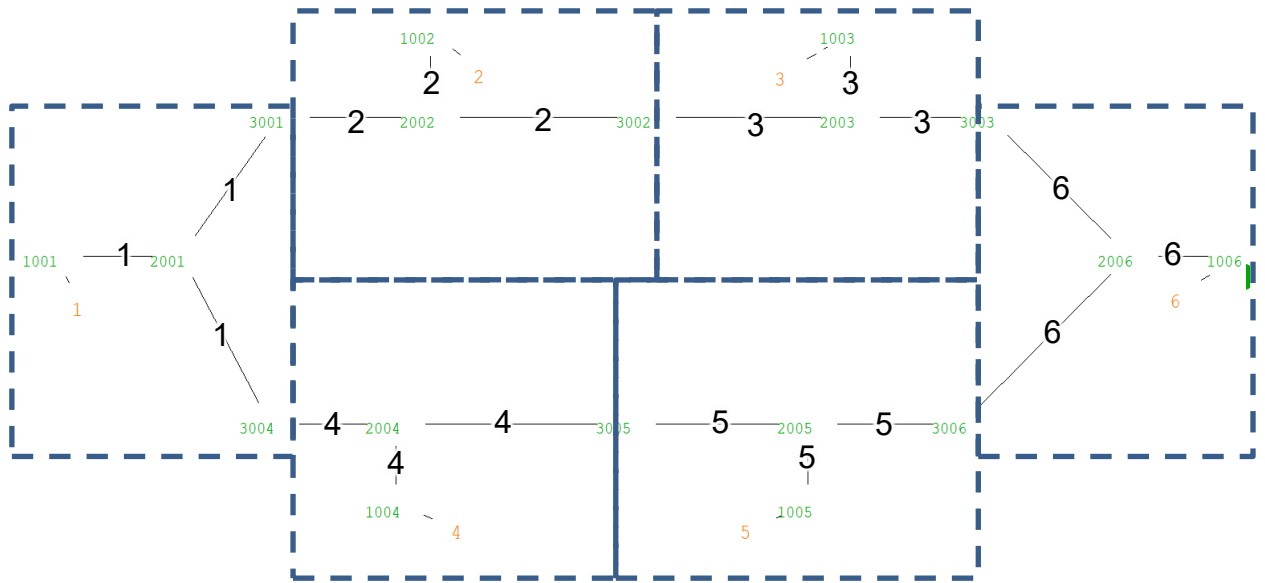


- **Ride provider.** Demand matrix of ride providers referred as drivers ($D = 370$) is a fixed matrix and a subset of M . These are trips within M , who has spare ride capacity and willing to take rides on the way to their destinations. The ride supply is 10% to 20% of the total demand matrix M .
- **Ride demander.** The demand matrix of the riders (R), which is a subset of M , are car-self driver, who considers using a ridesharing service. In this study, R is varied by 10% to 50% of M .

7.3.2 Ride matching implementation

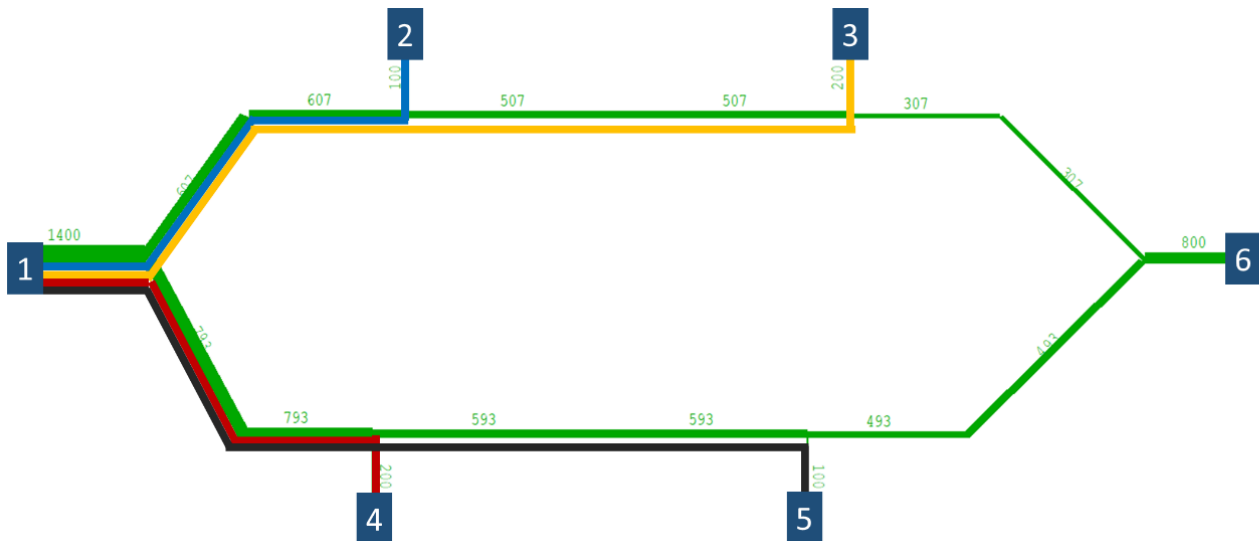
Step 1. In this study one pick-up and drop-off per zone is assumed. Every link ($l = Node1 - NodeB$) is assigned to a zone z (e.g., 1001-2001=1, 2001-3001=1) When a link (e.g., 2002 - 2003) crossed two zones ($z = 2$ and 3) a node (3002) is introduced where the zone boundary intersects the link (Figure 7.3).

Figure 7.3 Network showing links assigned to zone number



Step 2. As D_t and R_t are the subset of M , the assigned path of M as shown in Figure 4.3 are used to derive P_t^D and P_t^R . Figure 7.4 shows all paths originated from zone 1. SATPIG module within SATURN is used to obtained path and route flow.

Figure 7.4 Trip assigned from zone 1 showing multiple paths



Step 3. Paths are disaggregated by links, and as each link is assigned a zone, paths are expressed as a sequence of zone numbers. The example below shows paths for zone 1 to all zones are expressed by zone sequence (Table 7.1)

Table 7.1 Path aggregation by zone sequence

Path	Node Sequence	Zone Sequence	Zone Sequence (without duplicates)
1	1001-2001-3001-2002-1002	1-1-2-2	1-2
2	1001-2001-3001-2002-3002-2003-1003	1-1-2-2-3-3	1-2-3
3	1001-2001-3001-2002-3002-2003-3003-2006-1006	1-1-2-2-3-3-6-6	1-2-3-6
4	1001-2001-3004-2004-1004	1-1-4-4	1-4
5	1001-2001-3004-2004-3005-2005-1005	1-1-4-4-5-5	1-4-5
6	1001-2001-3004-2004-3005-2005-3006-2006-1006	1-1-4-4-5-5-6-6	1-4-5-6

Step 4. Driver path capacity $c_{p^D,t}^{od}$ is obtained from the demand of the ride provider d_t^D applied in Equation 1. Average vehicle capacity $c^{veh} = 4$ and average car occupancy $o^{veh} = 1.4$ are assumed. Table 7.2 shows the calculation of supply for the paths shown in Table 7.1.

Table 7.2 Calculation of supplier path capacity

Path	$d_{p^D,t}^{od}$	$d_{p^R,t}^{od}$ (30% of M)	c^{veh}	o^{veh}	$c_{p^D,t}^{od}$
1-2	10	30	4.0	1.4	26
1-2-3	20	60			52
1-2-3-6	61.46	92.19			159.80
1-4	20	60			52
1-4-5	10	30			26
1-4-5-6	98.54	147.81			256.20

Step 5. String search of the supplier and demand path is carried out to find out all or partial path match. For example, supplier path 1-2-3-6 is matched with rider path 1-2-3-6 as whole path match or 1-2, 1-2-3, 2-3 and 2-3-6 as partial match.

Step 6. As string search results end up with multiple ride demand path for one supplier path, priority of the ride matching is carried out by minimising the cost of the supplier and demander path as shown in Equation 2 and 3. Network parameters are assumed as:

$$VOT = 30 \text{ ppm}$$

$$VOC = 6 \text{ ppk}$$

$$f(td^{od}) = 30 \text{ ppk. This is the partial element of ride service fee.}$$

$$t^p = 30 \text{ seconds.}$$

Step 7. Sharing capacity $c_{p^D,t}^{od}$ reduced by the $d_{p^R,t}^{od}$, alongside $d_{p^R,t}^{od}$ is reduced at the same time using Equation 4 and 5 respectively. Table 7.3 shows the reduction of sharing capacity when ride is matched.

Table 7.3 Calculation of adjusted supplier path capacity after satisfying demand

Path	$c_{p^D,t}^{od}$			$d_{p^R,t}^{od}$ (30% of M)		
	Initial Capacity	After Full path match	After Partial path match	Initial Demand	Unsatisfied d after full path match	Unsatisfied d after partial match (1 st iterations)
1-2	26	0	0	30	4	4
1-2-3	52	0	0	60	8	8
1-2-3-6	159.80	67.61	59.61	92.19	0	0
2-3	26	0	0	30	4	4
2-3-6	52	0	0	60	8	0
3-6	78	0	0	90	12	12

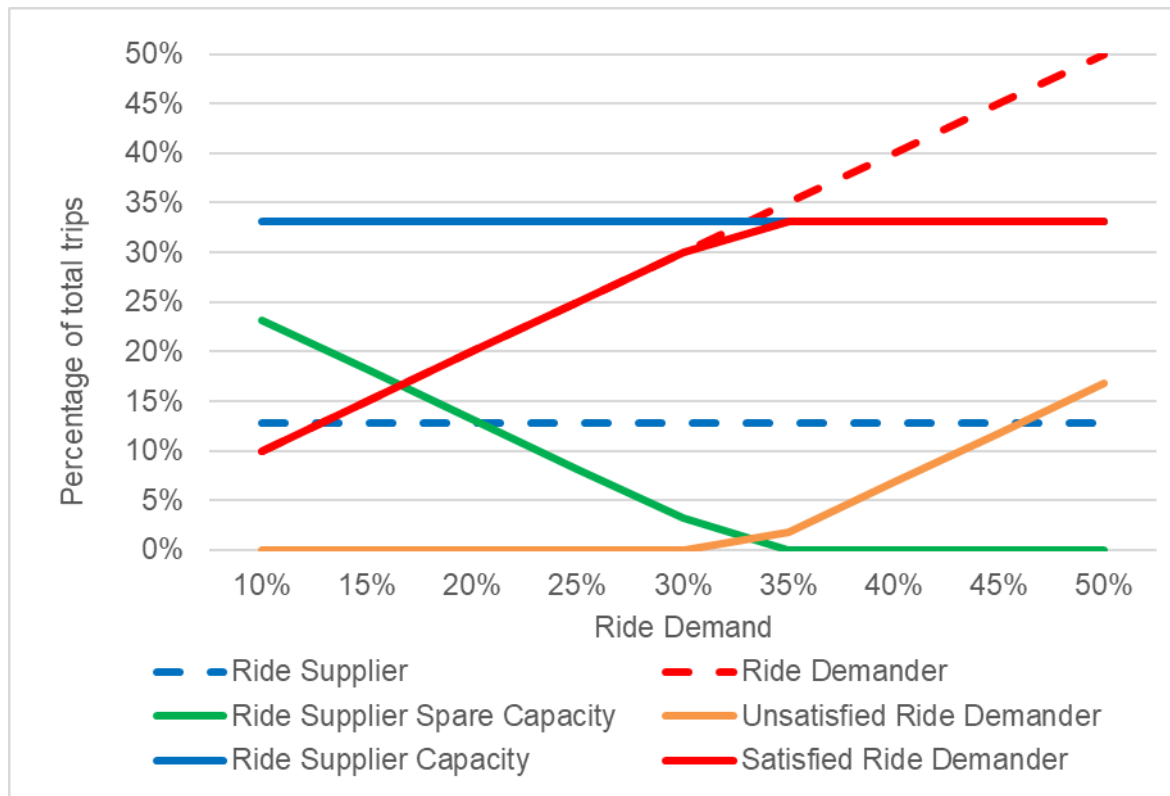
7.4 Result and Analysis

The ride matching algorithm is applied to the small-scale test network shown in Figure 5.1. Total demand flow of the model is 2900 vehicles, whereas ride supplier demand is 370 vehicles. These trips are existing trips within 2900 vehicles that offer ride to the demander. The ride demand is varied by 10% to 50% of the 2900 vehicles and applied to each O-D movement.

7.4.1 Impact of ride supply and demand

Figure 7.5 shows the number of ride supplier and demander as well as available ride capacity and unsatisfied ride demand varying by the change in ride demander.

Figure 7.5 Ride supply change by increase in ride demand

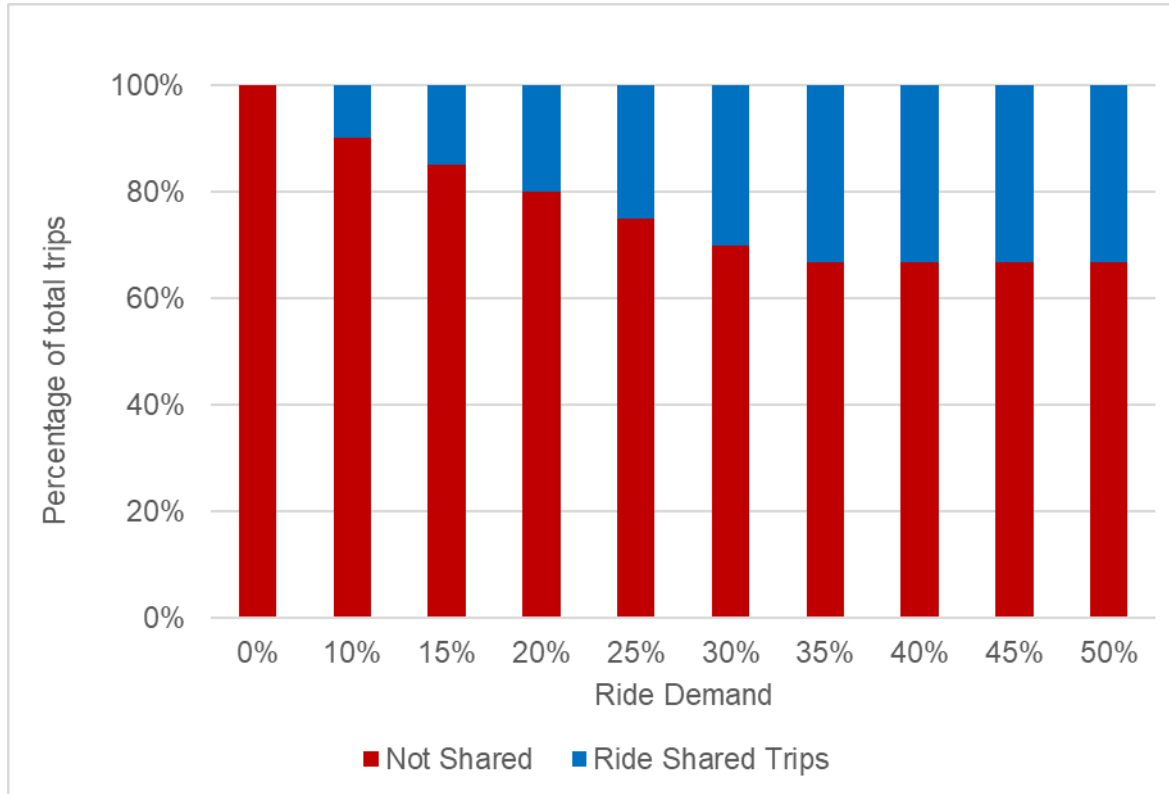


The figure above shows that ride sharing capacity reduces with the increase in ride demander up to approximately 33% of the total demand in the network. When the ride demand increases over 33% of the total demand in the network, there is no available ride sharing capacity. At this stage unsatisfied ride demand starts to increase. Initially, full path match between rider supplier and demander is established. This means ride supplier of a particular zone at first serves the ride demander of the same zone assuming no significant rerouting and no additional pick-up and drop-off time on the way to its destination. When all ride demand of the of same zone is satisfied, the spare ride capacity is used to establish partial ride for the next least cost demander path on its way to the destination.

Figure 7.6 shows total number satisfied riders and trips with no ride share as the percentage of total network demand. With the fixed ride supplier in this analysis the rate of increase ride sharing trips reduces when all supply capacity utilised. The

relationship between the ride capacity and demander is not exactly linear as this capacity is utilised with least cost demander path to satisfy a ride.

Figure 7.6 Satisfied ride by increase in ride demand



The comparison of scenarios (10% to 50% ride demand variation) of ride share demand illustrates the importance of a critical mass of participants to make a ridesharing system operational. Both supplier and demand benefit from a high number of participants. Ride demanders obtain a higher figure in satisfied rides and suppliers can reduce their trip costs by picking up demanders.

7.4.2 Impact on revenue and cost

Based on the ride matching process the impact on revenue generation is also analysed in this study. 30 pence per kilometre of ride sharing fee is assumed for this test. Figure 7.7 shows the effect of revenue with increase of ride demand. Initially with low ride demand when sharing space is available, full ride match within the same zone is established. Full match within the same zone is accomplished when ride supplier takes on rider for its entire journey without any stopping at intermediate points (traffic zones). At ride demand 30% of the total flow all full ride matches are satisfied and spare ride capacity is consumed by the partial ride

matches which is pick or/and drop off riders. As the ride demand increases linearly with very high demand, full ride matches utilise most of the ride capacities.

Figure 7.7 Satisfied ride by increase in ride demand

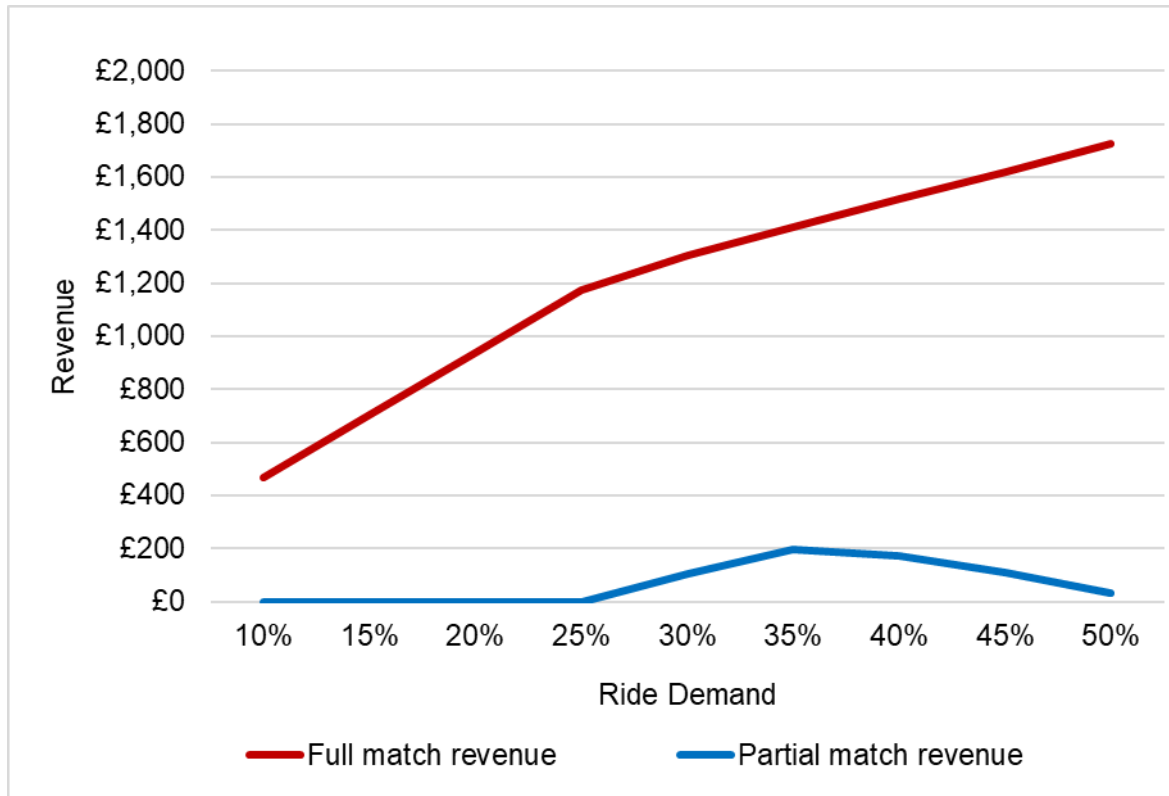
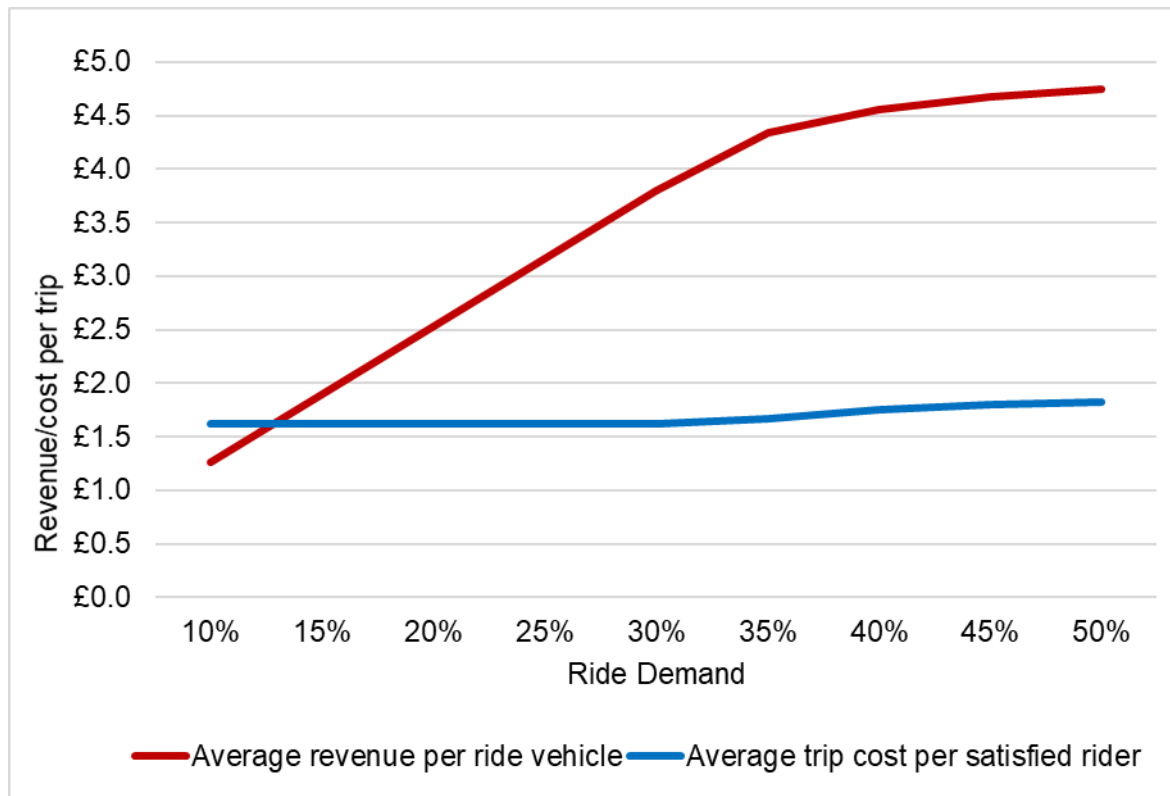


Figure 7.8 also demonstrates the increase revenue per ride supplier and cost per rider with the change in ride demand. Revenue per ride supplier increases linearly until ride vehicle with spare space travel to other zones to pick-up or/and drop off passengers. Similarly, when ride demand increases at and over 35% of the total demand average cost per rider increases as long distance riders share the cost of travel with the short distance riders by proportion of the distance they travelled.

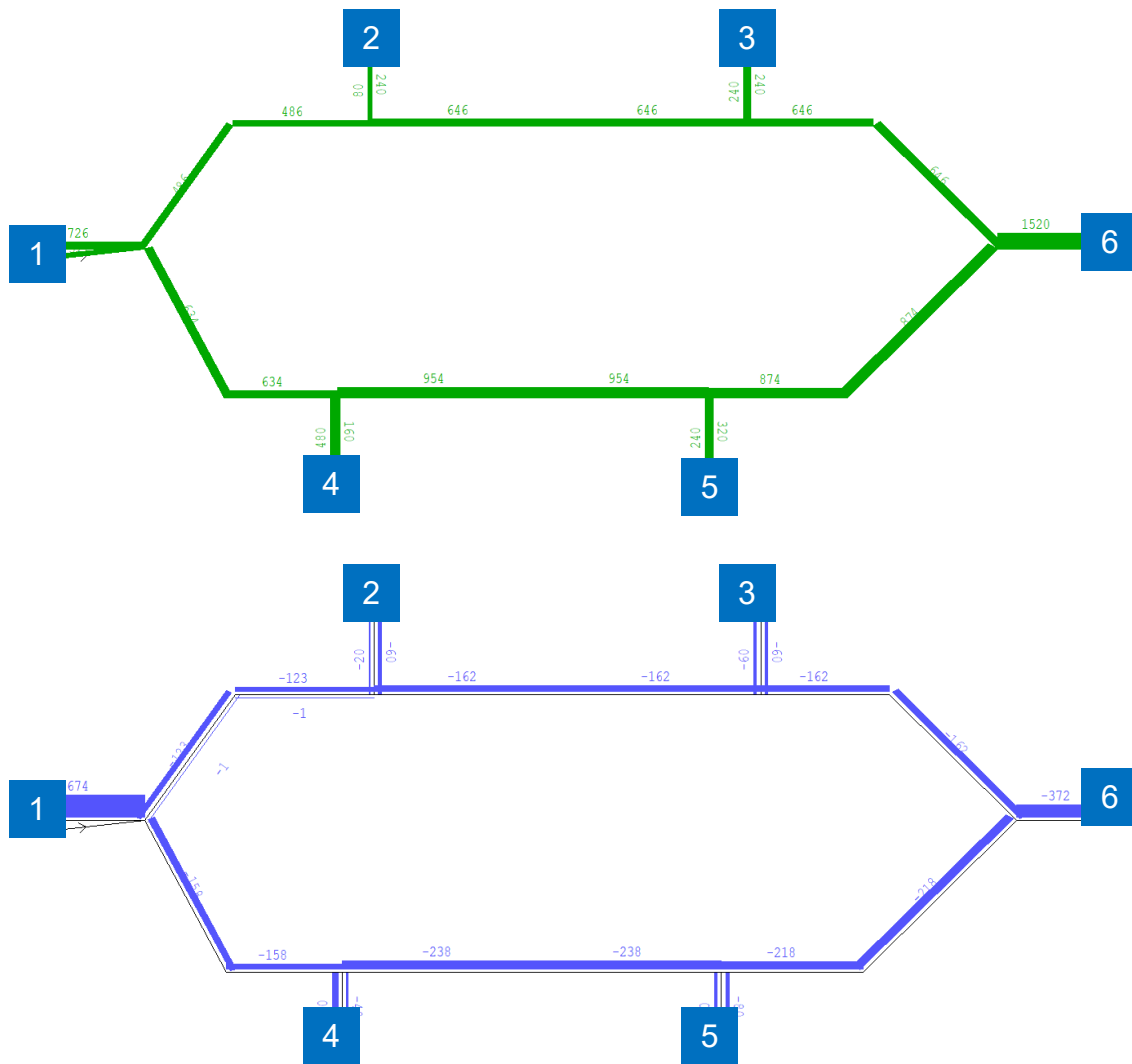
Figure 7.8 Change in average trip revenue and cost by increase in ride demand



7.4.3 Impact on Road Network

The route flow for each path is calculated after deducting satisfied ride demand from the total route flow. This reduced route flow is then applied to the network using fixed path assignment in SATURN. The SATDB module is used to assign the route flow on each link. The path assignment output can be obtained using SATEASY. Figure 7.9 shows that the assigned traffic flow including ride sharing trips for ride demand 20% of the network demand using fixed assignment path established with no ride sharing path assignment (top figure). The bottom figure shows flow difference plot (no ride share flow minus ride share flow) between after ride sharing and no ride sharing. The bandwidth in blues show that all from o-d movement network flow reduces as ride share is satisfied.

Figure 7.9 Fixed trip assignment with ride sharing (20% ride demander)



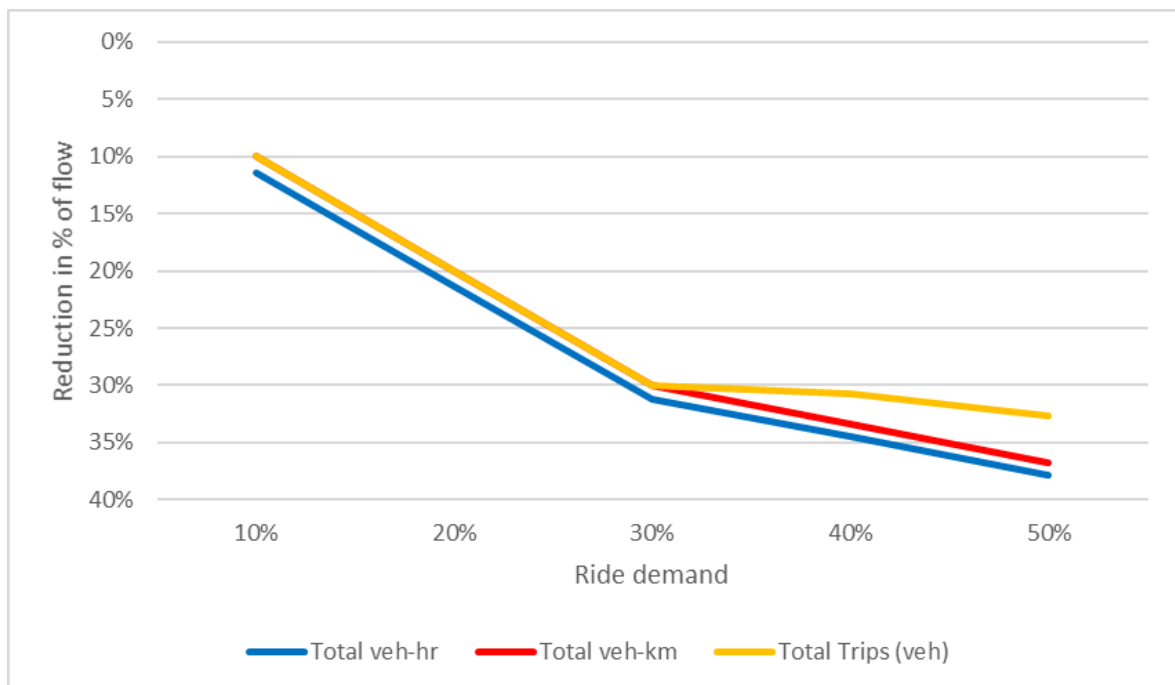
The fixed network assignment is carried out with the reduced route flow obtained by varying ride demander at 10%, 20%, 30%, 40% and 50% of the total route flow. SATSTAT is used to obtain network performance for these networks and demand scenarios. Table 7.4 summaries the network wide statistics to show the change in network statistics by change in ride demander.

Table 7.4 Network statistics by change in ride share demander

Network Statistics	No RS	10%	20%	30%	40%	50%
Total Travel Time (veh-hr)	732	648.8	575.7	503.3	479.7	455.2
Total Travel Distance (veh-km)	40639.9	36572.6	32509	28445.3	27068.8	25674.9
Average Speed (km/hr)	55.5	56.4	56.5	56.5	56.4	56.4
Total Trips (veh)	2900	2610	2320	2030	2008	1954
Average Queue (veh)	12.87	1.99	0.93	0.52	0.44	0.38

Figure 7.10 shows the reduction in percentage of total flow by change in ride demand. With 20% ride demand of the total trips the total vehicle, total travel distance and total travel time reduces by 20%. The linear relationship of the reduction of these parameters up to all spare ride capacity utilised (33% ride demand) is because when total vehicle in the network reduces, congestion reduces significantly.

Figure 7.10 Change in total vehicles, travel time and travel distance



7.5 Conclusion

The ride matching algorithm in this study establishes matching the trips of suppliers (private car drivers) and demanders (travellers willing to move from private car). The algorithm described here offers a straightforward solution for the matching problem, as it simplifies the matching problem in several ways.

- Precise pick-up and drop-off point are not used. Each zone is assumed to have one pick-up and drop-off point.
- The representation of a path in the road network is reduced from a sequence of links to a sequence of zones. Within the zone boundary demander can be picked up and dropped off, which is external node at the centroid connection for each zone.
- Trips are only matched within one time interval.

Thus, the advantages of the ride matching algorithm are:

- The run time is reasonably fast to solve relatively complex problem.
- The matching algorithm is suitable for both integer and non-integer demand.
- Can be integrated with multiple path assignment e.g., Wardrop Equilibrium.

The ride matching algorithm established in this study are applied in a network with few simplified assumptions. These are:

- Only one vehicle class is used in this study. However, the algorithm can be implemented in a model of multiple user classes with different VOT and VOC. And multiple trip purpose can share trips with the ride supplier.
- In this study, ride supplier is assumed to be a subset of total demand matrix. As the ride supply matrix is fixed, a separate ride supplier (e.g., automated taxi) as a new vehicle class can be applied in the proposed ride matching process.
- Ride demander is also assumed to be a subset of total trip matrix. Thus, ride demanding trips can be considered in person trips obtained from mode choice model (e.g., transfer from bus or rail trips) and then independently apply in the matching algorithm in the trip assignment stage.
- Fixed pick up and drop off time assumed in this study can be the function of boarding trips.
- After establishing the ride match, reduced total flow is assigned to a network using fixed path assignment. However, when ride match is established for a

certain supply path, the route may become faster compared to other alternate routes. Thus, applying a Wardrop equilibrium assignment would break the connection between the demander and supplier. An option of iterative steps of ride matching process with Wardrop equilibrium assignment can be considered to deal with this problem. Although this iterative process may increase the model run time when the network size is scaled up.

- Optimisation process to establish rules to prioritise the ride demander paths may also increase the run time when the network model is scaled up.
- The ride matching algorithm is tested by varying ride demander only. Other sensitivity tests by varies ride cost, supplier demand etc. can be performed to understand the performance of the ride matching process.

This study shows that ride supplier 13% of total trips satisfies ride demand of 35% of the total demand, which is equivalent to 2.6 vehicles demand per ride providers. This figure is very high compared to the result found by Friedrich *et al.* (2018) 25% ride supply satisfied 28% of total demand. But this is mainly because Friedrich *et al.* (2018) used 100% of external ride demand from public transport as a potential rider but keeping the network congestion level same assuming 70% of the existing trip remain unchanged.

One of agent-based simulation study by Fagnant and Kockelman (2018) found that one SAV can replace 11 conventional vehicles, which is very high found for this study. However, Fagnant and Kockelman (2018) considers vehicle relocation strategy in to recycle the same SAV which is out of scope for this objective.

This ride matching algorithm as part of the research is applied to a city scale network to understand the performance shared modelling regime and estimate the impact to road capacity and delay.

Chapter 8

General Discussions

8.1 Purpose of the chapter

This final chapter combines the thesis as a whole and critically assesses what the research contributes to understanding the impacts of AVs and shared mobility in urban road networks. It brings together the aims and objectives, explains how they were pursued, consolidates the principal findings from the movement, toy-network and city-network analyses, and reflects on methodological strengths and limitations. The discussion then positions the results within the literature reviewed earlier, draws practical and policy implications, and sets out a programme for future work, including items that were intentionally not included in the present scope. The structure mirrors the signposting used throughout the thesis.

8.2 Restating aims and objectives and evaluating achievement

8.2.1 Aims and objectives

The research aimed to assess the impact of autonomous vehicles and ride-sharing on the urban network using the SATURN modelling tool. Two primary objectives supported this aim. First, to design and test suitable parameters in SATURN to model AV behaviour. Second, to model ride-sharing in SATURN in order to examine its effects on capacity, delay, route choice and network efficiency.

8.2.2 Objective 1: designing and testing SATURN parameters for AV behaviour

This objective has been fully achieved. Chapters 4 to 6 developed a flow-theory-based mapping from AV characteristics to SATURN inputs, with explicit treatment of turn saturation flow (LSAT), gap acceptance (GAP), stacking capacity (STACK derived from ALEX), and generalised cost where relevant to AV user classes. These inputs were embedded in an iterative workflow, implemented through SATDB and batch procedures, that updates LSAT, GAP and STACK at the movement and link level according to the proportion of AVs assigned at each iteration.

At junction level, the tests demonstrated large and interpretable capacity gains. For unopposed turns at priority junctions, LSAT increased to 3,388 pcu/hr under 100% AV when headway alone changed, and to 3,789 pcu/hr when both headway and

mean vehicle length changed, almost eliminating delay under the stated flows (Test Scenarios 1-2). For opposed turns, capacity and delay improved progressively as headway, GAP and safety distance were varied in Scenarios 3-5, with the comparative plots showing the combined effects clearly. For a signalised junction, adopting an AV start-up response-time formulation yielded an approximate 43% increase in capacity at 100% AV and large delay reductions (Scenario 6).

At network level, the toy-network runs showed substantial first-order benefits: an 82% reduction in total travel time, a 96% reduction in average queues, and a shift towards shorter routes, once AV parameters were applied under a 100% AV assignment (Scenario 7). Incorporating AV generalised-cost settings produced only small additional changes in global totals, although it affected path allocation in ways consistent with cost sensitivities (Scenario 8).

The City of York application confirmed that these benefits scale under realistic network conditions. As AV penetration increased from 0% to 100%, total travel time decreased by around 12%, average speed rose by about 12%, and average queues halved, while total distance changed little. This indicates that benefits were driven by capacity and delay mechanisms rather than by inflated path lengths. Spatially, the largest time savings concentrated at signalised inner-city bottlenecks, with smaller changes on strategic links that already operate near free flow.

The framework was benchmarked against a PCU-based treatment of AVs. Across toy and city networks, flow-theory results were closest to an AV PCU of about 0.7 for global totals, while PCU-based runs tended to show larger reductions in the incidence of high V/C at 100% AV because they discount effective demand as well as operational times.

Two choices in the model setup limit how the results can be interpreted. First, signal timings were not optimised within AV scenarios, which isolates supply-side effects of AV parameters but likely understates achievable benefits on coordinated corridors. Second, the flow-theory treatment focused on junction mechanisms; the comparative discussion identified the need for AV-adjusted speed-flow curves on strategic links to represent mid-link phenomena consistently.

8.2.3 Objective 2: modelling ride-sharing in SATURN

The second objective has been partially achieved. Chapter 7 developed a ride-matching algorithm compatible with non-integer flows and mesoscopic path

sets under Wardrop UE. Paths are reduced to zone-sequence strings to enable efficient matching; supplier path capacities are computed from demand and average occupancy; matches are prioritised on generalised cost with a distance-based fee and a fixed pick-up time, then supplier capacity and unsatisfied rider demand are updated after each match.

A controlled toy-network application showed that the algorithm runs quickly, integrates with multi-path UE outputs, and is suitable for both integer and non-integer demand. Reduced route flows after matching can be re-applied to the network to measure changes in traffic volumes, delays and queues. While a full equilibrium feedback loop that alternates matching and re-assignment was beyond scope due to runtime considerations, the steps and batch procedures necessary for such an extension were identified.

8.3 Methodological strengths and limitations

8.3.1 Strengths

Mesoscopic model with city-scale coverage. SATURN's simulation-assignment structure models turn-specific capacities, lane sharing and GAP acceptance, while iterating to user equilibrium at network scale. This makes it well suited to assessing AV impacts where junction processes, rather than mid-link constraints, govern performance.

Transparent parameter mapping. The flow-theory mapping from headway, speed and effective vehicle length to LSAT, with corollary updates for GAP and STACK, provides a clear link between AV characteristics and operational capacity. The iterative SATDB procedure ensures that changing AV shares at each movement feed back into the next assignment.

Reproducibility and scalability. The city-scale workflow for York uses standard SATURN modules and a documented sequence of assignment, data extraction, parameter update and re-assignment, making it replicable in other networks where SATURN coding and data are available.

Benchmarking against practice. The close alignment between flow-theory results and an AV PCU of around 0.7 provides a practical translation for planning contexts that continue to use PCU-based models.

Pragmatic ride-sharing formulation. The zone-sequence matching approach operates on equilibrium path sets without bespoke agent-based software, yet preserves a cost-based rationale for prioritising matches.

8.3.2 Limitations

Behavioural scope. The analysis adopts static user equilibrium for all classes. This isolates the supply-side consequences of AV headway and interaction changes, but it excludes coordinated, system-optimal AV routing and dynamic traffic assignment.

Control strategies. Signal timings and offsets were held at base values. This is a conservative choice for identifying AV-only effects at signals and suggests that joint optimisation could yield additional benefits.

Mid-link effects on strategic roads. The present implementation emphasised junction mechanisms. Strategic corridors operating near free flow would require AV-sensitive speed-flow curves to capture any mid-link capacity gains.

Demand responses. Total trips were held constant and there was no explicit modelling of induced demand, mode shift or peak spreading. The scope was limited to first-order operational effects.

Ride-sharing feedback. The algorithm applied a single matching step followed by fixed-path loading. A converged scheme that alternates matching and UE assignment remains a priority for future work.

External validity. The City of York application is informative for a typical UK city with many signalised junctions and a tractable runtime, yet transfer to cities with different geometries and control philosophies should proceed with local calibration and, where necessary, mid-link capacity representation.

8.4 Critical analysis with the literature

The results are consistent with the literature reviewed in Chapter 2 and extend it by embedding the capacity mechanisms in a mesoscopic assignment environment.

Headway-driven capacity. The central mechanism, namely that shorter headways and coordinated behaviours increase discharge rates, underpins the movement-scale and toy-network results and reflects expectations from longitudinal automation studies and flow-theory adaptations of capacity. The thesis adopted

values and relationships in line with these strands and demonstrated their consequences at junctions and signals.

Facility-type dependence. The City of York maps showed that benefits concentrate at signalised inner-city links with high lost times and complex conflicts, while longer, higher-standard corridors near free flow show modest changes unless mid-link capacity is explicitly modified. This pattern is coherent with the literature's attention to facility type and control regime.

PCU-based practice. Extending PCU factors to AV classes remains common practice. The present benchmarking showed that a 0.7 PCU factor is a reasonable proxy for the flow-theory approach in global metrics, while the V/C comparison cautions that PCU discounting is likely to show larger reductions in apparent congestion on strategic links.

Shared mobility modelling. The ride-matching routine addresses a gap in equilibrium models that require non-integer matching and path-set integration, providing a mesoscopic alternative to agent-based platforms for exploratory analysis, consistent with the thesis' focus on tractable city-scale workflows.

8.5 Implications for practitioners

The modelling translates into several practice-ready messages.

- Use mesoscopic assignment with explicit junction mechanisms when evaluating AVs. Verify junction coding, LSAT values and turn priorities before introducing AV parameters, and confirm that GAP settings reflect local practice at priority junctions and roundabouts.
- Map AV headway and safety distance assumptions to LSAT, GAP and STACK systematically. Apply the iterative SATDB procedure so that movement-specific AV shares are reflected in subsequent runs. Use toy networks to prove the parameter pipeline, then scale to full models.
- Expect the largest early benefits at signalised urban bottlenecks. Communicate that strategic corridors near free flow will show smaller changes unless mid-link speed-flow curves are updated for AV effects.
- Run a PCU-based sensitivity as a cross-check. An AV PCU of around 0.7 provides a practical benchmark for global totals, while the stronger reduction of high V/C links in PCU runs should be interpreted with care.

- Treat signal optimisation as an enhancement, not a precondition. The AV framework can be applied without re-timing. Where policy allows, use SIGOPT and offset optimisation to test marginal gains and report joint effects explicitly.
- Deploy ride-sharing tests using the path-based matching routine. Begin with a fixed pick-up time and a simple fee, test feasibility and orders of magnitude, then consider iterative matching with UE as performance permits.

8.6 Implications for policy-makers

The findings offer a firm basis for policy decisions about readiness and appraisal.

Evidence for cautious capacity planning. The framework provides transparent first-order impact of how increase of AV shares could reduce delays and queues at bottlenecks. It retains compatibility with PCU-based planning practices through the demonstrated equivalence in global metrics.

Scope and caveats. The results are conditional on static user equilibrium, fixed demand and no optimisation of signal timings. Appraisal seeking broader system change should include induced demand, mode shift and peak spreading modules, and consider whether coordinated or system-optimal AV routing is appropriate to the policy question.

8.7 Future research directions

The thesis identified several extensions; the following programme integrates those with additional items that were intentionally not included in the present scope.

8.7.1 Shared mobility at city scale

City-scale shared mobility with human-driven vehicles. Extend the Chapter 7 algorithm to a full city network to quantify network-wide effects of ride-sharing under UE with fixed demand. This draws directly on the algorithm's non-integer matching, path-set integration and fast runtime demonstrated at toy-network scale.

Progression to city-scale Shared AV ride-sharing (SAV-RS). Once the human-driven shared-mobility baseline is in place, apply the same matching routine with the AV class active so that sharing and AV capacity effects can be evaluated

jointly at urban scale. The review's taxonomy distinguishes SAV ride-sharing from car-sharing and frames how unoccupied AV trips arise between served trips.

8.7.2 8SAV-CS (car-sharing) in a mesoscopic framework

Represent SAV-CS as a distinct class with its own generalised-cost parameters, access rules and parking constraints, consistent with the review's description of SAVs as combining elements of car-sharing and taxi services. Evaluate changes in vehicle kilometres, vehicle hours, average queues and V/C distributions relative to both the no-sharing baseline and the SAV-RS case. Where parking or access governs flows, use link- or node-level penalties to reflect availability or charges.

8.7.3 UAV (empty vehicle relocation)

Integrate unoccupied autonomous vehicle movements explicitly, recognising that empty trips between served trips or towards self-parking are operationally significant and may increase veh.km in constrained urban networks. Introduce a dedicated empty-vehicle class with near-zero value of time and an appropriate operating cost, then construct relocation matrices between zones of surplus and deficit for post-assignment loading. Appraisal should track additional veh.km, changes in average queues and V/C ratios, and interactions with signalised bottlenecks.

8.7.4 AV-adjusted mid-link capacity on strategic corridors

Complement the junction-focused flow-theory inputs with AV-sensitive speed-flow curves on longer links, then iterate assignments to test impacts on orbital and inter-urban corridors. This responds directly to the comparative discussion that flagged mid-link phenomena as an outstanding representation gap.

8.7.5 Signal policy variants under AV scenarios

Relax the conservative assumption of fixed timings by employing SIGOPT and offset optimisation to quantify the marginal effects of re-timing in AV scenarios and to understand how shorter AV headways interact with stage structure and coordination. Report joint effects separately from AV-only parameter changes.

8.7.6 Iterative ride-sharing equilibrium

Alternate matching and UE assignment until convergence so that matching affects route choice and vice versa. The steps and batch processing used in Chapter 7

provide the necessary starting point; future work should examine convergence speed, stability and runtime at city scale.

8.7.7 Demand-response modules and cross-city replication

Move beyond first-order operational effects by adding induced demand, mode shift, origin-destination choice and peak spreading, using the present results as a baseline scenario. Replicate the framework across multiple UK city models with different junction mixes and control policies to assess transferability and to identify context-dependent factors.

8.7.8 Benchmarking against other mesoscopic modelling platforms

Future work should employ industry-standard mesoscopic platforms, such as PTV mesoscopic tools and Aimsun Meso, to evaluate the impact of AVs and independently verify the results reported here. Cross-platform testing with harmonised inputs and common metrics, including sensitivity and uncertainty analysis and calibration against observed data, would reveal model and network resolution effects, strengthen the conclusions, and clarify the extent to which the findings generalise across other networks and demand contexts.

8.8 Concluding Remarks

This thesis has shown how a mesoscopic simulation-assignment tool can represent AV capacity effects coherently through explicit, reproducible inputs grounded in traffic-flow theory, and how those effects scale from junctions to a realistic city network. The movement-scale tests and toy-network experiments verified the mechanisms and quantified their effects; the City of York application demonstrated system-wide benefits and spatial patterns that are consistent with expectations about facility type and control. Benchmarking against a PCU-based treatment provides a bridge to planning practice and supports the pragmatic use of an AV PCU around 0.7 for global totals.

For practitioners, the work offers an implementable workflow, realistic expectations about where benefits arise, and a defensible way to cross-check against PCU-based sensitivities. For policy-makers, it provides transparent first-order evidence for appraisal and programme design, together with explicit caveats about demand responses and signal policies. The thesis has been deliberate in keeping scope to first-order operational effects under user-equilibrium behaviour. The future-work agenda set out above, which includes city-scale shared mobility,

Shared AV ride-sharing, SAV-CS and explicit UAV relocation, as well as AV-adjusted mid-link capacity and signal optimisation, follows logically from the methods and results already established. In sum, mesoscopic assignment frameworks such as SATURN can capture the near-term operational impacts of AVs in a way that is both theoretically grounded and practically useful, while also providing a robust platform for the next phase of research on shared mobility in AV-enabled cities.

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