MAVEN

Managing Automated Vehicles Enhances Network

Deliverable nº: 4.1:

Cooperative adaptive traffic light with automated vehicles

(Initial version)

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Executive Summary

The main goal of MAVEN is to manage automated vehicles (AVs) that are connected with an intelligent environment in an urban environment. This goal contributes to the EU objective of reconciling growing mobility needs with more efficient transport operations, lower environmental impacts and increased road safety. To achieve this goal, MAVEN will deploy Cooperative Intelligent Transport Systems (C-ITS) technology, which is coordinated with intelligent traffic management and control applications to enable road infrastructure to monitor, support and orchestrate vehicle movements, via structuring the negotiating processes between vehicles and the infrastructure.

Predominantly, C-ITS applications are mostly used in an unidirectional manner by enabling dedicated features at the receiving end, for example, vehicles receiving Signal Phase and Timing (SPaT) data for trajectory planning applications. MAVEN challenges this with actual cooperation between two communicating entities operating bilaterally. Moreover, the rapid progress currently being made in network and satellite technologies enables automated vehicles to interact reliably with pervasive infrastructure systems. With this target, this deliverable serves as a beginning of work package 4: road automation (WP4).

The scope of MAVEN focuses on the urban environment and specifically at signalized intersections and signalized corridors. Within this scope, the state-of-the-art automated driving on motorways, C-ITS such as Green Light Optimal Speed Advisory (GLOSA) and adaptive traffic light control algorithms are developed for organising the flow of infrastructure-assisted automated vehicles. Furthermore, the development of a Local Dynamic Map (LDM) is emphasized here due to its core property of infrastructure implementation.

This deliverable presents the joint work on road automation that have been done by consortium partners. To give a brief description, four types of traffic control methodologies are described in order to give an overview of them regarding the predictability of the traffic control algorithm. The tools and methodology that are relevant to WP 4 are also described. The most relevant tool is simpla and it captures the characteristic properties of automated vehicles in comparison with conventional vehicles by an appropriate parametrization of vehicle models provided by the simulation software. Queue modelling research is the first key output described in the document and its future integration to ImFlow queue modelling is expected in a later phase. Then two GLOSA implementations are discussed, one based on actuated traffic control and another on a plan stabilization algorithm for adaptive control. Platooning is one of the approaches of MAVEN.

The document also contains preliminary results of the queue modelling and traffic control stabilization. The queue length estimation shows large improvements when information from automated vehicles is fused into the model. Up to 40% reduction for the average error was shown. The largest benefits were visible for high traffic volumes, because this increases the chance of receiving vehicle information at 20% penetration rate. For adaptive control stabilization, results showed 25% reduction in average prediction error, while maintaining similar traffic efficiency. More advanced parameters were added to combat specific side effects, like the prediction stagnating at a certain value due to an extension. This resulted in a small further improvement, but most notably in a solution for the stagnation problem.

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Abbreviations and definitions

Abbreviation / Term	Definition
Acceptance criteria	The criteria that a product must meet to successfully complete a test phase or meet delivery requirements.
Acceptance test	Formal testing conducted to determine whether or not a system satisfies its acceptance criteria and to enable the acquirer to determine whether to accept the system or not.
Adaptive	The network optimizer looks forward to minimize cost (queue, stops, wait time, queue spillback, etc.) based on the configured policies. The signal group is activated at the start of the current stage (containing the signal group) when a demand is set for the signal group. The signal group is activated in a planned stage (containing the signal group) when an implied demand is set for the signal group.
Adaptive Unconditional	Same as traffic adaptive, with the differences that the signal group is activated unconditionally at the start of a stage (containing the signal group). This detection type should be configured for coordinated signal groups to allow the optimizer to begin changing the stage in anticipation of the demand.
ADAS	Advanced Driver Assistance Systems
Architecture	The organisational structure of a system, identifying its components, their interfaces, and a concept of execution amongst them.
AV	Automated Vehicle
C-ITS	Cooperative Intelligent Transport Systems
CAM	Cooperative Awareness Message
CAV	Cooperative Automated Vehicles
CEN/ISO	European Committee for Standardization / International Organization for Standardization
Conflict	Two traffic streams are conflicting and traffic will collide if one does not yield for the other, generally this situation is prevented by traffic lights.
CPU	Central processing unit
CV	Connected Vehicle
Design	Those characteristics of a system or components that are selected by the developer in response to the requirements.
Dynamic green wave	Green wave that is not based on fixed cycle times and offsets, but based on current traffic demand.
EC	European Commission
EPA	Environmental Protection Agency
ETSI	European Telecommunications Standards Institute
FCD	Floating Car Data
Figure of merit (FOM)	A figure of merit is a quantity used to characterize the performance of a device, system or method, relative to its alternatives. Two types of FOM: un-unified and unified are proposed in this research, as shown in section 6.2.
GLOSA	Green Light Optimised Speed Advisory
GPS	Global Positioning System

HAD map	Highly Automated Driving map
HGV	Heavy Goods Vehicles
HMI	Human Machine Interface
HW	(Hardware) Articles made of material, such as cabinets, tools, computers, vehicles, fittings, and their components [mechanical, electrical and electronic]. Computer software and technical documentation are excluded.
I2C	Infrastructure-to-car
I2V	Infrastructure-to-vehicle
ICT	Information and Communication Technologies
ID	Identifier
ImFlow Configurator	The ImFlow Configurator is a standalone application used to configure and simulate an ImFlow system. The ImFlow Configurator is designed to be used by Traffic Engineers.
KAR	Korte Afstands Radio (Dutch for Short range radio), an older technology to request priority at an intersection. It generally has more interference and much less bandwidth than 802.11p.
KPI	Key Performance Index
LDM	Local Dynamic Map
MAVEN	Managing Automated Vehicles Enhances Network
Measure of effectiveness (MOE)	Measures of Effectiveness (MOE) are measure designed to correspond to accomplishment of mission objectives and achievement of desired results.
MPC	Model Predictive Control
MPR	Market Penetration Rate
OBU	On-board Unit
Permissive green	In this case a signal group has multiple movements (e.g. straight and right turn) of which one conflicts with another signal group. Common permissive greens that have green light at the same time are VRUs together with straight/right turn of vehicles and straight/left turn of opposing vehicle signal groups.
PMT	Project Management Team
R-ITS-S	Roadside ITS Stations or roadside unite (RSU) as part of the Cooperative Intersection
ReMP	Requirements Management Plan
RSU	Road Side Unit
Saturation flow	The maximum flow in vehicles per hour that can be achieved. Often used in queue modelling to predict the speed at which a queue discharges during green after 6 seconds of acceleration/ reaction time.
Signal group	Set of signal heads that are always green at the same time. There can be multiple lanes in one signal group, for example 2 left turn lanes will be in the same signal group, but also two directions can be in one signal group when they are on the same lane, like one lane that allows both right, straight and left turns.
Specification	A document that describes the essential technical requirements for items, materials or services including the procedures for determining whether the requirements have been met or not.

Spillback	Phenomenon that a queue is long enough to block an upstream intersection. Effectively this means switching the light to green upstream will not result in any flow due to the intersection being blocked by waiting vehicles.
SRS	System Requirements Specification
Stage	Set of signal groups that are usually green at the same time. Most traffic light controllers optimize stage-based, but small differences in timing between signal groups can occur due to constraints of the conflict matrix. When one signal group has no more traffic, some control strategies allow alternatives for it during a stage.
Stakeholders	The people for whom the system is being built, as well as anyone who will manage, develop, operate, maintain, use, benefit from, or otherwise be affected by the system.
SUMO	Simulation software (Simulation of Urban Mobility)
SW	(Software). Computer programmes and computer databases.
TLC	Traffic light controller
TMC	Traffic Management Centre
Traceability	Ability to trace the history, application or location of that which is under consideration.
V2I	Vehicle-to-infrastructure
V2V	Vehicle-to-vehicle
V2X	Vehicle-to-anything
VA	Vehicle Actuated. Also refer to ‘Vehicle Actuated Control’.
VECOM	COMpact VEhicle identification and priority, based on transponders communication through inductive loops.
Vehicle Actuated Control	Virtual detectors are detectors used when physical detectors are not available (in the field). Data from virtual detectors is estimated by the system based on the measured flow from upstream or downstream physical detectors. This data is used to estimate the intersection exit of entry flows based on the applicable traffic movements.
VRU	Vulnerable road user
WP	Work Package

1 Introduction

This deliverable (D4.1) contains the results of work package 4 (WP4), road automation. It describes the scheduling and signal timing strategy for Traffic Light Controller (TLC) optimization (task 4.1) as well as Floating Car Data (FCD)-based lane dependent queue estimation (task 4.2). This report is the draft version deliverable of the work package on road automation. The final version (D4.4) will be released in project month M28, latest 31st December 2018. The final version also includes results from tasks 4.3, Multi-intersection optimization and local level routing, and task 4.4, which is about the inclusion of special road user categories and vulnerable road users.

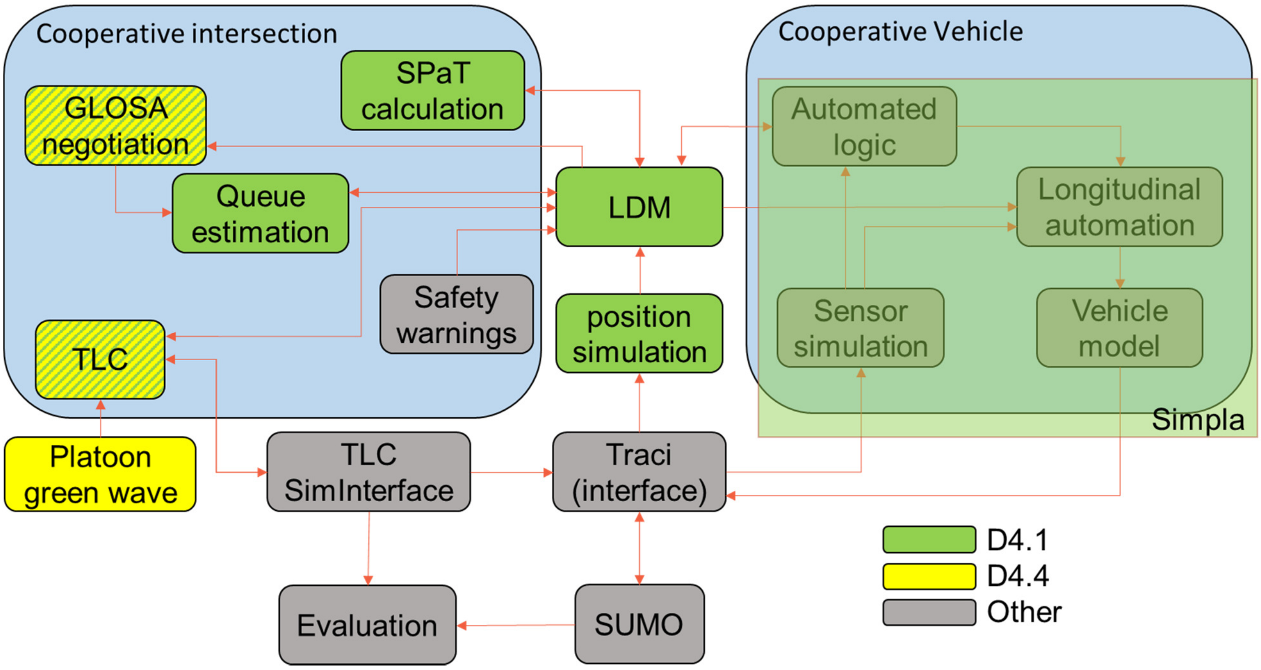

Figure 1-1: WP4 work in the MAVEN context

Figure 1-1 presents the work in this deliverable in the context of the MAVEN simulation architecture from deliverable D2.2 [1]. The colours indicate which part of the work is in the current deliverable and which is in other work packages.

The components in green are completed and reported in this deliverable D4.1. It should be noted that the Local Dynamic Map (LDM) considered here is only for the infrastructure. This enables simulation of vehicles as well, but in WP3, a different vehicle LDM will be implemented.

The components in yellow will be reported in D4.4. The green wave development work is already ongoing, but still in an early research phase and will therefore be reported in the final report. The GLOSA negotiation use case and the TLC algorithms are currently functional, but will be further developed throughout the project and updated in D4.4. Therefore, they are yellow/green dashed.

Several components (grey) are not covered by this deliverable. First of all, the evaluation element is based on an implementation from the COLOMBO project, of which details can be found in the COLOMBO evaluation paper [2]. Only the evaluation methodology will be described in this report where it is relevant. Similarly, the software required for interfacing the traffic light controller with the Simulation for Urban MObility (SUMO) software, was also developed in the COLOMBO project and is published in the COLOMBO simulation environment paper [3]. Second of all, the safety warnings element was modelled in WP3 and will be tested in the field using results from WP5, enabling technologies. Since there will be no SUMO simulations or direct algorithm development related to the traffic light controller with regards to safety, this element is not covered in this deliverable. Lastly, the vehicle aspect is covered by WP3, vehicle automation. However, a model is required for simulations using the SUMO software. The simpla extension implements this and is completed for MAVEN.

1.1 Structure of this document

The document continues with Section 2, the background information of contemporary traffic control methodologies. Section 0 describes the methods and tools required for the research. These are simpla, the LDM and the position simulation. Queue modelling is discussed in a separate section, Section 4, as this is a key research topic in MAVEN. It forms the basis for accurate GLOSA and efficient adaptive traffic control. Two of the traffic control methodologies, actuated and adaptive control, are used to implement the GLOSA use case and will be described in Section 0 and Section 6 respectively. Lastly, Section 7 gives the conclusion and the further research is presented.

2 Traffic control methodologies

This section gives an overview of the most common control methodologies used. Since one of the main use cases in MAVEN is GLOSA, special attention is given to the predictability of the traffic control algorithm.

2.1 Static control

The simplest form of traffic control is static or fixed-time control. Even though little intelligence is required inside the controller cabinet nor any investment for sensor technology, the maintenance costs can still be high. This is due to the manual calibration effort required to keep the plans effective. Formulae and software tools [4] are available to calculate these plans, but for every significant change in traffic demand, the procedure has to be repeated.

The plans are calculated based on average flow and include a margin to cope with cycle-by-cycle demand fluctuations and prevent queues from forming. Most of the time these margins are unnecessary and increase the delay time for all other traffic. When average demand fluctuates by time of the day, multiple static programs are often loaded, which are switched on at predefined times of the day.

Day-to-day differences can still cause unnecessary queues and System Activated Plan Selection (SAPS) is often used to cope with this. For this system, a few sensors are placed at strategic locations in the network to detect congestion and/or measure traffic volume. The system dynamically decides when to switch between several pre-configured plans.

Irrespective of the amount of static plans and the plan selection method, the dynamics for GLOSA are the same. The control strategy is perfectly predictable, but has a risk of forming congestion, which impedes the efficiency of a speed advice.

2.2 Actuated control

Actuated control is based on sensors detecting whether traffic is present or not. Typically, two functions for detection are used: stop line detection and gap detection. Stop line detection checks if there is any demand at a signal group. If there is no traffic in all signal groups of a stage, this stage will be skipped. Gap detection is used for extension of green light beyond the minimum duration. This means as long as there is demand, the green duration will be extended until the maximum green time is reached. This is illustrated in Figure 2-1. The solid green rectangles represent the minimum green time and the hatched rectangles the optional time available for extension.

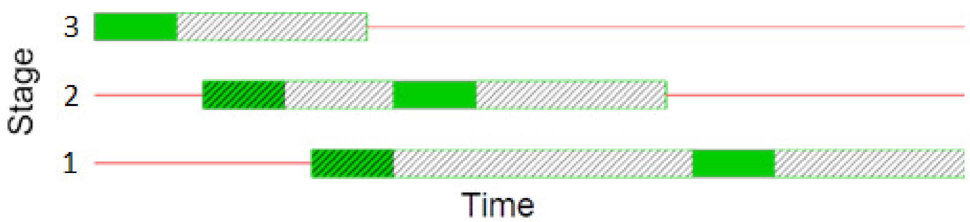

Figure 2-1: Actuated control dynamics

Investment costs of actuated control are higher due to the required sensors. Apart from added sensor maintenance, the calculation of the signal plans requires much less updating. The traffic engineer sets the minimum green time based on safety requirements, since in general drivers do not expect very short green durations. The maximum green time is based on the maximum desired cycle time. This may require rebalancing when traffic demand changes considerably.

The plan stability is very low as can be seen in Figure 2-1. The plan in the example has a minimum green duration of 6 seconds and a maximum of 20. This means that there is 14 seconds uncertainty when the next stage starts and 28 seconds for the start of the third stage as is indicated by the increasing hatched areas. Providing speed advice based on this data will be difficult.

2.3 Semi-fixed time control

Most commonly used for contemporary GLOSA solutions are semi-fixed time control strategies, like for ODYSA [5]. These are based on a fixed time control plan, but the switching moment can occur between a configured minimum and maximum time. This is illustrated in Figure 2-2, which shows the guaranteed green with solid green rectangles, the default configured green duration is indicated as the sum of the solid green and the hatched light green. The maximum allowed flexibility is the total hatched box. A default green time of 20 seconds is used, while both at the beginning of a stage and at the end there is a flexibility of (-3, 3) seconds. Meaning the absolute minimum and maximum green times are 14 seconds and 26 seconds respectively.

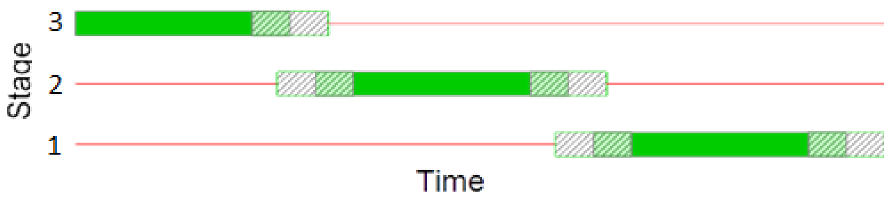

Figure 2-2: Semi-fixed time control dynamics

Important for the stability is that there is a fixed cycle time. This means the flexibility is not cumulative, i.e. if the first stage is extended up to $t = 23$ seconds, the second cannot reach the maximum green time of 26 seconds anymore. It would have to extend to the maximum switching moment to reach the default green time of 20 seconds. This also shows a weakness of this method in congested situations. If the first stage is slightly congested it will use up all flexibility, even if the second stage is heavily congested.

Despite the constrained flexibility, the plan stability is still problematic, due to the moment the decision is taken. Until the previous stage enters the (light green) hatched area, there is still 6 seconds uncertainty for the switching moment. Only once the switch is initiated, there is certainty. The amber time is left out of the figures to keep them easy to understand, which is typically 3 seconds. This is followed by typically 2 seconds of all-red clearance time before the next phase can start. Therefore, until 5 seconds before the start of green there is a 6-second uncertainty for the moment of switching.

The original GLOSA application for this system was developed to display speed advice on a static panel at approximately 500 m upstream of the intersection. The speed advice was intended to be used until approximately 100 m before the stop line at a point where the driver starts to slow down, anticipating on a slightly delayed start of green. For connected and automated vehicles, the speed advice potential is much bigger as they can receive continuous updates of the speed advice. When continuous updates are applied to this semi-fixed time control strategy, it would imply large changes in speed advice are possible. A sudden decrease of time to green prediction from 8 to 5 seconds (green starts early) or a freeze for 3 seconds when reaching 5 seconds to green are both likely with the previously discussed flexibility of (-3, 3) seconds. This can lead to a jump in the speed advice of up to 60%.

2.4 Adaptive control

Adaptive control is based on a model of the approaches towards the intersection. As an adaptive control example, in Figure 2-3, a schematic view of a queue and arrival model is shown. Vehicles enter the model when they are detected by the entry detector. The x-axis represents the distance to the stop line in travel time. In this example the travel time from the entry detector for queue 1 (Q1) is 15 seconds and therefore the vector reaches up to *t* = 15. Every second, vehicles in the arrival pattern are moved one field closer to the stop line, which is indicated by the "t = 0" column. The queues accumulate at the stop line and discharge with counts from the stop line detector.

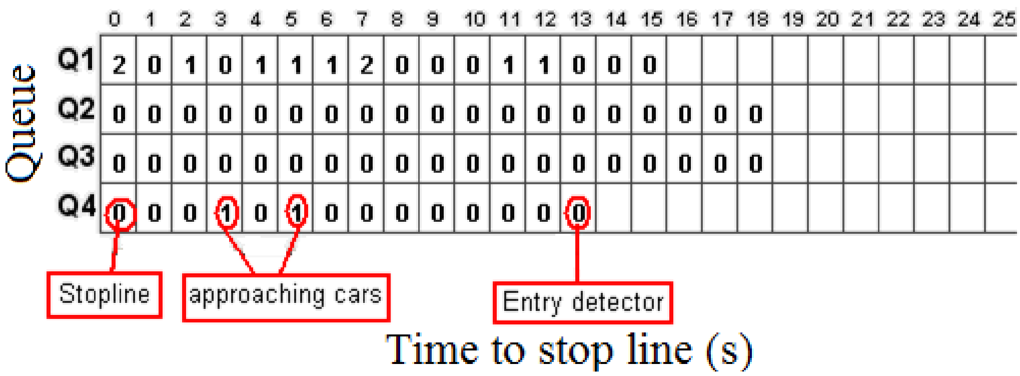

Figure 2-3: Queue and arrival flow modelling in adaptive control

In work package 4, the adaptive control algorithm ImFlow [6] is used. ImFlow uses the model of approaching and waiting vehicles to evaluate different possible control solutions. They are evaluated using a cost function that minimizes delay and stops for all traffic approaching the intersection. Calibration effort for this control method is minimal, since the algorithm optimizes the green duration by itself. Precise configuration of safety timings and detector location is required. Maintenance costs are minimal except for sensor maintenance. Throughput and delay for this control method are optimal, since every cycle can be precisely adjusted to cycle-by-cycle demand fluctuations. In case of congestion, the model knows which stages are most congested or could even cause spillback to other intersections and allocate most green time there while respecting a maximum waiting time. This in contrast to semi-fixed time control, which allocates the spare time according to a first-come-first-serve principle and actuated control, which has a pre-configured amount of extra time for each stage.

In theory, the predictability could be as low as for actuated control. However, with the modelling of the approaching vehicles, the control algorithm already knows beforehand how much a certain phase will be extended beyond the safety minimum. Disrupting factors can be detection errors, signal groups without entry detection (e.g. a pedestrian or bicycle approach with only a push button), signal priority and pre-emption calls.

3 Tools and methodology

This section gives an overview of the tools and methodology required for the work on the infrastructure in MAVEN. There are subsections for simpla, which is an extension to SUMO for automated driving, the LDM, which is a local dynamic map holding all relevant information for the use cases and the position accuracy simulation required for realistic position information from simulated vehicles.

3.1 Simpla

A promising possibility to enhance the future traffic efficiency is the formation of platoons by automated vehicles. In this work, we regard a platoon as a group of automated vehicles following each other with a reduced time headway and possibly employing additional control schemes to maintain a coherent state within the group. Although and because the jurisdictional details for such an operation are still to be clarified, it is highly relevant to study the expectable effects on city traffic. MAVEN focusses these studies on (signalized) junctions, where the greatest effect may be expected from a compactification of traversing traffic flows.

To evaluate the impact of automated vehicles, and especially platooning, on city traffic, MAVEN employs traffic simulations with the program *SUMO* (Simulation of Urban MObility), which is a microscopic traffic flow simulator. The term ‘microscopic’ refers to the fact that the simulation represents each vehicle as an individual entity.

As no platooning functionality was included in *SUMO* at project start, MAVEN developed a lightweight, highly configurable plugin called *simpla* (SIMple PLAtooning), which controls the dynamical adaptation of operational regimes for defined groups of vehicles. Such operational regimes correspond to the vehicles’ control modes which can be either the solitary mode or one of several platoon modes. The full list of configurable modes is:

- Solitary (mode when not driving in a platoon);
- Platoon leader (vehicle driving at the front of a platoon);
- Platoon Follower (vehicle driving within a platoon, but not at the front);
- Catch-up leader (vehicle which committed to join a platoon further downstream and is either driving solitary or at the front of a platoon); and
- Catch-up follower (vehicle within a platoon whose leader travels in catch-up mode).

Technically, this is realized by specifying different ‘vehicle types’ in *SUMO*, i.e., parametrizations of the vehicle properties including its dynamics, corresponding to the different operational modes, and switching between them based on the current traffic situation and additional platooning parameters provided by the user.

We call a vehicle with an original vehicle type for which the user specified a mapping to the platooning types, a Platooning-vehicle (P-vehicle). Only these vehicles will be able to go in platooning modes. For P-vehicles *simpla* assures that they adhere to the following platooning rules:

1. The P-vehicle switches to the appropriate platoon mode if it follows (or is followed by) another P-vehicle on the same lane within a configurable ‘platooning range’.

2. A P-vehicle, which travels solitarily or as platoon leader switches to the catch-up leader mode if another P-vehicle is within a configurable downstream range (larger than the platooning range) on the same lane. For this it is not required that a direct following situation is encountered.
3. A P-vehicle in a platoon whose leader switches to the catch-up mode switches to catch-up follower mode.
4. A P-vehicle leaves the platooning mode if condition 1.) for forming a platoon is violated for more than a configurable amount of time.
5. Before switching from one operational regime to another a safety check is performed, which ensures that the vehicle may safely operate without exceeding the desired maximal deceleration specified for the target vehicle type. If the switch is not successful, the vehicle slowly reduces its speed (with a configurable rate) to establish a situation where it may safely execute the switching.

For more details, see the extended documentation, which was integrated into the *SUMO*-documentation: http://sumo.dlr.de/wiki/Simpla

simpla does not pose strong requirements on the vehicle types mapped by user (although it does require that they have the same length for instance). However, there are some guidelines for the parametrization of the platooning models, which we follow in MAVEN:

1. Parameters for human imperfection (parameter `sigma=0`) are disabled for all modes.
2. The time headway (parameter `tau`) of the platoon follower and the catch-up follower modes are reduced.
3. The values for the desired speed (parameter `speedfactor`) of the catch-up modes are slightly increased.
4. The lane-change behaviour of the follower modes is set to ‘strategic only’. This means that the platoon may only be left for strategic reasons (i.e., if the route of the follower deviates from the route of the leader) and not due to cooperative or tactical considerations.

3.2 Local Dynamic Map

The Local Dynamic Map (LDM) is at the centre of most C-ITS systems. It is a database containing information about vehicles, traffic light status and other traffic relevant information. The key advantage of the LDM architecture is that the data is stored based on map references. A possible query would be to ask all vehicles approaching a certain signal group. This is opposed to geo-databases, where a user would first have to calculate the geographical area of the approach to the signal group and then filter which vehicles are heading towards the intersection and which are actually on the egress lanes. As explained in deliverable D2.2 in the architecture, the LDM connects many components in MAVEN. Apart from the WP5 specific content, work undertaken on the LDM has been finalized.

Two messages are defined to which a MAVEN component can subscribe to. The first is the LDM signal data message, shown in Figure 3-1.

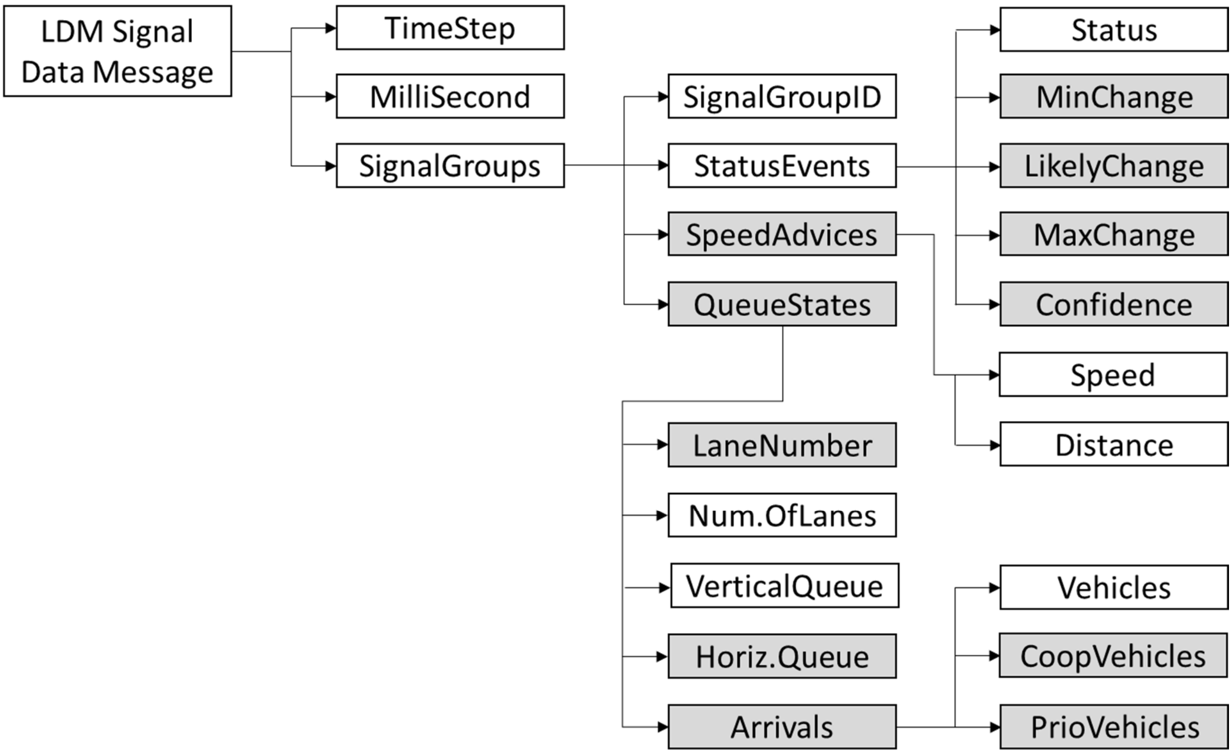

Figure 3-1: LDM signal data message design

The LDM signal data message is built up following the ASN.1 encoding. Unlike V2X messages, which use ASN.1 UPER (Unaligned Packet Encoding Rules), these messages are PER (Packet Encoding Rules). The main difference is that UPER is slightly more compressed, but much slower due to the many bit shifting operations needed for encoding and decoding.

The Figure 3-1 indicates mandatory elements as white and optional as grey. It starts with mandatory timing information followed by a compound object of the signal groups. A compound element consists of several sub-elements and there can also be more than one object. For each signal group, the ID and the status is mandatory. Speed Advice is optional, because it is not always available (for instance when there is no demand on a signal group there is no prediction and thus no speed advice). The queue states are optional as well, but always provided in case of ImFlow controllers for MAVEN. Within the status there are many options to indicate predictions for the next change, these are optional because predictions are not always available. For the queue length there is a distinction between horizontal - the actual length in meters – and vertical queue length, which is the number of vehicles waiting. Arrivals are also always provided in the MAVEN case, but can distinguish between equipped cooperative (automated) vehicles and vehicles with priority. The value in “vehicles” is cumulative. For example, if there are three vehicles approaching, of which one is unequipped, one is unequipped, but has priority and one connected automated vehicle (CAV), then the values would be: vehicles = 3, CoopVehicles = 1 and PrioVehicles = 1.

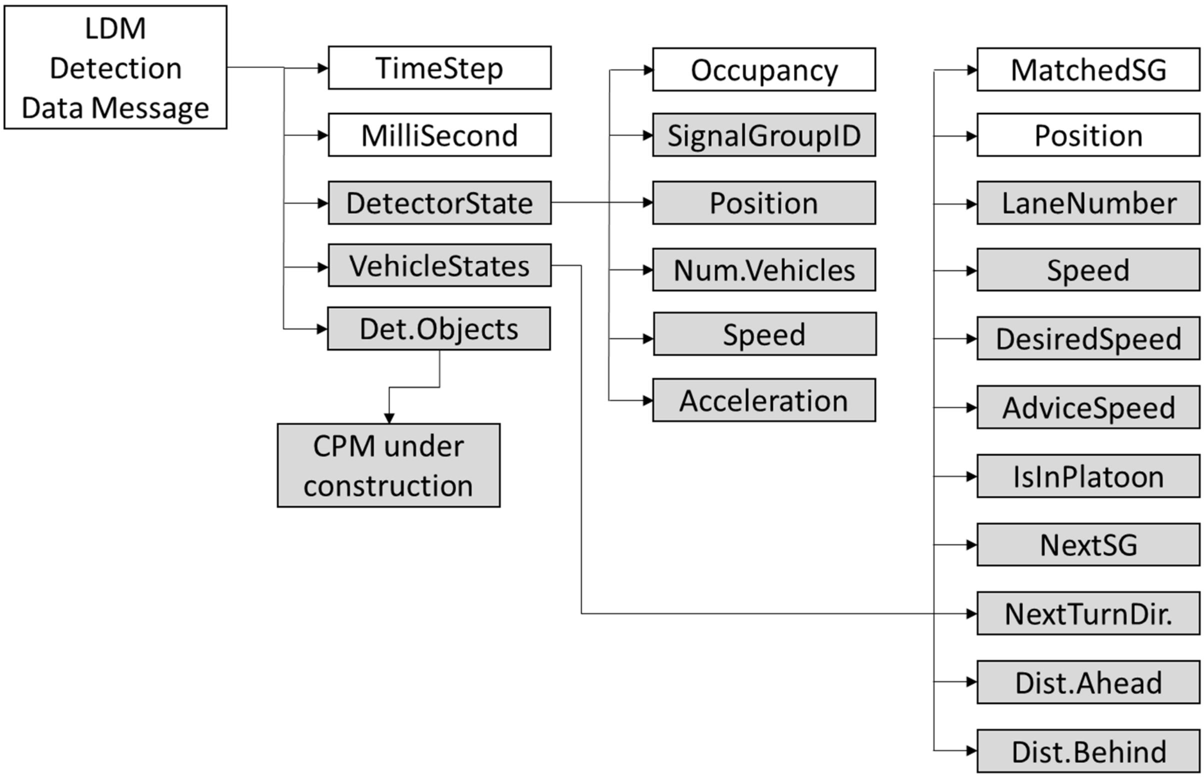

Figure 3-2: LDM detection data message design

The detection data message is shown in Figure 3-2, the figure is built the same way as for the signal data message. Traditional detectors used for presence are included in “DetectorState” objects. The “DetectedObjects” element, on the other hand, is based on the Collaborative Perception Message (CPM), which is part of WP5 and will be merged into the LDM later. However, this is based on object tracking sensor data for safety and therefore not applicable for traffic control simulations.

3.3 Position simulation

The position of a vehicle measured by a Global Positioning System (GPS) sensor in real world scenarios is not always quite precise. On one side, it is influenced by cost factors, forcing the commercially available units to use only one GPS frequency, on the other side the urban scenario that we consider poses a difficult challenge for any GPS system as the urban corridors have only a limited view of the sky. In such a situation the GPS signal is blocked by buildings that surround the corridor and the precision of the position drops significantly [10].

In our case we simulate automated vehicles within a microsimulation framework. Every such simulated vehicle can provide the user with its exact (up to machine precision) position coordinates. In order to simulate the real world conditions, we use additive Gaussian noise to distort the original data,

$$(x_r, y_r) = (x_{sim}, y_{sim}) + N(0, \Sigma) \quad 3\text{-}1$$

where $(x_{\mathrm{sim}}, y_{\mathrm{sim}})$ is the "true" simulated position of the vehicle, (x_{r}, y_r) is the approximate real world position of the vehicle, N denotes the normal Gaussian multivariate distribution, and Σ is the covariance of the distribution parameters, which is a heuristic 2×2 covariance matrix in this case.

4 Queue modelling

Queue length has been regarded as one of the key parameters in the process of signal plan design, as estimates of queue length may be used as a part of a criterion that is minimised by systems that provide coordinated control of signalised intersections. Numerous studies discuss the problem of queue development and its influence on travel delay, for example [12][17][22][25].

Typical queueing models from the first group are defined in [7][8][16]. These models are the first principle models, meaning that they are derived from underlying physical principles of the queue formation and dissipation process with some ad-hoc corrections accounting for the stochastic nature of the queuing process. In cases where the installed equipment allows for dense or event-driven sampling of detectors, more elaborate deterministic approaches may be used to estimate the position of queue tail [15][20].

Literature on queue estimation from first principle models can be categorized into two modelling classes [19]:

- models based on the conservation law, using the cumulative traffic input–output information; and
- models based on shockwave theory.

Stochastic properties of queue development are directly taken into account by Markov chain models, as for example [23][25]. These models describe the queueing as a stochastic process with probabilities of queue change being given by probability distributions.

The third class of models found in literature are black-box models trying to predict the queue length based on known “training”' data. These include autoregressive models [13], neural networks [14], combination of neural networks and fuzzy logic [18], or neural network constructed with the help of genetic algorithms [24].

With the development of vehicles equipped with Radio Frequency Identification (RFID) and GPS technologies, more theoretically formulated models appeared, refining the original estimate of the queue length from the input-output formulation using the conservation law to vehicle delay estimates [9][21]. The obstacle with which the proposed methods have to deal with in this case is the significant inaccuracy in determining the position of the vehicle in urban areas by GPS.

A promising, yet largely theoretical approach is outlined by Comert [10], in which the author studies the probability distribution of queue tail at an isolated signalised intersection in case that the queue contains a certain amount of automated vehicles (AVs). Typically, the AVs are able to determine their position much more precisely and, with the help of other sensors built into the vehicle, they announce to the Road Site Unit (RSU) also other important data from their surroundings. The approach has been tested only in a simulated environment and currently assumes a certain arrival profile (i.e. Poisson, it does not and probably cannot completely include the effects of gating by an upstream intersection).

4.1 Meaning of queue length

The queue length reported by different models is not always related to the same quantity. Different models work with different queue length definitions. An overview of possible queue length characteristics is given for example in [22] and [17]. In the further text the queue length will always correspond to the *uniform maximum queue reach* as defined by [22] and provided by the percentile correction to the Highway Capacity Manual (HCM) 2000 average back of queue formula in Chapter 16, Appendix G of [7].

4.2 Model structure

The queue length model used by WP4 in MAVEN has the following schematic structure:

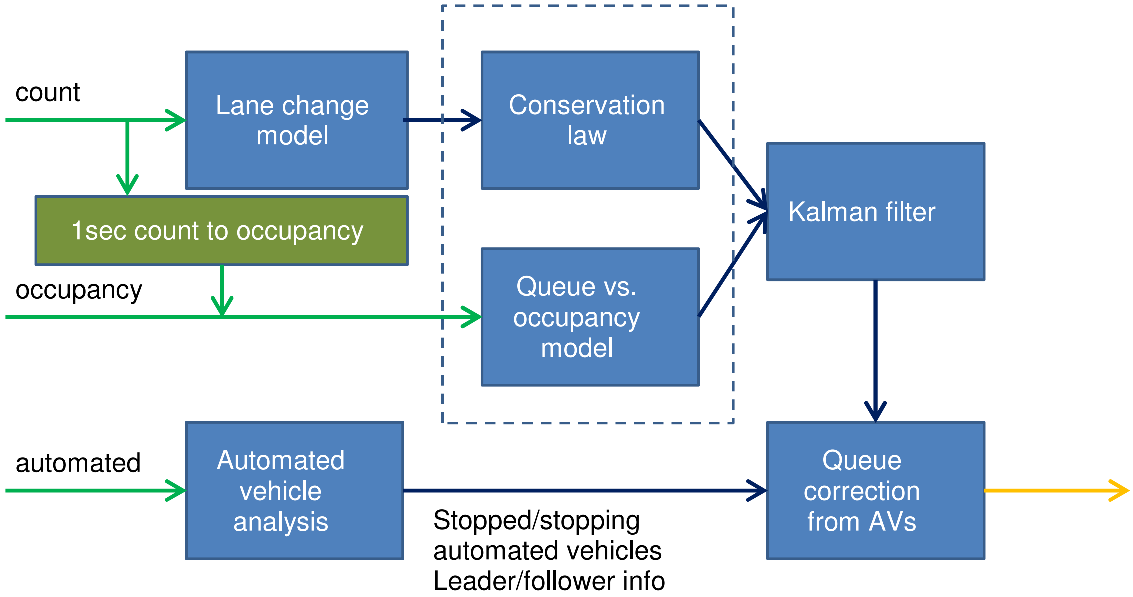

Figure 4-1: Block diagram of the MAVEN queue length model structure

4.3 Lane change model

The first component of the model is a subsystem that models how vehicles change lanes on multi-lane roads after being recorded by upstream detectors at the beginning of the modelled intersection arm. This model is data-driven, based on autoregressive identification of most likely discrete distribution of lane changes so that the input-output balance of the whole section remains intact, i.e.

$$\sum_i c_{\mathrm{upstream},i} = \sum_j c_{\mathrm{stopbar},j} \qquad 4\text{-}1$$

where $c_{\text{upstream},i}$ denotes vehicle count on the upstream detector for lane index i, $c_{\text{stopbar},j}$ is the vehicle count on the stop-bar for lane j. Written in matrix form it means continuously estimating matrix $\boldsymbol{R}$ such that

$$\boldsymbol{c}_{\text{stopbar}} = \boldsymbol{R}\boldsymbol{c}_{\text{upstream}} \qquad \text{4-2}$$

where $\boldsymbol{c}_{*}$ are vectors containing upstream and stop-bar detector measurements.

4.4 Estimation without using information from probe vehicles

For the estimation we start with the basic state-space model in the form of conservation law

$$q(t) = q(t-1) + I(t) \times S \times z(t) \qquad \text{4-3}$$

i.e. the initial queue is updated by the number of discharged vehicles and by the number of new additions into the existing queue. Here, $q(t)$ is the queue length, $I(t)$ is the demand – the count of incoming vehicles on the lane, S is the saturation flow of the lane, and $z(t)$ is the green length (or green ratio in case that the model is cycle-based).

In case of no information about queue discharge, an additional model is used to estimate the number of vehicles that left the queue

$$y(t) = q(t) - \hat{q}(t-1) + I(t) \qquad \text{4-4}$$

where $y(t)$ is the amount of cars passing the stop-bar, and $\hat{q}(t-1)$ is the estimate of the last queue length.

The above model holds for an overflow queue, i.e. for situation when even after the end of the green signal, the queue length is nonzero. If during the green signal the whole queue discharges, we set explicitly

$$q(t) = I(t) \times r(t) \qquad \text{4-5}$$

with $r(t)$ the red duration. This means the queue is formed only by cars probably caught by the red signal, and

$$y(t) = I(t) \times z(t) + \hat{q}(t-1) \qquad \text{4-6}$$

meaning that from the total number of arrivals, only those that arrive during green will continue, and that the initial queue completely discharges.

The above equations form a state-space model with $q(t)$ as the state and $y(t)$ as a measurable output variable. In this formulation, a Kalman filter (or its non-linear variant) can be used to correct the model prediction based on measured model output. If the passage over the stop-bar $y(t)$ cannot be measured, we must rely on the measurements provided by "strategic detectors" at connected road segments and use vehicle turning rates to reconstruct back an estimation of $y(t)$.

These relations are typically determined by traffic engineers at the moment of intersection design. Unfortunately, the common traffic engineering praxis works with daily averages, and the turning rates often vary during the day.

4.5 Occupancy correction

In the case that the upstream detector overflows and the queue tail reaches behind it, the standard approach described above does not work anymore. Similarly, as the queue length grows, the estimation becomes less precise. In order to address this, our model is augmented with linear queue length – occupancy model in the form

$$q(t) = \kappa O(t) + \sigma \qquad \text{4-7}$$

where $O(t)$ is the time occupancy of the detector and κ and σ proportionality constants that depend on the distance of the detector from the stop-bar and on detector size.

4.6 Remarks

1. The equations mentioned above are formulated for average values and detector sampling with relatively low frequency. That is, in the time period (typically say 5 minutes) we have average demand denoted by I_t, average length of the green signal z_t and average output y_t. However, real queue lengths are instantaneous at time instants t or $t-1$. By incorporating only small corrections, the model can be adopted to dense detector sampling as it is used e.g. at the Helmond test site.
2. The formulations in Sections/paragrahs 4.4 and 4.5 are simplified and hold for a constant cycle length of traffic lights. In this case, $z(t)$ is expressed as a ratio of green length to the whole cycle length. The model can be easily extended to variable cycle lengths.
3. During the estimation the model is valid practically only when the queue exists. When there is no queue, the model degenerates. However, this point can be used for calibration – the queue is zero and we can start the computation if its length anew.
4. The model taking care of the beginning of the queue does not have the property of observability. This drawback is compensated by the second part of the model holding for the end of the queue.

4.7 Troubles

1. For the standard state-space estimation the model matrices are assumed known. Here, the matrices are formed by saturated flow S and possibly also by turning rates. Both these variables should be known from the intersection design. In reality, their knowledge is only approximate and they should be continuously estimated.
2. The vehicle count entering most of the equations is measured on a “strategic detector” at the entrance to an intersection arm (which could be the start of an egress approach) or at least sufficiently distant from the stop-bar. For this detector we suppose that it is never saturated, i.e. it could not happen that the queue tail reaches behind it.
    a. The existence of such a detector at every intersection arm may be a too strict assumption

b. The condition of an unsaturated detector during the whole day is also quite ambitious.
c. To certain extent the occupancy-based correction mentioned in Section 4.5 helps in this case at least when the queue tail approaches the detector.
d. We do not explicitly address the case when the detector is completely saturated over the whole signal plan cycle and assume that from the viewpoint of the whole system this constitutes an exceptional case (due to traffic accident, weather conditions, roadworks etc.).

4.8 Queue length estimation using information from probe vehicles

A significant improvement to the problem of queue estimation using the input–output formulation can be achieved by incorporating information from probe vehicles into the queueing model. The information obtained from AVs can be used for more precise estimation of the actual queue length on a lane and use it to for calibration. Our previous standard approach could calibrate only if the queue completely discharged which on high-volume intersections typically does not happen during the rush hours.

In the MAVEN setup, every AV that approaches an intersection can be used as a probe vehicle as it provides the RSU with regular updates of vehicle position, speed and its surrounding vehicles on the lane.

We assume that the information coming from the AVs can be used for our purposes constitutes at least from:

- *lane index*, a number of lane that the vehicles are travelling on at the moment (at least Hyundai AVs are able to measure this);
- *vehicle position*, precise enough that we can estimate the distance to the stop-bar (and possibly also estimate the lane in case that lane index is not present); and
- *vehicle speed*, measured in a sufficiently short period that from its drop we are able to recognize the moment where the car joined the back of the queue.

Our approach works on the following simple principle: We continuously analyse data provided by AVs to the RSU and from the data-set we extract time and vehicle position from the stop-bar at the time instance when the vehicle enters the queue. When a car enters the queue, its speed drops below the so-called crawling speed (in our case defined as 1 m/s) for some time. Alternatively, we can analyse the differences in vehicle position to estimate the vehicle speed. The queue length determined by AVs is then defined as the maximum distance from the stop-bar of all AVs with a low enough vehicle speed and driving on the same lane.

The queue length estimated by the model is then corrected using the estimated position of the last queueing AV by merging the Kalman-filtered values from the conservation law model (which are normally distributed) and the (possibly not completely accurate, see 3.3) AV position for which we also assume normal distribution.

4.9 Remarks

The correction code as outlined above assumes that when a vehicle stops, it stops in the queue. Situations as unguarded pedestrian crossings are not taken into account yet.

4.10 Preliminary results

Lane change model

The lane change model has been tested on Prague-Zlicin and Helmond networks. The tests show that for moderate-to-intense traffic conditions our data-driven approach works well, as the measured data provides enough evidence for estimating the intra-lane movements. The situation becomes worse as the vehicle count decreases as the model does not have enough evidence to prefer a particular variant against all others.

Figure 4-2: Intersection approach overview

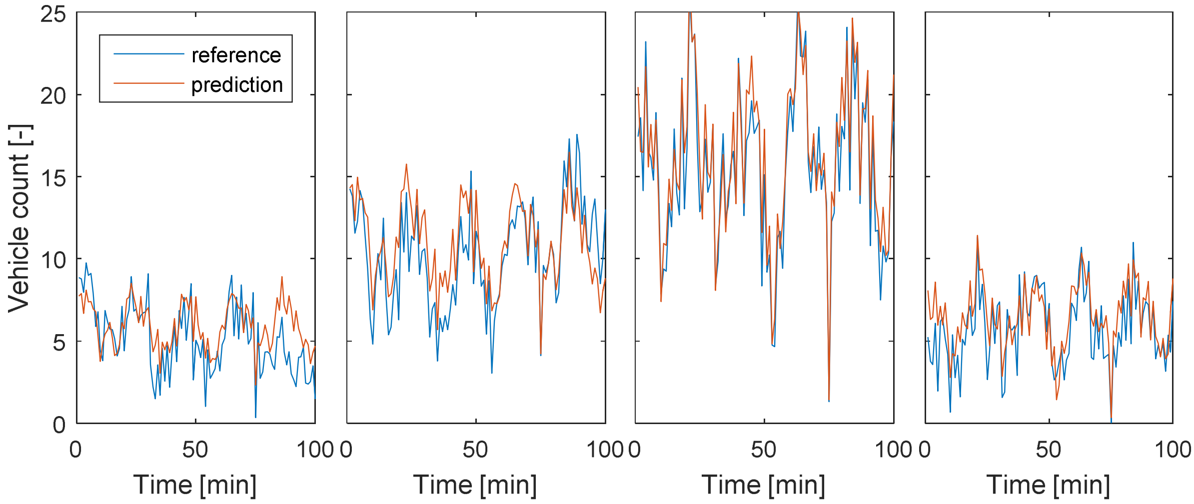

Figure 4-3: Prediction (red) and real (blue) values of vehicle counts at stop-bar detectors

Figure 4-2 shows a satellite image of the situation in Helmond, intersection 701 (Europaweg/Hortsedijk), while Figure 4-3 shows the results of the prediction and real value of vehicle counts at stop-bar detectors. The situation is at a two-lane urban arterial road that branches into four lanes. Traffic volume is approximately 2400 veh/hr, absolute error is 4.13–5.98, standard error is 0.154–0.199, and mean standard error over all lanes is 0.182.

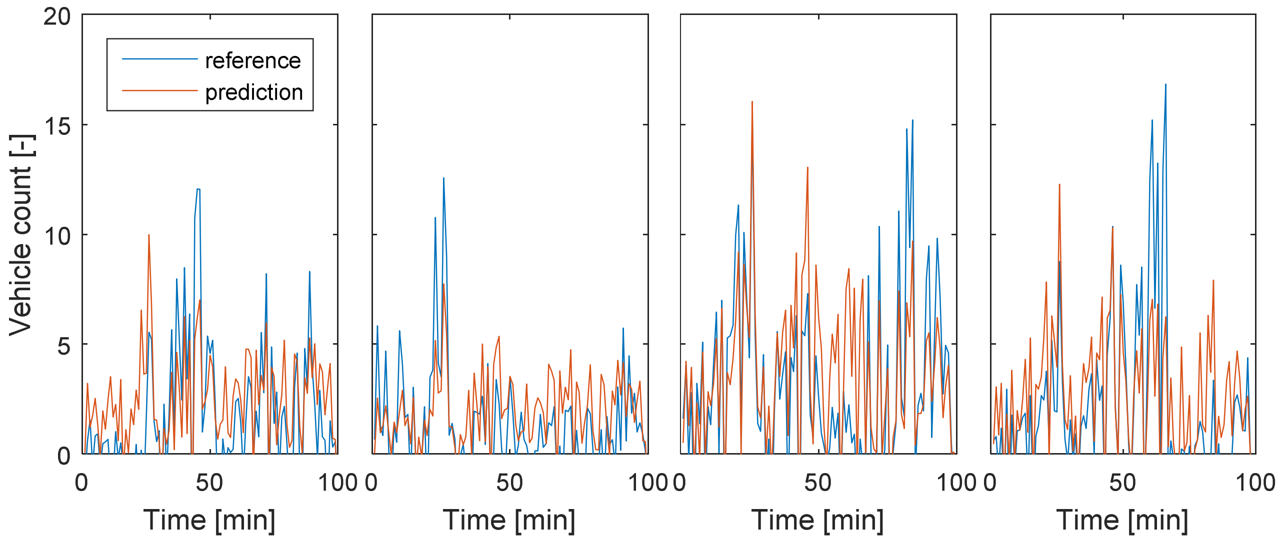

Figure 4-4: Prediction (red) and real (blue) values of vehicle counts at stop-bar detectors

Figure 4-4 shows the prediction and real value of vehicle counts at stop-bar detectors at a two-lane urban arterial that branches into four lanes. Traffic volume is approximately 600 veh/hr, absolute error is 4.24–8.23, standard error is 0.158–0.273, and mean standard error over all lanes is 0.202.

Queue length estimation

The queue length estimation model has been tested on Prague-Zlicin and Helmond networks as well. It uses information about lane changes to estimate the number of vehicles that arrive into the queue tail at every modelled lane and provides the user with an estimate of the horizontal queue starting at the stop bar. The current results indicate that the AV correction significantly improves the initial accuracy of the model, see the figures below. Of course, the accuracy of the proposed model is limited by the accuracy of the lane change model: In case that the lane change model does not predict the arrivals into the modelled lanes correctly, the resulting queue length estimate will be incorrect as well. However, this occurs mostly in periods with low traffic volume and very short queues (usually up to 3 vehicles) that discharge completely on the next green signal.

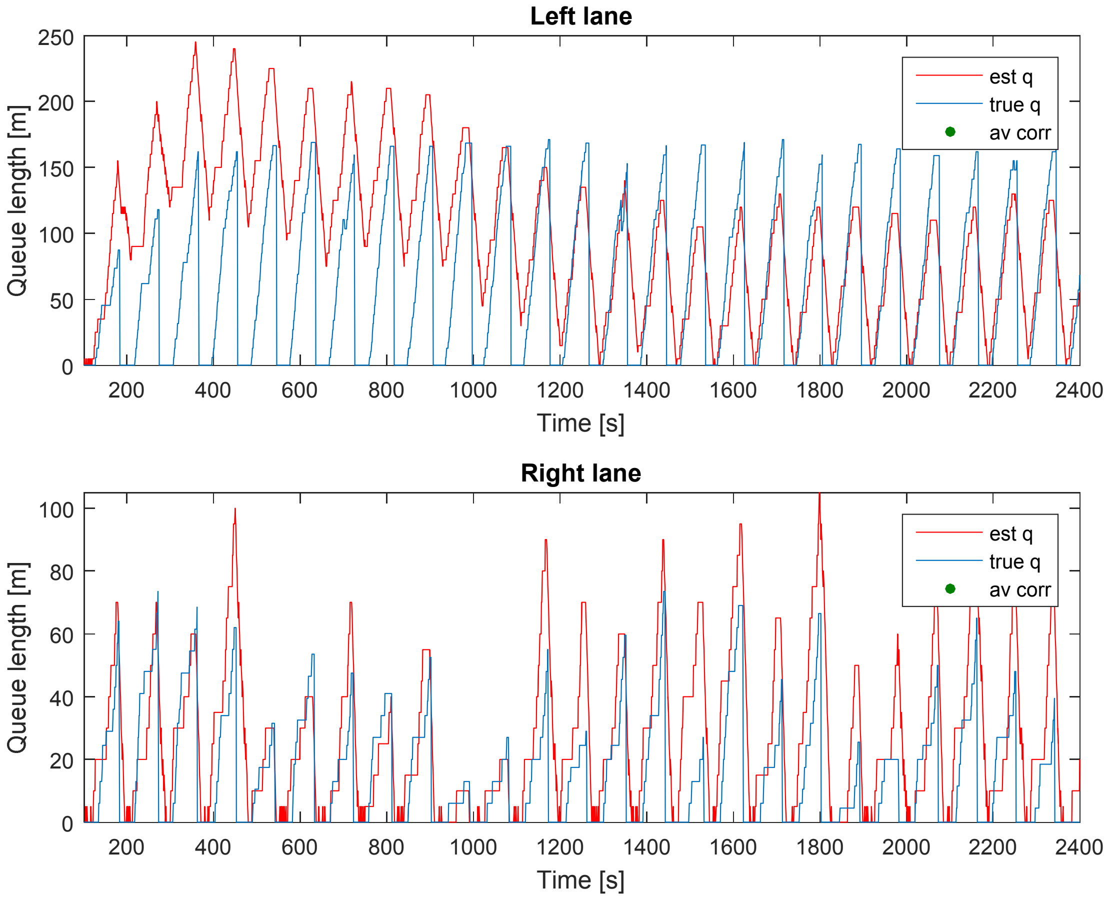

Figure 4-5: Queue length estimation without correction from AVs at two-lane approach. Note the significant error of the model on the left lane, which is due to integrating nature of vehicle conservation law.

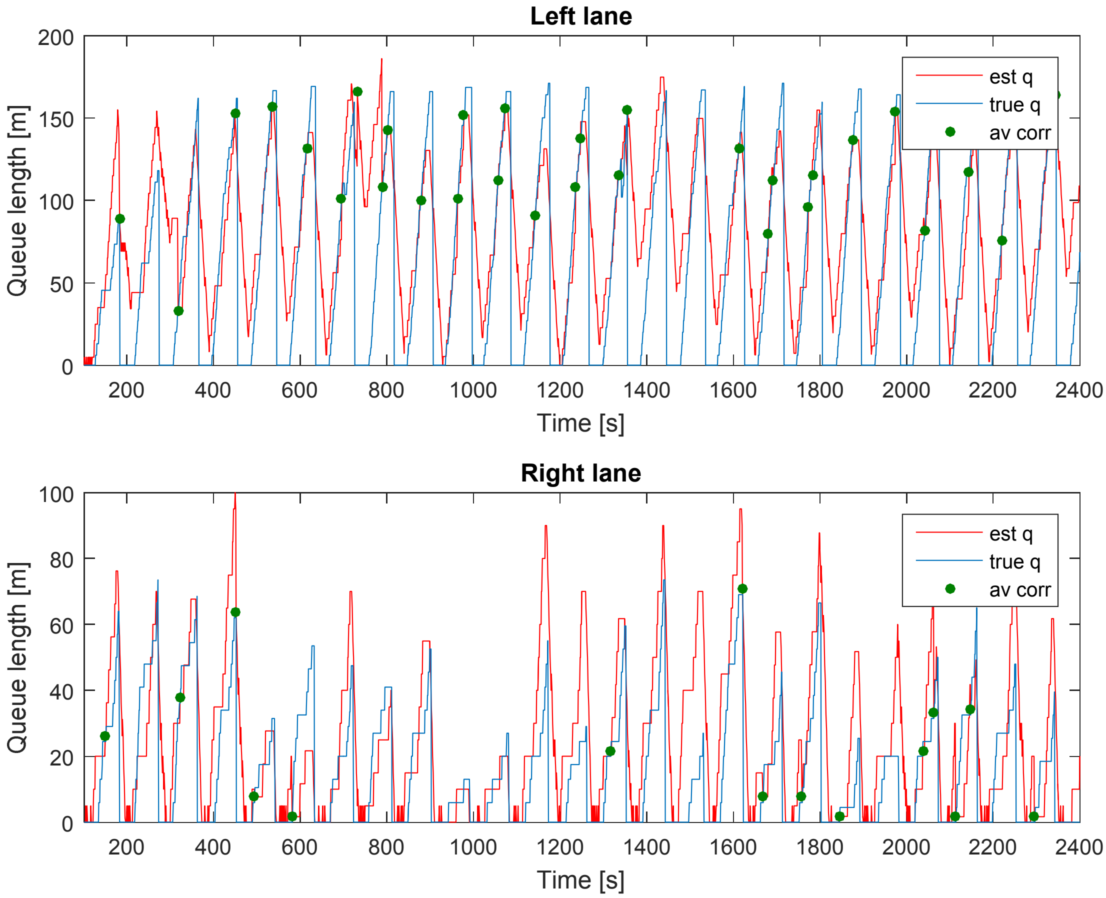

Figure 4-6: The same approach as in Figure 4-5, with queue model that incorporated the information from AVs. Simulated AV penetration rate 20%, flow approximately 1200 veh/hr.

The summary of results for the experiment from Figure 4-5 and Figure 4-6 is shown in Table 4-1. We can see that in denser traffic conditions even for 20% AV penetration rate the information from automated vehicles significantly improves the mean error for longer queues and has certain positive effect in correcting outliers as well.

Table 4-1: Results for queue length estimation at high traffic volume

	Maximum difference [m]			RMSE [m]		
	No AVs	AV correction	Improvement	No AVs	AV correction	Improvement
Left lane	210	166	21.0%	1.35	0.799	40.8%
Right lane	95.0	73.7	22.4%	0.423	0.354	16.3%

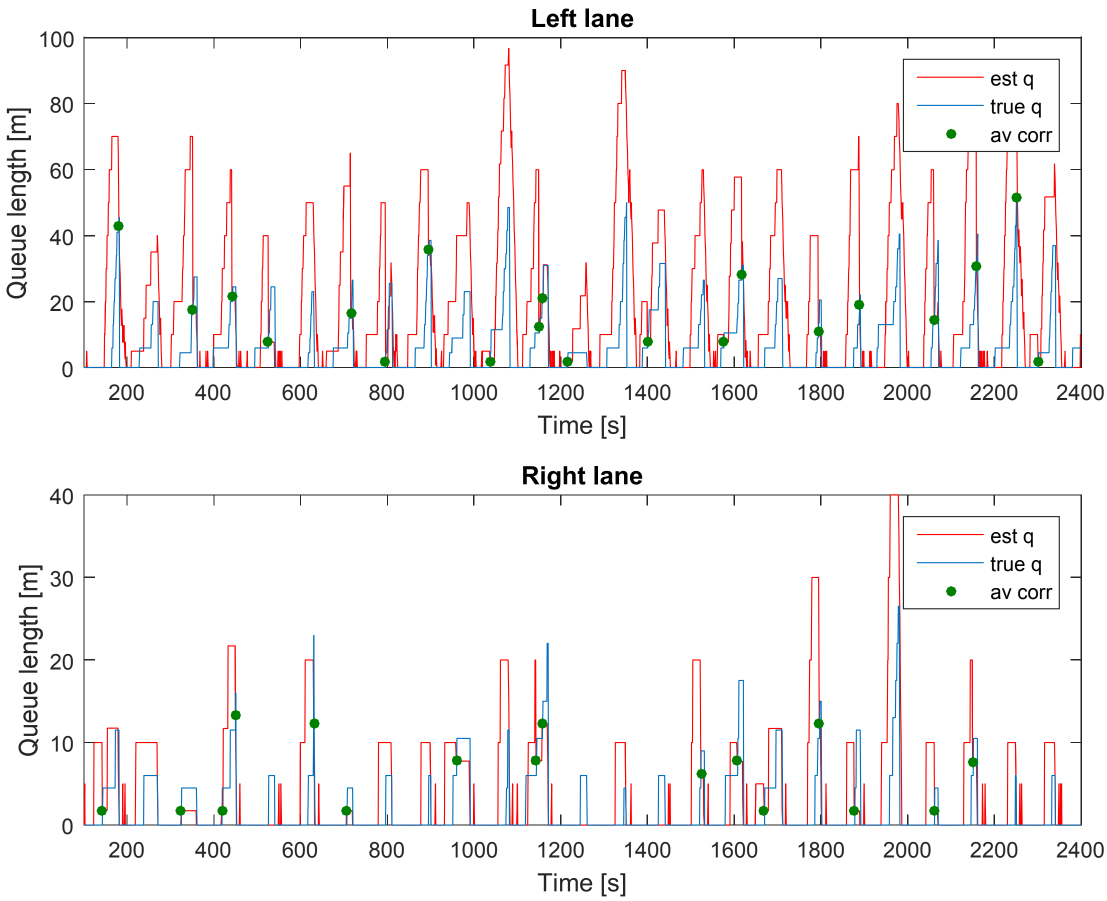

Figure 4-7: The same two lanes again, 20% penetration rate, incoming flow approximately 600 veh/hr.

Table 4-2: Queue estimation results for low traffic volume

	Maximum difference [m]			RMSE [m]		
	No AVs	AV correction	Improvement	No AVs	AV correction	Improvement
Left lane	70	70	0%	0.289	0.271	6.2%
Right lane	13	13	0%	0.0673	0.0673	0%

As shown in Figure 4-7 and Table 4-2, the lane change estimation does not work so well in this case. Due to very low traffic volume, when the queue estimation drifts away from the true value, there are in many cases no automated vehicles that would provide on-line information to correct the estimate. The mean estimate is still slightly better for the lane with more traffic, but the outliers are not corrected in this case.

5 Actuated traffic control with green light optimal speed advisory

The GLOSA algorithm is implemented in the traffic simulator SUMO. The main concept of this algorithm is that vehicles receive SPaT messages containing switching times of the next traffic light. An on-board assistance system in the vehicle computes an optimal approaching speed so that the vehicle can pass the traffic light without stopping. The GLOSA algorithm needs the following configuration data for its calculations:

- For each approach, static information:
    - Maximum allowed speed boundary, e.g. 50 km/h
    - Minimum recommended speed boundary, e.g. 30 km/h
    - Incremental step size for speed recommendations, e.g. 10 km/h
    - Maximum covered distance from stop line for GLOSA speed recommendations, e.g. 500 m, also depending on distance to neighbouring intersections

The example in Figure 5-1 illustrates the functionality of the GLOSA algorithm more in depth.

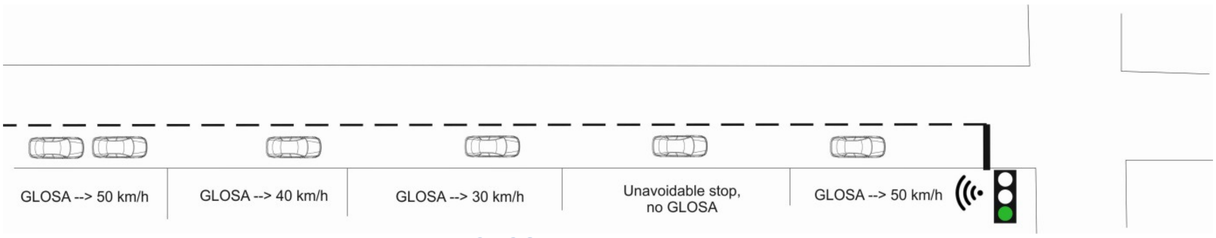

Figure 5-1: GLOSA speed advice zone concept

The road is separated into several sections with distinct speed recommendations. The vehicles that are located in these sections are all approaching the traffic light. They all receive speed advisories based on the switching times transmitted by the signal controller. The speed advisories correspond to the caption inside the respective section. The recommendations for the approach speeds vary between the minimum speed and the maximum allowed speed boundary, incrementing with the defined step size. Speed recommendations below the minimum speed boundary won't be transmitted, a stop might be unavoidable.

Based on the optimization goals, the algorithm can extend green phases to allow a higher number of vehicles to cross the intersection, e.g. at peak time. These goals can be for example to minimize the overall waiting time or to minimize emissions. The possibility of phase extension results in a highly dynamic signal program that is recalculated continuously. This could be problematic in terms of usability since users don't know if they can trust the predictions they receive. To provide a certain amount of reliability for users, the probability of the predictions will be delivered within the SPaT messages for given horizons (e.g. 10 seconds).

In MAVEN, GLOSA will be coupled with the existing platooning approach simpla (see Section 3.1). This results in platoons and not individual vehicles requesting signal switches.

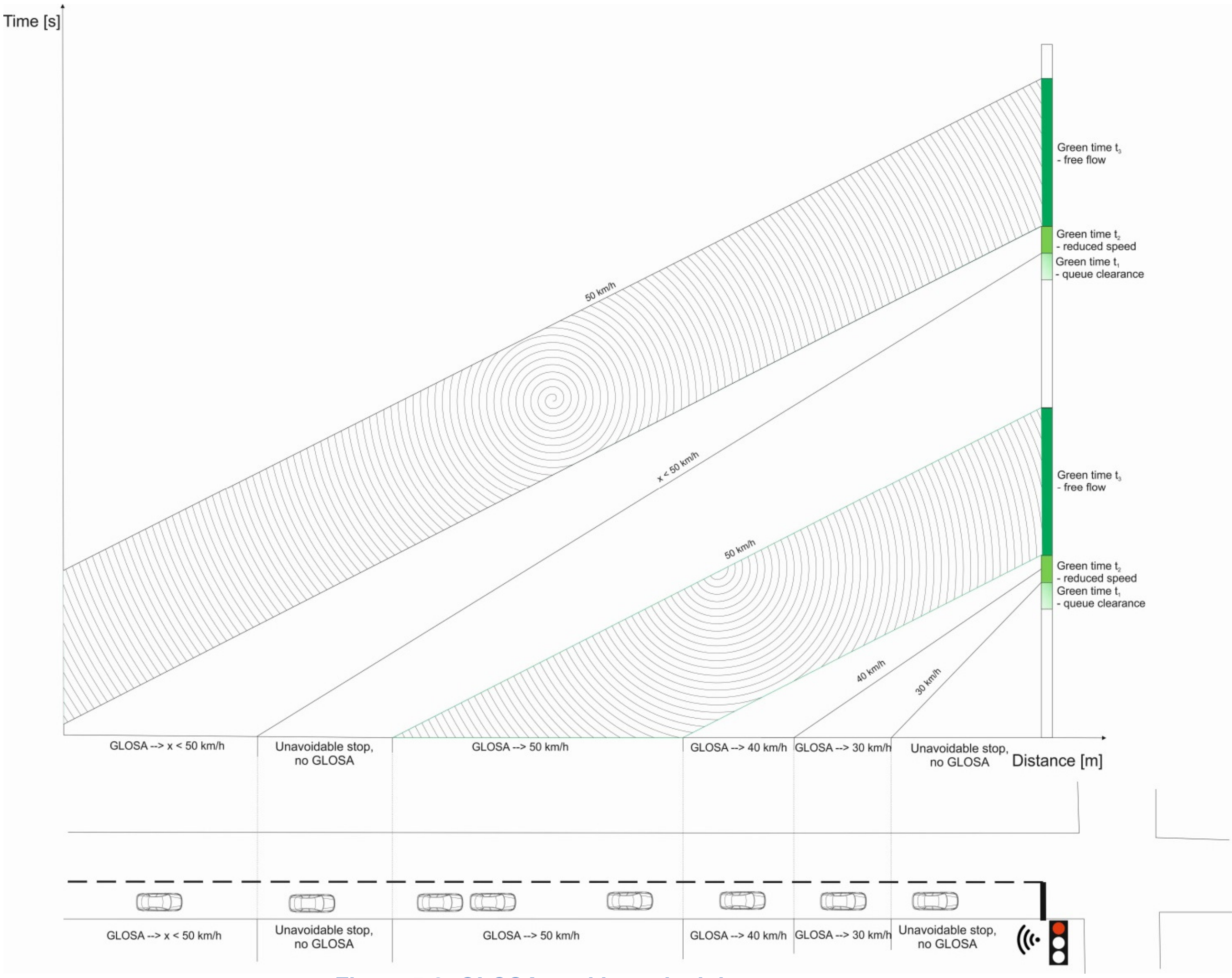

Figure 5-2: GLOSA working principle

In order to further smooth the traffic flow, queue length estimation will be used to clear the line of waiting vehicles at the beginning of a green phase before the platoon of cooperative vehicles arrives. The GLOSA recommendations always refer to this moment of clearance. It also takes into account the vehicles in the arrival pattern (see Figure 5-2).

To estimate the queue length at a traffic light we propose the method described in [26], which will be briefly described in the following. The principle of this estimation method is depicted in Figure 5-3.

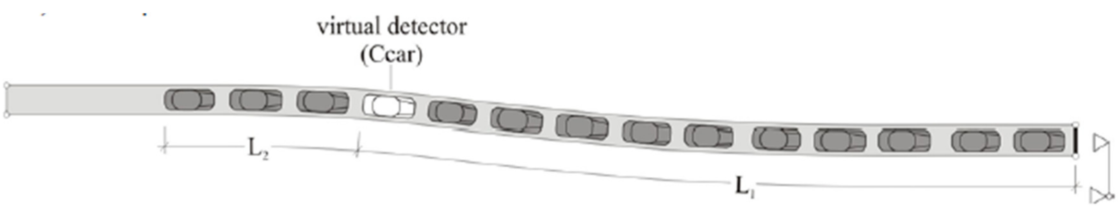

Figure 5-3: Queue length estimation principle, Source: [26]

We have a queue of vehicles waiting in front of a red traffic light. The total length of the queue is L, composed of a measurable length L_1 from the stop line to a virtual detector and a length L_2 from a virtual detector to the end of the queue that has to be approximated. The virtual detector is any vehicle that has vehicle-to-infrastructure (V2I) communication technology on-board. Its communication devices transmit its position and its speed to the traffic light controller.

As soon as the detection vehicle stops at a red light, we can measure the length L_1 given the detector's position and determine the number of vehicles waiting in front of it.
The approximation of L_2 will be described in the following. Priemer states that the expectation value of the maximum queue length of L_2 is equal to:

$$E(\max L_2) = \lambda_2 * E(\max w_2) \qquad 5\text{-}1$$

Where λ_2 is the arrival rate of the vehicles within L_2 and $E(\max w_2)$ is the expectation value of the maximum waiting time. The arrival rate of vehicles within one red phase is assumed to be constant which means, its estimate results in:

$$E(\lambda_2) = \lambda_1 = \frac{d_v}{\Delta t} \qquad 5\text{-}2$$

This means, the arrival rate is simply the distance between detector and stop line divided by the time interval between the arrival of the detector and the begin of the red time period.
The last value we need is the expectation value for the maximum waiting time. This value is composed of the remaining red time t_{rs} and the blocking time $t_b(d)$, the service time of the vehicles in front of the last vehicle in the queue, or:

$$E(\max w_2) = t_{rs} + t_b(d) \qquad 5\text{-}3$$

The blocking time is, of course, dependant on the distance between the last vehicle and the stop line.

This method will be adapted in the MAVEN context to match the specific use cases and test areas. For the positioning of the detector vehicles, a high precision positing tool (e.g. DGPS) has to be used to enable the assignment of detector vehicles to single lanes. This might be important for the estimation of queue lengths for different OD relations at an intersection or when more than one lane exists for one or more directions.

6 Plan stabilization for adaptive control

6.1 Algorithm design

Traffic control algorithm ImFlow is designed for adaptive real-time model predictive traffic light control. The principle concept of the ImFlow system is the optimiser, which uses the cost formula to optimize traffic signal timing, see the following schematic formula:

$$StateCost = Cost_1 + Cost_2 + Cost_3 \ldots + Cost_n \qquad 6\text{-}1$$

This $StateCost$ is applied to each signal group of each intersection to calculate the intersection cost for the planned signal timing, during the whole configured planning horizon. The optimiser will compare many alternative signal-timing plans and execute the plan with the lowest intersection cost. Specific policies can be configured by the user, respectively to $Cost_1$ to $Cost_n$. ImFlow uses this state cost function to evaluate different possible control solutions. From this it chooses the optimal one that minimizes delay and stops for all traffic approaching the intersection, more details can be found in Section 2.4.

The plan stabilization of traffic light controllers in MAVEN benefits from the “configurable cost” character of adaptive control-ImFlow, to prevent the optimizer to change the planning frequently or by a large deviation. Instead of giving more priority to drivers on the main corridor directions, the plan stabilization stabilizes the planned signal timing - particularly close to the green phase - so that drivers on these GLOSA available directions, receive reliable speed advice in order to pass the green light.

The extensibility of this adaptive control algorithm allows for adding new elements to the cost function, which makes the ad-hoc intended plan not preferable anymore comparing to the original plan. By doing so, it helps to overcome overly frequent change of signal plan, and to increase the reliability and accuracy of predictions for the time to green. Furthermore, it helps drivers modifying their speed to meet the green phase of the traffic light.

As shown in formula 6-1, the adaptive algorithm allows for adding new elements to the state cost formula, for instance, adding a configurable cost to $Cost_1$.These new elements aim at adding cost to an ad-hoc intended plan (for example, a deviated plan from original plan after the time to green advice already announced to drivers) by ImFlow, if this plan disrupts stability of GLOSA function on the main directions. A patent for a new algorithm adding such plan stabilization was applied. This should make the control algorithm more suitable for GLOSA, without deteriorating the average traffic delay significantly. The implementation of this cost function (*C*) is further explained in the following formulae 6-2 and 6-3:

$$C = \frac{c.d^2}{TTG_{t-1}} \qquad 6\text{-}2$$

$$d = TTG_{t-1} - TTG_t - T \qquad 6\text{-}3$$

The configurable weight for stability (*c*) is a parameter that allows the traffic engineer to configure the importance of stability with respect to the other control targets. The deviation (*d*) is calculated using the difference between the time to green (*TTG*) of two consecutive time steps. The time period of a time step (*T*) is used for the expected decrease of the *TTG* as time elapses. The cost is quadratic with respect to the deviation because higher deviations are increasingly worse for the driver acceptance of a speed advice. Furthermore, the cost is inversely proportional to the TTG_{t-1}. This is because the closer to green, the more impact a deviation in the plan has. This close-to-green "punishment cost" feature is a major improvement compared to semi-fixed time strategies, which allow for flexibility around the stage transition and could result in change of time to green prediction very close to the actual moment of the transition. The application of this cost function during a real-time simulation of a scenario with c=10 from Section 6.3 is shown in the table below. This table only gives 11 seconds of calculation for reference purpose.

SG8	c	TTG_t	TTG_{t-1}	T	d	Jumped	Cost
1	10	14	15	1	0	no	$10\times(0)^2/15=0$
2	10	20	14	1	-7	yes	$10\times(-7)^2/14=35$
3	10	19	20	1	0	no	$10\times(0)^2/20=0$
4	10	18	19	1	0	no	$10\times(0)^2/19=0$
5	10	17	18	1	0	no	$10\times(0)^2/18=0$
6	10	16	17	1	0	no	$10\times(0)^2/17=0$
7	10	15	16	1	0	no	$10\times(0)^2/16=0$
8	10	14	15	1	0	no	$10\times(0)^2/15=0$
9	10	5	14	1	8	yes	$10\times(8)^2/14=45.71$
10	10	4	5	1	0	no	$10\times(0)^2/5=0$
11	10	3	4	1	0	no	$10\times(0)^2/4=0$
…	…	…	…	…	…	…	…

Table 6-1: Cost incurred on the stabilized signal group 8, using cost function 6-2

As can be seen from Table 6-1, the intentions to jump were not penalized enough in this scenario, and they result in successful unwanted jumps (a change in *TTG*, $d \neq 0$). To solve this, a higher c can be configured here. From a mathematical perspective, the results of cost function increase linearly to c but quadratic to deviation d. However, a jump of -7 followed by a jump of +8 is only +1 for the actual realization of the green phase. Therefore, increasing the weight c, would stabilize this scenario without any large cost to the traffic efficiency. The cause of these jumps are new approaching platoons detected by the queue model, which would justify changing the duration of some phases.

Regarding configuration of cost function 6-2, there are two advantages that can be adapted to get the best results of different networks. First one is that it can be activated on a per signal group basis. For example, this new element is only applied to the signal groups that require stabilization. The through direction of the main road generally has the largest amount of traffic and, therefore, the highest benefit of GLOSA and plan stabilization. Other directions can be more flexible because they do not require a cost for plan stability. In this way the controller is able to combine the best outcomes of two aspects: stability for the main direction and flexibility for the others. This is shown schematically in Figure 6-1; only the third stage has a fixed start of the green. The other stages are completely flexible and even their order could be changed if this is more optimal for the traffic flow (i.e. first stage 2, then 1 and finally 3).

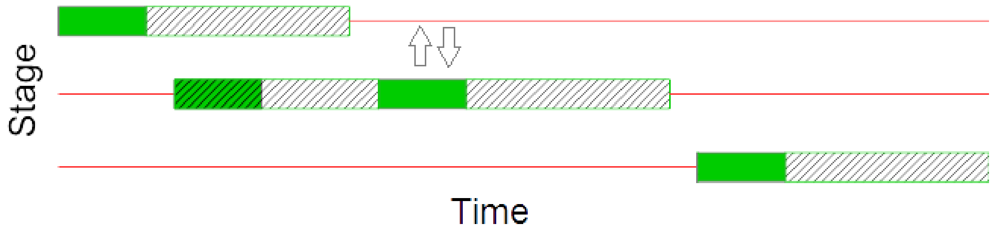

Figure 6-1: Stabilized adaptive control dynamics

During early testing, two unwanted cases of extending *TTG* (negative *d*) are seen during simulation:

1. "flat line" of several consecutive seconds have been observed where ImFlow keeps making small consecutive deviation *d* of 1 second to avoid high quadratic cost. This mostly occurs when a queue departs slower than expected. When this "flat line" situation where cost function didn't prevent *TTG* jumps and *TTG* is successfully frozen each time step, TTG_{t-1} stays the same and the cost will not change for the duration.
2. Under the same situation of case 1, cost function prevented *TTG* jumps for the first few seconds, and TTG_{t-1} is going down 1 second each time step as planned. However, at the end the choice is between either ending the current green phase at that instant or delaying the planning of the stabilized direction 1 second further. This means for certain, that all remaining vehicles have to wait for another cycle. This gives a relatively high cost due to a vehicle actuated element in the original cost function.

MAVEN has worked further to advance the cost function in order to deal with the above mentioned situation on the Helmond network in the MAVEN project. The idea of memory, which "remembers" the previous *TTG* deviation *d* and adds more cost to small consecutive jumps (also can be seen as "creeping up/down" on *TTG* suggestion or speed advice) by using the cost function, is proposed. Accordingly, three new terms are introduced: memory accumulation parameter α, memory dissipation parameter β and extension level EL. In short, α and β are two configurable parameters that are used to calculate memory at the end of each time step, shown in formulae 6-4, 6-5 and 6-6. Literally, d_t is the *TTG* deviation at time step t between an intention plan and the old plan of ImFlow controller. M_t is the memory at time step t. Extension level refers to the extension level of vehicle actuated (VA) control. EL can be set to 0, 1 or 2. When EL is set to 0, VA extension is enabled as the baseline scenario setting of the network; When EL is set to 1, VA extension is disabled for all signal groups if the next planned stage is stabilized; When EL is set to 2, VA extension is disabled for all signal groups if any of the future planned stage is stabilized. The last one of EL=2 is very extreme and should be used with caution.

$$if\ d_t \times M_t > 0, \qquad M_{t+1} = \alpha\, M_t + d_t \qquad 6\text{-}4$$

$$if\ d_t = 0, \qquad M_{t+1} = \beta\, M_t \qquad 6\text{-}5$$

$$if\ d_t \times M_t < 0, \qquad M_{t+1} = \beta\, M_t + d_t \qquad 6\text{-}6$$

Where $\alpha > 0$, and $0<\beta<1$; $d_t \times M_t > 0$ means d_t and M_t have the same sign; $d_t \times M_t < 0$ means d_t and M_t have the opposite signs.

M_t is calculated at the end of each time step, *d'* is introduced here to take the higher value between d_t and $d_t + M_t$, see formulae 6-7 and 6-8. Then *d'* is used to update *d* in cost function 6-2.

$$if\ d_t \times M_t > 0, \quad d' = Max(|d_t|, |d_t + M_t|) \qquad 6\text{-}7$$

$$if\ d_t = 0\ or\ d_t \times M_t < 0, \quad d' = d_t \qquad 6\text{-}8$$

Formulae 6-4 to 6-8 showed the logic process of this advanced cost function. The basics of this algorithm is, that the memory of previous *TTG* deviation is accumulated via parameter *α* to punish continuous *TTG* deviation in the same direction, thus "remembering" the persistent and unwanted behaviours of *TTG* deviation. On the other hand, the memory of previous *TTG* deviation is dissipated via parameter *β*, for situations where none ($d_t = 0$) or opposite direction *TTG* deviation are shown, thus "forgetting" and punishing less to encourage stabilization behaviours. This is also to enable future stabilization in a different direction. Once the target signal group of stabilization switches to green, the memory is reset to 0.

The advantages of this advanced cost function algorithm are threefold. First, tracking the flexibility of adaptive control ImFlow to further smooth and stabilize planning effectively; second, the introduction of *β* insures the functionality of cost function, by preventing memory overflow or even preventing unpredicted situations where cost are "too high" for ImFlow to optimize; Lastly, these parameters are subjected to configuration for an individual network according to local polices. So it takes advantages of the flexibility of adaptive control, without deteriorating the network performance, see impact results from Section 6.3 for reference.

6.2 Simulation methodology

To implement the algorithm design introduced in the Section 6.1, a corridor with multiple intersections in Helmond was built up using SUMO, shown in Figure 6-2. Six intersections: intersection 701, 702, 704, 101, 102, 103 are distributed on this stretch of corridor, with the same main direction, east-west through directions 2 and direction 8 for each aforementioned intersection. Respectively, signal group 2 of each intersection is east-west bound and signal group 8 is west-east bound.

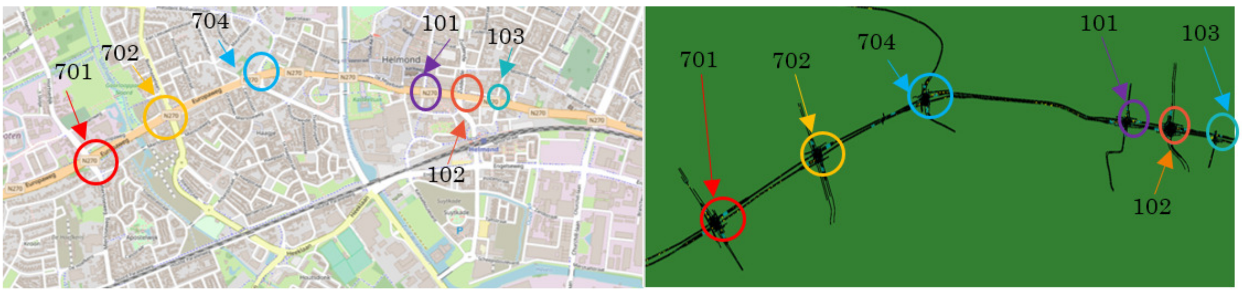

Figure 6-2: Case study of Helmond (left) and the simulation network in SUMO (right)

- Intersection 701, Hortsedijk/ Europaweg

- Intersection 702, Boerhaavelaan/ Europaweg
- Intersection 704, Prins Hendriklaan/ Kasteel-Traverse
- Intersection 101, Zuid Koninginnewal/ Kasteel-Traverse
- Intersection 102, Zuidende/ Kasteel-Traverse
- Intersection 103, Penningstraat/Smalstraat/ Kasteel-Traverse

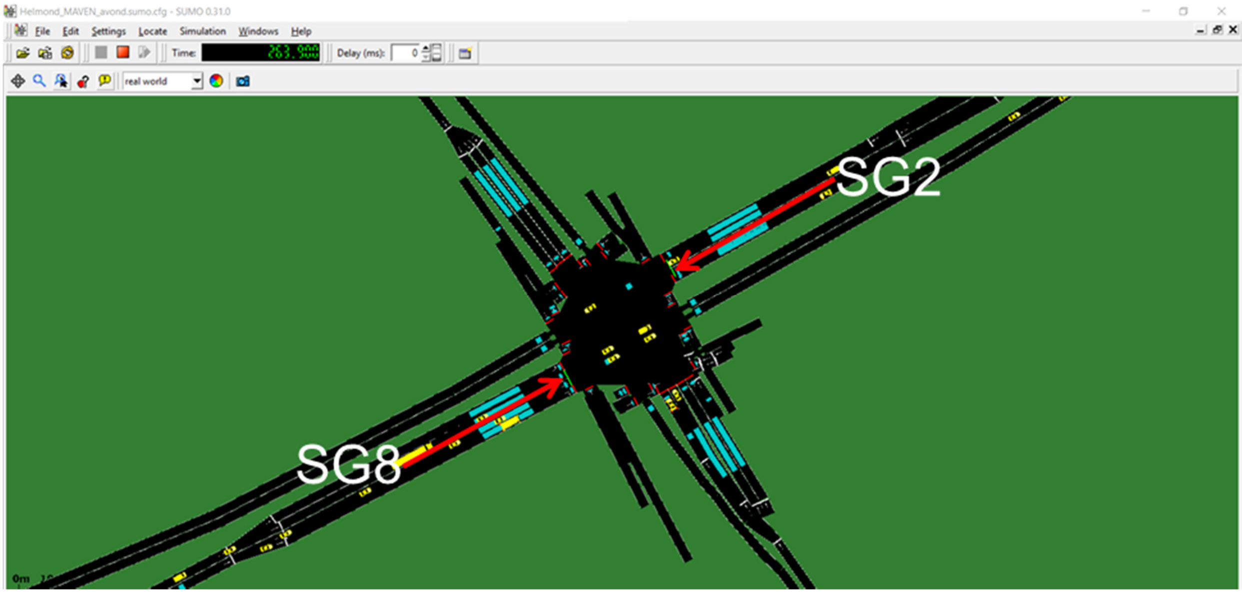

Figure 6-3: Helmond Intersection 701, Hortsedijk/ Europaweg

Figure 6-3. The configuration of the two signal group, SG 2 and SG 8 of intersection 701 are almost identical. They contain the same number of lanes (two lanes each), have the same saturation flow (1800 vehicle/hour), same number of signal heads and they both appear in the same stages/ stage assignment. The simulated traffic is detected in SUMO, then the detected vehicle information is sent back to ImFlow to calculate and optimize the signal timing plan. After making the decision of which plan to choose (the algorithm design of Section 6.1 applies during this process), ImFlow sends back the chosen plan to SUMO to continue the simulation. The detection type of SG 2 and SG 8 are both set to adaptive unconditional in ImFlow configurator. Therefore, stabilized GLOSA can be provided to these two signal groups together with the same configuration of parameters mentioned in Section 6.1.

The automated vehicles using these signal groups will follow GLOSA and plan stabilization is enabled when applicable. For the overall performance of the network, it is important that the largest stream of traffic receives the speed advice, which are main directions, SG 2 and SG 8. In addition, the signal groups with plan stabilisation are set to only SG 2 and SG 8 because they act almost as one. Adding more signal groups could impede flexibility, and in turns negatively impact the performance of the network, while applicability of GLOSA on local roads is much less. The developed simulation method is also intended for implementation for cyclists on this corridor in a later phase of MAVEN.

The speed advice is directly applied to traffic participants using the TraCI interface of SUMO. Speed advice is applied from 350 m before the stop line and is subject to a range of 30 - 50 km/h for vehicles. Slower speeds are not considered realistic. Faster speeds are simply above the speed limit. The speed advice algorithm is straightforward: the distance to the stop line is divided by the time the vehicle can first pass the stop line. This time includes both the time to green (*TTG*) and the time required for any queue ahead to discharge. The prediction of *TTG* is logged during the entire simulation. Afterwards, the actual *TTG* can be calculated by stepping back from the moment the light turned green. The comparison is not considered relevant when *TTG* > 60 seconds, because this is too far in the future, traffic participants would still be at an upstream intersection. Therefore, these cases are filtered out of the statistics.

The simulation network has sufficient space for vehicles to enter the network even in case of long queues due to congestion. If there is no severe congestion, the throughput is the same for all simulations. Another possibility is that one or more signal groups are blocked upstream and had too little traffic entering. This makes it easier for the controller to serve the other traffic with low delay and results in an unfair comparison to normal traffic demand situation of all other simulations because the solution would be unacceptable in the field.

To build statistically significant data, the simulations are performed with 5 runs of 2 hours evening peak hour per traffic control scenario, which comprises of different configured parameters, such as c, α, β and EL. The simulation study is set up according to the following hierarchy rules:

1. Higher configurable value of a chosen parameter when a low value is not sufficient to deliver satisfactory performance. In this study, we increase the c value of function 6-2.
2. Trigger coordination of more parameters when a single parameter (after analysing the simulation results following rule 1) is not enough or has a specific unwanted element, like the flat line described in the previous section. In this study, α is triggered to coordinate with c when increasing c alone is not effective; β and EL are triggered when the best results from c and α combinations are found. The latter case is to see whether β and EL can improve the performance further when c and α combinations are already giving good results.
3. The parameters α, β and EL are advanced tuning parameters at a level of detail not likely to be used in commercial exploitation. These parameters may also introduce unexpected statistical noise, due to situations that would not trigger every simulation run. Therefore, their effect cannot be determined by taking two data points and assume other values can be extrapolated.

Following the aforementioned rules of simulation scenarios built-up, all simulation scenarios are based on the same network configuration, same simulation method and operations. Thus, different scenarios are listed in Section 6.1 according to different parameters, and results of these scenarios will be discussed in Section 6.3. The numbering follows the logic of scenario's and sub-scenario's. A major scenario 1, 2, 3, etc. has an increasing c value. The first level of sub-scenario has a different α, e.g. 2.1, 2.2, etc. The last level varies β and EL, resulting in for example 2.2.1 and 2.2.2.

During the simulation, the delay time and the amount of stops are tracked for every traffic participant. Overall averages are reported in the results Section 6.3 for impact, delay and stops. The impact is a measure of traffic efficiency that can give a quick overview of the performance of a simulation scenario.

Table 6-2: Simulation scenarios list

Scenario No.	*c*	*α*	*β*	EL
0 Baseline	0	0	0	0
1	30	0	0	0
2	60	0	0	0
2.1	60	2	0	0
2.2	60	4	0	0
2.2.1	60	4	0.5	0
2.2.2	60	4	0.5	1
2.2.3	60	4	0.95	0
2.2.4	60	4	0.95	1
2.3	60	8	0	0
2.3.1	60	8	0.5	0
2.3.2	60	8	0.5	1
2.3.3	60	8	0.95	0
2.3.4	60	8	0.95	1
2.4	60	16	0	0
2.5	60	32	0	0
3	90	0	0	0
4	120	0	0	0
5	150	0	0	0
6	180	0	0	0
7	210	0	0	0
8	240	0	0	0
9	300	0	0	0
10	480	0	0	0
11	600	0	0	0

As explained in Section 2.4, one can expect that adaptive control such as ImFlow has higher flexibility, therefore better performance and less impact on a traffic network. Respectively, we can identify impact as a MOE that indicates the performance of an adaptive control algorithm. It is defined by the following formula:

$$impact = \frac{\sum_{i=0}^{i=I} delay_i + 8\ stops_i}{I} \qquad \text{6-9}$$

The formula sums over all traffic participants (*I*) and calculates the average impact. It can be applied to the total network or to a single signal group. In this study, the impact is calculated based on traffic participants using intersection 701 because for one, the network is quite big to observe changes from different scenarios if all participants are taken into account. Actually, they are "diluting" the changes in performance; for two, only parameters of signal groups 2 and 8 of intersection 701 are changed for each scenario. Naturally, intersection 701 is the point of interest.

The value 8 in formula 6-9 is often used as a rule-of-thumb factor by traffic engineers. It is based on CO_2 emissions and road user comfort of not stopping. The most interesting signal groups are the ones where the stabilized GLOSA service is applied. Therefore, these signal

groups will be reported separately as well on measures of effectiveness such as MRE (mean relative error) and PC (perceived change).
A mean square error (MSE) is calculated as a good indicator for overall reliability of the data and is commonly used in many fields of science. However, the TTG_{t-1} in formula 6-2 indicates the sensitivity of TTG deviations close to the actual moment of turning on green and we need to penalize deviations harder by adding a higher cost. Therefore, another measure of effectiveness, the mean relative error (MRE) was added, which divides the error by the remaining *TTG* and expresses this as a percentage. In this study, MRE is designed as a stability measurement that specifically targets the potential performance of GLOSA.

The other stability measure is the Perceived Change (PC), which represents the percentage change between two consecutive predictions relative to the remaining *TTG*. The calculation of this measure is described in the formula 6-10:

$$pc = {\sum_{t=1}^{T} \frac{\alpha\, TTG_{t-1} - TTG_t}{min(TTG_{t-1}, TTG_t)} 100\%} \Big/ {\sum_{t=1}^{T} \alpha} \qquad \text{6-10}$$

$$\alpha = \begin{cases} 0, TTG > 60 \\ 1, TTG \leq 60 \end{cases}$$

The PC measure serves to estimate the users' perception of the system. For example, an original plan of a TTG prediction sequence of three time steps is 50, 49, 48, an alternative intention plan A is 55, 44, 53 and another alternative intention plan B is 55, 54, 53. Plan A and plan B have the same MSE if we calculate their values: MSE of plan A = $[(55\text{-}50)^2 + (44\text{-}49)^2 + (53\text{-}48)^2]/3=25$ and MSE of plan B = $[(55\text{-}50)^2 + (54\text{-}49)^2 + (53\text{-}48)^2]/3=25$. However, the user will see the GLOSA prediction jumping around in plan A more quickly than plan B, and the user will consider the information as an unreliable source. This would hurt compliance rate greatly. Therefore, a low value for this PC is important for users' perception.

To sum up, lower MRE and lower PC are preferred from a GLOSA stability perspective. At the same time, network performance (impact) should not be deteriorated too much to hurt the flexibility of adaptive traffic control ImFlow. A figure of merit, FOM_un-unified is proposed to evaluate the performance of each simulation scenario, as shown in formula 6-11. In a nutshell, the lower the FOM_ un-unified is, the better the result of the scenario is.

$$FOM = Impact^2 \times MRE \times PC \qquad \text{6-11}$$

FOM_un-unified takes into account the balance between traffic efficiency (indicated with *impact*) and stability (indicated with *MRE* and *PC*). Square value of impact is to balance the appearance of MOEs in formula 6-12. To conduct data analysis more conveniently and to have overview of comparing to baseline scenario, this arbitrary formula of FOM_un-unified is transformed to FOM_unified in formula 6-12.

FOM_unified:

$$FOM_{uni} = Impact_{uni}^2 \times MRE_{uni} \times PC_{uni} \qquad \text{6-12}$$

Where,

$$Impact_{uni} = Impact \div Impact_{baseline}$$
$$MRE_{uni} = MRE \div MRE_{baseline}$$
$$PC_{uni} = PC \div PC_{baseline}$$

Section 6.1outlined the algorithm design of plan stabilization for adaptive control ImFlow. Section 6.2 introduced the network of simulation study area and showed the simulation methodology directing this research. Based on the algorithm and the simulation methodology, simulations were conducted and the results are shown in Section 6.3.

6.3 Results

The network configuration and simulation scenarios are explained in Section 6.2. First, scenario 0, 1, 2, 3 ...11 (different *c* in the cost function 6-2, given no *α, β* and EL in functions 6-4 to 6-8) are simulated on the study network with different *c*, ranging from *c*=0~ 600. When 0<*c*≤240, the interval of *c* is 30; when *c*>240, bigger intervals of *c* are used. This is due to hardware constraints of around 200 minutes for a simulation with 5 runs. Also, as we carry out simulations, similar patterns of results in accordance to expectations. With increasing *c*, the MRE and PC reduce at a limited damage on the impact. After a certain *c* value, increasing *c* alone is not making much of a difference on performance results. Most likely all cases where the cost function is used to evaluate a change of TTG were already filtered out and the only remaining instability is due to constraints in the control plan. Therefore, a smaller interval of *c* is redundant in this situation for simulation results purpose. The simulation raw data and calculation of MOEs can be seen in

below.

Table 6-3 Data of scenario 0 to 11, *c*=0~600

No.	c	α	β	EL	impact	MRE	PC	Impact_uni.	MRE_uni.	PC_uni	FOM_uni.
0	0	0	0	0	24136	17.737	4.28	1.0000	1.0000	1.0000	1.0000
1	30	0	0	0	24288	16.402	3.37	1.0063	0.9247	0.7888	0.7387
2	60	0	0	0	24262	15.753	3.11	1.0052	0.8881	0.7276	0.6529
3	90	0	0	0	24595	15.602	3.29	1.0190	0.8796	0.7703	0.7036
4	120	0	0	0	24236	14.085	3.23	1.0041	0.7941	0.7562	0.6055
5	150	0	0	0	24041	13.526	3.55	0.9961	0.7626	0.8301	0.6280
6	180	0	0	0	24032	13.860	3.35	0.9957	0.7814	0.7838	0.6072
7	210	0	0	0	23600	14.221	3.12	0.9778	0.8017	0.7289	0.5587
8	240	0	0	0	24033	12.878	3.14	0.9957	0.7260	0.7350	0.5291
9	300	0	0	0	24057	12.583	3.039	0.9967	0.7094	0.7106	0.5008
10	480	0	0	0	24279	12.594	3.236	1.0059	0.7100	0.7567	0.5436
11	600	0	0	0	24150	13.866	3.034	1.0006	0.7818	0.7094	0.5552

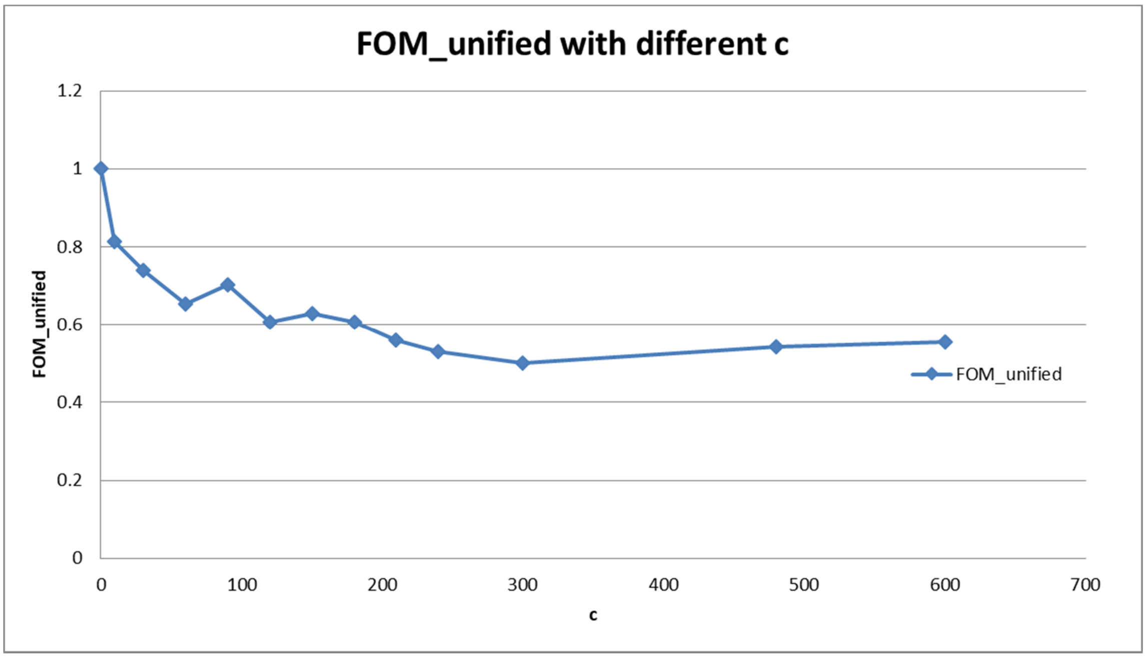

Figure 6-4: Results of scenarios with diff c, given no α, β and EL

With these data above, the FOM_unified curve respect to different *c* is shown in Figure 6-4. As can be seen from the graph below, configuring $c \neq 0$ has an obvious decrease of FOM_unified. Considering the value of FOM_unified, scenario 0 is 1 and scenario 1 (c=30) is 0.738, with 26% decrease comparing to scenario 0. It means that scenario 1 has an improvement of 26% comparing to baseline scenario, scenario 0. Seeing this, an ad-hoc scenario of c = 10 is simulated (data is not included in
), which gives an improvement of 19%. It proves the expectation of "significant improvement when $c \neq 0$". FOM_unified of scenario 2 to scenario 9 shows much less improvement with FOM_unified fluctuating to lower values, then towards stable values.

These results show that the advanced cost function algorithm design has significant improvement regarding plan stabilization. MOEs of stabilization, such as MRE and PC (shown in Table 6-3), decrease when a *c* value is configured, which means the signal groups with GLOSA are more and more stabilized. At the same time, impact of all traffic on intersection 701 does not deteriorate much if we look at the Impact_unified column in Table 6-3. Scenario with extremely high *c* value is also simulated. The results of FOM_unified are even increasing and the performance deteriorates beyond c = 300. Observing the simulations, there are some cases where *c* alone cannot improve the stabilization anymore. For example, the consecutive small jumps caused by constraints as explained in Section 6.1. Beyond c = 60, the cost function still improves stability, but at the same time causes the controller to hit constraints more often. Therefore, the FOM_unified does not decrease steadily anymore as a lot of random noise is introduced in the simulations.

Now that the results and indicated pattern of FOM_unified with increasing *c* value alone are shown, scenario 2 of c = 60 is chosen for further simulation study. There are three reasons to choose
c = 60. Firstly, higher *c* value did not cause FOM_unified to decrease and is not improving the

performance. Secondly, c = 60 shows generally good and with less random noise, even after 20 runs of testing for one scenario. Lastly, increasing c value alone is deteriorating impact on the network level, especially when c is too high, for example, c >600.

According to the rule 1 and rule 2 of simulation methodology in Section 6.2, the next parameter in line, α is triggered, to study whether α can solve some situations where increasing c did not. As listed in Section 6.1 different α, α = 0, 2, 4, 8, 16, 32 are configured for scenario 2.1 to scenario 2.5, under the same c = 60. In this situation, the scenario 2.1: α = 0, c = 60 with no β and EL, is used as the benchmark for the calculation of Impact_unified, MRE_unified, PC_unified, and eventually FOM_unified. The results of FOM_unified are graphed in Figure 6-5 below.

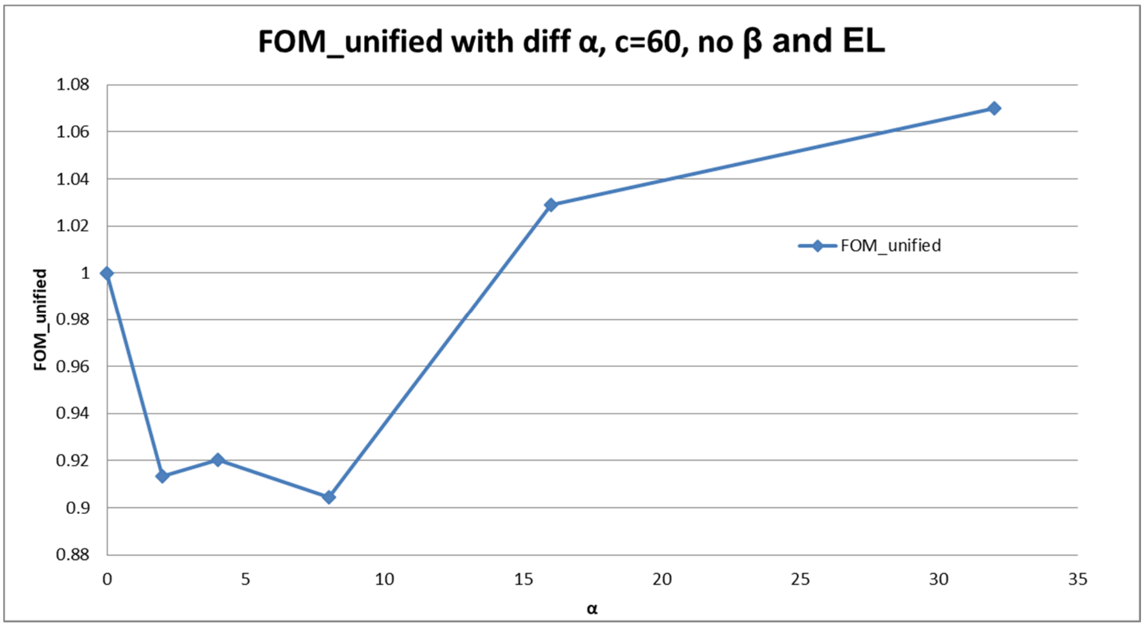

Figure 6-5: Results of scenarios with diff α, c=60, no β and EL

Tentatively, α = 4 and 8 have lower FOM_unified comparing to α = 0 and they are giving better performance. It means that the algorithm of accumulating memory in cost functions 6-4 to 6-8 are solving some consecutive small deviation situation.

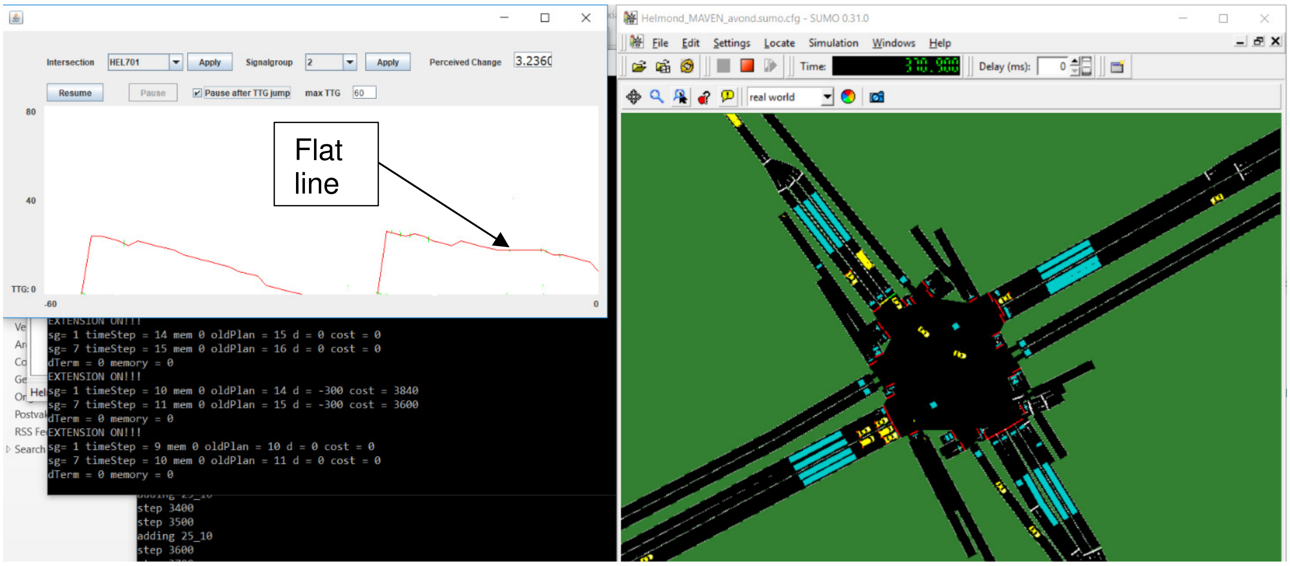

Figure 6-6: An example of small consecutive jumps, "flat line" situation

By closely observing the simulations and cost calculation output of each time step, we can see that the situation of several small deviation of 1 second (shown in Figure 6-6) in a prediction cycle are significantly reduced. Since this type of *TTG* deviation resemble the shape of keeping flat for several seconds, we define them using the analogy "flat line". These kinds of changes in the field would result in a speed advice that keeps slowly decreasing, which is especially uncomfortable and frustrating for drivers who are trying to follow the GLOSA and keep having to slow down. When a count-down bar would be displayed to users, they may even think it is malfunctioning when it freezes.
On the other hand, configuring α with extreme higher values such as 16 or 32, gives an opposite impact as expected, shown in Figure 6-5. The results are worsen comparing to no α. This unwanted effect is preliminarily regarded as the result of too extreme punishment cost from accumulating memory that introduced other complicated and more deviated situations for ImFlow to optimize. This would not give a fair comparison anymore with the baseline scenario due to more cases of randomness and complication.

From Figure 6-5, the results of scenario 2.2 and 2.3 are the most promising ones. Further simulation of scenarios 2.2.1-2.2.4 and scenarios 2.3.1-2.3.4 are built according to rule 2 of the simulation methodology in Section 6.2. Parameters β and extension level (EL) are triggered in these eight scenarios. After performing these simulations, data was collected, analyzed and compared to baseline scenario 2.2 (c = 60, α = 4, β = 0, EL = 0). The results of introducing β and EL are graphed in Figure 6-7.

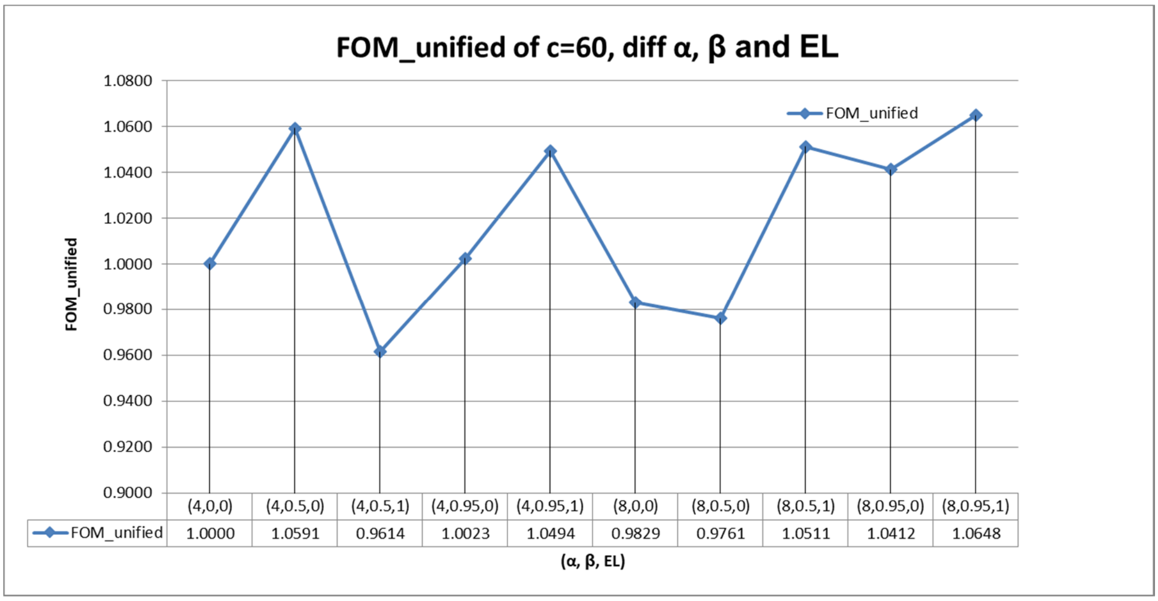

Figure 6-7: Results of scenarios with c=60, diff α, β and EL

As seen from above graph, for $c = 60$, $\alpha = 4$, setting β to 0.5 or 0.95 and EL to 0 makes the results a bit worse, but setting EL to 1 may ($c = 60$, $\alpha = 4$, $\beta = 0.5$, EL = 1) or may not ($c = 60$, $\alpha = 4$, $\beta = 0.95$, EL = 1) give an improved result. Additionally, for $c = 60$, $\alpha = 8$, setting β to 0.5 or 0.95 and EL to 0 makes the results relatively better, but setting EL to 1 give worse results ($c = 60$, $\alpha = 8$, $\beta = 0.5$, EL = 1 and $c = 60$, $\alpha = 8$, $\beta = 0.95$, EL = 1). Setting EL to 2 was also tried, the FOM_unified of scenario ($c = 60$, $\alpha = 4$, $\beta = 0.5$, EL = 2) is 1.0232. It is 2.32% worse than scenario ($c = 60$, $\alpha = 4$, $\beta = 0$, EL = 0) and 6.43% worse than scenario ($c = 60$, $\alpha = 4$, $\beta = 0.5$, EL = 1). Similarly deteriorating results are produced from other scenarios that have a configuration of EL = 2. Therefore, all EL = 2 scenarios are left out of the comparison in Figure 6-7.

With more simulations from other interesting scenarios, for instance, c = 120 or c = 210 (see acceptable results for these scenarios in Figure 6-4), Similar uncertain conclusions are shown. Therefore, their data are excluded here.

More simulations can be conducted for the further research of Helmond network or other traffic networks in SUMO or Vissim, using ImFlow for the adaptive traffic control. This would result in better calibration guidelines. At this stage, the algorithm was proven to be effective and several conclusions can be drawn:

- The advanced cost function algorithm of Section 6.1 is effective. The algorithm is well-designed, especially targeting on balancing the traffic efficiency of adaptive traffic control and the stability for GLOSA functionality.

- The simulation methodology derived from this algorithm is functional and can be developed further. The methodology was already disseminated so other researcher in the field can use similar traffic simulation methodology. In particular, it can deliver better plan stabilization analysis and debug the network until the best results are shown.

- The advanced memory features β and EL show very little effect. More research is needed to arrive at calibration guidelines. Preliminary, it can be concluded that β is probably too ineffective to be configured in the future. This would increase operational costs and endanger exploitation of the system. The EL can be set at a default value without the need of calibration as it filters out specific unwanted cases that have little impact on the overall results.

7 Conclusion and further research

7.1 Conclusion

The main objective of this deliverable is to provide a joint understanding of work package 4, road automation, from the project partners. To this end, this document serves as a prelude, by introducing the tools and methodology required for WP4, describing the queue modelling, the traffic control methodologies and signal timing strategy for TLC optimization. While MAVEN has a separate WP for evaluation, preliminary results of the queue modelling and signal plan stabilization were important to prove the algorithm effectiveness.

With the available information, work and results shown from Section 1-6 in this document, we can reach some preliminary conclusions. These can enlighten us about the road automation within the MAVEN context, which is important for the further research in WP4, which will be reported in the final version of this deliverable (D4.4). The future work will mostly focus on multi-intersection optimization and local level routing, for which this document paved the guidelines and directions.

The most significant results of this deliverable are about the queue model and plan stabilization for adaptive control. Data fusion of information from traditional detectors and automated vehicles resulted in up to 40% reduction for the average error of the queue length estimation. The largest benefits were visible for high traffic volumes, because this increases the chance of receiving vehicle information at 20% penetration rate. For adaptive control stabilization, results showed 25% reduction in average prediction error, while maintaining similar traffic efficiency. More advanced parameters were added to combat specific side effects, like the prediction stagnating at a certain value due to a green extension. This resulted in a small further improvement, but most notably in a solution for the stagnation problem.

More detailed conclusions are listed below:

- Analysis of the state-of-the-art revealed that among the four types of traffic control (see Section 2), semi-fixed time control is most commonly used for contemporary GLOSA solutions. Adaptive control has advantages due to its flexibility in the control algorithm yet it needs to be stable enough to be accepted by users.

- The LDM is a central point for all cooperative functionality. It can be seen as a data array with location references, which stores dynamic data from various relevant actors. Extensions for automated driving were made and successfully tested by using it for the queue modelling research.

- Position simulation with realistic measurement error emulation plays an essential role for testing queue modelling. The proposed advanced model was used successfully for the queue model research.

- The simpla extension of SUMO for automated driving is a promising possibility to enhance the future traffic efficiency by the formation of platoons of automated vehicles. It will be implemented in work package 7.

- The lane-based queue length model still has room for improvement, mainly in situations where the traffic flow over multiple lanes is low and the detector measurements do not provide enough insight into lane changes between the detectors. This results in incorrect identification of vehicle counts contributing to particular lane queues. The resulting error may be corrected by AV in case that their penetration rate is reasonably high, but for low traffic volumes and low penetration rates of AVs there is insufficient opportunity for corrections. This is acceptable, because at low traffic volumes the impact of incorrect queue information is less important.

- The configurable cost function for plan stabilization of adaptive control with ImFlow shows significant effects even when *c* is set as small as 30. Increasing this value shows further improvement, leading to the conclusion that this parameter can be used to implement different policies with respect to level of importance of stability.

- The advanced cost function parameters *α, β* and EL were effective against stagnating predictions (so-called "flat line" where the prediction freezes at the same value for 3 or more seconds).

- The extension level (EL) parameter is the most straight-forward for combatting the aforementioned flat-lines. As it is basically a constraint, it guarantees certain flat-line situations will not occur anymore.

- Both values of *c* beyond 150 and the advanced cost function parameters *α, β* and EL show very small changes in traffic efficiency and plan stability. While a general downward trend for higher values of *c* could be observed, individual data points are inconclusive due to statistical noise.

7.2 Further research

This document contains collaborate work and results of deliverable D4.1. Further work should stand on the concrete results to enhance networks with automated vehicles within MAVEN. The following is of interest for potential further work:

- Regarding the aspect of queue model, the current queue model will be further analysed to assess its behaviour in different scenarios with different structure of multi-modal traffic, varying AV penetration rate and intersection layout.
- To facilitate better estimates of lane capacity, the influence of multi-manoeuvre lanes on lane saturation flow will be further investigated.
- The model developed will be also compared with the queue length estimator of ImFlow. This isolates the effect of adding Kalman filtering to the conservation law model and differences in correction heuristics. Possibly, information provided by both models will be merged to provide better queue length estimates since accuracy of queue length is a major factor of GLOSA.
- Simpla will be applied to platoon simulation under MAVEN context.
- It is of significant interest that, the simulations of plan stabilization for adaptive control will be enhanced on multi-intersections scenarios on the network of Helmond.
- The deployments of configuring multiple parameters are flexible but need more testing. The goal is to arrive at deployment guidelines for default configurations.
- Investigating plan stabilization with adaptive control with off-peak traffic demand is also interesting. The optimal parameter tuning may be different because high traffic demand results in higher costs for delay time, when a less optimal but stable control solution is chosen.

References

[1] MAVEN consortium, D2.2
[2] COLOMBO evaluation paper
[3] COLOMBO simulation environment paper
[4] Wong, S.C., Group-based optimisation of signal timings using the TRANSYT traffic model, Transportation Research Part B: Methodological, Volume 30, Issue 3, 1996, pp. 217-244.
[5] Katwijk, R., Bakri, T., Vukovic, D., Hogema, J.H., Providing Speed Advice to Vehicles Approaching an Intersection: Evaluation and Lessons Learned, Transportation Research Part B 92nd annual meeting, Washington DC, USA, 2013.
[6] Van Vliet, K., Turksma, S., ImFlow: Policy-based adaptive urban traffic control First field experience, European Congress on Intelligent Transport Systems, Dublin, Ireland, 2013.
[7] HCM2000, Highway Capacity Manual. Transportation Research Board. 2000.
[8] Akçelik, R., Time-dependent expressions for delay, stop rate and queue length at traffic signals. 1980.
[9] Comert, G., Simple analytical models for estimating the queue lengths from probe vehicles at traffic signals. Transportation Research Part B: Methodological, 2013, 55: 59-74.
[10] Comert, G., Queue length estimation from probe vehicles at isolated intersections: Estimators for primary parameters. European Journal of Operational Research, 2016, 252.2: 502-521.
[11] Cui, Y., Ge, S.S., Autonomous vehicle positioning with GPS in urban canyon environments. IEEE transactions on robotics and automation, 2003, 19.1: 15-25.
[12] Friedrich, B., et al. Data fusion techniques for adaptive traffic signal control. IFAC Proceedings Volumes, 2003, 36.14: 61-66.
[13] Ho, C.H., Hwang, T.L., Modeling real-time dynamic queue length for urban traffic control systems. In: Intelligent Vehicles' 94 Symposium, Proceedings of the. IEEE, 1994. p. 438-442.
[14] Ledoux, C., An urban traffic flow model integrating neural networks. Transportation Research Part C: Emerging Technologies, 1997, 5.5: 287-300.
[15] Liu, H.X., et al., Real-time queue length estimation for congested signalized intersections. Transportation research part C: emerging technologies, 2009, 17.4: 412-427.
[16] Mück, J. Using detectors near the stop-line to estimate traffic flows. Traffic Engineering & Control, 2002, 43.11.
[17] Mystkowski, C.; Khan, S. Estimating Queue Length Using SIGNAL94, SYCHRO3, TRANSYTY-7F, PASSER Ⅱ-90 and CORSIM. In: Transportation Research Board. Paper Submitted for Publication and Presentation at the 78th Transportation Research Board Annual Meeting. Washington DC, USA. 1998.
[18] Quek, C., Pasquier, M., Lim, B.B.S., POP-TRAFFIC: A novel fuzzy neural approach to road traffic analysis and prediction. IEEE Transactions on Intelligent Transportation Systems, 2006, 7.2: 133-146.
[19] Ramezani, M., Geroliminis, N., Queue profile estimation in congested urban networks with probe data. Computer-Aided Civil and Infrastructure Engineering, 2015, 30.6: 414-432.
[20] Sharma, A., Bullock, D., Bonneson, J., Input-output and hybrid techniques for real-time prediction of delay and maximum queue length at signalized intersections. Transportation Research Record: Journal of the Transportation Research Board, 2007, 2035: 69-80.
[21] Tiaprasert, K., et al., Queue length estimation using connected vehicle technology for adaptive signal control. IEEE Transactions on Intelligent Transportation Systems, 2015, 16.4: 2129-2140.

[22] Viloria, F., Courage, K., Avery, D., Comparison of queue-length models at signalized intersections. Transportation Research Record: Journal of the Transportation Research Board, 2000, 1710: 222-230.
[23] Viti, F., van Zuylen, H., Modeling queues at signalized intersections. Transportation Research Record: Journal of the Transportation Research Board, 2004, 1883: 68-77.
[24] Vlahogianni, E.I., Karlaftis, M.G., Golias, J.C., Optimized and meta-optimized neural networks for short-term traffic flow prediction: a genetic approach. Transportation Research Part C: Emerging Technologies, 2005, 13.3: 211-234.
[25] Van Zuylen, H.J., Viti, F., Delay at controlled intersections: the old theory revised. In: Intelligent Transportation Systems Conference, 2006. ITSC'06. IEEE. IEEE, 2006. p. 68-73.
[26] Priemer, Christian, Friedrich, Berhnhard: A Method for Tailback Approximation via C2I-Data Based on Partial Penetration.

Appendix A: Literature review

In addition to the literature review carried out for MAVEN D2.2, a more extensive review was carried out for the work in WP4. This is to ensure we built on the latest work and not duplicate it. A MAVEN representative visited the TRB conference in 2017 to study and discuss the state-of-the-art with active scholars. From the presentations and discussions the most relevant papers for the MAVEN project were selected and extensively reviewed. The results of that are presented in this appendix. Note that due to personal discussions, some papers are not from TRB, because an author referred the project to another paper that would be more relevant. For some papers there are also references that have been analysed in detail to understand the work completely, these are also listed at the end in the “citation” section of the reviews.

1. Intersection Control System for Cooperative Automated Vehicles (CAV)

Title
Developing an Optimal Intersection Control System for Cooperative Automated Vehicles
Summary of the work
In this paper, an enhanced algorithm: Optimal Control Effort - real-time (OCRT), is developed to optimize the movement of CAVs through intersections (only single lane intersections are considered in this paper). The aim is to find a solution that reduces the delay while at the same time minimizing the control effort (i.e. avoid aggressive acceleration levels to ensure that the ride is comfortable for the passengers). This paper begins with proposing a comprehensive and extended vehicle model, using nonlinear equations of motion, Kinematic and dynamic constraints. The nonlinear features produce computational challenges to obtain a solution in real-time. Necessary simplifications such as convexifying the problem is used to guarantee a fast solution process. Through these simplifications, a good compromise between optimality and fast computation is achieved. Specifically, this paper solves the problem numerically instead of providing analytical solutions. The system presented in [1] is discretized using Model Predictive Control (MPC). Pontryagin’s minimum principle is used to formulate the problem and then it is used in convex optimization. Since the developed intersection control is novel with no traffic light control, a scheduler is placed at the intersection. Time slots for each vehicle to cross conflict zones, within the intersection is allocated. With the introduction of the scheduler and time slots for each vehicle, a combination of speed advisory and traffic control is presented. Simulations with different traffic inflows for a major and a minor roads are performed. The major road inflows ranges from 500 veh/h to a maximum of 1200 veh/h for a roadway saturation flow rate of qc = 1700 veh/h/lane. The minor road inflows range from 250 veh/h to 600 veh/h. Detailed vehicle information is captured during the simulation: velocity, acceleration, delay, CO_2 emissions, fuel consumption, etc. Note that the fuel consumption is computed along the vehicle trajectory using the VT-Micro model. The results are compared to the results of [1] (i.e. Optimal Control Nonlinear (OCN)) and when the intersection is controlled by a roundabout (R), a stop sign (SS) and a traffic signal (TL). The results of the (R), (SS) and (TL) approaches are obtained using the INTEGRATION software, using the same input as the proposed algorithm. Noted that the INTEGRATION software also uses the Rakha-

Pasumarthy-Adjerid (RPA) car-following [2] and acceleration model that are embedded in the proposed algorithm. The results also show that the proposed algorithm outperforms the other strategies producing lower delays up to 55 % and an average CO_2 emissions reductions of 10%, relative to the best intersection control strategy (in this case the roundabout). One disadvantage of this proposed algorithm is the estimate time of the vehicle reaching the intersection, in order to compute the solution. Once that is achieved a real-time solution is obtained through convex optimization. Initial estimates of the arrival times can be based on historical data, however further research is needed to develop good initial solutions.
Results relevant to MAVEN
The focus of MAVEN is on automated vehicles which can communicated and cooperate with traffic lights control. The novel algorithm in this paper can enlighten traffic light control design in MAVEN in the following aspects: The non-linear modelling of CAV behaviour is relatively accurate and it could be compared with simpla. Although non-linear can cause computational problem, simplifying the problem such as convexifying can help to solve this numerical computation problem; This control algorithm applied cost function from [1]. The cost function can be comparable to the cost function in section 6 of this deliverable, D4.1. The RPA car-following model [2] can model the car-following behaviour of AVs by calibrating the AV parameters. This can be compared with the car-following model in SUMO and check its applicability to implement and load a novel car-following model into simulations of MAVEN; This algorithm had better results comparing to Optimal Control Nonlinear (OCN), (R), (SS) and (TL) approaches. Results are built and tested on single intersection network with arbitrary simplification. The usability of this control algorithm on complicated adaptive control intersection is yet to be tested.
Citation (multiple if relevant, e.g. multiple deliverables)
Youssef Bichiou and Hesham A. Rakha, Developing an Optimal Intersection Control System for Cooperative Automated Vehicles, Transportation Research Board Annual Meeting, 2017. **Referenced papers:** [1] Bichiou, Y., H. A. Rakha, and A. Roman, Developing an Optimal Intersection Control System for Automated Connected Vehicles. Submitted to IEEE Transaction, 2016. [2]Rakha, H., P. Pasumarthy, and S. Adjerid, A simplified behavioural vehicle longitudinal motion model. Transportation letters, Vol. 1, No. 2, 2009, pp. 95–110.

2. Model Predictive Control (MPC) and GLOSA in Connected Vehicle (CV) environment

Title
Combining Model Predictive Intersection Control With Green Light Optimal Speed Advisory In a Connected Vehicle Environment
Summary of the work

Combination between GLOSA and signal control is not a new idea. But most inductive loops are unable to provide frequent updates about individual approaching since they are fixed in limited locations. Upcoming V2I technology will allow vehicles to communicate more accurate movement data more frequently. It is also capable of providing information back to vehicles approaching the intersection. This means that V2I communication is able to influence driving behaviour and trajectories. Several authors have proposed mechanisms for determining Green Light Optimal Speed Advisory (GLOSA) for vehicles approaching an intersection. However, they do not use MPC to find optimal solutions. Connected Vehicle (CV) technology allows Model Predictive Control (MPC) to be integrated with GLOSA, making the best use of this future technology to improve traffic conditions for all motorists.

This paper proposes the optimal control schedule that minimises delay. It suggests that this optimal control schedule can best utilise traffic data that varies second-by-second and it can be found via MPC with suitable state space reduction techniques. Since the control algorithm utilises an underlying microscopic model, entering vehicles' trajectories can be modified with Green Light Optimal Speed Advisory (GLOSA). This allows drivers to adjust their speed profiles in order to have an efficient approach trajectory.

Unlike traditional signal control that determines the parameters such as cycle time, phase splits and offsets, this paper uses an alternative formulation that considers traffic control to be a scheduling problem. The scheduling algorithm takes as input a set of vehicles, and the intended routes for each vehicle. In addition, each vehicle has a location, speed and acceleration at the current time. All of this information could be sent to the intersection controller using V2I communication. The control algorithm works by enumerating possible future schedules and calculating their associated total cumulative delays within the planning horizon, attempting to find the optimal schedule with minimum delay. Since there are a finite number of arriving vehicles there are a finite number of ways to sequence vehicles through the intersection. However, it is impractical to enumerate them all in real-time because the number of possible sequences is (at least) exponential compared to the number of vehicles on all routes [1]. To overcome this computational complexity problem, Xie et al. [2] developed a polynomial time algorithm by framing single intersection traffic control as a job shop scheduling problem, and using elimination criteria to reduce the size of the search state space. These elimination criteria are also examined. In this paper, an algorithm is developed that works with a more realistic, car-following traffic model, and the effect of combining GLOSA with MPC signal control is examined. The car-following model used in this paper are defined with several rules. Rule (1) and (2) ensure that, minimum headway between vehicles are kept and no collisions will occur. Braking at the maximum speed will occur if these minimum distances are not kept. Rule (3) is employed only if the antecedents of rules (1) and (2) are false. Rules (4) and (5) adjust the vehicle's updated acceleration, a', for the following simulated time step, to make it within the range of the vehicle's maximum acceleration rate and maximum deceleration rate. Once a' is known, the updated values v' and x' can be calculated.

Two techniques, platoon clustering and elimination criteria are applied to achieve state space reduction when the proposed algorithm grows exponentially. Generally, it is not beneficial to split platoons of vehicles apart due to intersection signalisation. Therefore, platoons are kept together in order to reduce the computational complexity of the algorithm. In order to reduce the computational complexity of the scheduling algorithm, similar elimination criteria to those used by Xie et al. [2] were introduced to prune the state space.

Four scenarios were tested: MPC with GLOSA, MPC without GLOSA, fixed time signal control with GLOSA, and fixed time signal control without GLOSA. Overall, the performance indicators reveal that model predictive signal control significantly outperforms fixed time signal control. Combining MPC with GLOSA improves performance further. These results are limited to several assumption/simplification of network, such as one lane single intersection, traffic only from two perpendicular direction, north and east bound.
Results relevant to MAVEN
A significant contribution of MAVEN is that it can improve urban intersections by combining CAVs with GLOSA to modify vehicle approaching pattern. In MAVEN, GLOSA will also be coupled with the existing platooning approach simpla (see Section 4). This results in platoons and not individual vehicles requesting signal switches. As explained in this paper, platoon clustering can be used for elimination criteria to achieve state space reduction. This can be an important factor to consider in MAVEN. In addition, the Literature review of signal control approaches in this paper is quite extensive and related to MAVEN, especially considering GLOSA, which can be used for work package 4 of MAVEN. Another interesting point to consider is the car-following model in this paper. It can be compared to the model being used in simpla, to examine how CAVs is forming platoon and how to keep the platoon clustering. Lastly, the generic scheduling algorithm that utilizes the structure of the state space is shown with pseudocode in this paper. It shows that the main problem is the large number of potential sequence with this algorithm. Elimination Criteria is introduced to prune the state space. Further possible research can be carried out to study/improve ImFlow selection process of control strategies.
Citation (multiple if relevant, e.g. multiple deliverables)
Simon Stebbins, Jiwon Kim, Mark Hickman and Hai L. Vu, Combining Model Predictive Intersection Control With Green Light Optimal Speed Advisory In a Connected Vehicle Environment, Transportation Research Board Annual Meeting, 2017. **Referenced papers:** [1] Papageorgiou, M., C. Diakaki, V. Dinopoulou, A. Kotsialos, and Y. Wang. Review of road traffic control strategies. Proceedings of the IEEE, Vol. 91, No. 12, 2003, pp. 2043–2067. [2] Xie, X.-F., S. F. Smith, L. Lu, and G. J. Barlow. Schedule-driven intersection control. Transportation Research Part C: Emerging Technologies, Vol. 24, 2012, pp. 168–189.

3. Cooperative Adaptive Cruise Control (CACC) at intersections

Title
<1> Eco-Cooperative Adaptive Cruise Control at Signalized Intersections Considering Queue Effects <2> Eco-cooperative Adaptive Cruise Control at Multiple Signalized Intersections: Network-Wide Evaluation And Sensitivity Analysis
Summary of the work

In general, eco-driving research can be categorized as freeway-based and city-based strategies. Unlike freeways, traffic stream motion along arterial roads is typically interrupted by traffic control devices. The study focus of MAVEN is at urban intersections with traffic controls. To include the works of eco-driving with CACC at intersections, two related papers are grouped and introduced.

<1> Unlike existing studies related to eco-driving on arterial corridors, which attempt to minimize idling time and smooth acceleration/deceleration manoeuvres without considering the impact of surrounding traffic, this paper considers not only the SPaT information, but also the vehicle queues at signalized intersection approaches.

Queue estimation and discharges are studied in the following literatures: [1], [2] [3], [4]. However, these studies didn't integrate the queue estimation into the algorithm to apply them in real-time applications. Moreover, most researches focus on optimizing speed profiles of equipped vehicles (EVs) upstream of the intersection and ignore the acceleration behaviour downstream of the intersection after the traffic signal turns green, which results in more fuel usage of vehicles proceeding through intersections. This paper conducts a comprehensive analysis of Eco-CACC systems on arterial roads, predicting vehicle queues upstream of a signalized intersection to develop fuel-optimum vehicle trajectories.

Firstly, this paper investigates the impact of the SPaT and the vehicle queue information on fuel consumption levels at signalized intersections. Secondly, the impact of vehicle queues on the Eco-CACC algorithm proposed in [5] is analytically investigated. [5] has demonstrated that the most critical strategy to reduce fuel consumption levels is to prevent vehicles from coming to a complete stop at the stop bar. This paper develops an Eco-CACC algorithm considering queue effects (Eco-CACC-Q) to minimize vehicle fuel consumption levels while proceeding through an intersection with the consideration of realistic deceleration and acceleration levels. Lastly, this paper also evaluates the benefits of the algorithm within a microscopic simulation environment (both single-lane and two-lane intersection approach are studied separately), and evaluate the impact of market penetration rates of probe vehicles and intersection configurations on the system performance.

The results illustrates the impact of queue length on the total fuel consumed. Both the Eco-CACC algorithms (Eco-CACC-O doesn't consider queue and Eco-CACC-Q considers queue) significantly reduce the fuel consumption of the Eco-CACC vehicles. The Eco-CACC-O algorithm reduces the fuel consumption by as high as 25% while the Eco-CACC-Q algorithm reduces the fuel consumption by 32%. Comparing the two algorithms, the Eco-CACC-Q algorithm produces fuel consumption levels that are 10% lower. Moreover, with longer queues, the cruise speed is smaller and the fuel consumption is larger. These results show that the Eco-CACC-Q algorithm can further improve the fuel efficiency of Eco-CACC vehicles.

With simulation results on single-lane and two-lane intersection approaches, the following findings are summarized: For single-lane intersection approach, the Eco-CACC-Q algorithm is the most efficient control strategy with reductions in fuel consumption levels as high as 11.4%; and compared with Eco-CACC-O, it reduces fuel consumption levels by approximately 4.5%; For two-lane intersection approach, the Eco-CACC-Q algorithm provides the most efficient control with reductions in fuel consumption levels for Eco-CACC vehicles as high as 19.2%; and compared with Eco-CACC-O, it reduces fuel consumption levels by approximately 5.6%.

As expected, both algorithms have a negative impact on the overall fuel consumption rate under lower Market Penetration Rate (MPR) of Eco-CACC vehicles. This is caused by the

intense lane changes around the controlled vehicles. Once the MPR is greater than 30%, the cutting in and lane change behaviours of non-Eco-CACC vehicles are reduced. Hence, the Eco-CACC algorithms generate fuel consumption savings at higher MPRs. These savings increase as the MPR increases. If all vehicles are Eco-CACC vehicles, the fuel consumption rate is reduced by approximately 17.0% for Eco-CACC-O, and 18.3% for Eco-CACC-Q demonstrating the benefits of the Eco-CACC-Q system.
This paper only investigated the impact of MPRs on the algorithm performance. Other factors, such as the length of the controlled segments, the traffic demand levels, the SPaT plan and the robustness of the algorithm to errors in wireless communication, should also be considered in future research (see paper <2>). Moreover, further improvements to the proposed Eco-CACC-Q algorithm should considering multiple signalized intersections in the optimization logic. Furthermore, the proposed algorithm only applied vehicle-to-signal communications to gather road traffic information, which was not sufficient to estimate the queue length accurately due to lane-changing and passing behaviour. In the future, we will introduce vehicle-to-vehicles communications to queue length estimation algorithm [6]. Finally, one drawback of the algorithm is that it fails once the road is over-saturated. Hence, we propose that we combine a speed harmonization algorithm [6] on arterial roads and signal optimization with the Eco-CACC-Q algorithm to solve this problem and to further improve the system.
<2> This paper is an extension of previous research <1>, Eco-Cooperative Adaptive Cruise Control for Multiple Signals (Eco-CACC-MS) is introduced and tested on multiple intersection networks using the INTEGRATION microscopic traffic assignment and simulation software, aiming at reducing vehicle fuel/energy consumption. It is also being comparing to Eco-CACC-O algorithm proposed in <1>, which is simply referred as Eco-CACC in this paper. The Eco-CACC-MS uses SPaT data received from each signal controller via V2S communication, to predict the queue length and to compute the fuel-optimum vehicle trajectory for an equipped vehicle. The algorithm estimates three optimal acceleration/deceleration rates for the equipped vehicle to minimize the total fuel consumption to pass the two intersections. Then the algorithm provides an advisory speed limit that allows the vehicle to pass multiple consecutive intersections without stopping.
For roads with more than two intersections, the system will always estimate the optimal trajectories for the equipped vehicles with the consideration of their two immediate intersections. Once an equipped vehicle passes one intersection, its optimal trajectory will be recalculated with the SPaT information of the two downstream intersections.
The sensitivity analysis of this paper considered factors such as market penetration rate (MPR) of equipped vehicles, number of lanes of the controlled segment, traffic demand rates, offset between the traffic signals, and distance between intersections.
For travel demand level test, different traffic flow demands from 300 to 700 vphpl (vehicle per hour per lane) were tested. The first test is a single-lane network and the second test is a two-lane network, both tests with 45s offset for the second signal with respect to the first signal. The results show some savings for all demand levels, but the overall demand of 300 vphpl has the best savings of 7.7%. These trends are the result of the increase in the number of the probe vehicles in the network. As the road gets close to the oversaturation level, lower-than-optimal results are seen and the network-wide savings decreases. Savings for the two-lane road are similar to the single-lane result, Eco-CACC-MS for a demand of 300 vphpl saved 7.9% more fuel than Eco-CACC. Similar to the single-lane road, the network-wide savings in fuel consumption decreased as the demand neared the oversaturation point.

For distance between intersections, which is an important variable that impacts fuel consumption savings, the results show that the shorter the distance between the intersections, more savings are achieved by the algorithm, which is 9.9% for 400 m between intersections. The range between the intersections cannot be very small based on the effective distance of the Dedicated Short-Range Communications (DSRC) technology that is implemented in the V2I communications between probe vehicles and signals. For different offset, the best savings were captured at a 600-m distance between intersections by using a 0-s offset. The fuel savings for Eco-CACC-MS is 0.5% more than Eco-CACC. For the number of lanes, the fuel savings of the single-lane road are greater at higher MPRs. Under 100% MPR, the reductions in fuel consumption are 7.3% higher for Eco-CACC-MS compared to the Eco-CACC. On the multi-lane road, due to lane-changing behaviour, there were small savings in fuel consumption for MPRs lower than 20%. For the two-lane network, savings in fuel consumption are 7.4% higher for the Eco-CACC-MS compared to the Eco-CACC system under 100% MPR. The results show that considering the queue enhances the algorithm performance. However, these findings are not general and need further investigation for different demand levels, signal offsets, and phase splits. The proposed Eco-CACC-MS system has limited application for oversaturated conditions due to rolling queues. Possible solutions include using vehicle-to-vehicle (V2V) communication to estimate the queue or to introduce speed harmonization [6] to restrict the traffic entering the intersection to maintain an under-saturated condition at all the times.
Results relevant to MAVEN
The queue estimation in these two papers are of interest to MAVEN because accuracy of queue length estimation is a major factor to GLOSA functionality. Moreover, MAVEN introduces V2V communications to queue modelling, which can help on estimating the queue length accurately due to lane-changing and passing behaviour. Relevant literature [6] can be referred regarding V2V communication. In MAVEN, a constant/ fuel consumption optimum deceleration rate can be applied to CAVs which have received GLOSA. This information should be communicated back from vehicle to infrastructure, to assist cooperative intersection SPaT calculation and platoon green wave. Paper <2> is relevant considering the algorithm Eco-CACC-MS is based and tested on multiple intersection networks. The tests in this paper studied the performance of the Eco-CACC (O and Q) algorithms on both single-lane intersection approaches and multi-lane roads. But it only investigated the impact of MPRs on the algorithm performance. MAVEN can include the SPaT plan, explore on the traffic demand levels variation (such as peak and off-peak hour), and also examine the robustness of the system architecture. Most relevant studies, like <1> and <2>, would fail once the road is over-saturated. MAVEN can test the oversaturated scenario and can refer to a speed harmonization algorithm in [6] for further research. Finally, the offsets and distances between multiple intersections on arterial road are to be considered in D4.3 of MAVEN.
Citation (multiple if relevant, e.g. multiple deliverables)

Source Papers:
<1> Hao Yang, Hesham Rakha and Mani Venkat Ala, Eco-Cooperative Adaptive Cruise Control at Signalized Intersections Considering Queue Effects, IEEE, 2016, pp(99):1-11.
<2> Hao Yang and Hesham Rakha, Eco-cooperative Adaptive Cruise Control at Multiple Signalized Intersections: Network-Wide Evaluation And Sensitivity Analysis, 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), 2017.

Referenced papers:
[1] G. Qian and E. Chung, "Evaluating effects of eco-driving at traffic intersections based on traffic micro-simulation," in 34th Australasian Transport Research Forum (ATRF), Adelaide, South Australia, Australia, vol. 34, no. 0092, 2011.
[2] G. Qian, "Effectiveness of eco-driving during queue discharge at urban signalised intersections," Ph.D. dissertation, 2013.
[3] Z. Chen, "An optimization model for eco-driving at signalized intersection," Ph.D. dissertation, Texas A&M University, 2013.
[4] Q. Jin, G. Wu, K. Boriboonsomsin, and M. J. Barth, "Power-based optimal longitudinal control for a connected eco-driving system," IEEE Transactions on Intelligent Transportation Systems, pp. 1–11, 2016.
[5] R. K. Kamalanathsharma, H. A. Rakha, and H. Yang, "Network-wide impacts of vehicle eco-speed control in the vicinity of traffic signalized intersections," in Transportation Research Board 94th Annual Meeting, no. 15-4290, 2015.
[6] H. Yang and H. Rakha, "Developemnt of a speed harmonization algorithm: Methodology and preliminary testing," 2015, submitted to Transportation Research Part B.

4. Decision making tool for applying Adaptive Traffic Control

Title
Big Data Analysis Based Decision Making Tool for Applying Adaptive Traffic Control Systems
Summary of the work
This paper develops methods to guide traffic engineers and decision makers to decide whether adaptive control is best suited for a given traffic corridor and/or intersections than existing control systems especially actuated traffic control systems. The methods are based on big data analysis using large amount of data from various sources such as loop detectors, travel time systems, 511 systems, weather, and special events. The ultimate goal is to develop an easy-to-use and easy-to-understand decision making procedure to help make decisions about where adaptive control systems should be deployed. Existing methods for such decision making are mainly based on before and after comparisons, using statistical or simple data analysis methods, e.g. using data collected for a few days by probe vehicles. With technologies advance, more and more traffic data can be collected from a variety of sources, including loop detectors, video cameras, mobile sensors, and connected and automated vehicles. It is thus interesting to investigate whether one can conduct decision making regarding adaptive control by leverage the large amount of traffic and related datasets. Big data analysis methods can be suitable for this purpose.

In this study, big data based quantitative analyses, such as volume, occupancy, volume capacity ratio, event, and weather on the study corridor, are conducted to evaluate whether adaptive signal is best suitable for a corridor. The data analysis methods, Support Vector Machine (SVM) to develop the decision-making tool. Linear SVM for LOS classification method is applied to classify data point into two classes. Using SVM, "good" signal performance (i.e., LOS A-C) can be distinguished from "bad" signal performance (LOS D-F). Results from the SVM models show that the misclassification errors decrease as the number of features that the model considers increases. Based on the SVM methods, a decision-making procedure is then developed to help deploying adaptive traffic signal control systems.

To summarize, the steps of the SVM-based decision making procedure for adaptive control deployment are:

1. Collect data (volume, $v_{critical}$, occupancy, event, weather, etc.), ideally for a few months or longer.
2. Check the data points LOS-based SVM to map the data point into graphs, actuated (section 1) or adaptive (section 2) or the other sections. Each data point represents a "vote" that section.
3. Count the votes. If section 2 gets more votes, adaptive control should be deployed. Otherwise, adaptive control is not recommended.

One limitation of the current study is that the data size is rather small and is limited to only one corridor. Although the data is inherently heterogeneous, dynamic, and contains errors, technically it is not true "big" data yet. More critically, due to this limited data size, the results from the above procedure may not be very accurate or reliable. The immediate next step is to accumulate more data from more corridors in terms of before and after the deployment of adaptive control systems. The results should be improved dramatically if sufficiently large datasets are collected and used.

This big data analysis methods are suitable for decision making. The key philosophy in big data analysis methods is for data "to speak." That is, one only cares about the correlations among data elements (i.e., the "what"), but not the underlying reasons behind the corrections (i.e., the "why"). This philosophy may not fit rigorous scientific investigation but, in any case, such methods can help better utilize the increasingly large amount of traffic data collected and being archived by transportation management agencies and the private sector, to make more informed decisions about traffic operations and other related decisions.

Results relevant to MAVEN
MAVEN is to manage automated vehicles that are connected with an intelligent environment in an urban environment. This goal of MAVEN contributes to the EU objective of reconciling growing mobility needs with more efficient transport operations, lower environmental impacts and increased road safety. Many of the test sites in MAVEN are real world traffic networks that contain pre-existed traffic control measures. Research of MAVEN so far already shows significant improvement on the existing networks. This paper provides methods to determine whether the existing traffic control is efficient. It can also determine the improvement of changing the existing control to adaptive control. The data analysis method is applicable to case studies in MAVEN because the data collected in MAVEN are inherently heterogeneous, dynamic, and contains errors. In section 6 of this deliverable, some randomness of simulations are observed with fix seed of

adaptive control algorithm ImFlow. These randomness may be better analysed using the data analysis methods in this paper. Future work of MAVEN includes data collection through camera detection. The methodology of this paper can also help the data analysis in that case.
Citation
Wan Li, Xuegang (Jeff) Ban, Big Data Analysis Based Decision Making Tool for Applying Adaptive Traffic Control Systems, Transportation Research Board Annual Meeting, 2017

5. Intersection communication for AVs

Title
STIP: Spatio-Temporal Intersection Protocols for Autonomous Vehicles
Summary of the work
This paper focused on developing a new intersection protocols, Spatio-Temporal Intersection Protocols (STIP), with a realistic GPS model. STIP protocols are V2V protocols that aim to increase the throughput at intersections while avoiding collisions. STIP protocols enable cooperative driving among approaching vehicles to ensure their safe passage through the intersection. In this paper, STIP is implemented in a hybrid emulator-simulator for vehicular networks, called AutoSim. A family of vehicular network protocols to manage the safe passage of traffic across intersections relies on vehicle-to-vehicle (V2V) communications and localization to control and navigate vehicles within the intersection area. Generally speaking, V2V communications using Dedicated Short Range Communications (DSRC) and Wireless Access in a Vehicular Environment (WAVE) to broadcast intersection safety messages to other vehicles in their communication range. Hence, Autonomous Vehicles (AVs) approaching an intersection use DSRC and WAVE to periodically broadcast information such as position, heading and intersection crossing intentions to other vehicles. These vehicles then decide among themselves regarding such questions as who crosses first, who goes next and who waits. STIP can be described as follows: all vehicles are assumed to follow the First-Come, First-Served (FCFS) policy, in which the vehicle with the lower arrival time to the intersection has the higher priority. In the scenarios that two or more vehicles arrive almost at the same time, they break the ties in favour of vehicles approaching on main roads. If the tie still holds, it is broken by Vehicle Identification Number (VIN), which has uniquely assigned to each vehicle. Three classes of STIP are introduced in this paper. 1) Minimal Concurrency Protocols (MCP) includes Throughput Enhancement Protocol (TEP) and Concurrent Crossing-Intersection Protocol (CC-IP) [1, 2]. In this category, the conflicting vehicle with higher priority can ignore the intersection safety messages from other lower priority vehicles and cross the intersection without slowing down or stopping. However, any lower-priority vehicle is super-cautious and, when it loses a competition, it comes to a complete stop before entering the intersection boundaries, and waits till it receives an EXIT message, from the higher priority vehicle. This message informs the lower-priority vehicle that the higher-priority vehicle has crossed the intersection and now the intersection area is safe

for its passage. This protocol is applied across all priority levels. 2) High Concurrency Protocols (HCP) includes the Maximum Progression Intersection Protocol (MP-IP) and the Advanced Maximum Progression Intersection Protocol (AMP-IP) [3].The main goal is to increase the parallelism inside the intersection area by allowing more vehicles to cross the intersection at the same time. This goal is achieved by allowing even conflicting vehicles to make maximal progress inside the intersection area, without sacrificing the primary goal of safety. This category allows even potentially conflicting vehicles to progress inside the intersection area, and the lower-priority vehicle gets to a complete stop before entering the conflicting cell, and waits till the higher-priority vehicle has crossed and cleared that cell. 3) High Concurrency Protocols with lowdown (HCPS). HCPS includes Advanced Cross Intersection Protocol (ACIP) and advanced Progression Intersection Protocol (APIP). In MCP and HCP, STIP protocols, potentially conflicting vehicles with lower priority must come to a complete stop outside or inside the intersection area to allow the safe passage of higher-priority conflicting vehicle. HCPS protocols allow lower-priority conflicting vehicles to slow down while approaching an intersection and prior to the conflicting cell, to provide the higher priority-vehicle with necessary time gap to cross. This will minimize a vehicle's need to get to a complete stop, and also the total number of stops and startups will be decreased significantly. The results indicate that STIP protocols are significantly outperforming the traffic light models. AP-IP has very negligible delay when dealing with low and medium-volume traffics. AP-IP outperforms the traffic light models with 30 seconds and 10 seconds of green light duration, respectively by 91.04% and 80.21%. Clearly, localization and positioning accuracy is crucial for safety applications such as intersection collision avoidance. Different methods can be deployed to improve the position accuracy such as using high-accuracy Differential GPS (DGPS), Wide Area Augmentation System (WAAS), gyroscopes and local sensing. However, all GPS receivers have finite accuracy, with commonly-used inexpensive GPS receivers having errors of up to a few meters. When dealing with high levels of positioning inaccuracy, each vehicle will use an updated safe distance parameter based on its GPS positioning error parameter. This increased buffer distance among following vehicles prevents vehicles from getting very close to each other and gives them the capability to slow down without causing an accident when the leader vehicle brakes suddenly. This paper designed a new generation of V2V-based intersection protocols: STIP, which significantly increase the throughput of the intersections and avoid collisions. The effects of GPS position inaccuracies are also studied by implementing realistic GPS models. Although STIP protocols are designed for autonomous vehicles that use V2V communication for co-operative driving in future intelligent transportation systems, they can be adapted to a driver-alert system for manual vehicles at traffic intersections. Local sensing technologies such as cameras and lasers can be combined with V2V and V2I communications to avoid any potential collisions and enhance localization accuracy.
Results relevant to MAVEN
A major focus of MAVEN is on opportunities that arises from traffic control and management that are based on automated vehicles, V2V and V2I communication. WP4 of MAVEN investigates these opportunities and challenges of connected environment and its effect on signal timing. To do this, the communication protocols of MAVEN play a leader

role throughout the project. This paper provides such a novel protocols, STIP. These protocols are also implemented on the arbitrary network, which showed that these protocols are significantly outperforming the traffic light models. To the least, these protocols can trigger some ideas for MAVEN studies. Another interesting aspect of this paper is the GPS localization and positioning accuracy. This is of great importance to section 3 of this deliverable and the future work. This paper also proposed methods of GPS correction which is practical if applicable in MAVEN.
Citation (multiple if relevant, e.g. multiple deliverables)
Reza Azimi, Gaurav Bhatia, Ragunathan (Raj) Rajkumar and Priyantha Mudalige, STIP: Spatio-Temporal Intersection Protocols for Autonomous Vehicles, ICCPS'14, Berlin, Germany, April 14-17, 2014 **Referenced papers:** [1] R.Azimi, G. Bhatia, R. Rajkumar, P. Mudalige. Vehicular networks for collision avoidance at intersections, society for automotive engineers (SAE) world congress. April 2011. [2] R.Azimi, G. Bhatia, R. Rajkumar, P. Mudalige. Intersection management using vehicular networks, society for automotive engineers (SAE) world congress. April 2012. [3] R.Azimi, G. Bhatia, R. Rajkumar, P. Mudalige. Reliable intersection protocols using vehicular networks, ACM/IEEE 4thinternational conference on cyber-physical systems. April 2013.

6. Environmental impacts of CAVs

Title
Anticipating The Emissions Impacts of Smoother Driving by Connected and Autonomous Vehicles, Using The MOVES Model
Summary of the work
This paper examines the emission impacts of CAVs, presuming that CAVs are programmed to drive more smoothly than humans. It uses the US Environmental Protection Agency's (EPA's) Motor Vehicle Emission Simulator (MOVES) to estimate CAVs' emissions based on driving schedules or profiles. In this paper, only urban road emissions were simulated. Several emission pollutants, such as Volatile Organic Compounds (VOC), particulate matters 2.5 (PM2.5), carbon monoxide (CO), nitrogen oxides (NOx), sulphur dioxide (SO2) and carbon dioxide (CO2) are considered to anticipate some of the emission impacts of CAVs. CAV driving profiles are envisioned to be smoother than those of human-controlled vehicles (HVs), because CAVs are expected to be faster and more precise than human drivers, in terms of reaction times and manoeuvring. Human drivers tend to create significant, frequent speed fluctuations (i.e., hard brakes and rapid accelerations) and have relatively long reaction times (e.g., 1.5 seconds). CAV technologies may rarely suffer from such fluctuations, allowing for smoother driving profiles, referred to here as Eco-Autonomous Driving (EAD) cycles. Hard braking and rapid acceleration events are associated with increased emissions, so, by smoothing HVs' existing driving cycles, this work anticipates the emission benefits of CAVs.

Differences in HV vs. CAV emissions estimation suggest valuable air quality improvement from CAVs, assuming CAVs are driven no more than HVs would be. The results from EPA cycles suggest that, in general, if HVs are replaced by AVs, greater emission benefits (up to 14% emission reductions) are anticipated in driving conditions where there are many hard acceleration and braking events, and for drivers with aggressive driving styles. The results from Austin cycles indicate the mean emission reductions are 10.89% for VOC, 19.09% for PM2.5, 13.23% for CO, 15.51% for NOx, and 6.55% for SO2 and CO2. Regression models revealed that passenger cars were found to be associated with lower emission reductions for VOC, PM2.5, CO, and NOx than passenger trucks. Diesel vehicles are linked with smaller emission reductions for these six types of emissions. The road links with higher average speeds have greater emission reductions for all emission species. At this point, the discussion of emission impacts of AVs is limited to the differences between the anticipated EAD profiles of CAVs and existing HV driving cycles. CAV profiles are envisioned to be smoother than HV cycles as compared to HV cycles. Other CAV-based technologies (like platooning of vehicles and CACC) may also save fuel and reduce emissions further.
Results relevant to MAVEN
Besides accommodating growing traffic and increasing road safety, a main objective of EU transport project is to obtain environmental sustainability and to achieve lower environmental impacts. MAVEN fits this goal by preparing and adjusting infrastructure systems. Combining with V2I and V2V communications, MAVEN is able to provide GLOSA to vehicles in order to reduce stop-and-go movements as well as sudden and fluctuated acceleration/deceleration. This paper shows the emission impacts of HVs and CAVs. In this paper, the emissions evaluation model MOVES are enhanced with the driving profiles of CAVs. The comparison of HVs and CAVs behaviours and emission impact are relevant to MAVEN infrastructure systems and they are important to be taken into account. Platooning of vehicles in D2.2 Annex 2 and CACC in urban environment mentioned in 3. Cooperative Adaptive Cruise Control (CACC) at intersections, also demonstrate achievability on these environmental aspects.
Citation
Jun Liu, Kara M.kockelman and Aqshems Nichols, Anticipating The Emissions Impacts of Smoother Driving by Connected and Autonomous Vehicles, Using The MOVES Model, Transportation Research Board Annual Meeting, 2017.