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MASTER'S THESIS ASSIGNMENT

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Student's name and surname (including degrees):

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Guides for elaboration

During the elaboration of the master's thesis follow the outline below:

- Describe the state-of-art in simulating urban traffic containing fully automatic vehicles on microscopic level.
- Describe vehicle-to-infrastructure communication and Green Light Optimal speed advisory (GLOSA) related context.
- Describe network building and demand modelling in SUMO, used car-following models, their alterations for fully automatic vehicles.
- Demonstrate the traffic management on selected assessment scenarios (selected use cases from MAVEN project).

Graphical work range: Will be specified by supervisor.

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Bibliography:

SUMO (Simulation of Urban MObility) [online]. Institute of Transportation Systems, DLR, Berlin, Germany. Available from: http://sumo.dlr.de

SEGATA M. Platooning in SUMO: An Open Source Implementation. Proceedings of the SUMO2017. Berichte aus dem DLR-IVT, vol. 31, 2017, pp. 51–62.

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Prague ....November 26, 2018

Declaration

I hereby submit for the evaluation and defence the master's thesis jointly elaborated at the CTU in Prague, Faculty of Transportation Sciences, and Linköping University, Department of Science and Technology.

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Effectiveness of a speed advisory traffic signal system for Conventional and Automated vehicles in a smart city

LINKÖPING UNIVERSITY

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April 2019

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Abstract

As the world population and the traffic demand are constantly inflating, there is a substantial need to procure a safe and effective method for traffic control and management. Thus, traffic signals operate to manage the flow of vehicles and vulnerable road users through intersections.

Intelligent Transport Systems (ITS) technologies based on vehicle connectivity and information exchange may overcome the cons of fixed-time traffic signals in coping with the unplanned traffic stream. The roadmap for operating connected vehicles in an urban environment is still in the planning phase and in order to achieve sustainable results, a proper management technique must control the flow of vehicles. Green Light Optimal Speed Advisory (GLOSA) utilizes infrastructure and vehicles communication through using current signal plan settings and updated vehicular information in order to influence the intersection approach speeds.

This thesis presents a traffic microsimulation study that investigates the state-of-the-art in traffic management (GLOSA) for vehicles in smart cities. The simulations are performed to analyze the effect on traffic performance when more drivers comply to the speed advice. The GLOSA management approach is also accessed for its capability to improve traffic efficiency in a mixed environment of conventional and automated vehicles, as well as in a full market penetration of only connected automated vehicles.

The simulations in this thesis undergo a fixed time traffic management for a fictious case with only straight forward traffic flow. Results show that GLOSA has a great impact on reducing the waiting time and enhancing the traffic performance for conventional driving in addition to further possibilities for introducing automated vehicles onto the road alongside conventional vehicles. Moreover, enhancements of automated vehicle parameters show significant results singly independent on operating the GLOSA management algorithm, with minor improvements while accompanied with GLOSA.

Full market penetration of connected conventional vehicles managed by the GLOSA technique results in achieving waiting time reduction of 66%, compared to having conventional vehicles without GLOSA connectivity. While increasing the percentage of GLOSA connectivity causes a decrease in trip delay ranging from 35 % to 70% reduction for 50% and 100% penetration rates respectively.

Simulations results for 50% or more compliance rates showed waiting time of values very close to the full compliance mode, which indicates that even if only half of the drivers comply to the GLOSA speed recommendation, this should have a significant impact on the traffic performance.

In a mixed traffic scenario, where automated vehicles share the road equally with conventional vehicles both having the same time gap, it was clear that there are no further benefits from introducing automated vehicles without decreasing their time headways.

The best traffic performance results achieved by using GLOSA, goes for connected automated vehicles having the lowest simulated time gap. The waiting time reduction reaches 95% and trip delay lessens to 88%.

Keywords: Traffic management, Micro simulation, Traffic flow efficiency (Travel time - trip delay), Green Light Optimal Speed Advisory (GLOSA), V2I communication, Conventional vehicles, connected vehicles, Automated vehicles, Mixed Traffic Environment, smart cities.

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1 Introduction

Nowadays, people drive their cars, take the bus or ride a bike to school, university and work, which compels road infrastructure to be continuously ameliorated in order to guarantee better accessibility and to accommodate the increasing traffic demand. Road users have different trip destinations as well as varying departure and arrival times. In addition, the world population is growing rapidly, contributing to an increase in daily trips and annual traffic demand which causes congestions and travel time escalation during peak hours. Thus, the need for implementing traffic control strategies has evolved in order to provide safe, orderly and efficient means of transport.

Traffic management is commonly used to control the flow of vehicles through intersections especially in an urban environment. Traffic signals are one of the most effectual form of traffic management and are extensively used in many cities worldwide (Mathew, 2014). Traffic signals play an important role in the daily trips of city inhabitants and visitors, as they orchestrate the movement of vehicles and vulnerable road users in a safe manner. The conflicts arising from movements of traffic in different directions are resolved by the time-sharing principle; at a given time, with the help of appropriate signals, certain traffic movements are restricted whereas certain other movements are permitted to pass through the intersection (Mathew, 2017).

While being bound to limited land use and low infrastructure capabilities; on one hand, the fixed-time traffic signals cannot cope with high traffic flow fluctuation through the day since the cycle time, phases and intervals are fixed (Mathew, 2017). Also, poor design of the traffic light system could be the reason for stop-and-go waves, which frustrates drivers, wastes fuel and increases air pollution (Cunningham, 2005). This implies significant negative impacts on the global economy state as well. On the other hand, actuated traffic signals use stationary loop detectors to sense vehicles presence and send their information to the controller, which enables slight adaptability to different traffic conditions (Mathew, 2017). Yet, there are still further possible improvements through increasing the number of detectors or changing the traffic controller mechanism while retaining fixed-time traffic control.

Connected vehicles operating through an intelligent traffic management system are based on maintaining a continuous information transmission to the traffic control within the defined communication range. New Intelligent Transport Systems (ITS) technologies such as Green Light Optimal Speed Advisory (Katsaros, et al., 2011) which is based on communication between infrastructure and vehicles and vice versa, can improve the traffic performance further (Wan et al., 2016). This state-of-the-art management technique will get more and more attention in the near future (Pereira et al., 2017). Moreover, research is currently ongoing in fields related to vehicle automation, which involves gradual transition from having conventional vehicles controlled by human drivers to vehicles controlled by computers.

Automation is expected to have high impact on improving the traffic efficiency by reducing the distance between vehicles, consequently leading to increase in road capacity (Pereira et al., 2017). Travel time reduction and capacity augmentation are among the expected results from operating connected and automated vehicles onto the road (Yang et al., 2016). The resulting benefits are credited to the information sharing between traffic control infrastructure and vehicles or due to the enhancement of vehicle capabilities.

Automated driving has become an important research trend in the field of cooperative intelligent transportation systems (C-ITS) and their applications in smart cities (Pereira et al., 2017). Although considerable research has been focused on modeling of automated and connected vehicles, management of those vehicles by road infrastructure is an emerging new subject and not so much practical development has been reported yet, especially in a mixed scenario involving other different vehicles types (Pereira et al., 2017).

1.1 Background

The roadmap for operating connected and automated vehicles in urban environment is still in the planning phase and in order to achieve sustainable results, a proper management technique must control the flow of vehicles as well. GLOSA, as one of the latest state-of-the-art in traffic management and ITS technologies based on vehicle-to-infrastructure (V2I) and infrastructure-to-vehicle (I2V) communication, has the potential to improve traffic efficiency by reducing the waiting times at traffic signals (Wan et al., 2016).

Vehicle connectivity and communication have created the possibility of new concepts for traffic signal control. The GLOSA approach uses traffic signal control information and current vehicles positions and speeds to recommend an appropriate speed for each vehicle and facilitate their movements (Stevanovic, A., Radivojevic, & Stevanovic, J., 2016). The aim of implementing GLOSA is to avoid the stop-and-go traffic and to increase the throughput.

While automated driving is speculated to increase road capacity and eliminate human errors (Pereira et al., 2017), it may have a negative effect on traffic flow in early field introduction phases. This reinforces a menacing challenge for road authorities in terms of traffic management and strategic planning of investment decisions (Calvert et al., 2017).

Earlier investigation included a mixed traffic environment between GLOSA equipped and non-equipped vehicles, i.e. not all vehicles receive the speed advisory messages from the intersection management (Wan et al., 2016). Even at low penetration rates, micro simulation case studies show that GLOSA equipped vehicles have a harmonizing effect on the motion of conventional vehicles which helps create smooth traffic flow, while optimizing fuel efficiency (Picron, et al., 2015). Research show that GLOSA yields substantial better utilization of infrastructure capacity, can reduce vehicles delay and emissions; consequently, leading to significantly influence the quality of life, which is a major goal of smart city initiatives (Pereira et al., 2017).

1.2 Problem Formulation

In the near future, both conventional and automated vehicles will be connected to intersection management systems and equipped with certain wireless communication capabilities. The main concern is how to manage the vehicles propagation through the intersection in an efficient manner. GLOSA as a proposed management technique for connected vehicles has not been examined in terms of the relation between its efficiency gains and the dependency on drivers' compliance to the advice received. The need for more research arises since drivers are not obliged to comply and follow the speed recommendation received, while full compliance is assumed on the side of automated vehicles.

From the traffic theory point of view, introducing shorter time gaps between vehicles could be a catalyst to increase the road capacity q_{CAP}, which is inversely proportional to the minimum average time headway t_{HW} between vehicles.

$$q_{CAP} = \frac{1}{[t_{HW}]} \qquad (1)$$

While it may be true that automated vehicles have an edge on minimizing their time gaps; accordingly increasing road capacity and traffic efficiency, early stages of partial automation may not be as positive for traffic flow and operational road capacity (Calvert et al., 2017).

The reasons for uncertainty are related to the unknown effects in practice. Also, there is a lot of ongoing research to discuss safety issues regarding sudden system shutdown or false object recognition and accident responsibility, as well as the effects of the interaction between automated and non-automated vehicles (Calvert et al., 2017).

When automated vehicles are first introduced, they are only partially automated, meaning that only some of the vehicle functionality is autonomous, such as for example the Adaptive Cruise Control (ACC), which regulates the distance to the vehicle in front. For the safety reasons mentioned earlier, most recent studies used larger desired time gap settings of values between 1.2 and 1.8 seconds for partial automated vehicles using ACC. Even though desired time gaps of human drivers are generally around a range of 0.5-1.5 seconds, this means that introducing partial automated vehicles will lead to higher average time headways and consequently lower capacities (Calvert et al., 2017). Nevertheless, the main problem in urban areas is not necessarily the capacity on the road links but is more of the capacity fluctuation at bottlenecks, lane merges and drops, and intersections.

To conclude, operating automated vehicles in an urban environment is a challenging topic accompanied with many disputes. Therefore, the urge for a proper and effective traffic management system emerges, in order to enhance the traffic flow results and to overcome the adverse impact in early automation implementation stages.

1.3 Study Objectives

The purpose of this thesis project is to contribute to the evaluation of the traffic signal control strategy GLOSA (Katsaros, et al., 2011) . The aim is to investigate how the effectiveness of GLOSA depends on drivers' compliance to the recommended speed advice and to assess the potential increase in effectiveness when introducing AVs with absolute compliance.

Also, the aim is to determine the possible outcome resulting from enhancing the automated vehicles capabilities such as implementing short time headways between vehicles in the future.

1.4 Research Questions

The fundamental core of this thesis project is guided by the following inquiries:

- How is traffic performance affected by human drivers' compliance to the recommended speed advice?
- Does the introduction of automated vehicles help GLOSA improve the traffic efficiency in a mixed environment? And how does changing the automated vehicles time gap affect the results?
- What are the expected gains when operating GLOSA with fully compliant automated vehicles with shorter time gaps?

1.5 Delimitations

The following delimitations are defined:

- Only isolated intersection signal control will be considered, thus coordination schemes between different traffic controllers will not be considered.
- Global positioning systems (GPS) accuracy is assumed to be optimal since position errors are not considered, in contradiction with the real time current GPS possible obtained efficiency.
- Vehicles travel through the intersection in a straight forward manner. Thus, no incoming turns are allowed from any opposing direction. This approach influenced by Faraj et al. (2017) is adapted for simplicity and to only reflect the effects of GLOSA.
- Vehicles are assumed to only have V2I connectivity. No form of V2V is assumed.
- Vehicle types are limited to connected conventional cars and connected partial automated vehicles (SAE level 2).
- Compliance is set to the same value for all conventional vehicles in each scenario, i.e. no variation in compliance between drivers.
- Human reaction time and automated vehicles processing time to adapt the suggested speeds are set to different constant values.
- Safety and legislations are not taken into consideration when modelling the automated vehicles.
- The pedestrians, trucks, buses and cyclists' movement are disregarded to simplify the model.

1.6 Methodology

The thesis work is a simulation project concerned with evaluating the results of implementing the latest state-of-the-art in traffic management GLOSA through "Simulation of Urban Mobility-SUMO". SUMO is chosen as it is an open source, highly portable, microscopic road traffic simulation package designed to handle large road networks. The thesis undergoes several methodological steps as follows:

- Literature review
- Model construction
- Model verification
- Defining the number of simulations replications needed based on confidence interval
- GLOSA algorithm development and implementation
- Running simulations
- Statistical analysis and assessment of simulation results

Literature review is done to acquire the latest information on intersection control management for connected and automated vehicles in smart environment. This is performed using keywords such as: “traffic signals” and “GLOSA” + “SUMO” and “Automated vehicles” or “Connected vehicles” + “Isolated intersection control”.

The base simulation model is built and defined by the inputs necessary to run the simulation. The Swedish computer software ‘CAPCAL’ is used for calculation of traffic signal phase planning based on the traffic volumes specified. Further model definitions to be found in chapter 6. The construction of the base model is followed by verification procedures among which the model behavior is compared with respect to traffic flow theory.

The mean and standard deviation values for a defined simulation output are calculated to include the uncertainty in the model, i.e. different simulation runs will give different results thus certain number of simulation replications has to be run in order to meet the confidence interval required.

In order to implement the GLOSA algorithm, a python script runs and connects to SUMO through TraCI, which is the short term for "Traffic Control Interface". Giving access to a running road traffic simulation, it allows to retrieve values of simulated objects and to manipulate their behaviour "on-line". TraCI uses a TCP based client/server architecture to provide access to SUMO. Thereby, SUMO acts as server that is started with additional command-line options.

Final step is running and assessment of the different simulation scenarios and analyzing the output results obtained in order to deliver the answers the research questions.

1.7 Outline

Chapter 2 presents terminology and different control strategies related to traffic signal control. While chapter 3 describes the benefits of connected vehicles which communicate their updated information to the infrastructure or other vehicles or both. It also includes the levels of vehicle automation starting from conventional vehicles to fully automated. Current practical and research progress is also discussed in this chapter, as well as the objectives of implementing automated vehicles in urban cities. Barriers and challenges facing the introduction of vehicle automation is presented while relating to partial automated vehicles and its dependency on adaptive cruise control.

Chapter 4 presents GLOSA as one of the latest technologies in traffic management, in addition to the expected gains from operating such traffic control technique.

Chapter 5 analyzes the major traffic simulation classification and demonstrating that microscopic simulation is used in this thesis project through the open source software SUMO. It also describes the necessary requirements and defined assumptions needed to run the simulation.

Chapter 6 features the simulation scenarios in addition to the definitions of road network attributes, vehicular demand, and modelling of vehicles in the simulation environment. This chapter also includes a description of the model verification which includes error checking and establishes that the model parameters correspond properly to traffic flow theory definitions.

Chapter 7 presents the results of the defined scenarios, while chapter 8 handles the discussion, and chapter 9 provides the thesis project conclusion and possible future work.

2 Traffic signal control

2.1 Traffic signal control for intersection management

Traffic lights control as one of the traffic management methods is an important and effective way to improve urban road capacity, ease traffic congestion and reduce vehicle delay time. The rationality and efficiency of traffic signal control strategy are directly related to the effectiveness of urban traffic management (Mathew, 2014). Therefore, extensive research has been ongoing to develop traffic signal control algorithms (Yang et al., 2016).

In order to understand traffic signal design, several expressions are explained below (Mathew, 2014):

- Cycle: one complete rotation through all of the traffic lights (Red, Green, Yellow).
- Cycle length: the time in seconds for a signal to complete the full cycle. It specifies the time interval between the beginnings of green of one direction/approach till the next time the green starts again for the same direction.
- Change interval/Yellow time: the time between the green and red signal for a certain direction.
- Clearance interval/All red: after each yellow, all red is a period where all signals show red for clearing off the vehicles in the intersection.
- Green interval: the green light timing for a certain approach.
- Red interval: the time of red-light indication for a certain approach.
- Phase: the green interval in addition to the change and clearance intervals that follow. While the light is green, non-conflicting movements are assigned into each phase. This coordinates the flow of different directions safely in each phase.
- Lost time: the time when the intersection is not utilized effectively for any direction. For instance, a certain signal turns to green from red, the first driver in the queue will take some time to recognize the signal which cause time loss before the vehicle moves and proceeds to cross the intersection. Lost time also occurs when the signal is red for all approaches i.e. during the switch from one phase to another, there is a clearance time required which implies all red for some time, lost time is the sum of all this time.

Traffic control strategies have been evolved with the aim of minimizing the total time spent by vehicles (Yang et al., 2016). In general, traffic control can be primarily divided into two elementary categorizations: (1) the fixed time/Pre-timed control and (2) the traffic responsive control. The fixed time control works well within closely spaced intersections with consistent traffic volumes and patterns through the defined times of a day but it cannot respond to traffic changes in real time since cycle length, phase plan, and phase times are pre-determined (Koonce, 2008).

To solve this drawback, researchers proposed the traffic responsive control which embraces both actuated and adaptive traffic control. Firstly, the actuated traffic control uses detector measurements such as inductive loops or pattern recognition cameras to cope with the traffic volume (Yang et al., 2016). Based on detection data, green time for each phase is extended. However, signal timing is subject to a set of pre-defined parameters like maximum green duration for instance (Chi et al., 2010). Also, minimum green time must be set for each phase in actuated control (Mathew, 2014). It resembles the shortest time allocated to extend the green period. While the maximum green time limits the length of a green phase, even if there is a continuous stream of vehicles passing through the detectors to retain the green.

Secondly, the adaptive traffic control which belongs to the latest generation of traffic control, adjusts signal timing parameters in real-time, to adapt to current traffic conditions. Adaptive signal phase plan is continuously regulated and tuned based on the fluctuating arrival patterns of vehicles at an intersection (Atkins, 2013). The traffic control assigns the green timing to each direction based on the predicted arrivals. Understandably, the length of each phase changes as vehicle arrival patterns change through the day (Atkins, 2013). Such systems can improve performance by 5 to 30 percent in areas with unpredictable or rapidly changing traffic volumes (Koonce, 2008). Needless to say, both perspectives of traffic responsive control performance mainly depend on the quality of detection systems (Koonce, 2008).

Predominantly, any type of the previously mentioned traffic signals is used to control the movement of vehicles passing through one isolated intersection. Traffic signal coordination is another management approach done to enable vehicles in a specified direction to get continuous green, when passing through successive closely spaced intersections (Mathew, 2014). This can minimize delay and trip duration/travel time and also increases throughput. Not all consecutive signals can be easily interrelated. Limitations for applying the coordination method are wide variations in road speeds or short signal timings for example.

Intersections are common bottlenecks in roadway systems and applying intelligent systems for controlling traffic congestion in urban roadways has been inevitable (Koonce, 2008). Traffic control makes the current roadway system operate more efficiently without building new roads or widening the existing ones which is often impossible due to scarce land availability. Examples of intelligent management systems include machine learning methods, fuzzy systems, and multi agents (Pereira et al., 2017), as well as enhancing vehicle-to- infrastructure connectivity as in GLOSA systems (Wan et al., 2016).

Traffic signal plan design (CAPCAL)

In order to obtain a realistic signal plan, the Swedish computer software "CAPCAL" is used for calculation of capacity, degree of saturation, traffic signal phase planning in addition to accessibility in roundabouts and intersections regulated by obligation to stop, yield or by traffic signals. Calculations can be made for both three and four armed intersections. Shuttle signals along a road stretch (two approach roads, for instance over a narrow bridge) can be also calculated. CAPCAL uses the methodology described in the Swedish transport administration's (Trafikverket) capacity manual (TRV2013/64343).

Input for CAPCAL is divided in Geometry/overview, Volumes, Signal, Calculation of Average Daily Traffic ADT and costs and calculation variables. For traffic signal design, CAPCAL computes the input values for safety time (All Red + Red-Yellow time), loss time which is the safety time plus part of yellow time not used to dissolve vehicles, in addition to the phase green time and total cycle length.

3 Vehicle Connectivity and Automation

C-ITS technology involves having vehicles link with each other and the infrastructure. This allows road users and traffic management to share and use information that was previously not available (Pereira et al., 2017). The vehicle connectivity concept is about contributing with useful information to guide the driver to make safer or more informed decisions, since the use of a connected vehicle doesn't imply that the vehicle is making any choices for the driver. It provides information to the driver, including potentially unsafe situations to circumvent, and then it is up to the driver to react and make the proper action (Murtha, 2015).

The main proposition of the connected vehicles (CV) framework lies in the power of wireless connectivity. A vehicle could be connected to another vehicle (V2V), where they transmit messages to each other with their information. This includes speed, location, travel route, braking, and loss of stability within a defined range of communication up to 300 meters or a travelled distance of about 10 seconds of driving at highways. Also, vehicles can be connected to the infrastructure such as traffic signals control or other stationary devices, thus having a vehicle-to-infrastructure (V2I) connectivity. Cars could also have connectivity and information exchange with any entity that affect them, and this connectivity type is abbreviated by (V2X) for vehicle-to-everything (Khair et al., 2017).

Connected vehicles have the potential to significantly mitigate the impact of millions of accidents every year (IEEE, 2018). By limiting the number of crashes, thousands of lives will be saved, and millions of injuries prevented. Also, Pereira et al. (2017) state that the main benefits from acquiring any vehicle connectivity type are safety and energy savings, in addition to real time traffic estimation and acquiring a smoother flow.

Currently, there are two perspectives on connected vehicles: the Google approach, where connected vehicles act as fully automated, also called autonomous vehicles engaging connectivity to enable self-driving mode i.e. if the system disengages or connection is lost, then the vehicle will not be able to locate itself and fail to recognize the surrounding environment. Other vehicle manufacturers take a different approach, where connected vehicles still possess manual vehicle control while having continuous real-time connectivity amongst vehicles and/or infrastructure (Khair et al., 2017).

In most cases, vehicles that incorporate advanced driver assistance systems (ADAS) and C-ITS can be considered as connected (IEEE, 2018). Vehicle communication and safety applications aim to increase situation perception and mitigate traffic accidents through wireless communication (IEEE, 2018). Without revealing personal information, this technology should enable transportation organizations to access vehicle data related to velocity, position and trajectory; allowing better management of traffic flow as the capability to address certain problems in real time (Murtha, 2015).

In addition to the driver receiving information, connected vehicles CVs could broadcast their information to transportation authorities to enhance the knowledge of prevailing road conditions, as well as to create historic data that will help authorities to better scheme and allocate future resources (Murtha, 2015). By deploying roadside devices, which read and exchange signals within these vehicles, the transportation agencies can extensively participate in a widespread implementation of the connected vehicle system (Murtha, 2015).

Connected vehicles and their applications are expected to form a foundational component of automated driving as they allow the swapping of sensor data among vehicles, cooperative positioning and map updating, as well as ease maneuvers between connected automated vehicles (IEEE, 2018). This anticipated technology will help to re-structure the automotive world, traffic engineering design and management operations in the future (Khair et al., 2017). It is a feasible alternative to help solve transportation issues faced by most countries.

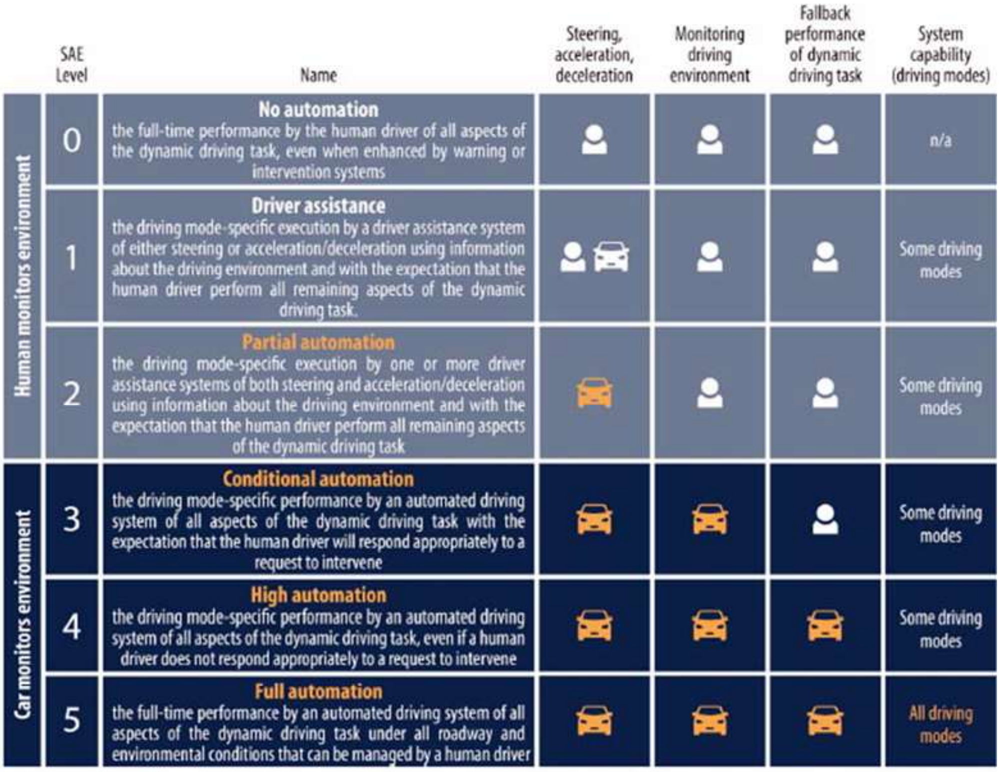
The necessity for integration of connected vehicles and effective long-range forethought has moved to the cutting edge of significance, especially since there is currently a greater need for providing infrastructure upgrades to accommodate connected vehicle technologies. If responsible planners start incorporating connected vehicles and the infrastructure, transportation systems will be supplemented (Khair et al., 2017).

CVs can have apparent benefits on the safety, operation and the environment of transportation networks are apparent. Based on recent studies, CV technology is able to expand capacity of existing transportation networks, in addition to increased road safety through the development of intelligent transportation systems, and implementation of these communication technologies amongst vehicles and infrastructure has the potential to yield benefits that will improve as time evolves (Khair et al., 2017).

Automated vehicles are the future smart cars: they are anticipated to be driverless, energy-saving and crash avoiding. The concept of having a fully automated vehicle means that it drives using built in cameras, sensors, computer processors, and data bases such as maps to control almost all of the human-driving functions (Rajasekhar et al., 2015) and without communication with other vehicles or infrastructure (Parent, 2013).

Automated vehicles have been a research matter for more than 30 years (Parent, 2013). In 1994, the Prometheus European project terminated 8 years of research with presentation of autonomous driving on the A1 highway close to Paris. In 2005, the DARPA Challenge ended with 4 vehicles racing more than 100 km along an off-road course fully automated. Two years later, the DARPA Urban Challenge presented several autonomous vehicles operating concurrently with manually driven vehicles in an urban environment. Recently, Google demonstrated automated vehicles running for thousands of miles in California and Nevada, forcing the obliged states to proceed with legislation concerning the operation of automated vehicles on public roads.

Different definitions for the levels of vehicle automation exist. The Society of Automotive Engineers (SAE) defines five levels; (1) Driver assistance, (2) Partial automation, (3) Conditional automation, (4) High automation and (5) Full automation. Driver assistance and partial automation are considered low levels of automation where the driver is still involved with certain tasks (Calvert et al., 2017). Figure 1 illustrates the dynamic driving tasks distribution between the human and the machine for each automation level, starting from the human driving mode (Zero Automation) to the fully automated driving (Level 5).



Source: Automated and Autonomous Driving, OECD/ITF, 2015 (adapted from SAE Standard J3016, SAE International 2014).

Figure 1 - Levels of driving Automation

The main challenge for vehicle automation is to customize existing conventional vehicle technology to a near expected autonomous vehicle (Rajasekhar et al., 2015). Many challenges act as barriers in implementation of automated vehicles technology. The barriers include the cost related to manufacturing and research of automated vehicles, the reliability of the technology, deployment rate, security and privacy concerns and standards and legislation to guarantee safe introduction of autonomous vehicles, where one of the most important barriers is to have safe and reliable autonomous vehicles on the road.

Autonomous vehicles will appear on the market if the legislative barriers involving safety can be removed (Parent, 2013). However, this approach does not seem to be accompanied with much improvement in terms of road capacity if automated vehicles are only autonomous and share the road with non-cooperative vehicles i.e. automated vehicles need to be connected and retrieve some guidance information or share their information to the traffic management centers.

Through communication, automated vehicles can become much more efficient. They can cooperate with the infrastructure to improve the flow of traffic by variable speed limits or intersection management (Parent, 2013). Automated and conventional vehicles can also cooperate to improve traffic safety and efficiency.

There seems to be a lot of potential for automated vehicles either in research or traffic management, safety and efficiency improvement. But the most important is safe implementation of this technology through applying stringent rules and standards to gradually transit to fully automation (Rajasekhar et al., 2015).

In this thesis, the use of the term "automated vehicle" refers to any level of automated technology, while the main focus of the contribution is on the lower levels of automation, specifically; the partial automated vehicle (SAE level 2) with Vehicle-to-infrastructure connectivity V2I.

Partial automated vehicles (SAE level 2) mainly depend on ACC for longitudinal propagation and speed control. Adaptive cruise control is known as dynamic cruise control or intelligent cruise control. ACC can maintain a set speed like conventional cruise control, but it can also have varied speed based on upfront traffic flow. This technology can not only make cruise control more useful, it is also a step towards automated driving. The fundamental idea is that a car can accelerate or decelerate automatically, based on its surrounding vehicles behaviour (Edelstein, 2017).

To perform such control, the vehicle must be equipped with sensors that detect nearby vehicles and potential obstacles. Most ACC systems use radar, although cameras and LIDAR (light waves) can be used as well. The sensors communicate with a processor that controls the throttle, brakes in addition to steering capabilities in partially automated vehicles (SAE level 2). A basic ACC system handles acceleration and deceleration, usually by locking onto the leading car in front with the built-in sensors and keeping a safe following distance and speed (Edelstein, 2017).

One of the major challenges facing ACC is that its sensors can be sensitive to bad weather. Severe weather conditions, like heavy rain or snow will bias the sensor located in the grille or under the bumper (Oponeo, 2018). Therefore, the sensors can become unable to distinguish the distance between the driving vehicle and the vehicle in front (this is more common with laser sensors than radar sensors). Also, ACC is unable to adjust to changing speed limits. This means that sensors can tell the speed of leading vehicles, but they are unable to adjust to changing speed limits. So, whilst ACC is convenient, the driver may be required to intervene and push the brakes to prevent random hazards on the road. Similarly, the ACC struggles to react to spectral objects or vehicles in other lanes. As technology develops, this will be less common, but on bending roads the system can suffer from separating lanes apart. On turning lanes, the system may indicate that a vehicle is upfront when it is in a different lane. Most of these issues can be resolved by using a pre-set speed, but it can discard the general autonomy of the ACC system.

At this stage, ACC is a long way from a comprehensive autonomous driving experience, yet it endures as an invaluable tool for many drivers around the world. In its current form, the system is good at moderating the distance from vehicles ahead, meaning that drivers don't have to alternate between the gas and the brakes repeatedly (Oponeo, 2018).

Adaptive cruise control is one of the driving assistance systems that could form the basis for fully automated driving. Sensors already deployed in ACC systems and partially automated vehicles will be crucial to fully automated vehicles in the future (Edelstein, 2017).

4 Green Light optimal speed Advisory GLOSA

GLOSA (Katsaros, et al., 2011) is one of the latest state-of-the-art in traffic management and ITS technologies; based on vehicle-to-infrastructure connectivity and interactive communication. It has the potential to improve traffic efficiency through suggesting speed change to vehicles approaching a signalized intersection, thus reducing the waiting times at traffic signals.

In section 4.1, the GLOSA algorithm is being described with a detailed explanation on how the system should work. Section 4.2 presents different evaluations and tests of GLOSA, in addition to the expected gains from operating such traffic control technique.

4.1 GLOSA algorithm

Stevanovic et al. (2016) state that the GLOSA management approach uses ongoing traffic signal control information such as phase schedule and remaining green time along with current vehicles information (speed, position, acceleration capability) in order to recommend an appropriate speed for vehicles and to facilitate their movement during the green interval

The intersection control receives information (position, speed) from each vehicle within the communication range as shown in Figure 2 . Based on the remaining green and red times acquired from the Traffic lights phase plan, the GLOSA algorithm runs in the traffic intersection control as in Table 1, then GLOSA sends the speed advice to the vehicles.

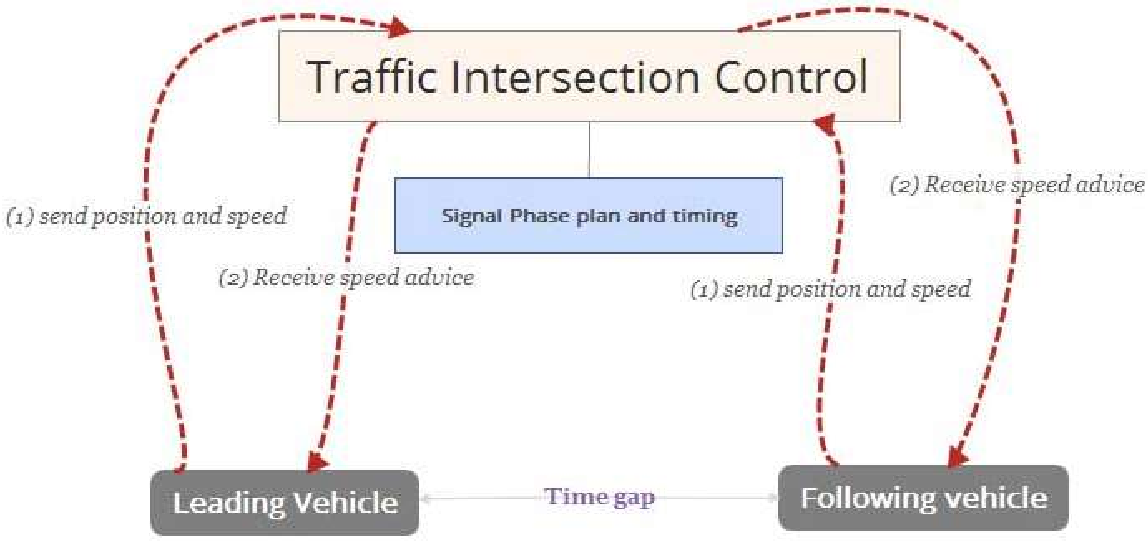


Figure 2 - GLOSA system architecture

The main point from implementing the GLOSA algorithm is to adjust the speed based on the current and upcoming traffic lights. Thus, in case of green signal and enough time to pass the intersection, speed is calculated based on the remaining green and the distance to intersection.

In other cases, when the time to pass is not sufficient or the light is not green, the speed is optimized based on the total time to reach green again or set to the minimum speed value. Table 1 illustrates the GLOSA algorithm in a detailed manner.

GLOSA abbreviations are described in detail as follows: *DistanceTI* is the distance to the intersection and *TTI* is the time to intersection; calculated instantaneously through the current vehicle speed (S) and *DistanceTI* where *TTI=DistanceTI/S*.

Vmin is the minimum advice speed of 5 (m/sec). *Rr* is the remaining red time in the signal time plan, *Rg* is the remaining green time, *Ry* is the remaining yellow time, and *S* is the GLOSA speed recommendation value. While *Tr, Tg,* and *Ty* are the total red, green, and yellow times in the signal plan respectively, taking into consideration that signal timing is known, which is not commonly the case in an actuated signal. In an actuated signal, *Tr* (as well as *Tg* and to some extent *Ty*) need to be estimated based on the traffic demand from the own and other approaching roads.

Table 1 - GLOSA implemented algorithm

Green Light Optimal Speed Advisory (GLOSA) Algorithm (Faraj et. al, 2017)

Receive information from Traffic lights inside the communication range defined

If light is *Red,* **then**

  If TTI ≤ Rr

    S = V_{min}

  If Rr ≤ TTI ≤ upcoming Green time (Rr+Tg)

    keep the current speed to pass during the upcoming Green light

  If TTI > upcoming Green time (Rr+Tg)

    Optimize the speed to catch the following next Green light

    S = max (d(t)/ (Rr + Tg), V_{min})

If light is *Green,* **then**

  If TTI <= Rg

    Maintain current speed

  If TTI > Rg

    Optimize the speed

    S = max (d(t)/ (Rg + Ty + Tr), V_{min})

If light is *Yellow,* **then**

  Check DistanceTI and Ry

   Accelerate accordingly **Or** Decelerate

Computing the recommendation speed is done for each vehicle individually when entering the communication range of the traffic intersection control. The speed advice is subject to some constraints such as time to intersection (TTI), minimum speed (V_{min}) and current light signal as well. The speed recommended should minimize the idling time of a vehicle based on the defined constraints and can be calculated as illustrated earlier in Table 1.

To further illustrate, for instance; if the light is green: there will be two states that the vehicle maybe in. The first case where the computed TTI is less than or equal to the remaining green time (i,e, TTI <= RG), then by using the current speed, the vehicle will arrive and pass through the traffic intersection. The second case: the computed TTI is greater than the remaining green time (i.e., TTI > RG); thus, the speed of the vehicle must be optimized over the distance to the intersection so that the TTI is sufficient to meet the next green light as the vehicle will not be able to pass through this current green signal.

Let's assume a vehicle approaching the intersection from East in the second signal phase as per Table 4 in section 6.1. The TTI is calculated based on the vehicle current speed and distance from the traffic intersection and since the vehicle was 200 meters away from the intersection with a speed of 14 (m/s) approximately; thus, TTI it is equal to 14.28 seconds at this exact simulation time step, while the remaining green is 3 seconds. The algorithm applies the optimization process each simulation time step as follows:

$$S = \max\left(\frac{d(t)}{Rg + Tr + Ty}, Vmin\right)$$

This equation produces a 6.875 (m/sec) speed which is adapted gradually instead of the original vehicle speed, taking into consideration that the algorithm acquires the maximum value from both the calculated speed recommendation advice and the minimum speed. This is done because if the vehicles get too close to the intersection, the generated speed advice could have very low or even negative value.

4.2 Previous applications of GLOSA

By reviewing the state of the art in traffic management and specifically GLOSA, the following cessation was discerned: Traffic efficiency can be enhanced through applying different approaches according to Kaths (2016). For instance, connected vehicles can provide the traffic intersection control with their trajectories in order to adjust the signal timing plan. Also, the vehicles could optimize their speeds based on the received advice messages from the intersection control, which is the core concept applied in this thesis project. Meanwhile, a model predictive control algorithm adapts mutual optimization of signal timing and vehicle speeds through integrating connected vehicles information in the feedback loop of traffic signal control.

The study by A. Stevanovic et al. (2013) implements the GLOSA management technique for both fixed-time control and actuated control. By sending speed recommendations to vehicles when using the fixed control, the waiting time at intersections decreases as the GLOSA penetration rate increases, which consequently improves the traffic performance. In case of using actuated control, the authors observe a reduction in the system performance due to unspecified phase durations (Tg, Ty, and Tr). Also, Stevanovic (2014) strengthen that GLOSA is unlikely to have a positive impact on traffic performance for actuated coordinated signal control.

According to Katsaros et al. (2011), GLOSA's optimal activation distance was found to be about 300 meters away from the traffic lights. For shorter distances than the optimal, the time to react is limited and further away there are no more considerable benefits. This study imparts that the maximum achieved benefits from increasing the GLOSA penetration rate reached 80% stop time reduction; taking into consideration that all drivers follow the speed recommendations.

Previous research by Wan et al. (2016) included a mixed traffic between GLOSA equipped and non-equipped vehicles, i.e. not all vehicles receive the speed advisory messages from the intersection management. Microsimulation case studies relay that even at relatively low penetration levels, the equipped vehicles have a harmonizing effect on the motion of conventional vehicles, thus contributing to better energy efficiency, while accompanied with a slight increase in travel times. In this thesis project, the mixed traffic environment involves conventional and partial automated vehicles but both vehicle types receive the speed recommendation advice based on the current traffic lights and the vehicle's current speed and location.

It is observed by Picron, et al. (2015) that vehicles never stop with 100% GLOSA equipped vehicles; leading to no waiting time in the simulations. Moreover, GLOSA has an impact on non-equipped vehicles that follow the behavior of equipped vehicles and also slow down when approaching an intersection.

Contrary to the existing systems that consider each traffic light separately, GLOSA as presented by Seredynski et al. (2013) performs speed optimization using a genetic algorithm which also takes traffic lights coordination into account; this means that several lights in sequence on a vehicle's route can be considered. Speed advice is provided to drivers for each segment and they also have access to all traffic light phases they will encounter on their routes. Through operating fixed time signal control in free-flow conditions, the coordinated multi-segment speed approach gives much better results than single-segment GLOSA.

Another genetic algorithm approach is also discussed by Li, Dridi, & El-Moudni (2014) where the authors tackle the problem of vehicles not crossing the intersection with maximum speed. The algorithm searches for the optimized vehicle speeds, according to the minimal fuel consumption and minimal total running time. The simulation results indicate that, in free-flow conditions, the optimized values can conserve fuel consumption by almost 70 percent, save total trip time by 12 percent compared to traditional method. Furthermore, it is again stated that coordination between neighbour intersections has a definite impact on traffic enhancement.

The analysis by He, Liu, H.X., & Liu, X. (2015) proposes a multi-stage control logic which aims to prevent vehicle idling stops at intersections. The results show that the speed advisory model endeavours to smooth the traffic and to reduce absurd vehicle acceleration and deceleration maneuvers leading to minimize fuel consumption.

The GLOSA system presented by Suthaputchakun et al. (2015) applies adaptive traffic control in a vehicle-to-infrastructure mutual information exchange environment, in addition to a priority scheme for heavy vehicles since they have the most fuel consumption among other vehicles. The simulation results demonstrate that improving the trucks throughput during the green light extremely reduces fuel consumption and CO_2 emissions as a result. To further enhance results when using adaptive control, the paper by Bodenheimer et al. (2014) increases the accuracy of the phase prediction and shortens the time window to the next possible signal change through usage of detectors and historic data.

The latest technology in GLOSA is implemented by Faraj et al. (2017). This scheme uses speed optimization for platoons of autonomous vehicles and relies on both V2I and V2V connectivity. The leading AV performs the optimization so that the platoon can hit the green light when arriving at the intersection. The following AVs run an intelligent decision algorithm to decide on the feasibility of joining the platoon. The algorithm from this study is modified and used in this thesis project.

To conclude, implementing GLOSA reduces fuel consumption and waiting time at intersections. But it is also concluded by Eckhoff et al. (2013) that GLOSA is not the absolute optimal management procedure in all traffic conditions. The study proves that there are several side effects from implementing GLOSA in dense traffic, including overall longer waiting times and more CO_2 emissions for unequipped vehicles.

In case of massive GLOSA deployment, safety has to be further studied as it is among the concerns of centralized GLOSA systems where the decision and control is done by the intersection control. This is due to the single point failure possibility and real time computational complexity (Picron, et al., 2015). Future work is suggested by Picron, et al. (2015) to assess the gain of cooperative traffic lights and the impact on user’s experience and acceptance, and also on those of non-equipped vehicles drivers.

5 Traffic simulation

Traffic simulation is reported by Barceló et al. (1998) as an operation that uses computer processing to imitate an actual system by building a simulation model which can be used to discover solutions by proposing diverse scenarios in the original system. Traffic simulation is utilized to assess and evaluate transportation systems. The simulation output results may be used for traffic authorities and management decisions for infrastructure improvements (Lansdowne, 2006). Based on the level of simulation detailed features, there are three main categorizations for traffic simulation models, specifically; macroscopic, mesoscopic and microscopic.

Firstly, a macroscopic model is used to simulate traffic by considering traffic elements such as speed, density, flow, and their relationships to each other (Dowling et al., 2004). Macroscopic models only offer low level of details. Such models were developed to represent traffic on the higher network of transportation in order to analyze the road level of service and to forecast the spatial extent and congestion that occurs.

Secondly, mesoscopic models are a combination between microscopic and macroscopic simulation models which can model large study areas with more comprehensive information than macroscopic models (Dowling et al., 2004). These models simulate individual vehicles or a group of vehicles, but describe their activities based on macroscopic relations (Savrasovs, 2009). On one hand, the microscopic model has the requirement of more detailed data to simulate traffic behaviour with the highest accuracy. One the other hand, this mesoscopic type of models is primarily used in the evaluations of traveller information systems and thus it can stimulate the routing of individual vehicles equipped with in-vehicle, real-time travel information systems (Dowling et al., 2004).

Finally, a microscopic model describes the most extreme level of details in traffic simulations. It models individual vehicles running along the road and the interaction between them (Olstam J. , 2005). Vehicles movement is determined by using a car following, lane changing and gap acceptance rules, acceleration and speed adaptation (Fox, 2012).

According to Krauss (1998), the dynamics of an individual vehicle is a function of the position and speed of the neighboring vehicles. This thesis project is a microscopic traffic simulation which focuses on the position and velocity of single vehicles in addition to the vehicle-to-infrastructure communication. The thesis work also considers the dynamical processes of car-following and lane-following models using the traffic simulator SUMO (P. A. Lopez, et al., 2012).

SUMO (Simulation of Urban Mobility)

SUMO (P. A. Lopez, et al., 2012) is a highly portable, microscopic road traffic simulation package designed to handle large road networks. It is mainly developed by employees of the Institute of Transportation Systems at the German Aerospace Center (DLR). The software development started in 2001 and it became an open source in 2002.

Microscopic traffic simulation via SUMO is used as an alternative tool to analytical methods for road traffic performance. A simulation model is constructed following SUMO's defined requirements including the traffic network characteristics, and vehicular traffic demand.

SUMO has its own format to represent a traffic simulation base model, so it requires a road network and traffic demand to be run the simulation. The model is built in *SUMO* as follows in Figure 3.

The scenarios are built in SUMO such that necessary files are defined and used as an input to the model. The simulation output is generated with an online interaction through the Traffic Control Interface *TraCI* section 5.1.4.

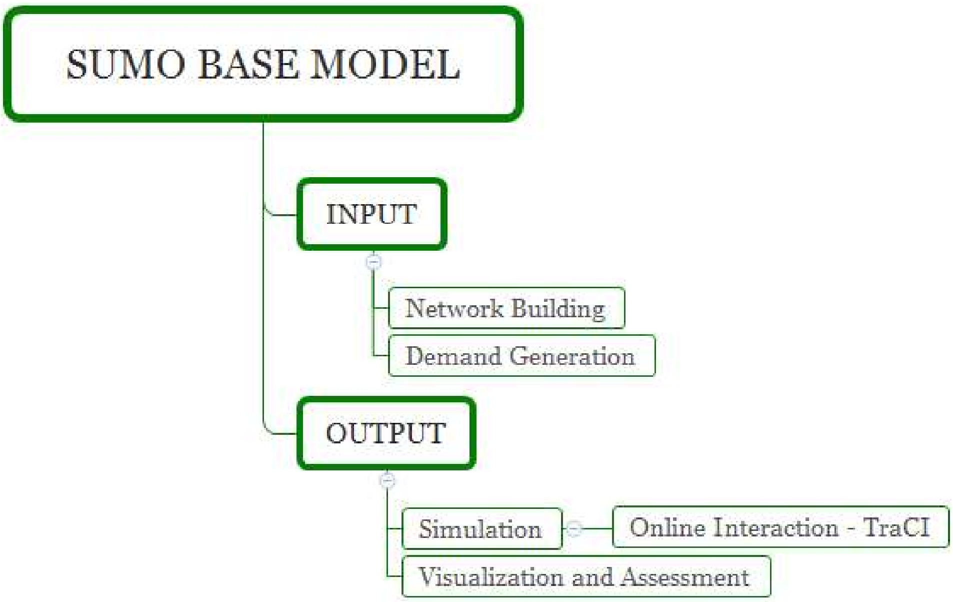


Figure 3 - SUMO Base Model

5.1.1 Network Building

A SUMO network file describes the traffic-related part of a map, the roads and intersections the simulated vehicles run along or across. At a coarse scale, a SUMO network is a directed graph. Nodes, usually named "junctions" in SUMO-context, represent intersections, and "edges" roads or streets. Specifically, the SUMO network contains the following information:

- Every street (edge) as a collection of lanes, including the position, shape and speed limit of every lane.
- Traffic lights logic.
- Junctions, including their right of way regulation.
- Connections between lanes at junctions (nodes).

Through SUMO's module, NETEDIT; the intersection is modified in order to make its attributes suitable to the specific simulation configuration settings. NETEDIT is a graphical network editor to create or modify SUMO networks. It is also used to debug network features and correct map importing errors, being one main important role is to edit the lane to lane connections and the traffic signal control logic.

5.1.2 Demand Generation

It is the process of creating the traffic demand to be modelled in the simulator. This includes the definitions of vehicle types, and routes which are all edges the vehicles will pass onto. Depending on the available input data, there are several ways to generate routes for SUMO.

By default, vehicles of a certain direction are spaced equally in time. SUMO's module 'DUAROUTER' with the option "randomize flows" generates trips with random arrivals based on the defined traffic volumes and input values for the car-following model. When randomizing the flow, SUMO specifies that the headways between vehicles in the same direction are equally distributed over one simulation period, while the number of vehicles (flow) is always the same. This is verified in section 6.7.

5.1.3 Car following model

Drivers' behaviors and vehicles longitudinal movement when following another vehicle are described by a car following model; an essential tool of any traffic simulation software, which affects the accuracy of results extremely.

There are two numerical integration methods to control the dynamic update of the vehicles' positions in the simulation. The default is a Euler update, which considers the vehicle's speed constant during one-time step. Instead, SUMO offers the ballistic update, which yields more realistic dynamics for car following models; considering constant acceleration during each time step. Ballistic update causes positions to be updated with the average speed between time steps instead of the current time step.

Car following models are described by equations governing the dynamics of the vehicle such as position and velocity. SUMO uses the Krauss car following model which belongs to the Safety-distance models' category, where the vehicles velocity is adjusted to keep a safe distance to the front vehicle (Pourabdollah, 2017). The following vehicle always adapt to the deceleration of the leading vehicle (Dayi Qu, 2014). The safe speed is calculated as follows:

$$V_{safe} = V_l(t) + \frac{g(t) - V_l(t).t_r}{\frac{V_l(t) + V_f(t)}{2b} + t_r} \qquad (2)$$

Where $V_l(t)$ represents the leading vehicle speed, $g(t)$ is the net distance gap to the leading vehicle, t_r is the driver's reaction time and b is the maximum vehicle deceleration (m/sec^2)

The car following model of a vehicle defines its speed in relation to the vehicle ahead. The default model (Krauss) always selects the maximum speed which is *safe* in the sense of being able to stop in time to avoid a collision.

The ideal speed is retrieved through the following equation to avoid having speeds larger than the maximum allowed speed and to follow its acceleration capabilities, where t is the simulation step duration.

$$V_{ideal} = \min\left[V_{max}, (V + at), V_{safe}, V_{Desired}\right] \qquad (3)$$

Driver Imperfection (Sigma)

The *sigma* parameter signifies the driver imperfection, with a range of [0, 1]. For values above 0, drivers with the default car-following model will drive *slower* than would be safe by a random amount (between [0, acceleration]). It causes random decelerations and is used to model a) speed fluctuations and b) slow-to-start behavior, causing increased headway between vehicles when accelerating from a stop. Automated vehicles are assumed to have an imperfection of value zero in order to reflect rapid responsiveness and stable system awareness.

Minimum gap

The *Min gap* parameter signifies the desired empty space after a leader vehicle and is set to 2.5 meters by default. The Car Following Model defines a vehicle's speed in relation to the vehicle ahead. The default model (Krauss) always selects the maximum speed which is *safe* in the sense of being able to stop in time to avoid a collision.

Reaction time

Drivers take actions with some delay regarding the evolving traffic situation. This reaction time is modelled in SUMO in various ways as (1) simulation step length, where vehicles select their speed simultaneously regarding the traffic state from the previous simulation step and (2) Action step length.

The simulation step length is the time between each decision made by the car following model. In order to simulate the driver reaction time, the action step length is introduced and defined through a separate attribute in the vehicle type flows definitions to a value of one sec which is equivalent to average human driver reaction. This means that the simulation is updated each time step (t = 0.2s) while the driver reacts each one sec.

Action step length parameter is used to decouple the simulation step length from the frequency of driver decision making. It can be defined as the duration between subsequent vehicle decisions. Decision-making starts directly after insertion which means vehicles inserted at different times may take decisions during different simulation steps.

During simulation steps without decision-making, vehicle positions are updated according to the previously computed acceleration. This attribute was applied to model the real human driver reaction time and the automated vehicles processing time, as we set the action step length to values equivalent to or less than the *Tau* value for each vehicle type in order to avoid collisions.

By default, the action step length is equal to the simulation step length which works well for the default step length of 1s. When performing sub-second simulation by setting a lower step-length value, it may be useful to maintain a higher action step length in order to model reaction times and in order to reduce computational demand and thus speed up the simulation. The action step length must be a multiple of the simulation step length.

Time Headway (Tau)

The *tau* parameter is intended to model drivers desired time headway (in seconds). Drivers attempt to maintain a minimum time gap of tau between the rear bumper of their leader and their own front-bumper + minimum gap to assure the possibility to brake in time when their leader starts braking and they need tau seconds reaction time to start breaking as well.

5.1.4 TraCI (Traffic Control Interface)

In order to implement GLOSA algorithm, a python script runs and connects to SUMO through TraCI, which is the short term for "Traffic Control Interface". Giving access to a running road traffic simulation, it allows to retrieve values of simulated objects and to manipulate their behaviour "on-line".

TraCI uses a TCP based client/server architecture to provide access to SUMO. Thereby, SUMO acts as a server that is started with additional command-line options and the external script (the "controller") is the client. The "controller" is a Python-Script which receives information about the simulation state from the server and then sends instructions back.

After connecting to the simulation, various commands can be emitted and executed till closing the connection or the specified simulation end time is reached. A python script runs the GLOSA algorithm presented in Table 1 and initiates a connection to SUMO through TraCI which enables the traffic control to retrieve all vehicle types' information.

TraCI controls and manipulates the vehicle speed and AVs time headway settings online. Both vehicle types are connected to the intersection control through a simulated wireless connection via TraCI. V2I connectivity is accomplished for all vehicles running in the simulation within a certain communication range. TraCI is used in this thesis work as the traffic signal control and GLOSA application is performed through a python script running on the TraCI plugin connected to SUMO.

5.1.5 Replications

As the vehicles arrival and driver behavior patterns are stated to be stochastic; a certain number of simulations runs (iterations) is calculated based on the confidence interval assigned. This procedure ensures having close-to-reliable results after calculating the mean and standard deviation values for the defined parameters (Burghout, 2004).

As simulations are run with random seed, stochastic vehicle and driver behaviors cause diverse results. A certain number of simulations runs – so called *replications* – is decided to reflect the randomness and provide valid results with defined reliability (Burghout, 2004).

The formula used to determine the final number of replications is

$$N(m) = \left(\frac{S(m).\,t_{m-1,1-\alpha/2}}{\overline{X}(m).\,\mathcal{E}}\right)^2 \qquad (4)$$

where,

N (m) = the number of replications required, given m replications

$\overline{X}(m)$ = the estimate of the real mean m from m simulation runs (samples)

S (m) = the estimate of the real standard deviation s from m simulation runs

α = Level of significance

$\mathcal{E}$ = Allowable percentage error of the estimate $\overline{X}(m)$; $\mathcal{E} = \left|\overline{X}(m) - m\right| / |m|$

$t_{m-1,1-\alpha/2}$ = critical value of the two-tailed t-distribution at a level α of significance, given m-1 degrees of freedom.

6 Description of the Simulation Model

This chapter includes the simulation main scenarios along with their sub-scenarios in a more granular perspective. The sub-scenarios show the variations in the model parameters such as penetration, compliance rates and vehicles time headway, taking into consideration that the traffic flow is constant for all the simulation scenarios. Definitions of road network attributes, vehicular demand, and modelling of vehicles in the simulation environment are also presented in this chapter.

If a vehicle equipped with GLOSA enters the traffic intersection communication range, the algorithm in the traffic control initiates the process of retrieving the required information for calculating the speed recommendation advice such as current vehicle speed, and distance away from the intersection. Based on the time for the designated vehicle to reach the intersection, the current signal light and remaining time, the traffic control sends the speed advice which appears on the GLOSA screen inside the vehicle. In a conventional vehicle, the driver will follow and adapt to this speed manually with a variance in reaction times, and compliance rates from one driver to another even though reaction times variation is not modelled in this thesis. If the vehicle was automated, it adapts the speed automatically with the defined machine response rate and full compliance.

In order to fulfill the aim of the thesis and answer the research questions, the following experiments in Figure 4 are to be modelled in the open source software “Simulation of Urban Mobility-SUMO" (P. A. Lopez, et al., 2012). The experimental scenarios include variations in human drivers’ compliance to the speed recommendation advice, in order to engage the GLOSA effect on traffic performance for conventional vehicles. The mixed traffic scenario helps investigate the improvements in traffic efficiency after introducing automated vehicles, while the last scenario analyses the benefits of operating 100% automated vehicles managed by GLOSA.

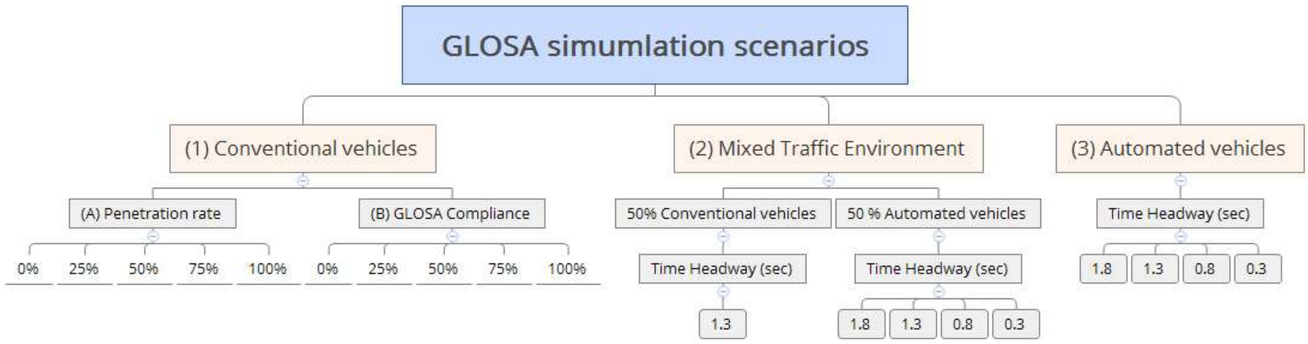


Figure 4 – Simulation scenarios and sub-scenarios

The simulation scenarios were modelled as follows: (1) Connected Conventional vehicles scenario, (2) Mixed scenario including Connected both Conventional vehicles and Automated vehicles, and (3) Connected Automated vehicles. All simulated vehicles are connected to the traffic control through a mutual exchange of information V2I and I2V, while scenario (1A) investigates what happens when only parts of the conventional vehicle fleet are connected to the traffic light.

To generate variations in vehicle arrival patterns and driver behaviors in each simulation, different seeds for the random number generator are used to run the simulations with which causes diverse output results for each simulation. The simulation output values are retrieved from the summary output file, generated by SUMO for each simulation step time, aggregated for the whole simulation period and presented in Table 2. While in order to ensure consistent comparison of the results between different strategies, the network, car-following model inputs and departure times of vehicles (as well as their destination and behavior) are the same for each replication.

In order to calculate the minimum number of replications required, an initial value (m) of 5 replications helps capture the model defined measures of effectiveness (waiting time, trip delay and average travel time) i.e. the simulation output values considered to calculate the number of replications required as per Table 2.

Table 2 - Simulation output values per replication

Replication	Seed number	Average Waiting time (sec)	Average Trip delay (sec)	Average Travel time (sec)
1	23420	88.24	333.35	476.67
2	23421	99.95	345.65	488.89
3	23422	87.85	333.92	477.18
4	23423	89.70	337.93	481.20
5	23424	89.87	341.39	484.62

Equation (4) from section 5.1.5 is used, where the mean and standard deviation of the output values are retrieved. The allowable error ($\mathcal{E}$) is 5 percent, while the level of significance (α) of 5 percent corresponds to a confidence interval of 95 percent.

It was concluded from equation (4) that 10 replications were needed to return a confidence interval of 95% for the waiting time output, while only one simulation replication is needed to generate 95% confidence for trip delay and travel time (on the metric and scenario with the highest deviance).

Finally, it was decided to run only 3 replications per scenario due to the repetitive change in simulation settings in terms of traffic signal design, vehicle attributes, and the large number of simulation scenarios in addition to the difficulty of generating the output results automatically. The low number of simulation replications arises as a new a limitation and will cause the simulation results to have only 80 percent confidence for the waiting time output but still 95% confidence for trip delay and travel time.

6.1 Traffic network

The simulation platform is a fictional four leg signalized intersection with one lane in each approach as in Figure 5. The traffic lights control system is a two-phase system with East-West directions as one phase and South-North as another phase. Vehicles travel in a straightforward manner i.e. no right or left turnings are allowed. This limited vehicle movement is adapted to simplify the project and was also performed by Faraj et al. (2017) in their simulations. The speed limit in SUMO is defined in m/s and set to 20 m/s on all road lanes as an approximate of a speed limit of 70 km/h.

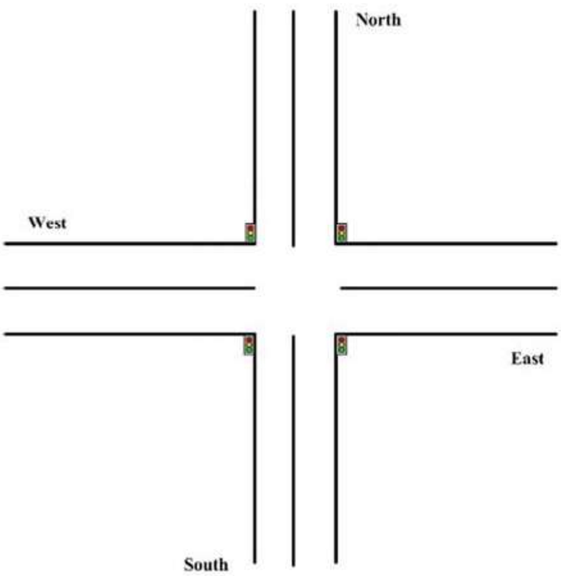


Figure 5 - Four leg signalized intersection

6.2 Demand

In this thesis, the simulated traffic flow defined from each origin to destination is based on fictional volume assumptions since it is not truly valid to acquire data for automated vehicles or a mixture between conventional and automated vehicles. The vehicle flow is given in vehicles per hour and direction as assigned in Table 3. The characteristics of both vehicle types (conventional and Automated), and behavior of drivers are clearly described in section 6.4 and 6.5.

Table 3 - Incoming traffic flow per approach

Approach	Traffic Volume (veh/h)
North	250
South	340
East	650
West	300
Total number of vehicles	1540

6.3 Traffic signal settings

The number of needed phases and the necessary green times as well as safety times presented in Table 4 - Phase signal timing and plan. Calculations were done using the Swedish software CAPCAL, see description in section 0 *Traffic signal plan design (CAPCAL)* based on the intersection geometry, flow definition and the road speed limit.

Table 4 - Phase signal timing and plan

Approach	Phase signal	Phase duration [sec]	Comments
North-South	GrGr	11	Green for North-South while Red for East-West
	yryr	4	Yellow for North-South while Red for East-West
	rrrr	3	All-Red for all approaches (safety time)
	ruru	4	Red-yellow for East-West
East-West	rGrG	23	Green for East-West while Red for North-South
	ryry	4	Yellow for East-West while Red for North-South
	rrrr	3	All-Red for all approaches (safety time)
	urur	4	Red-yellow for North-South

The TL parameters acquired from CAPCAL are as follows: Phase (1) *North – South* Green Light time, Tg = 11 sec; Phase (2) *East – West* Green Light time, Tg =23 sec; Yellow light time, Ty = 4 sec; Cycle time, C = 56 sec.

6.4 Vehicle characteristics

The vehicle types modelled in this thesis are limited to only two types: connected conventional cars and connected automated cars (SAE level 2).

Vehicles *departure lanes* and *speeds* are set to *best* and *max* respectively, which means that no vehicles should have a delay time when entering the simulation with a desired normally distributed near-max speed.

Table 5 defines the attributes related to the physical extent and capabilities of the vehicles apart from the driver-vehicle definitions. It is relatable that there could be differences in vehicles of the same type and there should be differences between connected conventional and automated vehicles in terms of acceleration, deceleration or other features but the thesis aims to limit the variables as much as possible to be able to focus on the main topic and analyze the thesis scope scholarly.

Table 5 – vehicle capabilities and physical attributes

Vehicle type	Length(m)	Width (m)	Maximum Acceleration (m/s^2)	Maximum Deceleration (m/s^2)
Conventional/Automated	4.3	1.8	2.2	4.5

While the vehicles' length, width, acceleration and deceleration are set for all vehicles types identically as per Table 5, the parameters in section 6.5 are tweaked to model each vehicle type separately. Those parameters include speed distribution and car following model characteristics such as the *Action step length, sigma, tau,* and *minimum gap*, and also incorporate vehicles shapes and colors.

6.5 Driver Behaviour characteristics

The SUMO flow definitions xml file was used to implement vehicles' behavioral attributes exposition. Table 6 shows the car following model (Krauss) parameters used on SUMO simulation tool.

Table 6 - Car following model (Krauss) parameters

Car-following model parameters Vehicle type	Driver Imperfection (Sigma [0,1])	Min Gap (m)	Time headway in seconds (Tau)	Reaction time in seconds (Action step length)
Conventional	0.8	2.5	1.3	1.0
Automated	0	2.5	0.3, 0.8, 1.3, 1.8	0.2

Speed distribution

SUMO models the speed of vehicles, such that a vehicle keeps its chosen speed factor for the whole simulation and multiplies it with the edge speed limit to compute the actual speed for driving on this edge. Thus, vehicles can exceed edge speeds. However, vehicle speeds are still capped at the vehicle type's maximum speed.

The ideal desired speed of a vehicle is given by the minimum between its maximum speed and the multiplication of its speed factor by the speed limit on the approach:

Desired speed = min {vehicle maximum speed, *speed factor* * Road speed limit}

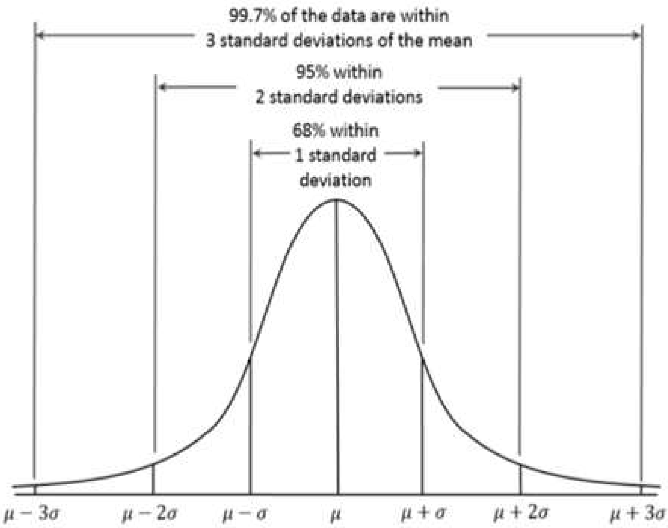


Figure 6 - normal distribution

The normal distribution presented in Figure 6 is a probability function that describes how the vehicles' speed values are distributed in a symmetric order. Even though vehicles maximum speed is set to V_{max} = 70 km/hour, the defined normal distribution for vehicles speed (speed factor), controls how each vehicle behave on the road.

SUMO controls the variation in vehicle speed by having a vehicle maximum speed, road speed limit, as well as upper and lower speed bounds from the normal distribution. The s*peed factor* defined in the string *(1.0, 0.1, 0.6, 1.0) follows* a normal distribution of vehicles speed based on mean, standard deviation, minimum and maximum values. For both vehicle types, the *speed factor* defined will result in a speed distribution where 95% of the vehicles drive between 80% and 120% of the legal speed limit defined, while the other 5% will drive from 60% up to 100% the speed limit.

6.6 Modelling of drivers' compliance to GLOSA

Vehicles speeds are defined by the normal distribution in section 6.5 along with a certain road speed limit modelled as a maximum speed that vehicles can't exceed. While running the GLOSA algorithm, the vehicles have an additional restriction as they are not allowed to drop below a certain road speed since drivers don't intend to drive at very low speeds in real life. This is simulated with having a minimum road speed**,** thus; vehicles' behaviors are modelled to choose speeds within the lower and upper speed bounds i.e. there is no advice sent to any vehicle with less than 5 (m/s). Therefore, once the calculated speed recommendation value is less than the minimum speed, it is disregarded, and the minimum speed is sent to the vehicles instead, which forms a constraint for controlling the GLOSA process.

The simulation outputs include the average trip waiting time, trip delay and travel time in seconds for the running vehicles and average trip speed in meters per second as well. The simulation results are first evaluated with reference to the scenario (1B): "connected conventional vehicles" for zero GLOSA compliance. Then further comparisons are done to illustrate the occurring enhancements to the scope.

For the first scenario (1B), the drivers' behavior in terms of compliance to the speed advice is evaluated for different percentages ranging from non-complying to fully complying drivers. While for the second scenario (Mixed traffic of conventional and automated vehicles), and third scenario (100% Automated vehicles); automated vehicles are assumed to have full speed compliance.

The human drivers' compliance is modelled through the following equation:

$$GLOSA_{des} = v_{des} + (v_{adv} - v_{des}) * CF \quad (5)$$

Where, $GLOSA_{des}$ is the desired speed acquired when applying GLOSA. v_{des} is the desired speed of individual vehicles adapted according to the speed distribution in the simulation model. v_{adv} is the advice speed sent from the traffic control to the vehicle. CF is the human compliance factor ranging within the interval [0,100]

The values of compliance rates can be illustrated as follows, for example: 50% speed compliance means that if the driver was following a desired speed of 15 m/sec according to the normal speed distribution, and then receives the advice to decelerate to 10 m/sec, he chooses to keep a speed of 12.5 m/sec. Compliance is interpreted as how much the driver changes his speed in regard to the advice received.

6.7 Model verification

Model Calibration and validation are essential parts of any traffic simulation. Calibration is the process of adjusting model parameters in order to match the real-life scenario while validation is comparing the simulation outputs with actual results to check its accuracy (TSS, 2010). However, the lack of emulations or real traffic data for automated vehicles makes it only applicable to conduct some "best-of-knowledge" calibration and validation or so-called model verification in order to make a connection between the simulation model and the traffic engineering theory clear (Horiguchi et al., 2000).

Verification implies qualifying tests using virtual data sets in order to guarantee for example reasonable capacity levels in the intersection. This confirms that the model functions with respect to the implemented parameters such as total number of vehicles generated and arrival distribution patterns in addition to the saturation flow and road capacity.

Dowling et al. (2004) suggest that the verification task should be also done to check errors in the simulation model, and it includes the following three subtasks:

- Software error checking
- Input coding error checking
- Animation review

Software error checking consists of making sure that all known bugs in the software are considered. SUMO (P. A. Lopez, et al., 2012) is updated to the latest version (0.32.0) and software users' forum "Sourceforge.net" is being constantly checked. No bugs were detected, and all commands are functioning properly.

Input coding error checking is the process of checking and correcting discrepancies between the input data, in terms of the network, the traffic control and the demand, and the implemented simulation model. Only one issue was detected and corrected in this matter, which was severe deceleration above the emergency limit for few vehicles. This was due to a short yellow time. This was resolved by revising and re-designing the CAPCAL signal timing plan then increasing the yellow time to 4 seconds instead of 3 seconds as per the CAPCAL calculations.

Finally, the animation review consists of reviewing the animation of the simulation in order to discover errors not found in the two previous sub-tasks (Olstam & Tapani, 2011). There were no vehicles teleporting, jams, accidents, script malfunctions or any other issues detected in this last review.

In order to verify the model with respect to traffic flow theory; certain components are defined to successfully completing the verification process such as vehicle counts and arrival rate, taking into consideration that the unconnected conventional vehicles scenario is the one that undergoes the verification process.

Vehicle counts are classified into several categories amongst is the *Inserted vehicles* that resembles the total number of vehicles that entered the simulation network in all approaches (East, West, North and South). It was shown from simulation log files that the total number of vehicles generated and inserted in the simulations in each replication is equal to the total traffic input volume of 1540 vehicles defined through the SUMO *flows* file as in Table 3 in section 6.2. This is done to verify the whole design traffic volume being managed.

There is a coherent relation between the time headway and the vehicle arrival/generation. It could be argued that both are the same in the sense that vehicles are generated and inserted into the simulation with the concept of taking the desired time headway into consideration.

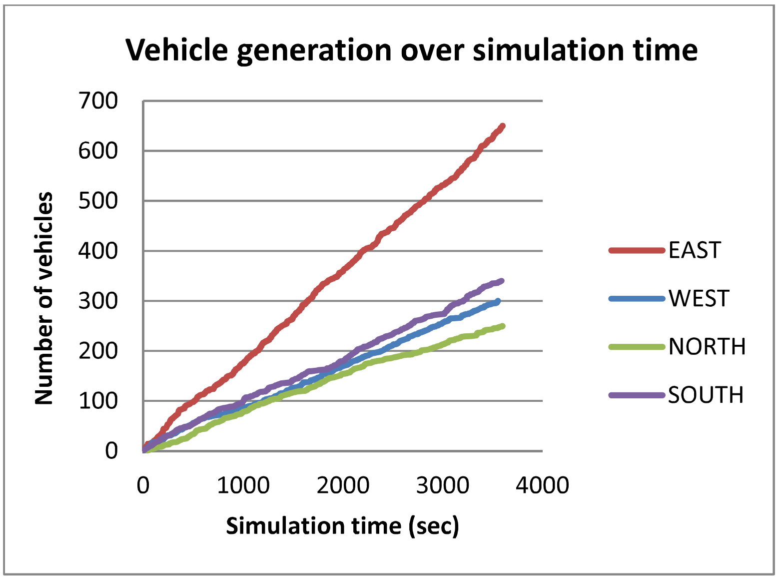


Figure 7 - Vehicle arrival/generation per approach

Figure 7 shows that the traffic counts for each approach are linearly increasing till the simulation ends and have nearly the exact same generation end time but what differs is the increment over time since each approach has a different traffic volume. This proves the equidistributional theory for the vehicle generation over the simulation period as stated in SUMO documentation, meaning that the limit of the proportion in any particular sub-interval is equal to the ratio of this interval to the whole simulation period.

Another important component to verify the model with respect to the traffic theory is the capacity flow. In order to retrieve the capacity values, saturation flow rate must be acquired. Saturation flow is an important value used in traffic signal design. It defines the number of vehicles in a very dense scenario where vehicles are constantly moving through a green light intersection for an hour (Bester & Meyers , 2005). Thus, it can be calculated as follows:

$$s = \frac{3600}{h_s} \qquad (6)$$

Where:

s = saturation flow rate (veh/h)

3600 = seconds per one hour

h_s = saturation headway

The saturation flow rate depends on roadway and traffic conditions, which can vary from region to another. Capacity is a traffic performance measure used to modify the value of saturation flow with respect to a real signal design. It overcomes the assumption that vehicles are moving with the same headway distance between each other and enhances the effect of the green in the signal plan. The capacity can be illustrated as the maximum hourly flow of vehicles that can be discharged under certain traffic conditions, roadway characteristics and signal plan (uidaho, 2012). The capacity value is retrieved as follows:

$$c = \frac{g}{C} * s \quad (7)$$

Where:

c = capacity (veh/h)

g = effective green time for the specified phase (sec)

C = cycle length (sec)

s = saturation flow rate (veh/h)

Since the saturation headway is assumed to be the same as the simulated headway equal to 1.3 seconds, therefore the saturation flow rate for all travel directions is 2770 (veh/h) approximately. Capacity is then calculated and presented in Table 7 based on the values of effective green time and cycle length acquired from the traffic signal plan implemented in Table 4 of section 6.2.

Table 7 - Capacity calculation for traffic flow verification

Approach	Effective green (sec)	Effective green/Cycle length	Theoretical Capacity (veh/h)	Capcal Capacity (veh/h)
North	11	0.196	544	480
South				472
East	23	0.410	1137	903
West				853

The signal design is based on the traffic flow from the east and south approaches as they contain the maximum volumes in each phase. Thus, those two approaches are only analyzed to verify the capacity in the simulation model with respect to the traffic flow theory.

According to basic traffic flow theory concepts, the flow-density diagram is a parabolic or triangular shaped curve used to determine the traffic state of a road. It consists of two vectors where the first is the free flow side of the curve starting from the origin of the graph while the second vector is the congested side with a negative slope to the point of congestion and zero flow. The intersection of both vectors is the apex of the curve and is considered the capacity of the roadway. This value is acquired from the simulations and plotted for the east and south directions, where the traffic flow is increased 1.15 and 1.30 times the original flow defined. The difference in the flow multiplication factor between the east and south directions goes back to having different traffic saturation flow and capacity. Flow-density relationships are depicted as in Figure 8, and Figure 9, then compared to the corresponding values in Table 7.

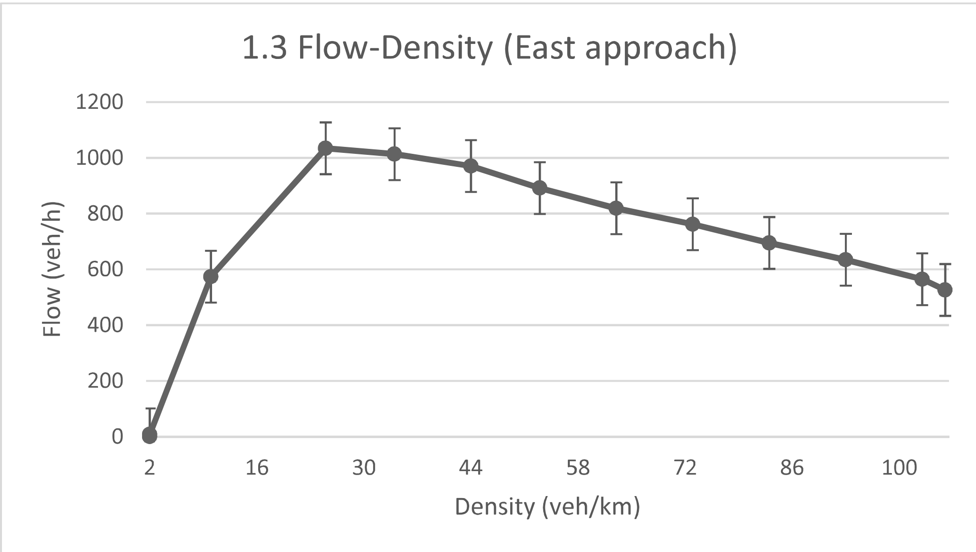


Figure 8 - Flow density relationship for East Approach (130% original traffic volumes)

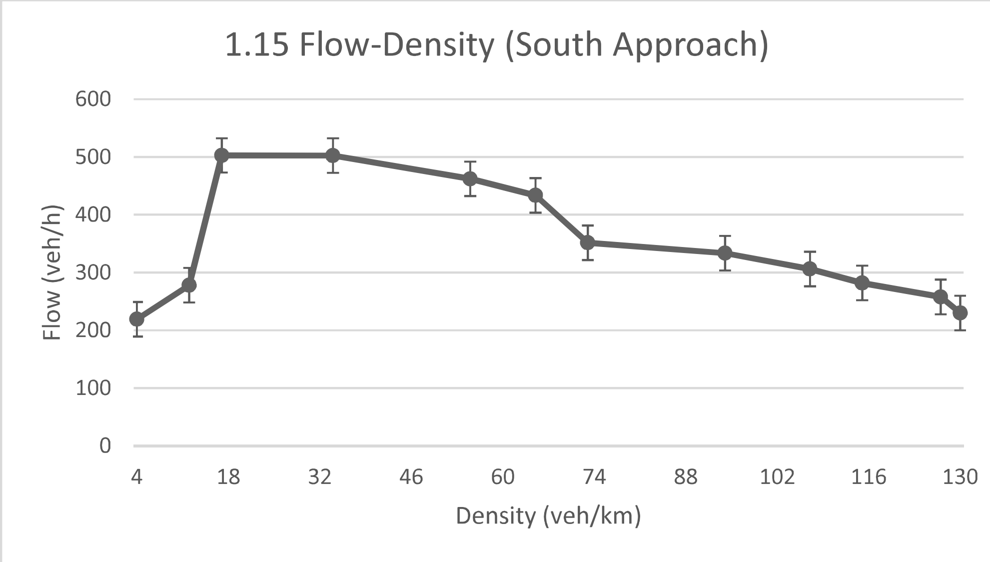


Figure 9 - Flow density relationship for South Approach (115% original traffic volumes)

It is apparent from the flow density graphs above that the capacity acquired from simulations for both directions correspond to the values of calculated theoretical capacity as well as the capacity retrieved from the Swedish Software for traffic signal design "Capcal", which verifies that the implemented model is valid from the traffic point of view.

7 Simulation Analysis

7.1 Communication range analysis

The communication range is the defined distance away from the traffic intersection where the vehicles start broadcasting their information allowing the traffic control to retrieve and use the data to better enhance the traffic conditions.

In this section, the communication range is being analyzed to determine the best distance ahead from the intersection for the vehicles to initiate the connectivity and information exchange. This range is based on the least average waiting time achieved assuming the presence of 100% connected conventional vehicles with 100% compliance to the speed recommendation advice.

The analysis is performed by monitoring changes in the output through a scatter plot of output variables against the individual input variable. The seed and all other model parameters are kept constant for each simulation run in this procedure, as the intent is to discuss the model outcome with the defined variable input (communication range).

This analysis enables questioning the robustness of the results. The seed number generated controls the vehicles arrival patterns and drivers' behaviors in each simulation run separately. This also means that by changing the seed, the whole simulation attributes vary including the vehicles and drivers' characteristics

To limit and bound the results, the scenario considered for the analysis is the connected conventional vehicles scenario with 100 percent speed compliance and 100 percent penetration as well, adapting the vehicle attributes and car following model parameters in Table 5 and Table 6 respectively.

The analysis is performed to check the GLOSA algorithm performance for different Vehicle-to-infrastructure communication ranges in order to apply the optimal range settings, based on the average traffic performance measures (waiting time, trip delay and trip travel time). The waiting time is the average time spent standing involuntarily and time loss/trip delay is the average time lost while driving slower than the desired speed and it also includes the waiting time; taking into consideration that the desired speed is defined by the speed factor.

To sum up, the input parameter considered in this analysis is the communication range within the running vehicles and the intersection control, while the output parameters are the waiting time, trip delay, and travel time. The communication range is analyzed using the OFAT method; thus, maintaining all the inputs the same for each run, to ensure the output change is only due to the change in this specific input parameter.

The aim of the applied analysis is to measure both the waiting time, trip delay, and travel time but the communication range decision is based upon obtaining the least possible waiting time values. The Communication range effectiveness is analyzed for the interval [100, 450] in meters. The range is firstly set to 100 meters away from the intersection, then incremented with an interval change of 50 meters for each analysis.

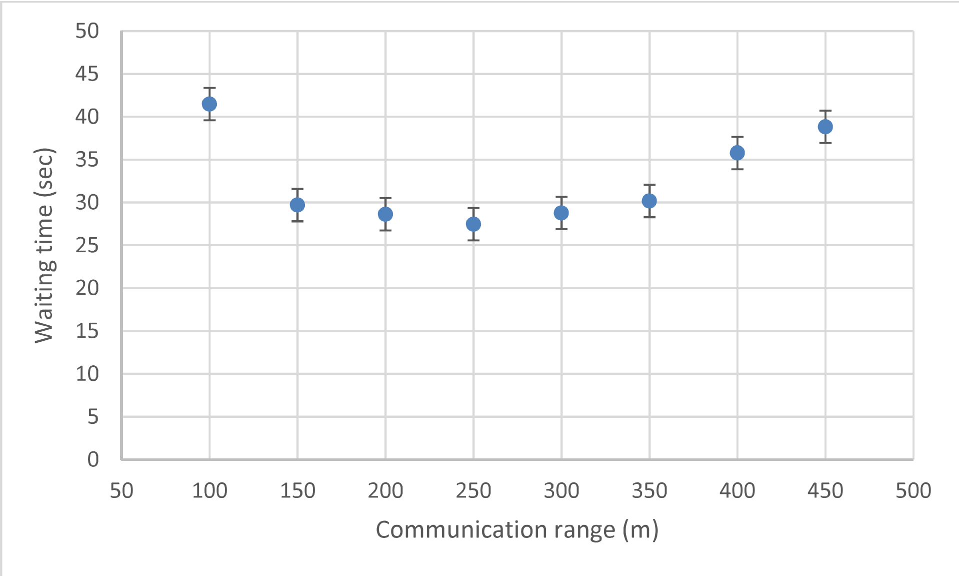


Figure 10 - waiting time analysis for different communication ranges

As shown in Figure 10, at communication range 250 meters; the average waiting time per vehicle has the smallest value equal to 27.45 seconds. While the average trip delay per vehicle from Figure 11 is 95.35 seconds for 1540 vehicles running for an hour, a route length of around 2630 meters with average trip travel time of 238.62 seconds.

As the communication range increases, the waiting time is expected to decrease while the delay increases due to earlier speed minimization than the desired speed. The vehicles should drive slower to avoid waiting at the intersection control which consequently will increase the trip travel time. However, the implemented GLOSA algorithm seems to fulfill this hypothesis since results manifest that the waiting time decreases as the range increases; but it also illustrates that the benefits of the algorithm drop after a certain distance and it is no longer feasible to implement it further away from the intersection as this will only lead to increasing the average trip delay and average trip travel time as well.

Moreover, the conducted analysis shows that when the communication range is too short, there is not enough time to reflect the algorithm benefits. Also, as the range increases further than certain limit; results get worse and no more benefits occur in terms of reducing the trip delay or waiting time.

Waiting time increases due to the insufficient distance for the algorithm to run and for the vehicles to adopt the speed advice. This makes the vehicles behave similarly to a normal scenario without connectivity and it is a valid reason that the algorithm doesn't have an effective result with very low distances. The delay analysis in Figure 11 shows the minimal value for the implemented settings at

300 meters away from the intersection, also the communication range of 300 meters enhances better values for the travel time output as in Figure 12.

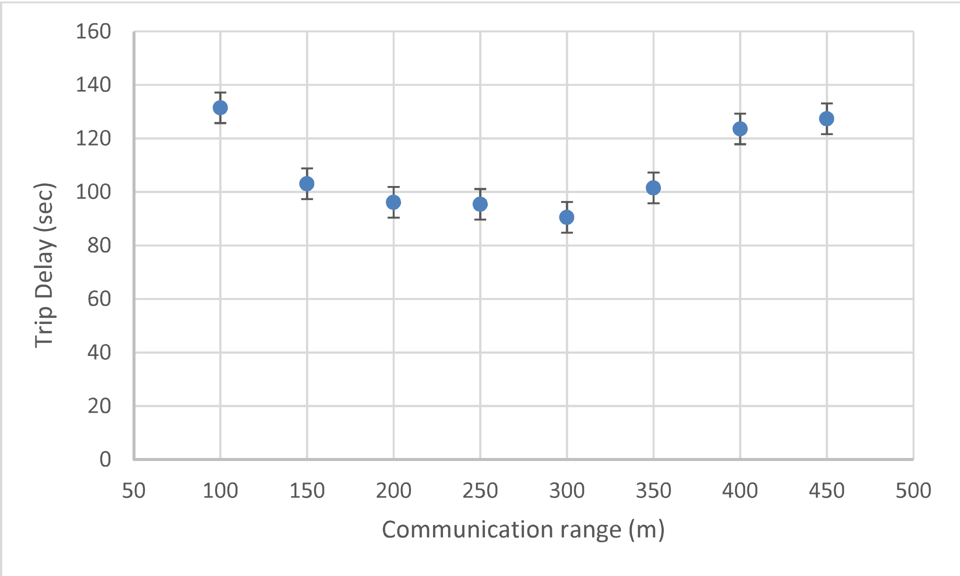


Figure 11 – Trip delay analysis for different communication ranges

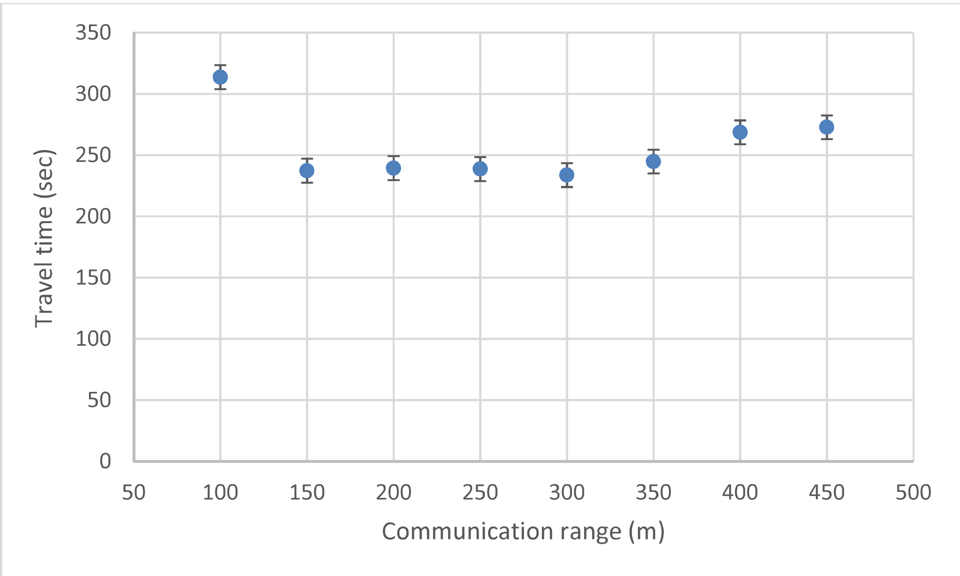


Figure 12 - trip Travel time analysis for different communication ranges

It is clear from Figure 11 and Figure 12 that trip travel times are directly proportional to the trip delay. In Figure 10, waiting time decreases as the communication range increases till 300 m away from the intersection control then its behavior changes to increase. From the analysis, it was obvious that the range of 300 meters is the best position to apply the algorithm with the simulation defined parameters for obtaining the least trip delay and travel time but it was clarified earlier in this section that the analysis aim is to acquire the range for the least waiting time which sets the communication range to be around 250 meters.

Another analysis is performed to measure the effect of applying the GLOSA algorithm for red lights and green lights separately i.e. the speed advice is only sent when the traffic signal light is red or green. The original implementation runs for both lights simultaneously which means that the algorithm operates the whole time. But in this procedure, the aim is to measure weights for the effectiveness in each case. Figure 13 shows that running the algorithm for the red lights only, results in decreasing the waiting time 13 percent less than the original scenario with no connectivity.

Figure 13 - waiting time for separate traffic lights

While applying it for the green lights, the GLOSA algorithm only yield improvements of 53 percent and 28 percent in waiting time and trip delay respectively, taking into consideration that the main functioning algorithm has an effect of 66 percent waiting time reduction and 70 percent trip delay reduction as presented in Figure 13 and Figure 14. Therefore, the GLOSA algorithm is decided to be run for both traffic lights simultaneously.

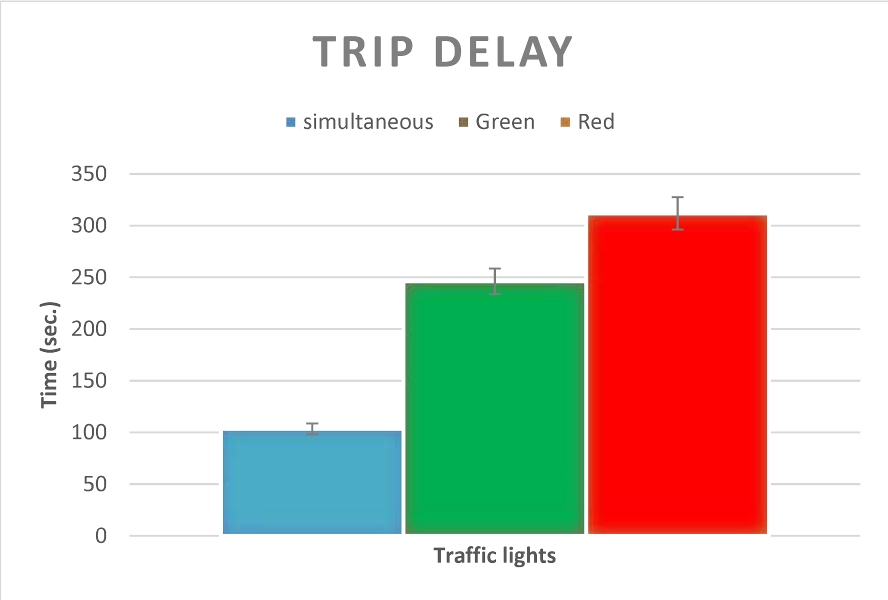


Figure 14 – Trip delay for separate traffic lights

7.2 GLOSA algorithm analysis

In most of the simulated scenarios, results are significant to some extent with casual overlaps in the confidence interval determined. Table 8 shows the effect of increasing the penetration rate of conventional vehicles equipped with GLOSA connectivity. The penetration rate is changed from 0 to 100% and full compliance to the GLOSA recommendation is assumed for the connected conventional vehicles. It is quite clear that the waiting time improvement is negligible for sub-scenarios of 25% and 50% penetration rates. The effect of connectivity only starts to appear when 75% of the market is penetrated to yield 19% waiting time reduction and 53% decrease in trip delay. The maximum waiting time reduction achieved was around 66% for full market penetration of GLOSA for connected conventional vehicles.

Table 8 - Traffic performance for different penetration rates and full compliance

Scenario	Penetration rate	Waiting time (sec)	Trip delay (sec)	Travel time (sec)
(1 A) Conventional vehicles	0 %	93.17±11.29	341.66±7.44	484.90±7.41
	25 %	92.21±9.44	277.33±38.02	420.58±38.05
	50 %	92.74±9.85	222.01±26.47	365.26±26.45
	75 %	75.70±5.31	160.18±22.21	303.43±22.18
	100 %	31.47±8.92	103.46±14.57	246.71±14.54

There is a plain inverse relation between the penetration rate and the trip delay, which is a good indicator that increasing the percentage of GLOSA connectivity causes a decrease in trip delay ranging from 35 % to 70% reduction for 50% and 100% penetration rates respectively, compared to the conventional vehicles sub-scenario (0% Penetration rate).

The first scenario (1A or 1B) with the (0% Penetration or 0% compliance) acts as a baseline to compare the results when changing the parameters in other sub-scenarios. Analysis is performed versus this main scenario when introducing different human compliance rates or implementing GLOSA and while introducing automated vehicles and their headways enhancement later. This comparison is done to measure the improvements in capacity in each different case.

Different compliance rates are only simulated in the first scenario (1B) for conventional vehicles as in Table 9, where the compliance rate is changed within the range [0,100] percentages, assuming full market penetration. Having 0% speed compliance corresponds to 0% penetration rate of connected conventional vehicles. While, full speed compliance can be interpreted as 100 % penetration rate of conventional vehicles using communication and thereby the market is being fully equipped and complying with GLOSA. The results for different compliance rates of conventional vehicles being equipped with GLOSA are presented in Table 9.

Table 9 - Traffic performance for different Human compliance rates for full GLOSA market penetration

Scenario	Compliance	Waiting time (sec)	Trip delay (sec)	Travel time (sec)
(1 B) Conventional vehicles	0 %	93.17±11.29	341.66±7.44	484.90±7.41
	25 %	110.59±6.87	309.88±26.43	453.06
	50 %	33.40±9.88	114.39±14.28	257.61±14.25
	75 %	31.70±8.90	95.34±15.27	238.58±15.26
	100 %	31.47±8.92	103.46±14.57	246.71±14.54

On one hand, for scenario (1 B), as all conventional vehicles are connected to the intersection control and receiving GLOSA speed guidance, simulations results for 50% or more compliance showed waiting time, average trip delay and average trip travel time of values very close to the full compliance mode. The drivers follow the advice to an extent which leads to great results in terms of reducing the waiting time and trip delay. The trip travel times are directly proportional to the trip delay values such that travel time durations increase when trip delay escalates. It is also clear that the trip delay decreases with increasing the compliance rates.

On the other hand, a negative effect on traffic flow is produced when drivers comply to the speed advice only to a limited extent. The waiting time output for the sub-scenario of 25% compliance increased more than the sub-scenario of 0% compliance, even though trip delay and travel time are slightly improved.

The mixed traffic environment scenario (2), includes partial automated vehicles being introduced to the road along with connected conventional vehicles where both vehicle types share the traffic volume equally along with 100% GLOSA penetration rate and full compliance to the speed recommendation.

The benefits of enhancing automated vehicles capabilities are investigated, along with implementing the GLOSA management technique through applying shorter time headways, while the no-connectivity mode indicates that both vehicle types are not connected to the intersection control and don't receive any speed advice. This is modelled to display the effect of enhancing other automation settings such as [sigma, reaction time] on improving the overall traffic performance. Simulation results for the mixed environment scenario (2) are presented in Table 10.

Table 10 - Traffic performance in a mixed environment for varied automated vehicles time headway

Scenario	Variable automated vehicles time gap (sec)	Control Algorithm	Waiting time (sec)	Trip delay (sec)	Travel time (sec)
(2) Mixed traffic [50% Connected Conventional vehicles with time headway of 1.3 seconds and 50% Connected Automated vehicles]	1.8	GLOSA	65.29±5.99	159.04±18.53	302.29±18.57
		No connectivity	111.04±10.35	286.29±19.17	429.54±19.19
	1.3	GLOSA	29.92±8.30	95.38±15.43	238.64±15.40
		No connectivity	85.45±10.00	168.45±21.85	311.71±21.83
	0.8	GLOSA	12.06±0.69	56.52±11.42	199.77±11.40
		No connectivity	45.90±4.31	83.88±5.77	227.14±5.74
	0.3	GLOSA	7.01±0.43	49.58±5.97	192.83±5.95
		No connectivity	22.50±4.41	47.02±5.94	190.27±5.93

The mixed traffic scenario (2) of traditional time headway of 1.3 seconds for both vehicle types, is compared to GLOSA full market penetration and compliance (1A or 1B) in order to measure the effect of introducing automated vehicles combined with GLOSA. Applying no-connectivity mode for the same sub-scenario, reflects the pure effects of automated vehicles settings. Thus, no-connectivity with lower or higher time headways shows how time headway affect the results. Also, GLOSA with different time headways shows the combined effect of time headway and GLOSA.

When analyzing the sub-scenarios (2) with respect to the sub-scenario of full GLOSA market penetration rate as in Table 8, results show that introducing the first version of automated vehicles with a time headway of 1.8 seconds which is higher than usual, leads to decreasing the road capacity, doubling the value of the average waiting time, and providing worse traffic performance results. While having automated vehicles with the same time gap as connected conventional vehicles, results in negligible improvements in traffic performance. This highlights that there are no further benefits from introducing automated vehicles without decreasing their time headways.

As presented in Table 10, the sub-scenario for automated vehicles with time gap of 0.8 seconds accomplishes 61% and 45% reduction in waiting time and trip delay respectively. Operating such time gap with no connectivity increases the waiting time but it decreases the trip delay with a rate of only 19%. Also, for the lowest possible time gap for automated vehicles in the mixed scenario, the waiting time is reduced to 77 % and 52% for trip delay in case of using GLOSA. Without using the GLOSA connectivity, 28% reduction in waiting time and almost the same progress in trip delay minimization of about 54%.

The final scenario (3) only contains the partial automated vehicles simulated with different time headway settings with simulation results retrieved in Table 11. Automated vehicles operating GLOSA with the same gap as connected conventional vehicles of 1.3 seconds provide the same values in waiting time with a slight improvement in trip delay results. Waiting time significantly decreases as well as trip delay even more without GLOSA connectivity compared to the mixed scenario of this sub-scenario.

Table 11 - Traffic performance for different automated vehicles time headway

Scenario	Time gap (sec)	Control Algorithm	Waiting time (sec)	Trip delay (sec)	Travel time (sec)
(3) 100% Connected Automated vehicles	1.8	GLOSA	137.56±5.87	275.38±10.30	418.65±10.31
		No connectivity	116.79±6.29	197.37±17.38	340.63±17.37
	1.3	GLOSA	29.36±8.16	78.02±22.04	221.29±22.01
		No connectivity	35.86±2.05	56.55±2.64	199.82±2.62
	0.8	GLOSA	6.09±0.85	49.36±8.62	192.61±8.63
		No connectivity	12.63±0.42	25.86±0.46	169.12±0.44
	0.3	GLOSA	4.40±0.46	38.19±14.42	181.45±14.41
		No connectivity	11.26±0.64	23.27±0.88	166.52±0.83

Waiting time of only 6 seconds can be guaranteed when reducing the automated vehicles time gap to 0.8 seconds and having GLOSA running at the defined communication range. Also, the delay reaches around 49 % reduction compared to the mixed traffic with 1.3-time gap. Without connectivity, the waiting time doubles to 12 seconds while the trip delay decreases to half the value of the automated scenario with the same time gap of 0.8 seconds.

At first sight, it could be illogical to have better performance results in the mixed scenario, but this is due to having both vehicle types with different time gaps of 1.3 and 1.8 secs. While for the automated scenario, there is only automated vehicles with the highest time gap which makes it reasonable to have worse results in this case. The best results in waiting time are achieved in GLOSA for the lowest simulated time gap (0.3 sec). The reduction reaches 86% and trip delay lessens to 63%. The effect of no connectivity reduces the delay again but, yet it increases the waiting time.

8 Discussion

After running the simulations and obtaining the output results, there are some topics that may be discussed, for instance; it is hard to judge the outcome of different compliance rates due to having minimum speed bounding constraint and drivers will always be tempted to adapt the minimum speed instead of the very low speed advice in those cases.

If the vehicles approach the intersection during a red-light signal and (TTI≤ Rr), the speed advice could be calculated and thus optimized but instead the minimum speed is sent to the vehicles by GLOSA. This is done since TTI is very short and there is no need to do it, and even if it was calculated, it will return a negative value leading to adapting the minimum speed as well.

When entering the communication range, a hypothesis is tested for vehicles receiving very low speed advice which leads to slowing down even though, the vehicle might be able to catch the current green if continuing its acceleration up to its desired speed. This is related to the TTI being based on current vehicle speed and in theory, the current speed could be temporary low due to being in an acceleration phase. As this seems to be a valid point, simulations were checked, and all the vehicles enter the network with maximum speed and they also never have a very low speed before entering the communication range. Thus, for an isolated intersection with no neighboring intersections or other reasons for being in an acceleration phase when receiving the advice so this issue is ignored in this study.

Employing high time gaps for the mixed environment or the automated scenario, doesn't return a much worthy effect. This can indicate that GLOSA is not an effective standalone solution for all traffic settings, but also automated vehicles settings should be enhanced to support GLOSA. In a mixed environment, on one hand, GLOSA offers great traffic enhancement for standard and low time headways settings. On the other hand, not implementing GLOSA is only considered effective if automated vehicles can operate at very low time headways compared to the same sub-scenarios operating GLOSA and running the same headways.

The flow of only automated vehicles while accompanied with running the GLOSA management technique in scenario (3), has a significant impact on simulation results and thus leading to improve the traffic performance in when connected automated vehicles can start to use headways like and less than human drivers. If there is no room for decreasing their time headways, then automated vehicles can only guarantee the same traffic improvement as per mixed traffic environment (1.3 seconds headway) or the connected conventional scenarios running with the traditional headway of 1.3 seconds as well. Also, automated vehicles undergoing the no connectivity mode appear to raise the traffic state operation in moderate to low headway capabilities.

The importance of applying the GLOSA algorithm for the yellow time is considered negligible due to the short time for the vehicles to reach the intersection. This also depends on phase signal timing, vehicles speed and acceleration capabilities.

Due to unavailability of automated vehicles behavioral data, the traffic volumes used were fictional. Better simulation results could be acquired when having real dataset to calibrate and validate the simulation model rather than just verifying it with respect to traffic flow theory. Needless to mention that according to the car following parameters defined in the simulation base model, drivers' maintaining the maximum and the minimum speed in a precise manner is not a reflection of real-life scenarios.

In the simulations, it was assumed that all drivers have the same time headway. Even though, time headway for human drivers in actual life is usually less than 1.3 seconds and it also varies from one driver to another. It would be better to have distribution for conventional vehicles time headway instead of having it as a constant value.

The first scenario (1A-penetration rate) assumes 100% compliance. The second scenario (1B-compliance rate) assumes 100% penetration rate. Either the drivers' compliance to GLOSA or the GLOSA market penetration rate are varied in scenarios (1A & 1B). Also, the rest of the scenarios (2&3), full market penetration and full compliance are assumed for both vehicle types (conventional and automated).

Full human compliance is simulated and interpreted as 100% GLOSA penetration rate. While the 0% GLOSA penetration rate scenario and the connected conventional vehicles environment with 0% compliance are simulated as no vehicle connectivity, thus no speed compliance will be applied, and those scenarios are modelled with no information received.

Uncertainty in simulation results is valid to a great extent due to applying simulations on fictious traffic volumes with limited vehicular movements in only a straight forward manner, thus no applicable validation and calibration can be performed to the built model. Moreover, the optimal communication range determined in this thesis project could vary when the simulation software, traffic volumes, signal plan timing and other attributes change.

9 Conclusions and Future Work

The simulations indicate that effects of GLOSA for connected vehicles with automated functionality in terms of shorter time headways are significant in improving traffic performance for the mixed traffic environment of both vehicle types, as well as for the 100% connected automated vehicles. Having full market connectivity and automation yields almost double the improvements in terms of waiting time reduction. Nevertheless, having higher time gaps never yields good results for any scenario, and causes doubling of the waiting time compared to both the mixed traffic scenarios (2) and automated vehicles (3) while operating GLOSA and having the traditional headway (1.3 secs).

Full market penetration of connected conventional vehicles managed by the GLOSA technique results in achieving waiting time reduction of 66%, compared to having only conventional vehicles without GLOSA connectivity. While increasing the percentage of GLOSA connectivity causes a decrease in trip delay ranging from 35 % to 70% reduction for 50% and 100% penetration rates respectively.

The best traffic performance results achieved by using GLOSA, goes for connected automated vehicles having the lowest simulated time gap (0.3 sec). The waiting time reduction reaches 95% and trip delay lessens to 88% from the waiting time and delay of unconnected conventional vehicles respectively.

GLOSA management technique has almost the same results for the mixed traffic scenario (2) including 50% connected conventional vehicles and 50% connected automated vehicles, as well as for the 100% connected automated vehicles scenario (3) with the traditional headway (1.3 sec).

No connectivity sub-scenarios produce relatively decent traffic performance results when having full market penetration of automated vehicles as in scenario (3) for traditional time headways and shorter. Results indicate that the introduction of partial automated vehicles with larger time gaps than the traditional ones will decrease the road capacity and traffic performance in the early stages of vehicle automation.

The traffic performance results from the mixed traffic scenario (2) with the largest time headway is almost half the waiting time and trip delay compared to the automated vehicles scenario (3) with the same time headway. This is due to having 50% conventional vehicles with a time headway of 1.3 seconds in the mixed traffic environment while there are only automated vehicles in scenario (3) which decreases the capacity in case of introducing the first version with the maximum time headway of 1.8 seconds.

As the GLOSA application rate increases for connected conventional vehicles, simulations show a very slow improvement in traffic conditions till near full market penetration. If there is a full market penetration of connected conventional vehicles with only 50% compliance, the results would be as good as having 100% drivers' compliance. Therefore, compliance needed to guarantee an efficient GLOSA system is around half the traffic volume only.

In this thesis project, the traffic management method implemented only considered an isolated intersection for simulations. Previous research emphasizes that there is room to improve results when expanding the intersection network in order to enable coordination schemes between several traffic intersections.

The current communication applied in the simulations involve vehicle and infrastructure information exchange. Traffic performance results could be enhanced through applying vehicle to vehicle connectivity, with platooning possibilities and priority for specific vehicles.

The scenario (1A) analyzes the effects of having different percentages of vehicles connected to the traffic control and running the GLOSA management algorithm, while scenario (1B) investigates the compliance of humans driving their conventional vehicles. Meanwhile, there is a possibility to configure different penetration and compliance rates in the same simulation.

Also, simulations focused on adapting a constant value for conventional vehicles time headway and human reaction times. This should be considered in further research through applying a probability distribution to implement variations in vehicle settings. In other words, most of the future work entails overcoming the project delimitations.

10 References

A. Stevanovic, Kergaye, C., & J. Stevanovic. (2013). Green light optimized speed advisory systems: Impact of signal phasing information accuracy. *Transportation Research Record: Journal of the Transportation Research Board, no. 2390*, 53–59.

Atkins. (2013). *atkins global.* Retrieved from adaptive traffic signal control ATSC: https://www.atkinsglobal.com/~/media/Files/A/Atkins-Corporate/north-america/sectors-documents/highways-and-bridges/library-docs/brochures/atkins-adaptive-traffic-signal-controls-6122013.pdf

Barceló, J., Ferrer, J., García, D., & Grau, R. (1998). Microscopic Traffic Simulation for ATT Systems Analysis A Parallel Computing Version. *France: Centre de Recherche sur les Transports*.

Bodenheimer, R., Brauer, A., Eckhoff, D., & Germ, R. (2014). Enabling glosa for adaptive traffic lights. *Vehicular Networking Conference (VNC), 2014 IEEE*, 167–174.

Burghout, W. (2004). A note on the number of replication runs in stochastic traffic simulation models.

Calvert, S. C., Schakel, W. J., & van Lint, J. (2017). Will Automated Vehicles Negatively Impact Traffic Flow? *Journal of advanced transportation, Vol. 2017*.

Chi, L., Recker, W., & Zheng, X. (2010). Optimization of control parameters for adaptive traffic-actuated signal control. *Journal of Intelligent Transportation*.

Cunningham, G. (2005). *Some traffic problems caused by traffic lights.* Minnesota.

D. Henkemans, M. L. (2001). *C++ Programming for the Absolute Beginner.* Cengage Learning.

Dayi Qu, X. C. (2014). Modeling of Car-Following Required Safe Distance Based on Molecular Dynamics. *Mathematical Problems in Engineering, vol. 2014*.

Dowling, R., Skabardonis, A., & Alexiadis, V. (2004). Guidelines for Applying Traffic Microsimulation Software. Final Report. *FHWA-HRT-04-040 Traffic Analysis Toolbox Volume III. Washington: FHWA*.

Eckhoff, D., Halmos, B., & German, R. (2013). Potentials and limitations of Green Light Optimal Speed Advisory systems. *2013 IEEE Vehicular Networking Conference, Boston, MA*, 103-110.

Edelstein, S. (2017, September 25). *Here is everything you need to know about adaptive cruise control*. Retrieved from Digital trends: https://www.digitaltrends.com/cars/adaptive-cruise-control/

Faraj, M., Sancar, F. E., & Fidan, B. (2017). Platoon-based autonomous vehicle speed optimization near signalized intersections. *2017 IEEE Intelligent Vehicles Symposium (IV), Los Angeles, CA*, 1299-1304.

Fox, K. n. (2012, January 9). *Introduction to Micro-simulation.* Retrieved from http://www.microsimulation.drfox.org.uk/intro.html

He, X., Liu, H.X., & Liu, X. (2015). Optimal vehicle speed trajectory on a signalized arterial with consideration of queue. *Transportation Research Part C: Emerging Technologies, vol. 61*, 106–120.

IEEE. (2018). *IEEE connected and autonomous vehicles*. Retrieved from http://sites.ieee.org/connected-vehicles/ieee-connected-vechicles/connected-vehicles/

Kaths, J. (2016). Integrating reliable speed advisory information and adaptive urban traffic control for connected vehicles. *Transportation Research Board 95th Annual Meeting, no. 16-0142*.

Katsaros, K., Kernchen, R., & Rieck, D. (2011). Performance study of a green light optimized speed advisory (glosa) application using an integrated cooperative its simulation platform. *Wireless Communications and Mobile Computing Conference (IWCM*.

Khair, J., Zeater, S., & Abukhalif, Y. (2017). Connected vehicles: an Innovative transport technology. *10th International Scientific Conference Transbaltica: Transportation Science and Technology*.

Koonce, P. (2008). *Traffic signal timing manual.* U.S. Department of Transportation, Tech. Rep. FHWA-HOP-08-024.

P. A. Lopez *et al*., "Microscopic Traffic Simulation using SUMO," *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, Maui, HI, 2018, pp. 2575-2582.
doi: 10.1109/ITSC.2018.8569938

Krajzewicz, D., Erdmann, J., Behrisch, M., & Bieker, L. (2012). Recent Development and Applications of SUMO - Simulation of Urban MObility. *International Journal On Advances in Systems and Measurements, 5 (3&4):128-138*.

Krajzewicz, Erdmann, J., Behrisch, M., & Bieker, L. (2011). SUMO – Simulation of Urban MObility: An Overview. *Proceedings of SIMUL.*

Krauss, S. (1998). Microscopic Modeling of Traffic Flow. *Investigation of Collision Free Vehicle Dynamics. Koln: Universitat zu Koln*.

Lansdowne, A. (2006). Traffic Simulation using Agent-Based Modelling. *England: University of the West of England*.

Li, J., Dridi, M., & El-Moudni, A. (2014). Multi-vehicles green light optimal speed advisory based on the augmented lagrangian genetic algorithm. *17th International IEEE Conference on Intelligent Transportation Systems (ITSC), Qingdao*, 2434-2439.

Mathew, T. V. (2014, February 19). Retrieved from https://nptel.ac.in/courses/105101008/downloads/cete_34.pdf

Mathew, T. V. (2014, February 19). Retrieved from https://nptel.ac.in/courses/105101008/downloads/cete_39.pdf

Mathew, T. V. (2014, February 19). Retrieved from https://nptel.ac.in/courses/105101008/downloads/cete_38.pdf

Mathew, T. V. (2017, March 8). Retrieved from https://www.civil.iitb.ac.in/tvm/nptel/tselnw48.pdf

Murtha, S. (2015, October 2). *Atkins*. Retrieved from Autonomous vs connected vehicles – what's the difference?: https://www.atkinsglobal.com/en-gb/angles/all-angles/autonomous-vs-connected-vehicles-whats-the-difference

Olstam , J. (2005). A Model for Simulation and Generation of Surrounding Vehicles in Driving Simulators. *Norrkoping: UniTryck*.

Olstam, J., & Tapani, A. (2011). A Review of Guidelines for Applying Traffic Simulation. *6th International Symposium on Highway Capacity and Quality of Service*.

Oponeo. (2018, May 18). *Oponeo*. Retrieved from https://www.oponeo.co.uk/tyre-article/autonomous-driving-systems-101-adaptive-cruise-control-acc-explained

Parent, M. (2013). Automated Vehicles: Autonomous or Connected? *2013 IEEE 14th International Conference on Mobile Data Management, Milan*, 2-2.

Pereira, A., Anany, H., Přibyl, O., & Přikryl, J. (2017). Automated Vehicles in Smart Urban Environment: A Review. *IEEE Smart Cities Symposium Prague*.

Picron, V., Lebre, M., Mouël, F. L., Ménard, E., Garnault, A., & Bradaï, B. (2015). Real scenario and simulations on glosa traffic light system for reduced co2 emissions, waiting time and travel time," arXiv preprint arXiv:1506.01965.

Pourabdollah, M. &. (2017). Calibration and Evaluation of Car FollowingModels Using Real-World Driving Data. *The International Conference on Intelligent Transportation Systems (ITSC).*

Rajasekhar, M., & Jaswal, A. (2015). Autonomous vehicles: The future of automobiles. *2015 IEEE International Transportation Electrification Conference (ITEC), Chennai*, 1-6.

Saltelli, A. (2002). Sensitivity Analysis for Importance Assessment. *Risk analysis : an official publication of the Society for Risk Analysis. 22. 579-90. 10.1111/0272-4332.00040.*

Savrasovs, M. (2009). Overview of Traffic Mesoscopic Models. *the 2nd International Magdeburg Logisitics PhD Students' workshop*, (pp. 71-79).

Seredynski, M., Mazurczyk, W., & Khadraoui, D. (2013). Multi-segment green light optimal speed advisory. *Parallel and Distributed Processing Symposium Workshops & PhD Forum (IPDPSW), 2013 IEEE 27th International.*, 459-465.

Stevanovic, A. (2014). Comparative evaluation of benefits from traffic signal retiming and green light optimized speed advisory systems. *The Transportation Research Board, Washington, DC*.

Stevanovic, A., Radivojevic, D., & Stevanovic, J. (2016). Impact of green light optimized speed advisory on unsignalized side-street traffic. *Transportation Research Record: Journal of the Transportation Research Board, no. 2557*, 24-32.

Suthaputchakun, C., & Sun, Z. (2015). A novel traffic light scheduling based on tlvc and vehicles' priority for reducing fuel consumption and co2 emission. *IEEE Systems Journal*.

TSS. (2010). *Microsimulator and Mesosimulator Aimsun 6.1 User's Manual. Spain: TSS-Transport Simulation Systems.*

Wan, N., Luckow, A., & Vahidi, A. (2016). Optimal speed advisory for connected vehicles in arterial roads and the impact on mixed traffic. *Transportation Research Part C: Emerging Technologies, vol.69*, 548-563.

Yang, K., Guler, S. I., & Menendez, M. (2016). Isolated intersection control for various levels of vehicle technology: Conventional, connected, and automated vehicles. *Transportation Research Part C: Emerging Technologies, vol. 72*, 109–129.