Automated Vehicles in Smart Urban Environment: A Review

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***Abstract*—Automated driving has become an important research trend in the field of cooperative intelligent transportation systems and their applications in smart cities. Automated driving both increases road capacity and eliminates human errors, one of the most common reason of traffic accidents. Both these aspects influence significantly the quality of life, which is a major goal of smart city initiatives. Management of automated vehicles by urban road infrastructure is a rather new subject and not so much practical development has been reported yet. Unfortunately, the available information is spread over fragments within other resources dealing with automated vehicles.**

In this paper, we provide an overview of major functionalities that have to be provided by both road infrastructure and an automated vehicle so that the vehicle can optimally navigate through an urban network with signalized intersections and we review the state-of-the-art publications providing approaches relevant to these core functionalities.

***Index Terms*—automated vehicle, urban intersections, cooperative intelligent transport systems, GLOSA, queue length estimation**

I. INTRODUCTION AND MOTIVATION

Automated driving has become an important research trend in the field of intelligent transportation systems, and researchers are already focusing on possible automated urban driving scenarios. Automated vehicle technologies allow the transfer of driving functions from a human driver to a computer. In many respects today's vehicles are also connected devices [1], and in the very near future they will also interact directly with each other and with the road infrastructure. This interaction is the domain of Cooperative Intelligent Transport Systems (C-ITS), allowing road users and traffic managers to share and use information that was previously not available, and to coordinate their actions.

This presents an important benefit for the Smart City community: automated and cooperative vehicles (also called *connected vehicles* or V2X – *vehicle-to-everything equipped vehicles*) have the potential to increase road and intersection capacity as they can collect traffic information for accurate estimations and also be coordinated to achieve optimal usage of road infrastructure. For instance, a *platoon*, which is a group of automated vehicles traveling together in a coordinated formation [2], allows harmonized behavior of vehicles not only at intersections, but also underway [3]. Relevant proposals for platoon formation strategies in urban intersections can be found in [3], [4], [5], [6], [7] and [8]. In addition, and most importantly, automated vehicles may eliminate human errors, one of the most common reason of traffic accidents. Traffic efficiency and safety both influence significantly the quality of life, which is one of the major goals of smart city initiatives.

Although substantial effort has been devoted to research and model automated and cooperative vehicles, which led to practical development as well, management of those vehicles by road infrastructure is an emerging new subject. At the present time and to the best of our knowledge, the available information is spread over in fragments within other resources dealing with automated vehicles, and not so much practical development has been reported, especially in urban scenarios.

Several former research projects (e.g. FP7 HAVEit [9], interactIVe [10]) focused on the topic of automated driving, but mostly on highways and on non-cooperative vehicles. Current research projects (e.g. FP7 AdaptIVe [11] or the German Stadtpilot [12]) try to head for automated driving even in urban conditions, while AutoNet2030 [13] approaches cooperation of automated driving based on vehicles sharing mutual information among themselves to elaborate the decision-making strategy. Nevertheless, these projects focus on individual automation, although appreciation of the role of infrastructure is growing – albeit still only as an information provider.

Therefore, the logical next step is the integration of automated driving into a traffic system, where automated vehicles collaborate with their sensed data and negotiate their intentions with an intelligent infrastructure that make smart decisions taking into account the abilities and goals of all road users.

II. MAIN FUNCTIONAL BLOCKS AND SCOPE OF THIS PAPER

The road infrastructure, denoted for simplicity "Intersection" in Fig. 1, consists actually of a traditional *Traffic Controller* (TC) responsible mainly for the control algorithms and logic of traffic signals as well as a *Road Side Unit* (RSU), responsible for communicating with the Automated Vehicles. Both, the Intersection as well as the Automated Vehicle interact with non-cooperative and non-automated vehicles as well. The Intersection also directly interacts with Traffic Network, consisting of adjacent intersections as well as the *Traffic Management Center* (TMC), in order to determine the optimal management of traffic in the adjacent part of the network and to impose the actual traffic policies (such as priorities for platoons of automated vehicles). The typical tools for such management are (a) advisory messages, including (i) local-level routing, (ii) trajectory planning and lane change advisory, and (iii) green light optimal speed advisory (GLOSA); and (b) traffic control optimization, that uses (i) queue length estimation, (ii) priority management and negotiation, and (iii) signal optimization.

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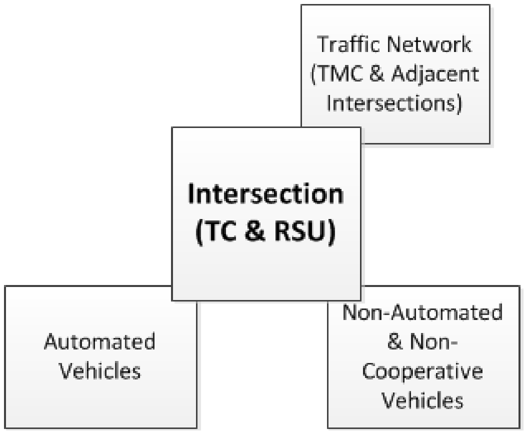

Fig. 1. Major physical components and definition of the scope of this paper.

Within this paper we focus on mapping the field of managing automated vehicles that communicate to each other and with the road infrastructure, mainly in a mixed urban environment. Our main objective is to provide study directions and results that can be a significant help for future research. Section III presents the state of the art divided into six subsections, one for each direction mentioned above, followed by a conclusion of challenges and possible further developments.

III. STATE OF THE ART

The process of decision-making of a typical automatic car (driver-less but not necessary cooperative) has four components [14]:

a) route planning that provides way-points that the vehicle should follow;
b) behavioral layer ("maneuver decision" in [15]) that analyses the environment and context to determine the driving behavior;
c) motion planning to select a feasible path; and
d) control system to correct the execution of the planned motion.

Table I shows main publications and approaches of automated driving management. Next, each section provides an overview of the most relevant publications related to the before mentioned four components of typical automatic car.

A. Local-Level Routing

The *local-level routing* is a specific type of route planning. It can be exemplified by route guidance systems that manage optimal vehicle trajectories using local information exchanged in real-time among vehicles and infrastructure. The decision-making in infrastructure-based systems is either (i) centralized (the TMC analyses received data and sends the optimal route information to vehicles) or (ii) decentralized, being either (a) autonomous (when each TC&RSU receive reports of traffic information from TMC and calculate optimal routes to vehicles) or (b) dependent (TMC collects traffic data and shares link travel times to vehicles) [70]. Local-level routing algorithms contribute mainly to the reduction of travel times.

Khanjary et al. [16] proposed an improvement of [71] and [72], combining distributed traffic control information and route guidance system based on a hierarchical fuzzy system, where the first layer focuses on street priority, the second layer deals with the measured speed and the third layer is for optimal route assignment and traffic light adjustments. A route guidance system, which depends on the travel time estimation of vehicles and also those traveling in the opposite direction is presented in [18], aiming to obtain the shortest travel time path of any vehicle from the intersection to its destination. A multi-agent system is introduced in [17], where vehicles are modeled as a hierarchical finite state machine (FSM) to find optimal routes based on static information, such as vehicle characteristics or the link travel time, as well as using dynamic data from vehicle communication. An application in [19] is able to predict congestion and reroute vehicles to semi-optimal routes, through the analysis of vehicles current positions, destinations, as well as selected routes by an information server. Tatomir and Rothkrantz [20] propose a hierarchical routing system, that consists of (a) route finding system (RFS) using an ant-based control algorithm and (b) timetable updating system (TUS) that receives information about routes covered by vehicles and then provides this data to the RFS.

Focusing specifically on emergency situations, the algorithm in [21] relies on up-to-date traffic information for optimal path planning and dynamic path choice using messages received just after a nearby accident. While Lee et al. [22] conclude that in the case of emergency vehicles, collaborative path clearing is difficult to implement as it requires all vehicles being equipped with the same technology, being route guidance the easiest method as it makes use of general road and traffic information.

Authors of [17] show that using a decentralized routing system shall be more effective than Dijkstra's shortest path algorithm, which transfers the congestion to a different location on the road network. The multi-agent simulations done by [19] show that algorithm efficiency is directly proportional to the number of the car navigation system users. The distributed algorithm in [20] is able to route vehicles in complex networks and is highly robust against failures of distributed parts due to its hierarchical leveling system.

B. Trajectory Planning and Lane Change Advisory

The *motion planning* of an automatic car is divided into *path planning* and *trajectory planning* in [14], while [15] also considers the maneuver decision (alike the behavior layer of [14] mentioned before). According to the planned path and the chosen maneuver and behavior, a smooth trajectory is selected and then optimized according to a dynamic model and/or the presence of obstacles along that trajectory [14], [15]. From the point of view of the intersection infrastructure [23], trajectory planning is a major method for intersection management, a type of *resource reservation* where space tiles are allocated consecutively as travel routes. This concept is used in some algorithms of signal optimization (discussed in Section III-F). For such purposes, cooperative traffic light controllers may be able to share standardized (by ETSI ITS G5

TABLE I

MAIN PUBLICATION AND APPROACHES OF AUTOMATED DRIVING MANAGEMENT.

Category	Implication	Approach	Description
Journey Advisory	Local Level Routing	Hierarchical fuzzy system [16], multi-agent system [17], travel time estimation of opposite direction vehicles [18], accuracy of vehicle passing through links [19], ant colony algorithm [20], Dijkstra algorithm with incident information [21], rule-based [22].	The route choice of vehicles takes into account traffic conditions as well as signal timings in order to minimize their travel time.
	Trajectory Planning and Lane Change Advisory	Survey of proposed methods [14], [15], [23], [24], model predictive control [25].	Real-time planning to find a trajectory along the selected route according to chosen manoeuvre and behaviour. In cooperative lane change systems, the decisions can be coordinated in order to achieve collision-free and reduce braking due to lane change.
	Green Light Optimal Speed Advisory (GLOSA)	Optimal control [26] [27], rule-based [28] [29] [30] [31] [32] [33] [34], signal phase state graph [35], genetic algorithm [36], augmented lagrangian method [37], model predictive control [38].	Informs the vehicle about the speed to reach the green phase at an intersection. The goal is to reduce stop times and avoid stop-and-go pattern as well as aiding "green waves" along coordinated intersections.
Traffic Control Optimization	Queue Length Estimation	Statistical modeling [39] [40], rule-based and discrete wavelet transform [41], real-time macroscopic model enhanced with by actual microscopic data [42], GPS and turning rates data, wave-speed algorithms and fall back algorithm (running average of the traffic flow) [43], trajectory-based [44] [45] and with shockwave analysis [46].	Automated (probe) vehicles provide more accurate speed and location of non-automated vehicles.
	Priority Management and Negotiation	Rule-based [34] [47] [48] [49], mixed integer linear program [50] [51], agent-based modeling [52] [53] [54], adaptive control [55], dynamical system [56], ant colony system [57], petri nets [58], convex sequential optimization [59], multi-agent system [60] and with heuristic, fuzzy logic and genetic algorithm [61].	Different priorities for vehicles or platoons at intersection require right of way negotiation to maintain required road safety and desirable policy.
	Signal Optimization	Rule-based [34] [62] [63], model predictive control [38], dynamic programming [64] [65], job scheduling [66] [67], predictive microscopic simulation [68], integer programming [69] [8], or reservation-based [3], [6].	The schedules of traffic lights' phase timings are according to traffic conditions based on vehicles' information, such as positions, speeds, and directions in order to improve traffic efficiency.

[33]) *MAP messages* that describe the physical geometry of the intersection to the vehicles nearby. On the other hand, from the vehicles' viewpoint, the popular approaches to motion planning are:

a) *variational methods*, representing the path as a function where the optimal path is found by using non-linear continuous optimization techniques [14];
b) *graph-search approaches* that represent the configuration space of the vehicle, in which the minimum-cost path can be found by Dijkstra, A^*, D^* algorithms, and the variations of thereof [14];
c) *incremental search (tree-based) approaches* that construct a tree of reachable states from the initial state of the vehicle, and reuse information from previous search; the selection of the best branch of such a tree is done by sampling [14], [15];
d) *local search approaches* that attempt to find the best single state transition for the vehicle to follow using a limited horizon of time and space [15];
e) other techniques as e.g. occupancy grids, cost maps, state lattices, and driving corridors [15].

Lane change advisory is yet another form of cooperation among automated vehicles, based on coordinated lane change decisions. The paper [25] presents a lane change control system for an automated vehicle, consisting of a path generator, a Model-Predictive Control (MPC) based vehicle steering and a wheel torque control. Given vehicle information and which lane, an optimal steering and braking actions are generated to avoid both moving vehicles and a static obstacles. Within the European project REDUCTION [24], The Minimizing Overall Braking Induced by Lane Changes (MOBIL) is a general lane change model which determines the incentive and risk associated with a lane change decision, taking into consideration immediately affected neighbors. The authors' analysis reveals that an optimal lane change model should reduce the number of lane changes and fuel consumption for all vehicles simultaneously.

C. Green Light Optimal Speed Advisory (GLOSA)

Green Light Optimal Speed Advisory (GLOSA, [26], [28]) systems aim to improve traffic efficiency by reducing waiting times at red signal and creating smooth traffic flow that avoids stop-and-go pattern, while optimizing fuel efficiency and reducing CO_2 emissions. In GLOSA, approaching vehicles receive information from cooperative traffic light controllers containing *Signal Phase and Timing* (SPaT) that have been standardized for ETSI ITS G5 [33]. This kind of system also creates the so-called "green wave" if traffic signals on a corridor are coordinated [28].

The two common approaches for speed advisory are calculating the *speed profile* or the *speed range* of a vehicle that is to cross an isolated intersection or arterial corridor given SPaT and vehicle's position and speed [29], [36]. New approaches extend those approaches to adaptive/traffic-actuated traffic light control [34], [35], [30], [38], [32], [31] and some authors focus on taking into account the interaction of vehicles in a mixed traffic (automated and non-automated vehicles) [26], [28], [37], [27].

Multi-segment GLOSA that finds the optimal speed through genetic algorithm (GA) for an arterial road with many segments is introduced in [36], simulating the same algorithm for two approaches, minimizing fuel or travel time. The authors of [37] propose a GA based on augmented Lagrangian method to tackle the problem of vehicles not crossing the intersection with maximum speed. Considering the surroundings, [27] includes the vehicle queues in a signalized arterial corridor in order to enable GLOSA. However, due its complexity and long running time, the paper approximates it by an optimization model which contains much fewer decision variables based on a sequence of optimal control of sub-problems. A hybrid system is presented in [34], by allying adaptive traffic light scheduling and GLOSA with a priority scheme for different types of vehicles. A different approach is presented in [35], in which the author simulated and made a field test of adaptive traffic lights that uses state graph to represent transitions of traffic signal phases and their occurrence probability. In 80% of all cases the GLOSA algorithm predicted signal changes 15 seconds in advance for a adaptive signal control. [38] also introduces predictability of signal by using theory of Model Predictive Control (MPC), considering more than two conflicting streams and delivering optimized signal timings based on signal groups and speed advisory information at the same time, also adjusting minimum green times, intergreen times and maximum red times.

Key findings of previous research reveal that on actuated-coordinated signals, GLOSA is unlikely to bring a higher positive impact on arterial traffic performance due to varying phases durations, and non-equipped GLOSA vehicles can also benefit when following a leader driving according to proposed speed profiles [32], [30], [31], while better results [26], [28], [29], [32] are achieve in higher penetration rates as well as in better quality of communication between traffic signals and vehicles [31]. Among concerns of centralized GLOSA systems, safety if a single failure occurs and computational complexity for real time application have to be studied in case of a massive deployment [28].

D. Queue Length Estimation Using Probe Vehicles

Automated *probe vehicles* can aid in more accurate estimation of the queue length of vehicles before the intersection for better traffic signal plans [43]. In addition, queue length can act as a trigger to adjust the signal settings at upstream intersections in order to avoid network gridlock [44].

In [40], queue length is estimated using the known proportion of automated probe vehicles in the queue, and their location-time information. While [39] present a stochastic model using maximum likelihood estimation to find estimators for arrival rate and probe proportion to evaluate queue length estimations at isolated intersections under different Market Penetration Rates (MRPs). Expected values and estimation errors are derived using probability distributions of number, location and joining time of probe vehicles in the queue. Also considering different MPRs of connected vehicles, [44] analyse three vehicle trajectory data based methods to estimate the queue length, where vehicle positions were characterized by discrete uniform distribution: (i) maximum likelihood (queue length estimator is the relative position of the vehicle located further apart from the intersection); (ii) method of moments (estimator is equal to two times the mean of the sampled relative positions); and (iii) kinematic wave theory (the intersection point of two shockwaves determines the maximum possible queue length). Similarly, [46] use vehicle trajectory data (location and speed) to identify and classify trajectory critical points for performing shockwaves analysis to estimate real-time queue length in isolated and coordinated traffic signal intersections. Still investigating trajectory data, [45] propose observe a large amount of data for a long period to determine a fitting function (speed function of position) in which the position and speed of automated vehicles during red phase traffic signal will be then used to calculate the queue end position.

Authors of [41] propose a rule-based algorithm for any distribution and saturation case, fixed or actuated traffic signal, and without information of overflow and arrival rate. The algorithm identifies three possible queue cases if vehicles are stopping or moving: (i) no queue, (ii) queue length is the location of the last automated vehicle, and (iii) least mean square error estimation. Additionally, a discrete wavelet transform (DWT) is applied for filtering noise at low penetration ratios to improve estimations accuracy. While [42] focuses on combine inductive loop detector and probe vehicle data in a real-time macroscopic model for fixed traffic control that compute vehicle arrivals into a queue using a look-ahead time and the speed of forming and recovering shockwaves for queue growth and discharge. Three algorithms that improve queue estimation are discussed in [43]: (i) uses GPS data and vehicles turning rates; (ii) in addition to (i), consider values of the reaction time, follow-up time, wave speed and traffic signal status; (iii) running average of the traffic flow for single lane at stop line.

The effectiveness of the queue length estimation depends heavily on the Market Penetration Rate (MPR) of automated vehicles [64], but also influenced by other factors like overflow, road saturation and arrival distribution [41]. While [44] show that it would require at least 80% MPR to guarantee maximum 10% average absolute relative error of the queue length estimation, [42] obtains queue length estimation within the range of a single vehicle error even at lower levels (i.e. 20%) of probe vehicle penetration. In under-saturated cases, [41] reaches root-mean-square error less than 30% of actual queue length with 10% MPR. Even further, [39] provides estimators able to point the true arrival rate values at 5% probe penetration level with 10 cycles of data, while [43] acquire the exact queue length by correcting estimations once the length of an accelerating queue can be determine when traffic light turns green.

E. Priority and Negotiation for Automated Vehicles

Each travel mode (car, trucks, buses, etc.) has its specific characteristics like travel speed, volume, priority level and vulnerability. Typically, passenger cars may benefit from *network/signal coordination* (also known as "*green wave*") to progress through several signalized intersections without stopping and therefore minimizing delays; public transport vehicles use *signal priority* (e.g. extending or inserting green phases) to improve transit performance and reliability; emergency vehicles use *signal preemption* to immediately switch from the current phase to a pre-selected phase to reduce travel time [51]. Vehicle and infrastructure can cooperate when the traffic signal control system receive requests from automated vehicles to generate optimal vehicle crossing at intersections according to the priority policy [51], [53].

There are two main ways how to deal with priority and negotiation: (i) centralized control systems [34], [50], [55], [51], [53], [49], [58], (ii) decentralized control systems [47], [48], [52], [54], [60], [59], [61]. Usually, *centralized control systems* correspond to a traffic controller at intersections that manages priority and vehicles requests to adjust in real-time the signal plans, the offset of a main-street or coordinated arterial [55] or the right of way to vehicles [57]. While in *decentralized control systems*, vehicles communicate among themselves to negotiate which vehicle has the right of way at the intersection [52], but most of the proposed systems still need 100% penetration rate of automated vehicles. Nevertheless, the common strategies aim at minimizing vehicle delays on traditional cycle-based operation [55].

Authors of [52] present an agent-based modeling (ABM) approach to self-organizing and cooperative intersection control of self-driving vehicles, in which each individual user select a specific Priority Level (PL) for their trip. A specific approach used a Binary Mixed Integer Linear Program (BMILP) in [50] for the coordination of buses through several intersections, adopting green reallocation strategy on a rolling horizon framework, predicting the time range of bus arrival and calculating the recommended bus speed based on remaining/expected queue, road geometry and normal signal timing plan. Considering the impacts of Transit Signal Priority (TSP), [55] formulated a system aiming to use the most deserving phase that is likely to contribute to higher passenger throughputs (transit buses and private cars). The distributed adaptive control system uses detectors readings to handle various boundary conditions of recurrent, non-recurrent congestion, and transit signal priority that can be deployed with pre-timed or actuated controllers. Focusing in emergency vehicles, [47] proposes an active and post-incident safety application to prioritize emergency vehicles (EVs), enabling vehicles to determine who should cross the intersections first by electing a cluster leader (acting as “virtual traffic light”) that will grant priority to EVs. [48] describes a rule-based emergency vehicle signal preemption system based on Cooperative Vehicle-Infrastructure System (CVIS), in which traffic lights phases change dynamically based on the position of approaching emergency vehicle and estimated clearance time of other vehicles. [49] presents an automated emergency vehicle green light (AEVGL) for signal preemption in which the Traffic Controller (TC) sets three strategies (all traffic lights to red, red flashing and EV direction green) and directly interact with the emergency vehicle even in low communication penetration. [51] propose a request-based mixed-integer linear program (MILP) for a multi-modal signal control strategy to deal with multiple priority requests, taking into account the delay impact of passenger cars for signal coordination and vehicle actuation. An agent-based cooperative optimization model is presented in [53], to process concurrent priority requirements, and a signal optimization model to coordinate the conflicting requirements. The timing plan is generated for the major demands, against the minor ones, and broadcast to all vehicles, enabling the creation of a platoon-based priority and speed adaption to relative vehicles. [56] extend a priority-based coordination framework for autonomous and legacy (non-automated) vehicles, the algorithm forms virtual platoons of vehicles on the same path that receive consecutive priorities and therefore negotiate the right of way of platoons.

Based on the negotiation concept, a Timed Petri Nets with Multipliers (TPNM) model was formed to propose a distributed clearing policy (DCP). The traffic control system is able to manage the vehicles individually, where the *right of way* is displayed to the driver by means of on-board signalization [58]. An agent based driver assistance system is presented in [54], where the system is able to bilaterally negotiate and trade the right to cross an intersection at a certain time by a Time Slot Exchange (TSE) mechanism, which takes into consideration the value of waiting time for different drivers. A different mechanism for right of way negotiation is supported by intelligent agents representing the vehicles’ interests. The mechanism enables right of way distribution at an intersection, based on network information as well as individual vehicle safety constraints and travel history [60]. Another decentralized solution relies on convex sequential optimization, while degrees of freedom for each vehicle are calculated to avoid potential collisions through local state constraints. Agents communicate time information to coordinate and agree on the right of the way at the expected time stamps within the intersection [59]. A multi agent distributed algorithm based on price negotiation is another possible approach to resolve different goal conflicts at urban intersections. The agents negotiate the cost and revenue of conflicts with each other in order to compromise and reach common goals [61].

A challenge of "green extension" and "red truncation" techniques is that they may sacrifice the capacity of the competing travel direction, thus disturbing the progression on the competing movements [50]. The need for platoon (vehicles with same priority level) coordination on the arterials is suggested in [52] by adjusting vehicle speeds through multi-hop communication and not only within the range of the intersection.

F. Signal Optimization in C-ITS

There are three main traffic light control systems: (i) *fixed-time*, in which pre-programmed signal plans are based on historical traffic data for different times of the day (TOD); (ii) *traffic-actuated* where real-time data is collected from sensors in order to react to certain traffic conditions by changing the length and/or order of signals phases and even skip unnecessary ones; and (iii) *adaptive* that, besides traffic-actuated characteristics, predicts near future traffic conditions and optimize signal timing based on a defined objective function [64]. In C-ITS, the cooperative behavior provides the traffic (light) controller (TC) with vehicle state information, e.g. with position, speed, and future travel direction so that the traffic light can better react to uncertain and rapid changes in traffic volume and make smarter decisions [34], [64], [66].

Several different approaches that use data from cooperative vehicles to optimize the traffic lights have been proposed. Oldest arrival first (OAF) algorithm, a variant of job scheduling with conflicts approach for an isolated intersection aiming at minimization of travel delay is provided in [66]. The algorithm treats approaching platoons as jobs and captures job conflicts with a conflict graph, then the first come first serve principle is applied to schedule the competing platoons in each flow and minimize the latency of the jobs. In [8], the authors present a bi-level model solved by a branch and bound algorithm that predicts the next possible time for each vehicle (automated or not) to cross the intersection and then select the optimal sequence which stimulate platoon formation and either minimize total delay or total number of stops.

Feng et al. [64] present a phase allocation algorithm that applies a two-level optimization in which the phase sequence and duration are optimized simultaneously based on predicted vehicle arrivals. At the upper level, a dynamic programming (DP) use forward and a backward recursion for calculation of the performance measure and retrieval of the optimal policy, while the lower level applies rolling-horizon approach to minimize total vehicle delay or queue length based on different operational policies (i.e. model-predictive control).

Younes and Boukerche [62] introduce an intelligent traffic signal controlling algorithm (ITLC) to reduce the waiting delay time and to increase the number of vehicles crossing each road intersection. The algorithm evaluates the traffic flow at each intersection and the largest traffic density is scheduled first, while constrained by the maximum allowable green time for that phase adjusted based on the estimated current location of the furthest vehicle in each traffic flow.

A predictive microscopic simulation algorithm (PMSA) is proposed in [68] to optimize signal timings using a rolling horizon strategy according to a cost functional that can include a combination of delay, stops and decelerations. A rule-based priority is used for simulation in VISSIM in which highest priorities phases are selected and the phase with the lowest cost is selected for the operation.

A decentralized control method that is also based on the rolling horizon principle is proposed in [65] to minimize the total queue length at intersections. The phase-based strategy algorithm is solved by dynamic programming and optimizes the traffic fluency and to minimize the waiting delay time. In [63], a real-time queue length estimation algorithm and traffic control method using the estimated queue length is introduced. The algorithm assigns vehicles to a group of vehicles in the same lane from the end of one green time to the beginning of the next, then elects group leaders who transmit their group queue length to the signal controller and, finally seek to minimum delay time and minimum queue length. Shao et al. [67] creates a scheduling model in which the traffic light gather data from vehicles and indicates after how long each vehicle should arrive at the intersection. Efficient branch and bound algorithms are proposed in [69] to find an optimal vehicle passing sequence and a heuristic to minimize the average queue size or average vehicle waiting time (modeled as number of late jobs and total tardiness, respectively). First, vehicles with same stream are grouped as jobs. The approach decentralize the problem to several vehicle sequencing problems as a special single machine scheduling problem that can process parallel jobs. A reservation-based algorithm is presented in [3], in which vehicles arriving at an intersection are grouped into "bubbles" (platoons), which are then optimally scheduled for passing through the intersection. The reservation concept is also explored in [6], where the proposed platoon-based multi-agent intersection management system classifies vehicles into leader or follower, and based on the estimation of platoon earliest time of arrival and clearance at intersections the intersection reserves a service time slot for the platoon.

New challenges are related to the implementation of real-time, complex, and computationally expensive optimization solutions for the traffic signal scheduling [34], while [3] states that reservation-based algorithms can be too computational costly. In addition, while optimized (adaptive and traffic-actuated) signal control can be highly flexible, predictability of signal timings can be difficult in such cases. Kaths in [38] points out the importance of algorithms that offers a combination of high flexibility and predictability of signal control systems in order to reach maximum benefits of GLOSA systems.

IV. CONCLUSIONS AND FUTURE TRENDS

In a scenario where road infrastructure (traffic controllers and/or road side units) is able to communicate with automated vehicles, several new challenging issues have to be solved, such as:

a) New traffic management policies for traffic management centers (TMC) in scenarios where more accurate traffic state estimations are available. For instance, managing priorities for different types of vehicles or coordination of them by individual advisory messages during congestions or in emergency situations.
b) The need of new optimization algorithms that are able to deal with mixed traffic (automated, non-automated and non-cooperative vehicles) to optimize vehicles trajectories, speeds and routes, based on estimated traffic, predicted arrival times of vehicles at intersections, traffic signal timings, etc.

c) Inter-operable algorithms that, besides "standard tasks" like queue length estimation or signal optimization, can support and work with other implications like Green Light Optimal Speed Advisory (GLOSA) as well as to promote network coordination ("green wave"), while handling priority management and negotiation of vehicles or platoons. Specially in feasible computational time for different intersections layout.

d) Change the perception of roles and responsibilities of traffic managers. Traffic management is becoming a strategic tool for delivering a whole range of transport policies in which the ultimate goal achieving a livable city, aiming improvements on qualitative rather than quantitative notion, i.e. it is more of a personal perception (less congestion, better air quality, walkable city).

e) Future research seems to focus on multi-agent systems, data fusion, as well as V2X communication, in addition to advisory based algorithms for real-time traffic intersection control optimization.

Coordination of the previously mentioned state-of-the-art topics in this paper is the expedient path to gradually implement automated vehicles in smart cities.

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