Traffic Efficiency Applications over Downtown Roads: A New Challenge for Intelligent Connected Vehicles

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Vehicular network technology is frequently used to provide several services and applications for drivers on road networks. The proposed applications in the environment of road networks are classified into three main categories based on their functions: safety, traffic efficiency, and entertainment. The traffic efficiency services are designed to enhance the moving fluency and smoothness of traveling vehicles over the road network. The grid layout architecture of the downtown areas provides several routes toward any targeted destination. Moreover, since several conflicted traffic flows compete at the road intersections, many vehicles have to stop and wait for safe situations to pass the road intersection without coming into conflict with other vehicles. The traffic efficiency applications in this scenario are designed to select the most efficient path for vehicles traveling toward their targeted destination/destinations. Moreover, other applications aimed to decrease the queuing delay time for vehicles at road intersections. In this article, we review several recently proposed mechanisms that worked to enhance the fluency of traffic over downtown road networks and point to the expected future trends in this field.

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1 INTRODUCTION

The vehicular network technology represents the ad hoc wireless communications among traveling vehicles over the road network. Moreover, it considers the wireless communications between vehicles and pre-installed road-side units at the investigated area of interest. This technology provides a flexible, reliable, cheap, and instant communication that has encouraged several researchers to incorporate it into the development of real-time applications. The basic requirement of these applications is to equip each vehicle with vehicular network transceiver, GPS receiver, and a digital

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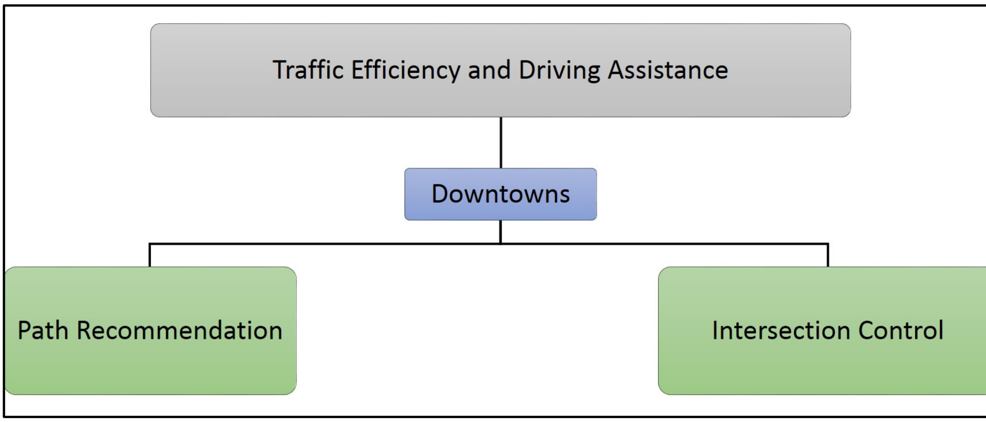


Fig. 1. Traffic efficiency aspects over downtown road networks.

map. This provides faster and more reliable communications compared to the Internet, where all communication are connected through the Internet Service Providers (ISPs) [1].

Using the vehicular network technology, traffic efficiency applications are the main applications proposed for improving traffic flow over road networks. Several applications have recently been introduced in this field, which mainly aim to reduce the duration of the trip, the fuel consumed, and the emission of harmful gases [25, 28, 36, 146, 148]. They also have positive effects on increasing the safety conditions of each driving trip [46–48, 145, 147]. Traffic efficiency parameters over any road network are highly connected to the behavior of the drivers there. Thus, most of the proposed traffic efficiency protocols aim to assist drivers in critical scenarios, such as road intersections, curvy roads, lane changes, or roundabouts, to mention a few. The previously proposed protocols in this field have targeted several aspects and points related to traffic efficiency issues. Figure 1 illustrates a brief summary of previous aspects that have been designed to achieve good traffic efficiency in downtown areas. In Figure 1, two different scenarios have been investigated: the selection of the most efficient path and the control of traffic at road intersections.

In downtown areas, traffic efficiency protocols have investigated the most efficient paths toward a single location [23, 25, 27, 28, 35] or several targeted destinations [43, 45]. The grid-layout architecture provides several path options leading toward the same destination to choose among them. The most efficient path in terms of the instant traffic conditions of the investigated area of interest and the driver's priorities is selected intelligently [23, 27, 37]. Moreover, traffic lights, roundabouts, or stop signs are installed at road intersections to control the competing traffic flows. The located traffic lights have been efficiently designed and scheduled; several instant traffic distributions and priorities of conflicting traffic flows have been considered [99, 100, 105]. This should minimize the vehicles' delay time at that signalized intersection. Traffic light scheduling systems have also been proposed to schedule the traffic lights cooperatively over the investigated area of interest. Finally, we investigate the future of efficient assistance protocols to assist drivers to pass smoothly through road intersections that are controlled by stop signs or roundabouts [141, 143, 144].

This article investigates the general details, specifications, metrics, and drawbacks of the existing traffic efficiency control protocols for several downtown road network scenarios. Section 2 presents the parameters that are used to evaluate and measure the traffic efficiency in detail. Section 3 investigates and compares the previously proposed traffic efficiency protocols over the downtown areas. This includes the different types of path recommendation protocols and traffic light scheduling techniques. Then, Section 4 discusses open challenges in this research area and presents some trends for enhancing this field of research. Finally, Section 5 contains the conclusion and some future trends and remarks regarding this article.

2 TRAFFIC EFFICIENCY PARAMETERS

Several research studies have been developed aiming to control and enhance the traffic efficiency parameters over the road network [49–53]. These applications are designed to maximize the moving fluency of daily traveling vehicles. Traffic efficiency applications are also designed to decrease the percentage of congested traffic and eliminate the reasons behind it in the investigated scenario. Three main parameters are used to measure the level of traffic efficiency in each scenario: traffic speed, traffic density, and traffic volume [30, 54, 55]. The details regarding each parameter are presented in the rest of this section.

2.1 Traffic Speed

The traffic speed parameter is measured for each area of interest; it represents the average speed of traveling vehicles [55]. The traffic speed in the downtown scenarios is slower than highway speeds. When an investigated area is more congested, we expect that the speed of traffic will be lower. In practice, it is difficult to track the speed of each vehicle over the road network. Thus, the traffic speed is measured over a certain area for a specific period of time. We have introduced two different definitions to compute the traffic speed over any road network: "time mean speed" and "space mean speed" [55–57].

Time Mean Speed. This is the measured average of vehicles' speeds when they are passing through a certain area during a specific period of time. Equation (1) computes the time mean speed (V_t) for m vehicles that are located on a limited area of interest. V_i is the individual speed of each vehicle (i) [55, 56],

$$V_t = \frac{\sum_{i=1}^{m} V_i}{m}. \tag{1}$$

In practice, the individual speed of each vehicle could be collected using an inductive loop detector at a certain spot over the investigated area of interest [58]. The vehicular network techniques have also been used to gather the individual speed of vehicles over a certain period of time [59, 60].

Space Mean Speed. This mechanism is more accurate than the time mean speed. This is because it takes the entire road segment into consideration. In practice, this mechanism tracks the individual vehicles' speed through consecutive images or videos that are taken from satellite pictures or real-time cameras [62–64].

Equation (2) computes the space mean speed (V_s) for n vehicles over a certain road segment. V_i is the speed of the ith vehicle during the tracking time there [55],

$$V_s = \frac{n}{\sum_{i=1}^{n} \frac{1}{V_i}}. \tag{2}$$

In general, the traffic speed parameter is sometimes used to expect the delay time as an alternative traffic efficiency parameter. That is, in the case where the traveling distance of the selected path is previously known, Equation (3) shows how to find the delay time using the traffic speed. It can also be used to find the approximate length of a certain path where the traveling time of that path is accurately measured: Equation (4) shows how to find the distance length of any path based

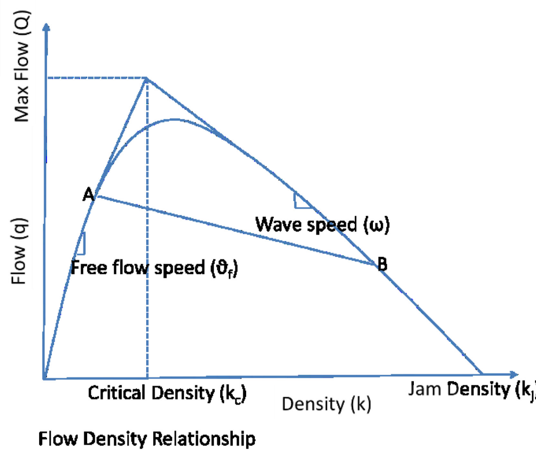


Fig. 2. Flow–density relationship.

on the computed traffic speed and the required time of that trip,

$$Time = \frac{Distance}{Speed}, \tag{3}$$

$$Distance = Speed \times Time. \tag{4}$$

2.2 Traffic Density

The traffic density parameter is measured by the number of vehicles located over a single unit of road length during a brief period of time. It is measured using the unit vehicle/mile or vehicle/km [55, 65]. The traffic density varies over the road network, and affects the traffic speed and traffic flow characteristics over the investigated area of interest. For instance, the traffic flow and the traffic speed are zeros for a certain area, if the traffic density is zero there. At the same time, if the traffic density reaches the maximum allowable density (i.e., vehicles saturate the entire road capacity), then the traffic speed and traffic flow are zeros in this scenario as well [66, 67]. However, between the zero density and the maximum density, there are several levels of traffic densities where the traffic speed and the traffic flow are partially affected.

Figure 2 graphically illustrates the general relationship among the traffic density, traffic speed, and traffic flow characteristics. As we can see from the figure, vehicles can proceed with the announced free flow speed (i.e., maximum allowable speed) as long as the traffic density is less than the critical density. Moreover, the traffic flow is increased when the traffic density is increased until it reaches the maximum traffic flow point.

However, when the traffic density of a certain road exceeds the critical traffic density, then both the traffic flow and the traffic speed are drastically decreased due to the resulting traffic congestion. Several studies have investigated the ranges of critical density and jam densities over several road network scenarios [68–70]. In traffic efficiency applications, researchers aimed to reduce the traffic density and increase the traffic flow [36, 44, 102]. This means the flow–density relationship has been deeply investigated for each road scenario. The optimal thresholds of traffic density and speed are set to achieve the best traffic fluency behavior [36, 70].

2.3 Traffic Volume

The traffic volume parameter is measured by the number of vehicles that pass through a certain area on the roadway during a specified period of time [55, 67]. The shorter the investigated period of time, the more accurate the traffic volume indications [66, 67]. However, this parameter is usually measured in three main standard periods: hour, day, and year.

Measuring the traffic volume per hour directly determines the traffic flow over the road network [55]. Traffic flow ranges usually specify several parameters regarding the investigated road scenarios including traffic speed, density, and familiarities [55, 66, 71]. The traffic volume can be measured on a daily basis as well, aiming to distinguish business days from weekends, vacations, or holidays [72, 73]. This can provide long-term traffic distribution statistics that are used for each investigated area of interest to predict its traffic characteristics at any time during each day of the week. Furthermore, the annual-base traffic volume studies provide more comprehensive statistics that accurately describe the traffic distributions and conditions of any specific investigated area of interest [74, 75]. This can provide extra details to help predict future traffic details more accurately.

In general, a longer period of time given to traffic volume assessment results in a greater amount of collected details. Thus, predicted traffic characteristics regarding the investigated area of interest were more accurate. However, a longer period of time requires extra costs, as represented in the required equipment maintenance and time to obtain the results. Video recording, inductive loop detectors, and vehicular network technology are used to obtain the traffic parameters over road scenarios, thus predicting accurate traffic characteristics there during the pre-determined period of time [72–75].

Several research studies have considered vehicles, trucks, bicycles, and pedestrians in the traffic volume computations [55, 66]. Other studies have only considered vehicles of all types by counting the vehicles during the determined period of time [66, 67]. The definition of the traffic volume can be flexible to meet the target of the study. The remainder of this article introduces the details of traffic efficiency protocols that use, affect, and enhance these parameters over the road network.

3 TRAFFIC EFFICIENCY OVER URBAN AREAS

Urban areas usually experience high traffic density and low traffic speed. A large number of targeted destinations, including residential complexes and/or service centers, are located in these areas. Several studies have previously investigated traffic characteristics and distribution in certain cities in downtown or urban areas [18, 30, 44, 102].

Traffic speed, density, and volume have been investigated for each road segment separately [30, 102]. This is to obtain or predict accurate real-time traffic situations in the area of interest. At the downtown areas, drivers spend the time of their trips either driving or waiting in a queue at road junctions, due to conflicting traffic flows. First, the time to pass any road is computed by using the physical constant length of that road and the estimated dynamic traffic speed parameter there. Second, the road intersection over the downtown areas are usually synchronized among the competing traffic flows using stop signs, traffic lights, or roundabouts.

Several traffic efficiency services have recently been proposed to enhance the traffic conditions through downtowns. These applications aimed to reduce the traveling time of each trip either by reducing the traveling time over the selected road segments or by reducing the waiting delay time at road intersections. In this section, we first investigate different types of path recommendation protocols that select the optimal path according to the set driver's priorities. The different parameters, considerations, and scenarios of these protocols have also been carefully investigated. Second, the road intersections that are controlled by traffic lights have been investigated. As explained below, many scheduling algorithms have been developed for traffic lights to efficiently utilize the

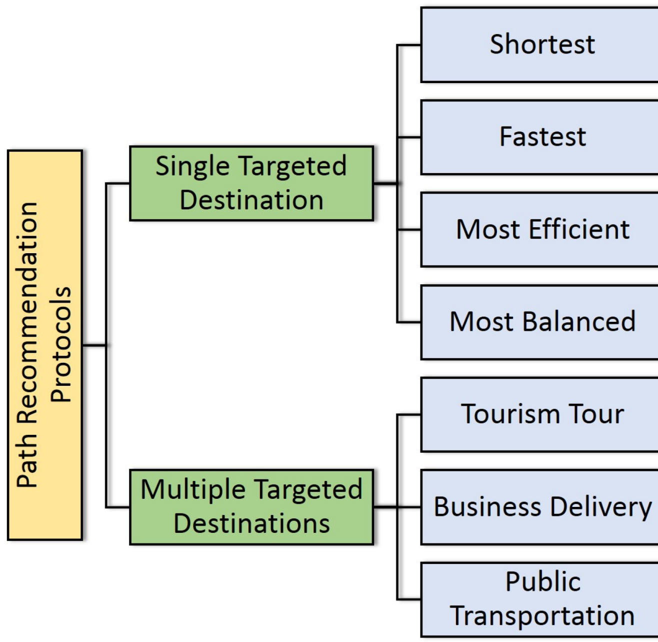


Fig. 3. Path recommendation protocols.

time and fuel parameters at road intersections that are controlled by traffic lights. This has been investigated for isolated traffic lights and networks of traffic light scenarios.

3.1 Path Recommendation

The grid layouts of modern downtowns contain options for paths that drivers can follow toward any targeted destination/destinations [30, 36, 44]. Each driver chooses a certain path of his/her trip according to the driver expectations regarding the selected path. For instance, some drivers choose the shortest or fastest expected path. Other drivers may choose a certain path to drop some passengers or products on the way toward their final destinations. Drivers may choose to travel a greater distance and/or for a longer time instead of passing by a common target destination located in the downtown, such as a hospital or school [18, 30, 30].

Figure 3 illustrates several considerations and types of the previously proposed path recommendation protocols over the downtown areas. The previously proposed path recommendation protocols are classified into two main categories: single targeted destination and multiple targeted destinations. The details of the different considerations and types of each main category are separately specified.

3.1.1 Single Targeted Destination. Most driving trips in the downtown areas target a single destination. Drivers leave their home toward their work or shopping center and vice versa. As shown in Figure 3, four main metrics have been considered in the literature to select the best path toward any targeted destination: distance, time, fuel consumption, and gas and traffic balance.

Shortest Path. The traditional path recommendation protocols consider the traveling distance of each candidate path as a main parameter of selecting the best path [7, 13, 14]. The starting point to look for an efficient path over the downtown areas is the shortest path. It also indicates a short traveling time and efficient selection in the idle traffic distribution scenarios [76, 77]. Several previous protocols aimed to select the shortest path between any two locations (i.e., origin and destination) over the road networks [6, 10, 11].

Early and basic protocols in this field have directly used the classic shortest path algorithms including Dijkstra's [2], Bellman–Ford [3], and *A∗* [4]. Algorithms and principles of the graph theory have also been used in this respect over the road network. The origin point, the targeted destination and the road intersections have been marked as verities on the road network graph. However, the road segments are indicated as the edges of the configured graphs. Shen et al. [5] have used the constrained shortest distance (CSD) querying graph to find the shortest path. The CSD is a fundamental graph query that selects the shortest distance between any origin point and the pointed destination without exceeding the previously given threshold.

After that, more sophisticated protocols have been created, mainly to enhance and speed up the performance of the traditional algorithms over the road network [6–9, 13, 14]. Edward He et al. [7] proposed a time-dependent algorithm that searches for the shortest path over the road network. It is mainly intended to reduce the delay time of Dijkstra's algorithm to find the shortest path. However, Goldberg and Harrelson [8] have proposed an efficient searching algorithm to select the path between the driver's original location and the location of the targeted destination over the road network graph. A linear memory space is used to store the best information regarding preprocessing the graph. This reduces the processing delay of finding the shortest path. Moreover, Zhang et al. [9] proposed an algorithm to store the most frequent path quires in a certain cache memory. Then, future requests for any path could be answered directly based on the cache, without the need for the costly computations and large required delay. Several other techniques include contraction node hierarchies [13] and recursive enhancement algorithms [14], which have also been used to increase the speed of the traditional searching algorithms and reduce the computation overhead.

Distributed and large-scale areas are considered advance challenges in this field. The traditional shortest path algorithms are very costly in terms of computations and required processing time [9, 12] as previously discussed. This cost is exaggerated in extended areas of interest. Most of the previously proposed enhancement techniques also have restrictions on memory or required processing time [6, 8]. Several protocols have been introduced targeting mainly large and extended downtown areas [6, 10–12]. Bast et al. [6] have developed an algorithm called "transit node routing." This algorithm aims mainly to increase the running speed of the traditional *Dijkstra's* algorithm in large road networks. It uses a bidirectional technique where two simultaneous searches, forward and backward, are used together. Several lookup tables are created between selected edges over the road network graph. Moreover, Zhang et al. [10] have combined the metrics of distributed streaming computing with lightweight indexing. First, the graph of the road network must be partitioned. Then, the best edge to enter and exit each portion must be found. It is then necessary to find the shortest path between the entry and exit points. Finally, all the portions are connected together to collect the extended path. Table 1 summarizes the main techniques and parameters that have been considered in this field.

Fastest Path. Finding the fastest path (i.e., the path with the least required travel time) between the *driver's* original location and his/her targeted destination is a more challenging process than finding the shortest path. This can be justified by the fact that several dynamic traffic parameters are included in the process of measuring and estimating the travel time of any path. These parameters include the traffic speed of located road segments in the selected path and the waiting delay time at intersections or at congested exist ramps on the connecting roads. Thus, they need to be investigated for each path in a real-time fashion.

Several protocols have significantly modified the traditional path finding algorithms to dynamically consider real-time traffic parameter changes [22, 78, 79]. Other protocols have developed new algorithms that use the real-time centralized gathered traffic data [15, 20, 21, 26]. These algorithms

Table 1. Shortest Path

General Technique	Used Algorithms	Protocol Examples	Advantages	Drawbacks
Classic Shortest Path Algorithms	Dijkstra's, Bellman–Ford, $A*$, Graph Query	Shen et al. [5]	Finding the shortest path	Slow, Costly Computations
Enhanced Shortest Path Algorithms	Bi-directional, Cash Memory, construction hierarchies, recursion	Edward He et al. [7], Goldberg and Harrelson [8], Zhang et al. [9]	Faster than classic algorithms	Costly required computations
Distributed Algorithms	Simultaneous Searches, Partitioning graph	Bast et al. [6], Zhang et al. [10]	Distribute the computations	Require Synchronization

outperform the traditional algorithms in terms of processing delay time and computation complexities. Yamashita et al. [20] have introduced a path recommendation system designed primarily to reduce traffic congestion and the vehicle's traveling time. This system utilizes a central processor that gathers the traffic information from all previous routes shared by cooperative drivers. Drivers request the best route toward a certain destination from the central processor. The later processor replies and enriches the selected option with accumulated traffic information. The central processor estimates future traffic characteristics at each road segment based on all received route plans. Moreover, Inoue et al. [21] have introduced a path recommendation system that focuses on eliminating traffic congestion over downtown areas. After gathering the required traffic parameters, k possible routes are selected toward each vehicle's destination. This includes the shortest path besides $k-1$ and other alternative paths; all of the k selected paths should pass through predetermined relay points on the investigated road network. The traveling distance (i.e., length) of each path is less than or equal to a pre-defined threshold. Among these paths, the fastest route is selected considering the gathered real-time traffic data in that area.

Several $geo-cast$ and efficient traffic data gathering assistance protocols have been proposed [22, 24] to reduce the effects of the bottleneck problem, especially for extended areas of interest or highly congested areas. Lakas et al. [22] proposed a zone of reference (ZOR) model to set the boundaries of the area of interest. It consists of the coordinates of the angles representing the geometrical region covering a given area. The central processor only gathers the traffic regarding the coordinated area, and drops all other messages received from vehicles located outside of the defined ZOR. The processing time of the Dikestra's algorithm is reduced due to the smaller amount of data required. Kitani et al. [24], have proposed another efficient data gathering technique. In this work the buses, which have predetermined routine paths, are used as carriers to gather the traffic parameters of regular traveling cars. Then, the traffic data reports are only delivered to the central processor in specific periods of time without any redundant information.

In general, the centralized based protocols suffer from several other issues. These include latency, which causes late recommendations and expired considered gathered data, central point of processing (i.e., processing delay), and single point of failure. Recently, several distributed path finding protocols have been designed to eliminate the centralization associated problems [16, 17, 30, 31]. These protocols distribute the real-time gathered traffic data among several processing units to obtain the best path cooperatively. Some studies [16, 17] have assumed the existence of intelligent traffic lights and/or traffic signals over the road that are equipped with transceivers. These would communicate with vehicles and other processing units over the network. These intelligent infrastructures can collect and process the real-time traffic parameters of traveling vehicles in the vicinity. The optimal path can then be recommended to each vehicle according to the used navigation algorithm. In this respect, Doolan et al. [16] and Gupte et al. [17] have proposed distributed infrastructure-based path recommendation mechanisms.

Table 2. Fastest Path

Model	General Technique	Used Algorithms	Protocol Examples	Advantages	Drawbacks
Centralized	Dynamic Shortest Path Algorithms	Dijkstra's, $A*$	[22, 78]	finding the fastest path	bottleneck, single point of failure, single point of processing, late decisions,
	Advanced Algorithms with Central Data	RIS, K-shortest path	Yamashita et al. [20], Inoue et al. [21]	decrease the delay time and processing complexities of traditional algorithms	
	Geo-cast Protocols	ZOR, routine paths buses	Lakas et al. [22], Kitani et al. [24]	reduce the bottleneck issue	
Distributed	Intelligent Traffic Lights and Signals	Dynamic navigation algorithm (DNA), vehicular network-based autonomous management (VAM)	Doolan et al. [16], Gupte et al. [17], Cao et al. [84]	eliminate the centralized model problems	require intelligent extra equipment and synchronization
	Distributed Path Finding Algorithms	ICOD, BeeJamA	Younes et al. [30], Wedde et al. [31]		

Furthermore, Younes et al. [30] and Wedde et al. [31] have proposed complete distributed path recommendation protocols. These protocols depend on pre-installed processors over the investigated area of interest. Several parameters and conditions are considered to select the location and functionalities of each processor. Younes et al. [30] have introduced ICOD as an intelligent distributed path recommendation protocol. It recommends that each vehicle pass through low traffic density road segments while traveling toward its targeted destination [28, 30]. ICOD is a completely distributed and self-adaptive path recommendation protocol, following a hop-by-hop recommendation pattern. It assumed Road Side Units (RSUs) at road intersections. These RSUs are capable of storing, processing, forwarding and receiving the traffic characteristics of all road segments there. The optimal path for each vehicle is selected cooperatively by these RSUs, where dynamic and continuous messages are transferred among them. Wedde et al. [31] then proposed the BeeJamA protocol, which is a distributed and self-evaluated approach. However, BeeJamA was developed following the behavior of bee during its foraging process. It introduced a multi-agent system that simulated a distributed architecture of vehicles and pre-installed infrastructure. The scalable area of interest was divided into a set of easily manageable areas, then the traffic characteristics of each area were gathered and processed separately. Each vehicle requested the best path to reach its targeted destination. At road intersections, the best exit (i.e., output road segment) is recommended to each vehicle. RSUs located at road intersections provide these recommendations directly to traveling vehicles according to the foreseen traffic characteristics of the vicinity and the locations of their targeted destinations. Table 2 presents structured details and parameters of previous proposed protocols in this field.

Most Efficient Path. The fuel consumption of any driving trip is one of the main priorities of the drivers. They always aim to reduce the cost of any planned driving trip. The fuel consumption is strongly connected to the gas emission parameter. Several path recommendation protocols have been proposed that consider the amount of fuel to be consumed and gases produced. At first glance, the shortest path or the fastest path can lead to an efficient path that consumes the least fuel and produces the smallest amount of emissions. However, dedicated research studies prove that the amount of fuel and gas are strongly affected by both the traveling speed and distance of moving vehicles [80–82]. Careful balancing between the distance length of the trip and the traffic speed of each path leads to a decrease in the fuel consumption parameter of that path. This indicates

Table 3. Most Efficient Path

General Technique	Used Algorithms	Protocol Examples	Advantages	Drawbacks
Specialized Shortest-Path	Dijkstra's	Kono et al. [32]	find the most efficient path	slow and not accurate
Efficient route	Neural Network	Campolina et al. [85]	reduce the fuel consumption and gas emission	need sensors and time to train the neural network
Fitness Equations	*TraffCon*	Collins et al. [26]	Considering and balancing several traffic parameters	central point
Speed/Time balancing	ICOD	Younes et al. [30]	balancing traffic speed and travel distance of the driving trip, eliminate centralization problems	need synchronization

that the most efficient path is located in between the shortest path and the fastest path. Many mathematical models have been used to estimate the fuel and gas amounts of each path over the road network [27, 86, 87].

Furthermore, eco-path protocols have been proposed that aim to efficiently control the amount of consumed fuel and produced gases during each vehicle's trip [26, 30, 32]. First, Kono et al. [32] have proposed an ecological path recommendation protocol. Simple Dijkstra's algorithm is run to find the path requiring the least amount of fuel. This protocol estimates the amount of required fuel to traverse each located road segment separately. This approach suffers from centralized approach issues such as bottleneck and single point of failure. However, the accuracy of estimating the fuel consumption of each path is a serious challenge in this approach, since the traffic situation may change on each located road faster than the process of gathering the real-time traffic data and selecting the required path.

Then, Collins et al. [26] introduced an algorithm for vehicle routing called *TraffCon*. This algorithm aims to reduce the traveling time of vehicle trips and decrease fuel and gas parameters. Equation (5) illustrates the considered parameters and weights of these parameters while selecting the most efficient path (R_{rv}) toward any targeted destination. As we can see from the equation, the fitness function considers three main parameters for each vehicle v that takes the route r: traveling time of the entire trip T_{rv}, used capacity of the road network during that trip C_{rv}, and fuel consumption of the vehicle in that trip F_{rv}. w_i represent the weights of the several parameters and the summation of these weights should be 1,

$$R_{rv} = w_1 \times T_{rv} + w_2 \times C_{rv} + w_3 \times F_{rv}. \tag{5}$$

Younes et al. [30] have proposed an economical variant of ICOD that mainly targeted the financial aspects of the planned trip. This worked by reducing the amount of used fuel and then reducing the harmful gas emissions from that traveling vehicle. This mechanism investigates the distance and time parameters of each path that can be followed by the vehicle toward its targeted destination, and selects the most balanced one. In a distributed fashion, at each junction the output flow for that vehicle is recommended based on the benefit ratio between time and distance parameters. Table 3 presents a comparison study for previously proposed traffic efficiency path recommendation protocols.

Balanced Path. Reducing the points of traffic congestion over road networks by distributing vehicles evenly all over the downtown areas produce balanced paths and enhance the traffic efficiency there. Several protocols have been proposed with the intention of recommending or forcing drivers to spend more time and/or travel a greater distance to serve the public traffic benefits [18, 19, 30]. Younes et al. [18] introduced two mechanisms, $Bal - Traf$ and $Abs - Bal$, to distribute the traffic all over the investigated downtown areas and prevent the appearance of highly congested road segments. The first mechanism ($Bal - Traf$) computes the traffic density of each road segment on the investigated area of interest. Any road segment that has a greater traffic density than the predefined saturated threshold density is defined as an overloaded road segment. The $Bal - Traf$ mechanism avoids recommending any overloaded road segment to drivers in their trip, unless other roads are more overloaded or there are no other options. However, the $Abs - Bal$ mechanism targets each road intersection, aiming to distribute the input traffic there among all output road segments in an even manner. RSUs at road intersections are used to assist traveling vehicles to move in a distributed manner. It recommends each vehicle to proceed toward its targeted destination, while keeping the traffic densities on all output road segments at the investigated road intersection close to each other.

However, some protocols have targeted certain road segments according to their context (i.e., located destinations). These protocols intended to decrease the traffic density for specific road segments (i.e., located at specific targeted destinations) and other segments that lead to them [29, 30, 33, 34]. Context-aware protocols [29, 61] considering the highly targeted destinations (e.g., hospitals, schools, etc.) over the road network have been proposed. Younes et al. [30] also considered additional conditions such as: weather conditions, pot-holes and obstacles [29]. In general, this protocol aimed to guarantee a low level of road traffic in commonly targeted services. It also aimed to introduce a comfortable trip to drivers and passengers without drastically increasing travel time of moving vehicles.

In addition, many protocols were developed to balance traffic flow after natural or terrorist disasters [19, 35, 36, 37]. Chakraborty [19] introduced a protocol for path recommendation after disasters. In these cases, most vehicles drive toward the closest emergency destination (e.g., hospital, survivors' center). This causes high traffic congestion in the road segments around targeted destinations, particularly for those located at the center of the targeted downtown area. Chakraborty connects all emergency targeted destinations to a virtual destination (VD) in a center point. Then, it recommends to each vehicle or survivor the best destination to target and the best path to follow toward that destination. Thus, the ratio of highly congested segments of the road network is reduced. However, Talarico et al. [35] proposed a routing protocol to find the optimal path and sequence for ambulances to reach the closest and most critical destinations. This protocol was primarily designed to evenly distribute the available ambulances over the investigated area of interest. A structured summarized comparative study among previously proposed balanced path recommendation protocols is presented in Table 4.

3.1.2 Multiple Targeted Destinations. In daily life, several driving trips target more than one destination. Efficiently planning these trips helps to increase the traffic fluency over the road network, and reduces the traveling time and cost of each trip. Buses, for example, have been designed with the intention of daily travel toward several stop destinations. Certain paths are determined for these buses, which can be rarely changed. Moreover, regular individual drivers may need to travel toward different destinations aiming to shop, entertain or just do some regular business. Different paths and sequences could be followed in multi-destination trips. Here, we investigate the details of multi-destination path recommendation protocols in three main intentions: public transportation, business delivery trips, and sightseeing tours or shopping trips. Table 5 summarizes the considered parameters and details of multi-destination path recommendation protocols.

Public Transportation. Public transportation in downtown areas that include several intended destinations during the same trip consists mainly of buses. As previously mentioned, buses have pre-determined paths to travel regularly over the road network. This means that the sequence trip

Table 4. Balanced Path

Balance purpose	**Used Algorithms**	**Protocol Examples**	**Details**
General Traffic Balancing	$Bal - Traf$, $Abs - Bal$	Younes et al. [18]	At each road intersection the incoming traffic is distributed in a balanced fashion among the output flows
Reduce Congestion at especial road segments	ICOD	Younes et al. [30]	Guarantee level of congestion-free at road segments around common targeted destinations and at specific roads (i.e., located at a hospital)
	Context-investigate	Casion et al. [61]	Investigate the special targeted destinations.
After Disaster	Virtual destination (VD)	Chakraborty [19]	After disasters, balance the traffic moving toward existing emergency locations.
	Distribute ambulances	Talarico et al. [35]	Distribute ambulances over the entire road network.
	Prioritized Routing	Gupta et al. [83]	prioritize the traffic among emergency, police buses and regular vehicles using minimum cost maximum flow algorithm

Table 5. Multi-Destination Path

Multi-destination Trip	**Protocol Examples**	**Waiting time at each destination**	**Details**
Public Transportation	Zhang et al. [40]	Short	Determine the best stopping destinations and the best turning point for each bus routine path
Business Delivery	Siam et al. [44]	Short	Determine the sequences of visiting the destinations, the path between each two successive destinations and meet the predicted deadline to reach each destination
Sightseeing Tours or Shopping Trips	Siam et al. [43]	Long	Determine the sequence of visiting the destination and path between each successive two destinations. Consider the traffic changes when the driver stays at any destination for an unexpected amount of time, to reschedule the rest of the trip

toward the stop destinations and the selected path between each two stop destinations are fixed. Several studies have been proposed to find the optimal path for each bus [38–40]. Many parameters have been considered, such as traffic distribution and locations of common targeted destinations over the investigated area of interest [38]. Zhang et al. [40] proposed a real-time protocol that selects the locations of stop points and turn points of each bus route. This protocol aims mainly to accelerate the arrival time of each passenger toward most common targeted destinations.

Business Delivery. Mail delivery or goods delivery drivers spend their day traveling from place to place to drop the products for customers. Drivers only spend a few seconds/minutes at each destination. In these trips, drivers usually need to go back to the starting point of the trip (i.e., company) to return the extra products and/or report regarding the delivery situations. Moreover, a deadline is usually assigned to each delivery process to ensure that drivers reach their destination before that time. Efficient planning of the trip toward the targeted destinations helps to meet these deadlines and satisfy the customer. Several mechanisms have been used to plan and select the path and sequence of destinations to visit in this aspect [41, 44, 45, 155]. Huang et al. [41] have proposed two approaches, basic and advanced versions, to select the most efficient path that satisfies the requirements of drivers and optimizes the trip cost in term of fuel consumption. Saim et al. [44] have also proposed a round-trip planner protocol that mainly considers the traffic distribution to find the most efficient path toward several destinations over the downtown area of interest. Dynamic and adaptive traveling salesman algorithm is developed in this protocol.

Sightseeing Tours or Shopping Trips. Travel toward several sightseeing or shopping centers in downtown areas differs from business delivery trips mainly in terms of time spent at each destination. Staying for a relatively long time at each destination faces a significant change in the traffic distribution over the road network. Thus, the rest of the trip needs to be rescheduled after each destination. Several protocols have been proposed aiming to efficiently plan tourism trips in certain cities, taking into account the location of each destination and the expected amount of time spent at each destination [42, 43, 45]. The early researchers have ignored the traveling time between these destinations as a negligible factor [42, 45]. However, in highly congested areas, reaching a certain destination may require a very long time, exceeding the time planned for the trip. Siam et al. [43] have proposed an efficient multi-destination path recommendation protocol that considers the predictable traveling time after visiting each destination. In the event that the traffic changes in an extreme un-predictable manner, the protocol works to reschedule the rest of the targeted destinations to find the best path according to the current required parameters.

3.2 Intelligent Traffic Light Scheduling Algorithms

Traffic lights are set at road intersections to control and schedule the competing traffic flows there. The early installed traffic lights are set to allow safe and fair sharing among flows of traffic competing for the road intersections. Fixed pre-timed scheduling algorithms that specify a certain period of time for each flow of traffic to proceed through the road intersection are first used [88–90]. Due to the continuous increases in traffic volume over the years, traffic light scheduling algorithms have become more and more intelligent [99, 100, 105, 106]. These intelligent scheduling algorithms have considered the real-time traffic parameters there [103, 110, 111]. The growing number of new traffic lights to control the traffic at road intersections over the downtown areas has encouraged the researchers to develop some cooperative scheduling algorithms. These cooperative algorithms require communications among the installed traffic lights to gather data regarding the expected traffic parameters moving toward each located traffic light to set its schedule efficiently [100, 107, 110].

Two main scenarios have been investigated in downtown areas for efficient traffic light scheduling techniques: isolated traffic light and network of traffic lights [98]. First, the scheduling algorithm of isolated traffic light considers the real-time traffic conditions at the signalized road intersection. No coordination nor communication with any of the surrounding traffic lights or traveling vehicles are considered in this scenario. Intelligent isolated traffic lights use the real-time gathered or predicted traffic parameters to set the schedule of the traffic light [102, 103, 114]. Second, in the network scenario, coordination among traffic lights located on the road network is required to guarantee smooth passing of vehicles at road intersections, and enhance the traveling time of vehicles on their route [100, 108, 109, 118]. Traffic lights on this road network can predict the arrival time, speed and density of vehicles' platoons there and set the scheduling algorithms accordingly. These mainly search for the most optimal schedule for each traffic light. In this section, we investigate the previous scheduling algorithms introduced for isolated traffic light scenarios and previous control systems introduced for networks of traffic lights. Furthermore, Table 6 systematically represents the main parameters and considerations of some previous isolated traffic light scheduling algorithms. Table 7 summarizes the main considerations and parameters related to traffic light systems in networks.

Table 6. Intelligent Isolated Traffic Light Scheduling Algorithms

Scheduling Technique	Examples	Gathering Traffic Data	Scheduling Algorithm	Advantages	Drawbacks
Pre-timed fixed schedule	Miller [88], Stoffers [89]	No data to gather	Rotate a fixed equal time for each phase of traffic light cycle	Safe sharing of the road intersection	Not good for high traffic volumes, decrease the throughput of the intersection
Historical-based schedule	Wiering [94], Mouavi et al. [97]	Long-term historical traffic characteristics	Using machine learning algorithm to obtain the optimal schedule based on the historical gathered data	More efficient than fixed schedule in terms of utilizing the intersection throughput	Cannot predict the traffic demands accurately, not good for irregular traffic conditions
Dynamic schedule (Real-time based)	Khadilkar et al. [105], Tang et al. [109], Pandit et al. [101], Younes and Boukerche [118], Cruz-Piris et al. [106], Zhihui et al. [115]	Predicting, gathering or mathematically modeling real-time traffic parameters of the different input flows (e.g., traffic density, traffic volume, traffic speed, number of vehicles, expected arrival time etc.)	Dynamic real-time algorithms, intelligent scheduling algorithms, dynamic optimization models	Considering the real time conditions, increase the efficiency of each road intersection in terms of delay time and utilized throughput	High cost in terms of required equipment and computation
Efficient schedule (Fuel and Gas)	Mungur et al. [103], Li et al. [112], Abdalla et al. [113]	Estimating the fuel consumption and gas emissions of competing traffic flows if they move or wait the traffic signal	Intelligent scheduling algorithms using the fuel consumptions and gas emissions	Efficiently utilize the fuel and reduce the gas emissions	Accuracy and costly
Context-aware schedule	Younes and Boukerche [121], Mu et al. [123], Hakim et al. [104], Barzilai et al., [122]	Investigating the vehicle types or characteristics and the drivers and passengers situations	Prioritizing the competing traffic flows based on their traffic context	Safe schedule for traffic lights considering emergency vehicles and emergency cases	Require fast and accurate communications

3.2.1 Isolated Traffic Lights. Scheduling a single located traffic light at a road intersection has been investigated intensively over the road network. This includes setting the cycle parameters of each located traffic light, where the period time for each phase in that cycle and the sequence of phases are selected. Early traffic lights have been permanently scheduled as engineers set the cycles and the parameters of each traffic light while installing it [88–90]. Early pre-timed scheduling algorithms have set a certain fixed period of time for each flow of traffic without considering the real-time or historical traffic characteristics [89, 90]. Miller [88] has previously investigated the settings of fixed cycle traffic signals. He derived the optimum signal settings according to the delay formula that is designed to reduce the average delay time of each vehicle at road intersections. Stoffers [89] has proposed an approach for scheduling traffic lights. The main concepts and terms of traffic light scheduling have been defined in this work. Traffic lights installed at each road intersection are operated by a rotating time switch that progresses at equally spaced instances of time in the pre-timed schedule algorithms. This is good for low traffic volumes and mainly helps to safely scheduled competing traffic flows (i.e., prevent accidents between conflicting traffic flows). Figure 4 shows a four-direction signalized intersection and an example of fixed pre-timed schedule for the traffic light located there.

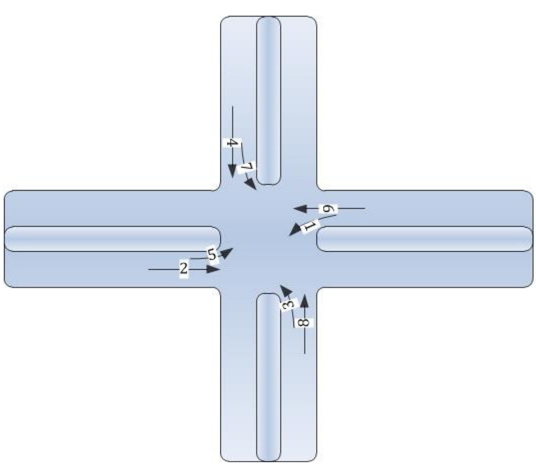
Table 7. Intelligent Traffic Lights Controlling Systems

The system	Gathering Traffic Data	Schedule Technique	Tested Area	Centralized/ Distributed	Arterial/ Network
OPAC [130]	Rolling horizon approach to predict the arrival traffic at each signalized intersection	Dynamic programming techniques	Five different 30 minute data sets of a signal controlled intersection in Tucson, Arizona	Centralized (Modeling)	Network
SCOOT [125]	Cyclic Flow Profiles (CFP) Model to estimate the length of the queue	Heuristic incremental optimization plan (elastic)	Five cities in UK: Glasgow, Coventry, Worcester, Southhampton, and London	Centralized (Modeling)	Network
Yu and Recker [126]	Heuristic real-time data gathering	Decision-making problem for Markov model	Simulated grid-layout	Centralized (Modeling)	Network
RHODES [129]	Based on real-time detecting data, spatially and temporally predicts the future traffic distribution	Advanced dedicated data structure and real-time communications are used to find the optimal schedule of the located traffic lights	Ten-intersection arterial segment in Tucson, AZ, a nine-intersection arterial segment in Seattle, WA, and a diamond interchange in Tempe, AZ	Centralized (Modeling)	Arterial and Network
TUC [131]	Store and forward model	Linear quadratic regular theory	Thirteen signalized junctions and 61 links, and based on the Glasgow network	Centralized (Modeling)	Network
SCAT [127]	Historical model of traffic over the downtown	Optimization algorithm	Downtown of Sydney	Centralized (Modeling)	Arterial
GLIDE [132]	Based on instance traffic gathering long-term traffic predicting	Allocating green time of each traffic light, linking traffic lights together and centralized control of all traffic light system	Urban area of Singapore	Centralized (Modeling)	Network
TCC [128]	Vehicular network gathers the real-time traffic characteristics	Mathematical solutions and fuzzy logic techniques	Simulated grid-layout	Centralized	Arterial
CCAP [134]	Tracking the entering and exiting platoon of vehicles at the first traffic light on the arterial street	The scheduling algorithm sets the schedule of the traffic lights located on the arterial street to allow tracked platoon of vehicles to pass that intersection without stopping	Simulated grid-layout	Centralized	Arterial
V-Grid [135]	Virtual grid model	The scheduling algorithm sets the schedule of the traffic lights located on the arterial street to allow tracked platoon of vehicles to pass that intersection without stopping	Simulated grid-layout	Centralized	Arterial
Chen et al. [136]	Uses a graph model to represent the traffic network	A branch and bound algorithm for obtaining the optimal schedule of each traffic light. Then, Genetic algorithm is used to find the best coordination	Kaohsiung city in Taiwan	Centralized	Network

(Continued)

Table 7. Continued

The system	Gathering Traffic Data	Schedule Technique	Tested Area	Centralized/ Distributed	Arterial/ Network
Huang et al. [137]	Synchronized Timed Petri nets	Master–slave controller of the urban traffic system are all concurrent states	Simulated grid-layout	Centralized	Network
Tree [133]	Stochastic traffic	Coordinated reinforcement learning. The Junction Tree Algorithm (JTA) based reinforcement learning	Network containing 18 signalized intersections in VISSIM	Centralized	Network
Framework [138]	Vehicular network gathers the real-time traffic characteristics	Optimizer methods	Simulated grid-layout	Distributed	Network
DALI [140]	Controllers receive real-time information from detection systems	Reinforcement learning is used to optimize the traffic light schedule	The City of Richardson's road network was created in MATISSE. The model includes 1365 road segments and the city's 128 signalized intersections	Distributed	Network
MARLIN-ATLIN [139]	Vehicular network gathers the real-time traffic characteristics	Multi-agents reinforcement learning	Fifty-nine intersections in Downtown Toronto	Distributed	Arterial
ATLs [118]	Vehicular network gathers the real-time traffic characteristics	Priorities schedule based on the traffic density and arterial street location	Simulated grid-layout	Distributed	Arterial



P/T	1	2	3	4	5	6	7	8
0-T	R	G	R	R	R	G	R	R
T-2T	R	R	R	G	R	R	R	G
2T-3T	R	R	G	R	R	R	G	R
3T-4T	G	R	R	R	G	R	R	R

R: Red
G: Green
T: Fixed period of time
P:Phase

Fig. 4. Fixed pre-timed schedule for isolated traffic light.

More dedicated scheduling algorithms have been introduced by considering traffic distribution at rush hours, nights or holidays. Historical traffic characteristics have been gathered and analyzed regarding the competing traffic flows at the investigated signalized road intersection for a long period o time. Then, the traffic distribution there during a certain period of time can be predicted using neural networks [91], reinforcement learning [92] or fuzzy logic [93] techniques, based on the gathered historical data. The traffic light is scheduled according to the predicted traffic characteristics [94–97]. Investigating the historical traffic characteristics and introducing models of traffic changes helps to set the phases of located traffic lights efficiently where different schedules are selected for each part of the day and different types of days (i.e., working day, vacation, weekends) [95]. Wiering [94] introduces a scheduling technique for traffic lights designed to reduce the overall waiting delay of vehicles at the downtown intersections by using multi-agent reinforcement learning algorithms. Mouavi et al. [97] have used two modern and intelligent techniques, deep neural network and reinforcement learning, to predict the traffic distributions at signalized road intersections. Thus, more efficient traffic light schedules have been generated based on the traffic light predictions. This type of scheduling algorithm performs highly compared to the traditional fixed pre-timed scheduling techniques. However, they cannot accurately predict the traffic demands, particularly in accidents or other scenarios that change the regular traffic conditions.

Recently, dynamic and adaptive algorithms appear to intelligently schedule the competing traffic reaching the road intersections simultaneously, while considering the real-time traffic distributions and changes at each road intersection [101, 109, 118]. Dynamic traffic light scheduling algorithms require real-time traffic data gathering equipment [104]. Inductive loop detectors, optical information systems, camcorders, sensors and vehicular network technologies are used to collect the instant parameters of the input traffic flows at that junction [101, 106, 118, 152]. Then, the schedule of the traffic light located there can be set efficiently. The efficient schedule of a certain traffic light aims mainly to maximize the throughput parameter of that intersection and minimize the delay of traveling vehicles [105, 119].

Several algorithms have been introduced to schedule the located traffic light efficiently using the dynamic real-time gathered traffic data. Different machine learning methods have been developed to find the optimal schedule of located traffic lights [105, 109, 116]. Khadilkar et al. [105] predict and estimate the traffic density of vehicles in the competing traffic flows. Then, multiple linear regression method is used to find the best schedule of the investigated traffic light. Tang et al. [109] specifically considered four-way road intersections, with the set of signal lights located at these legs encoded to be used by a genetic algorithm. The latter algorithm allocates the schedule of each located traffic signal considering the real-time gathered traffic data.

However, some research studies have introduced new scheduling algorithms that outperform traditional machine learning algorithms and investigate the real world [101, 102, 118]. Pandit et al. [101] proposed an adaptive traffic signal control algorithm inspired by the job scheduling problem on computer processors. It aggregates an equal number of vehicles in platoons, where each platoon is scheduled at the targeted road intersection as a single job. Then, the first arrived platoon is scheduled first; this algorithm has minimized the waiting delay time of vehicles at synchronized junctions. Younes and Boukerche [118] have virtually defined a ready area in the boundaries of the signalized road intersection. Then, they investigated the traffic situation inside that configured ready area. The sequence of phases were set to schedule the more dense traffic flow first. In addition, the green time for each flow of traffic was scheduled considering the location of the last vehicle located inside the ready area in that flow of traffic (i.e., the time required for that vehicle to reach and pass through the intersection).

Recently, traffic lights have been scheduled using dedicated mathematical models. These model the traffic at road intersections and propose an optimization schedule that utilizes the time and capacity of the signalized intersection [106, 115]. Cruz-Piris et al. [106] introduced an automatic optimization of traffic light schedules using genetic algorithm to expand the throughput of each located road intersection. This algorithm has been applied to a cellular automata simulator that provides realistic results under certain predefined conditions. Zhihui et al. [115] have reconstructed the optimization problem of traffic light scheduling using traffic supply and demand during different time periods. The traffic light schedule is constructed using the Krill-Herd algorithm, where irritative search of the best schedule in a multi-dimension time and space was cooperatively obtained under several traffic conditions.

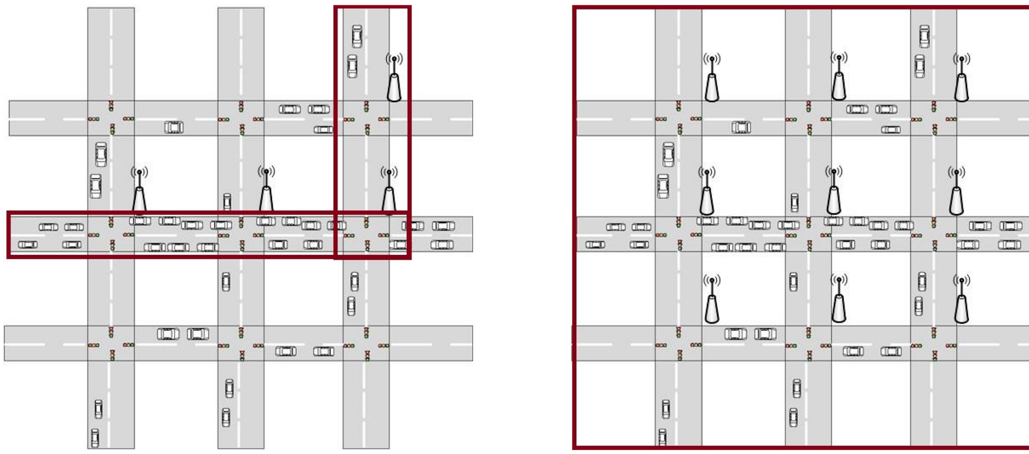
Following the advanced development of intelligent traffic light scheduling algorithms that consider real-time and dynamic parameters, several efficient scheduling algorithms have been designed. These algorithms aim to reduce the consumption of fuel and the emission of gases, which are more sophisticated targets for protecting the planet [103, 112, 113, 153]. In this field, some smart scheduling algorithms have investigated the effects of the scheduling algorithms on traffic efficiency in terms of fuel and gases as secondary parameters [114, 118]. However, other studies have primarily considered these aspects while scheduling the phases of traffic lights. Mungur et al. [103] proposed a dynamic scheduling mechanism that mainly considered the gas emissions of each vehicle on a separate road lane. First, the level of gas emissions harmful for health within each lane is configured statistically. This is by finding the optimal notorious threshold value based on the environment and the capacity of the investigated junction. Then, when the level of gas emissions of any vehicle reaches the configured harmful level, the traffic light opens for that lane with a higher priority over other scheduled lanes. This scheduling algorithm has been proposed and tested for Mauritius area. Moreover, for more efficient traffic light scheduling, Li et al. [112] proposed a temporal-spatial coordination model that formulated all possible trajectories at the investigated signalized junction. Then, two control algorithms are proposed to schedule the competing vehicles at road intersections; the main consideration of these algorithms is to increase the operation efficiency in terms of minimizing energy consumption and pollutant emissions. Meanwhile, Abdalla et al. [113] particularly considered reduction of CO2 in the proposed adaptive traffic light scheduling algorithm.

Few and very recent scheduling algorithms have considered the context of the competing traffic flows in terms of vehicle types [120], number of passengers in each vehicle, and the social situations of drivers and passengers [122]. Early context-aware traffic light scheduling algorithms have been proposed to achieve safe sharing among regular vehicles and emergency vehicles [121, 124]. Higher priorities are assigned to the emergency vehicles to reach their critical destinations quickly and safely without waiting at the signalized intersections. Younes and Boukerche [121] have considered the scheduling of traffic lights where one or more emergency vehicles exist in the competing traffic flows. Higher priorities have been assigned for traffic flows containing an emergency vehicle. These priorities have also been ranked for several traffic flows with different types of emergency vehicles. Mu et al. [123] have proposed an algorithm that uses the preemption route principle to reduce the delay time of emergency vehicles at the signalized junctions. Hakim et al. [104] have only considered the length of each vehicle to set its priority (i.e., trucks have higher priority to pass signalized road intersections before regular vehicles). Fuzzy TOPSIS algorithm is used in [104] to find the optimal schedule of each traffic light.

Furthermore, Barzilai et al. [122] have introduced an efficient scheduling algorithm for locating traffic lights that requires social details regarding drivers, passengers (e.g., number of passengers in the vehicle, handicapped person, or even a woman in labor) and vehicle types to prioritize them before deciding the timing schedule for the competing traffic flows.

3.2.2 Network of Traffic Lights. Traffic lights are installed at all/most road intersections over downtown areas. Several algorithms have scheduled the phases of each individual traffic light intelligently, as illustrated in Section 3.2.1. Traveling vehicles in the downtown areas pass through several signalized road intersections during their trips. Thus, several advanced coordination systems among installed traffic lights are used to enhance the smooth movement of traveling vehicles during their trips [118, 125, 127–129, 133, 135, 149, 156].

Some of these coordination systems have targeted the arterial street scenario (i.e., highly used route) as a part of the downtown road network [118, 128]. In this scenario, only the located traffic lights on the arterial street communicate to cooperatively set the optimal schedule to each one of



(a) Arterial street scenario (b) Close network scenario

Fig. 5. Networks of traffic lights.

them. However, other traffic light control systems, named close networks, have considered all the traffic lights over the downtown area [125, 129, 133, 135]. In the later scenario, all traffic lights installed at the road network communicate and cooperate with each other to find the best schedule for each traffic light, while considering the neighboring traffic lights. This is according to the general traffic distribution and real-time traffic conditions over the associated road network. Figure 5 graphically shows an example of these two scenarios that illustrates the differences between them.

Scheduling several traffic lights cooperatively to enhance the traffic efficiency conditions over the downtown areas is a very promising project for drivers and traffic management systems. This is due to the fact that the schedule provides vehicles with long-term smooth movement and reduces the overall traffic congestion over the investigated area of interest [118]. However, these systems usually face several challenges including: (1) Gathering or predicting the traffic distribution/characteristics over an extended area of interest. (2) Unexpected traffic conditions, such as traffic accidents or emergency vehicles. (3) Finding the optimal schedule for each traffic light. Several cooperative traffic light scheduling systems have considered and developed a certain mathematical model to predict and estimate the traffic distribution over the downtown area [125, 130, 131, 150]. These models require regular traffic parameters of each road segment in the investigated downtown to be gathered to predict long term characteristics. Thus, the predicted characteristics of traffic flows at the signalized road intersection are utilized accordingly to set that traffic light schedule. A few examples of previous studies in this field are summarized below, including some details regarding the optimal scheduling algorithms.

Gartner proposed optimization policies for adaptive traffic signal control system (OPAC) [130]. It has applied the rolling horizon approach to predict the arrival of traffic to each road intersection over the downtown area. Then, the optimal schedule of each located traffic light at the investigated area of interest is set, considering the traffic distributions of all surrounding traffic lights. A dynamic programming technique is used to obtain the most optimal schedule. Moreover, Robertson and Bretherton introduced an on-line traffic model and real-time signal optimizer [125] that optimized the networks of fixed-timed traffic lights based on continuous traffic volume measurements of the investigated downtown area of interest. A historic optimization among the potential timing plans selects the best schedule for each traffic light with the main objective of decreasing the queue length of each traffic flow.

A simple and direct modeling technique is introduced by Yu and Recker [126]. They first developed a Markov traffic lights control model, based on the heuristics traffic characteristics of the investigated area of interest. It formulated the control of each traffic light as a decision making model that considered the heuristic traffic conditions of the investigated area of interest. However, Mirchandani and Head proposed a hierarchical model of the traffic control problem [129]. It predicted the parameters of all traffic flows at each road intersection to enable proactive control of the traffic light network. Advanced dedicated data structure and real-time communications are used to cooperatively find the optimal schedule of traffic lights located on the road network. Finally, Diakaki et al. have used the store and forward modeling to gather the urban network traffic. They also used the linear-quadratic regular principles to find the optimal schedule of the network of traffic lights over the investigated urban areas [131].

Some research studies have focused on a certain geographical area of interest, investigating the traffic distribution over there during long period of time. Then, they historically built the model of the traffic distribution there to be considered in the traffic light scheduling system. Sims and Dobinson have previously proposed the SCAT system for downtown Sydney [127]. SCAT is the coordinated adaptive traffic signal that improves the movement of traffic on arterial streets. It is a centralized system that chooses the phases of each traffic light among predefined constant monitoring sets over an arterial street, according to traffic demands. Meanwhile, Kenog introduced GLIDE, a dynamic computerized traffic light control system that has been proposed for the urban areas of Singapore [132]. A central processor unit is used to guarantee the green waves at signalized junctions. The main consideration of the traffic light scheduling algorithms is the traffic volumes that are gathered in the central processor using wire loop detectors.

These systems barely respond to unexpected traffic conditions over the area of interest. The traffic lights are mathematically scheduled without any consideration to accidents or emergency vehicles, thus, they may drastically decrease traffic efficiency in some downtown scenarios. In addition to the high computational complexity of these systems (particularly for extended areas of interest) this is a real challenge that delays the performance of the system.

More adaptive traffic light scheduling systems have been proposed to overcome the mathematical statistical scheduling models [128, 133, 135]. These systems consider the real-time traffic characteristics of the investigated area of interest. Inductive loop detectors, camcorders and real-time communications are used in this respect. Then, the optimal schedule of each located traffic light is obtained based on the current traffic distributions, in addition to the real-time predicted traffic distributions. The real-time traffic distribution is usually gathered in a specific central processor traffic management unit. Mathematical optimization models or machine learning and intelligent algorithms are then applied to find the optimal traffic light schedule for each located traffic light. Here, we investigate some famous research studies that have been proposed in this field.

First, using the vehicular network, Tomescu et al. have introduced a green-wave control system that considers the behavior of the drivers [128]. This system combines the mathematical solutions and fuzzy logic techniques. In a central traffic control point, the traffic conditions are gathered using vehicular network technology in real-time fashion. Besides the mathematical models, the system predicts short-term behaviors of existing vehicles. Based on these two factors, the central processor computes the green time for each traffic light phase and the green-wave offset for all traffic lights located on the arterial street.

By tracking platoons of vehicles, Wang et al. [134] have proposed a cooperative collision avoidance predictive control algorithm (CCAP). It assists vehicles to smoothly pass through several signalized road intersections over the entire arterial street. This algorithm works by tracking the entry and exit time of each platoon of vehicles at the first road intersection on the arterial scenario. Then, it mathematically predicts the arriving time on the next intersection on that street. This algorithm sets the schedule of traffic lights located there to allow the tracked platoon of vehicles to pass that intersection without stopping. V-Gride system [135] is an extension of the CCAP algorithm proposed by Wang et al. [134]. In this system, Hou et al. have applied the CCAP algorithm on a virtual grid that indicates the road intersections and the traffic distributions around these intersections. This grid is used to model the movement of vehicles and predict their future locations. Based on this grid-model, each located traffic light is scheduled with respect to guaranteeing safety for competing traffic flows, in addition to enhancing smooth movement of vehicles over the arterial road scenario.

However, Chen et al. [136] have introduced a new model to represent the traffic flows over the urban area graphically. They developed, a branch and bound algorithm to obtain the settings of each traffic light in the network system. After that, a genetic algorithm was used to obtain the best schedule for all located traffic lights over the investigated areas of interest. The experimental studies have successfully investigated the scenario when vehicles change their direction as a real-time challenge. In the machine learning and artificial intelligent environment, several research studies have been proposed. First, Huang et al. [137] have proposed a design and analyze methodology for urban traffic control systems using the technology of synchronized timed Petri network. They configure the master-slave model to several traffic light phase scenarios (i.e., two to eigh phases). Moreover, Zhu et al. have modeled the traffic signals in downtown areas on a stochastic traffic environment [133]. Then, a coordinated reinforcement learning technique is used to develop the Junction Tree Algorithm (JTA). The latter algorithm obtains the best cooperative schedule of each traffic light in the network.

Handling the entire road network with a central processor has shown good performance in the literature in terms of enhancing traffic efficiency over downtown areas. However, due to the scalability of modern downtown areas, depending on the centralized processor to handle the schedules of all traffic lights introduces several problems and issues. This includes bottleneck problems and high delay in scheduling the traffic lights and collecting the traffic characteristics of the large investigated area of interest. As a consequence, several distributed traffic light scheduling systems have recently been developed [118, 139, 140, 153, 157]. These systems aim mainly to distribute the mission of the central traffic light scheduling system among several processing units. Each unit handles a part of the geographical area of interest. This enhances the efficiency of cooperative scheduling traffic light systems based on the divide and conquer principles [139].

For modern cities, Barba et al. have introduced a smart city framework that completely depends on intelligent traffic lights assumed over the targeted downtowns [138]. These traffic lights independently gather the traffic data of traveling vehicles. They regularly update internal traffic situations of the road segments in the vicinity. Communications among these traffic lights expand the vision of traffic distribution to cover the entire downtown area. Then, these intelligent traffic lights recommend the best approach for each traveling vehicle. The schedule of these traffic lights is also set intelligently to adapt to the real-time traffic distribution there.

Several distributed traffic light scheduling systems have been introduced that utilize the multi-agent principle [139, 140, 151, 154]. In these systems, each traffic light is treated as an agent that individually controls the traffic of its surrounding road segments. Coordinations among these agents enhances traffic efficiency over the investigated area of interest. Torabli et al. [140] proposed a self-adaptive cooperative multi-agent traffic light scheduling system. Traffic lights installed at road intersections collaborate with each other and adapt their schedules while considering the real-time traffic conditions and the selected schedules of adjacent traffic lights. The reinforcement learning technique is used to optimize the schedule of each traffic light and guarantee the scope of collaborations among these traffic lights. Moreover, El-Tantawy et al. [139] have introduced a system of multi-agent reinforcement learning for integrated networks of adaptive traffic lights. Each agent (i.e., traffic light) is responsible for the control of traffic flows around a single traffic junction. Then, these agents play a balance priority game, each traffic light (i.e., agent) learns and applies to the best schedule considering all traffic light policies. Real-time testing in the extended downtown of Toronto has proved the efficient performance of this system.

ATLs [118] was recently proposed for scheduling arterial street traffic lights. This system provides communication among traffic lights located at the arterial street using vehicular network technology. Each traffic light sends a statistical report to its direct neighbors. Then, higher priorities are assigned to the arriving platoons of vehicles on the arterial street. Each traffic light individually sets its schedule, considering the real-time traffic distribution of the competing traffic flows to schedule the phases according to traffic density and priorities.

4 DISCUSSION AND CHALLENGES

In this article, we have reviewed the most recent applications of vehicular network technology that have been dedicated to enhance the traffic efficiency over downtown road networks. These applications include conserving traveling time, distance and fuel consumption, and reducing the gas emissions of each traveling vehicle, as well as, considering the safety conditions of drivers and vehicles. The grid-layout of most modern cities provides several paths that could be followed toward any targeted destination, and the most efficient path has been selected according to the drivers' interests and priorities. Section 3.1 has deeply investigated and categorized the previously proposed path recommendation protocols.

However, the grid-layout architecture contains several road intersections where conflicted traffic flows compete to pass. This introduces hazardous areas, where most traffic accidents usually happen. Several tools, techniques and policies have been used to control the competing traffic flows at road intersections over downtown areas, such as traffic lights, stop signs and roundabouts. These techniques cause a queuing delay at each road intersection while waiting for other flows of traffic to pass. Recently, several efficient techniques have been used, and most of these research studies have considered the signalized road intersections, where the phases of each traffic light are scheduled efficiently. Traffic light scheduling algorithms have been deeply investigated in Section 3.2. The scheduling phases of each traffic light have been investigated for each individual traffic light. Moreover, each traffic light has been investigated in a cooperative network of neighboring traffic lights.

Although traffic lights are very commonly seen at road intersections, some intersections are left un-signalized even over the architecture of modern cities. The conflicted traffic flows should strictly follow the driving rules and policies to safely pass through these intersections. Drivers usually use their visual communication and driving experience to pass smoothly through road intersections in downtown areas. Bad weather conditions and obstacles such as trees, buildings or big trucks prevent clear vision at these road intersections. Exhausted or careless drivers may also wrongly estimate the situation and cause high traffic delays or collisions with other conflicted traffic flows there. In the environment of vehicular networks, these challenges can be illuminated. The communications and advanced technologies can be used to collect accurate and real-time traffic distributions in these areas, then assisting drivers and providing driving recommendations (i.e., time, direction and speed of passing the road intersection).

Very few studies have targeted the un-signalized road intersections over downtown areas [141–144]. Assisting drivers to enter, exit or even drive through a roundabout according to each driver's location, targeted destination and surrounding traffic distribution was studied in Reference [141]. The authors proved that more safe and efficient conditions have been obtained at roundabouts by following their driving assistance protocol. These driving assistance protocols are not very common lately, due to the expected evolution of autonomous driving. Researchers have begun to consider autonomous driving maneuvers as the future of vehicles. For instance, Joshue et al. [142] have introduced a case study of autonomous driving maneuvers in roundabouts. A lateral control on roundabouts had been introduced that considered entering, exiting and lane changing on roundabouts.

In general, the un-signalized road intersection is considered an open topic for future development using new technologies and communication techniques. Several driving assistance and/or control protocols are expected to be proposed that aim to enhance the safety and efficiency conditions. These include assisting drivers at stop signs, roundabouts or completely uncontrolled road intersections. The context and priorities of competing traffic flows have never been investigated. Thus, more real-time cooperative protocols could be developed for these scenarios as well.

The article has investigated real-time traffic efficiency control mechanisms at grid-layout downtown areas. While the grid-layout is the most common topology of designing downtowns, several other topologies have been used. The challenge of adapting these protocols and mechanisms for real downtown scenarios is highlighted as another open topic of research that could be tackled in this field. Moreover, a mixed design of downtown and highway streets has recently become a more common architecture in most modern cities. The heterogeneous attributes of the different road components in these scenarios raise several issues, while thinking of traffic efficiency control applications. Developing traffic efficiency control protocols for these scenarios can be a serious challenge that researchers should address in future studies.

Finally, in smart cities where several types of technologies have been utilized to support several automatic and accurate applications, vehicular network technology has been considered as an option for controlling and assisting traffic over road networks there. Traffic efficiency applications over road networks in a smart city environment could have different considerations, requirements and issues to handle. Thus, developing traffic efficiency controlling protocols for smart cities using the vehicular network technology is a modern challenge that requires more future research investigation.

5 CONCLUSIONS AND REMARKS

In this article, we have reviewed recent dedicated traffic efficiency applications in downtown areas. Traffic characteristics over the downtown areas are reviewed in several real-time parameters stated in the article. After that, selection of the most efficient path and its several considered aspects has been deeply investigated. Then, the efficient algorithms for scheduling traffic lights individually or as a part of a system were presented. Finally, the article presented a discussion regarding the existing traffic efficiency control mechanisms, and highlighted several open challenges for future research in this field. This includes controlling the traffic efficiently at un-signalized road intersections. Real-time communications and advanced technologies could be utilized to develop assistance driving protocols. These protocols would help to increase the fluency of traffic and reduce queuing time of vehicles at these intersections. Consideration of the context and priorities of traffic flows at un-signalized road intersections are open topic of research as well. Considering several design topologies while developing the traffic efficiency application protocols and adapting the existing protocols to these scenarios is another open challenge in this field. Moreover, the heterogeneous downtown scenario, where highways are existed as part of the downtown area, is a challenge that has not been tackled by researchers in this field. Developing traffic efficient applications for road networks in the smart cities environment using the technology of vehicular networks is a new open challenge. Different requirements and considerations are essential for adapting existing traffic efficiency applications in the smart city environment.

REFERENCES

[1] R. Gasmi and M. Aliouat. 2019. Vehicular ad hoc NETworks versus Internet of vehicles—A comparative view. In *Proceedings of the 2019 International Conference on Networking and Advanced Systems (ICNAS'19)*. 1–6.

[2] E. W. Dijkstra. 1959. A note on two problems in connexion with graphs. *Numer. Math.* 1, 1 (1959), 269–271.

[3] R. Bellman. 1958. On a routing problem. *Quart. Appl. Math.* 16, 1 (1958), 87–90.

[4] P. E. Hart, N. J. Nilsson, and B. Raphael. 1968. A formal basis for the heuristic determination of minimum cost paths. *IEEE Trans. Syst. Sci. Cybern.* 4, 2 (1968), 100–107.

[5] Meng Shen, Baoli Ma, Liehuang Zhu, Rashid Mijumbi, Xiaojiang Du, and Jiankun Hu. 2018. Cloud-based approximate constrained shortest distance queries over encrypted graphs with privacy protection. *IEEE Trans. Inf. Forens. Secur.* 13, 4 (2018), 940–953.

[6] Holger Bast, Stefan Funke, Domagoj Matijevic, Peter Sanders, and Dominik Schultes. 2007. In transit to constant time shortest-path queries in road networks. In *Proceedings of the Meeting on Algorithm Engineering and Expermiments*. Society for Industrial and Applied Mathematics, 46–59.

[7] Edward He, Natashia Boland, George Nemhauser, and Martin Savelsbergh. 2018. A dynamic discretization discovery algorithm for the minimum duration time-dependent shortest path problem. In *Proceedings of the International Conference on the Integration of Constraint Programming, Artificial Intelligence, and Operations Research*. Springer, Cham, 289–297.

[8] Andrew V. Goldberg and Chris Harrelson. 2005. Computing the shortest path: A search meets graph theory. In *Proceedings of the 16th Annual ACM-SIAM Symposium on Discrete Algorithms*. Society for Industrial and Applied Mathematics, 156–165.

[9] Detian Zhang, An Liu, Zhixu Li, Gangyong Jia, Fei Chen, and Qing Li. 2018. Effective shortest travel-time path caching and estimating for location-based services. In *Proceedings of the Annual Conference on the World Wide Web*. 1–21.

[10] Dongxiang Zhang, Dingyu Yang, Yuan Wang, Kian-Lee Tan, Jian Cao, and Heng Tao Shen. 2017. Distributed shortest path query processing on dynamic road networks. *VLDB J.* 26, 3 (2017), 399–419.

[11] Robert Geisberger, Peter Sanders, Dominik Schultes, and Daniel Delling. 2008. Contraction hierarchies: Faster and simpler hierarchical routing in road networks. In *Proceedings of the International Workshop on Experimental and Efficient Algorithms*. Springer, Berlin, 319–333.

[12] Daniel Duque, Leonardo Lozano, and Andrés L. Medaglia. 2015. An exact method for the bi-objective shortest path problem for large-scale road networks. *Eur. J. Operat. Res.* 242, 3 (2015), 788–797.

[13] Ulrich Lauther. 2004. An extremely fast, exact algorithm for finding shortest paths in static networks with geographical background. *Geoinfo. Mobil. Forsch. praktisch. Anwend.* 22 (2004), 219–230.

[14] Wei Zeng and Richard L. Church. 2009. Finding shortest paths on real road networks: The case for A. *Int. J. Geogr. Inf. Sci.* 23, 4 (2009), 531–543.

[15] M. Wang, H. Shan, R. Lu, R. Zhang, X. Shen, and F. Bai. 2014. Real-time path planning based on hybrid-VANET-enhanced transportation system. *IEEE Trans. Veh. Technol.* 64, 5 (2014), 1664–1678.

[16] R. Doolan and G. M. Muntean. 2013. VANET-enabled eco-friendly road characteristics-aware routing for vehicular traffic. In *Proceedings of the Vehicular Technology Conference (VTC'13)*. 33–37.

[17] S. Gupte and M. Younis. 2012. Vehicular networking for intelligent and autonomous traffic management. In *Proceedings of the 2012 IEEE International Conference on Communications (ICC'12)*. 5306–5310.

[18] M. Bani Younes, A. Boukerche, and G. Roman-Alonso. 2016. Traffic balancing-based path recommendation mechanisms in vehicular networks. *Wireless Commun. Mobile Comput.* 16, 7 (2016), 794–809.

[19] G. Chakraborty. 2015. Dynamic distribute route recommendation system for multiple destinations. In *Proceedings of the 12th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON'15)*. Hua Hin, Thailand, 1–5.

[20] Tomohisa Yamashita, Kiyoshi Izumi, and Koichi Kurumatani. 2004. Car navigation with route information sharing for improvement of traffic efficiency. In *Proceedings of the 7th International IEEE Conference on Intelligent Transportation Systems (IEEE Cat. No. 04TH8749)*. IEEE, 465–470.

[21] S. Inoue, K. Shozaki, Y. Kakuda. 2007. An automobile control method for alleviation of traffic congestions using inter-vehicle ad hoc communication in lattice-like roads. *Proceedings of the Globecom Workshops* (2007), 1–6.

[22] Moumena Chaqfeh and Abderrahmane Lakas. 2014. Shortest-time route finding application using vehicular communication. In *Proceedings of the 2014 IEEE Wireless Communications and Networking Conference (WCNC'14)*. IEEE, 3290–3295.

[23] Takuya Yoshihiro, Daichi Araki, Hiroki Sakaguchi, and Naoki Shibata. 2016. Reliable distance-vector routing for static-node-assisted vehicular networks. In *Proceedings of the 13th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*. ACM, 237–245.

[24] Ruobing Jiang, Yanmin Zhu, Tian He, Yunhuai Liu, and Lionel M. Ni. 2014. Exploiting trajectory-based coverage for geocast in vehicular networks. *IEEE Trans. Parallel Distrib. Syst.* 25, 12 (2014), 3177–3189.

[25] K. Collins and G.-M. Muntean. 2018. A vehicle route management solution enabled by Wireless Vehicular Networks. *Proceedings of the INFOCOM Workshops* (2018), 1–6.

[26] Kevin Collins and Gabriel-Miro Muntean. 2015. TraffCon: An innovative vehicle route management solution based on IEEE 802.11 p sparse roadside-vehicle networking. In *Transportation Systems and Engineering: Concepts, Methodologies, Tools, and Applications.* IGI Global, 1633–1666.

[27] T. Oguchi, M. Katakura and M. Taniguchi. 2002. Carbon dioxide emission model in actual urban road vehicular traffic conditions. *J. Infrastruct. Plan. Manage.* 695, IV-54 (2002), 125–136.

[28] Maram Bani Younes, Graciela Roman Alonso, and Azzedine Boukerche. 2012. A distributed infrastructure-based congestion avoidance protocol for vehicular ad hoc networks. In *2012 IEEE Global Communications Conference (GLOBECOM'12).* IEEE, 73–78.

[29] M. Bani Younes and A. Boukerche. 2013. Performance evaluation of a context-aware path recommendation protocol for VANETs. In *Proceedings of the IEEE Global Communications Conference, Exhibition and Industry Forum (GLOBECOM'13).*

[30] Maram Bani Younes, Azzedine Boukerche, and Graciela Roman-Alonso. 2014. An intelligent path recommendation protocol (ICOD) for VANETs. *Comput. Netw.* 64 (2014), 225–242.

[31] H. F. Wedde and S. Senge. 2013. BeeJamA: A distributed, self-adaptive vehicle routing guidance approach. *IEEE Transactions on Intelligent Transportation Systems* 14, 4 (2013), 1882–1895.

[32] T. Kono, T. Fushiki, K. Asada, and K. Nakano. 2008. Fuel consumption analysis and prediction model for Eco route search. In *Proceedings of the 15th World Congress on Intelligent Transport Systems and ITS America's 2008 Annual Meeting.*

[33] Sherin Abdelhamid, Sara A. Elsayed, Najah AbuAli, and Hossam S. Hassanein. 2016. Driver-centric route guidance. In *Proceedings of the 2016 IEEE Global Communications Conference (GLOBECOM'16).* IEEE, 1–6.

[34] Mariana Ramos de Brito and Fátima de L. P. Duarte-Figueiredo. 2017. D-Hop: A dynamic and distributed protocol for vehicle routing. In *Proceedings of the 2017 IEEE Symposium on Computers and Communications (ISCC'17).* IEEE, 1073–1078.

[35] Luca Talarico, Frank Meisel, and Kenneth Sörensen. 2015. Ambulance routing for disaster response with patient groups. *Comput. Operat. Res.* 56 (2015), 120–133.

[36] Linet Özdamar and Onur Demir. 2012. A hierarchical clustering and routing procedure for large scale disaster relief logistics planning. *Transport. Res. E: Logist. Transport. Rev.* 48, 3 (2012), 591–602.

[37] Arun Jotshi, Qiang Gong, and Rajan Batta. 2009. Dispatching and routing of emergency vehicles in disaster mitigation using data fusion. *Socio-Econ. Plann. Sci.* 43, 1 (2009), 1–24.

[38] Xiangjie Kong, Menglin Li, Tao Tang, Kaiqi Tian, Luis Moreira-Matias, and Feng Xia. 2018. Shared subway shuttle bus route planning based on transport data analytics. *IEEE Trans. Autom. Sci. Eng.* 15, 4 (2018), 1507–1520.

[39] Mahdavi Moghaddam, S. M. Hassan, K. Ramachandra Rao, G. Tiwari, and Pravesh Biyani. 2019. Simultaneous bus transit route network and frequency setting search algorithm. *J. Transport. Eng. A: Syst.* 145, 4 (2019), 04019011.

[40] Hu Zhang, Shuzhi Zhao, Huasheng Liu, and Shidong Liang. 2016. Design of integrated limited-stop and short-turn services for a bus route. *Mathematical Problems in Engineering* 2016 (2016), 1–9.

[41] Yu Huang, Bo-Hau Lin, and Vincent S. Tseng. 2017. Efficient multi-destinations route planning with deadlines and cost constraints. In *Proceedings of the 2017 18th IEEE International Conference on Mobile Data Management (MDM'17).* IEEE, 228–233.

[42] Anna Maria Parroco, Franco Vaccina, Stefano De Cantis, and Mauro Ferrante. 2012. Multi-destination trips and tourism statistics: Empirical evidences in Sicily. *Economics* 6, 2012-44 (2012), 1–27.

[43] Hisham Siam and Maram Bani Younes. 2019. An efficient multi-destinations trip planning protocol for intelligent transport system. *Int. J. Numer. Model.: Electr. Netw. Devices Fields* 32, 3 (2019), 25–48.

[44] Hisham Siam and M. Bani Younes. 2018. Multi-Destinations Round Trip Planner Protocol. In *Proceedings of the 2018 5th International Symposium on Innovation in Information and Communication Technology (ISIICT'18).* IEEE, 1–5.

[45] Duk-Byeong Park and Yoo-Shik Yoon. 2009. Segmentation by motivation in rural tourism: A Korean case study. *Tour. Manage.* 30, 1 (2009), 99–108.

[46] N. B. Hounsell, B. P. Shrestha, J. Piao, and M. McDonald. 2009. Review of urban traffic management and the impacts of new vehicle technologies. *IET Intell. Transport Syst.* 3, 4 (2009), 419–428.

[47] Alessandra Pascale, M. Nicoli, F. Deflorio, B. Dalla Chiara, and Umberto Spagnolini. 2012. Wireless sensor networks for traffic management and road safety. *IET Intell. Transport Syst.* 6, 1 (2012), 67–77.

[48] John Golias, George Yannis, and Constantinos Antoniou. 2002. Classification of driver-assistance systems according to their impact on road safety and traffic efficiency. *Transport Rev.* 22, 2 (2002), 179–196.

[49] Hamid Menouar, Ismail Guvenc, Kemal Akkaya, A. Selcuk Uluagac, Abdullah Kadri, and Adem Tuncer. 2017. UAV-enabled intelligent transportation systems for the smart city: Applications and challenges. *IEEE Commun. Mag.* 55, 3 (2017), 22–28.
[50] Guillaume Leduc. 2008. Road traffic data: Collection methods and applications. *Work. Pap. Energy Transport Clim. Change* 1, 55 (2008).
[51] Maram Bani Younes and Azzedine Boukerche. 2015. A performance evaluation of an efficient traffic congestion detection protocol (ECODE) for intelligent transportation systems. *Ad Hoc Netw.* 24 (2015), 317–336.
[52] Qasim Ali Arain, Muhammad Aslam Uqaili, Zhongliang Deng, Imran Memon, Jichao Jiao, Muhammad Akram Shaikh, Asma Zubedi, Aisha Ashraf, and Usman Ali Arain. 2017. Clustering based energy efficient and communication protocol for multiple mix-zones over road networks. *Wireless Pers. Commun.* 95, 2 (2017), 411–428.
[53] Jingjing Wang, Chunxiao Jiang, Kai Zhang, Tony Q. S. Quek, Yong Ren, and Lajos Hanzo. 2018. Vehicular sensing networks in a smart city: Principles, technologies and applications. *IEEE Wireless Commun.* 25, 1 (2018), 122–132.
[54] Christoph Sommer, Ozan K. Tonguz, and Falko Dressler. 2011. Traffic information systems: Efficient message dissemination via adaptive beaconing. *IEEE Commun. Mag.* 49, 5 (2011), 173–179.
[55] L. H. Immers and S. Logghe. 2002. *Traffic flow theory.* Faculty of Engineering, Department of Civil Engineering, Section Traffic and Infrastructure, Kasteelpark Arenberg 40 (2002), 21.
[56] Muhammad Tayyab Asif, Justin Dauwels, Chong Yang Goh, Ali Oran, Esmail Fathi, Muye Xu, Menoth Mohan Dhanya, Nikola Mitrovic, and Patrick Jaillet. 2014. Spatiotemporal patterns in large-scale traffic speed prediction. *IEEE Trans. Intell. Transport. Syst.* 15, 2 (2014), 794–804.
[57] Jinjun Tang, Fang Liu, Yajie Zou, Weibin Zhang, and Yinhai Wang. 2017. An improved fuzzy neural network for traffic speed prediction considering periodic characteristic. *IEEE Trans. Intell. Transport. Syst.* 18, 9 (2017), 2340–2350.
[58] Sing Yiu Cheung, Sinem C. Ergen, and Pravin Varaiya. 2005. Traffic surveillance with wireless magnetic sensors. In *Proceedings of the 12th ITS World Congress*, 173–181.
[59] Carolina Tripp Barba, Miguel Angel Mateos, Pablo Reganas Soto, Ahmad Mohamad Mezher, and Mónica Aguilar Igartua. 2012. Smart city for VANETs using warning messages, traffic statistics and intelligent traffic lights. In *Proceedings of the 2012 IEEE Intelligent Vehicles Symposium.* IEEE, 902–907.
[60] Hadi Arbabi and Michele C. Weigle. 2011. Monitoring free flow traffic using vehicular networks. In *Proceedings of the 2011 IEEE Consumer Communications and Networking Conference (CCNC'11).* IEEE, 272–2760.
[61] Fran Casino, Constantinos Patsakis, Edgar Batista, Frederic Borràs, and Antoni Martínez-Ballesté. 2017. Healthy routes in the smart city: A context-aware mobile recommender. *IEEE Softw.* 34, 6 (2017), 42–47.
[62] Anuj Puri. 2005. A survey of unmanned aerial vehicles (UAV) for traffic surveillance. Department of Computer Science and Engineering. University of South Florida, 1–29.
[63] Anuj Puri, Kimon Valavanis, and Michael Kontitsis. 2007. Generating traffic statistical profiles using unmanned helicopter-based video data. In *Proceedings of the 2007 IEEE International Conference on Robotics and Automation.* IEEE, 870–876.
[64] S. Tuermer, J. Leitloff, P. Reinartz, and U. Stilla. 2010. Automatic vehicle detection in aerial image sequences of urban areas using 3D HoG features. *Photogram. Comput. Vis. Image Anal.* 28, Part 3B (2010), 50–54.
[65] Liping Xia and Yaping Shao. 2005. Modelling of traffic flow and air pollution emission with application to Hong Kong Island. *Environ. Model. Softw.* 20, 9 (2005), 1175–1188.
[66] Robin T. Underwood. 1960. *Speed, Volume, and Density Relationships.* Pennsylvania State University, University Park, PA.
[67] Adolf D. May. 1990. *Traffic Flow Fundamentals.* PrenticeHall, Englewood Cliffs, NJ.
[68] Maen M. Artimy, William J. Phillips, and William Robertson. 2005. Connectivity with static transmission range in vehicular ad hoc networks. In *Proceedings of the 3rd Annual Communication Networks and Services Research Conference (CNSR'05).* IEEE, 237–242.
[69] Victor L. Knoop, Hans van Lint, and Serge P. Hoogendoorn. 2015. Traffic dynamics: Its impact on the macroscopic fundamental diagram. *Physica A: Statistical Mechanics and its Applications* 438 (2015), 236–250.
[70] Carlos F. Daganzo, Vikash V. Gayah, and Eric J. Gonzales. 2011. Macroscopic relations of urban traffic variables: Bifurcations, multi-valuedness and instability. *Transport. Res. B: Methodol.* 45, 1 (2011), 278–288.
[71] Wanli Min and Laura Wynter. 2011. Real-time road traffic prediction with spatio-temporal correlations. *Transport. Res. C: Emerg. Technol.* 19, 4 (2011), 606–616.
[72] Mark R. McCord, Yongliang Yang, Zhuojun Jiang, Benjamin Coifman, and Prem K. Goel. 2003. Estimating annual average daily traffic from satellite imagery and air photos: Empirical results. *Transport. Res. Rec.* 1855, 1 (2003), 136–142.
[73] Jin Ki Eom, Man Sik Park, Tae-Young Heo, and Leta F. Huntsinger. 2006. Improving the prediction of annual average daily traffic for non-freeway facilities by applying a spatial statistical method. *Transport. Res. Rec.* 1968, 1 (2006), 20–29.

[74] Craig Labovitz, Scott Iekel-Johnson, Danny McPherson, Jon Oberheide, and Farnam Jahanian. 2011. Internet Inter-domain Traffic. *ACM SIGCOMM Comput. Commun. Rev.* 41, 4 (2011), 75–86.

[75] David Carr, Ondine von Ehrenstein, Stephan Weiland, Claudia Wagner, Oliver Wellie, Thomas Nicolai, and Erika von Mutius. 2002. Modeling annual benzene, toluene, NO2, and soot concentrations on the basis of road traffic characteristics. *Environ. Res.* 90, 2 (2002), 111–118.

[76] Deepak Ganesan, Ramesh Govindan, Scott Shenker, and Deborah Estrin. 2001. Highly-resilient, energy-efficient multi-path routing in wireless sensor networks. *ACM SIGMOBILE Mobile Comput. Commun. Rev.* 5, 4 (2001), 11–25.

[77] Graeme Henkelman and Hannes Jónsson. 2000. Improved tangent estimate in the nudged elastic band method for finding minimum energy paths and saddle points. *J. Chem. Phys.* 113, 22 (2000), 9978–9985.

[78] Evangelos Kanoulas, Yang Du, Tian Xia, and Donghui Zhang. 2006. Finding fastest paths on a road network with speed patterns. In *Proceedings of the 22nd International Conference on Data Engineering (ICDE'06).* IEEE, 1–10.

[79] Hector Gonzalez, Jiawei Han, Xiaolei Li, Margaret Myslinska, and John Paul Sondag. 2007. Adaptive fastest path computation on a road network: A traffic mining approach. In *Proceedings of the 33rd International Conference on Very Large Data Bases.* VLDB Endowment, 794–805.

[80] Amgad Elgowainy, Jeongwoo Han, Jacob Ward, Fred Joseck, David Gohlke, Alicia Lindauer, Todd Ramsden, et al. 2018. Current and future united states light-duty vehicle pathways: Cradle-to-grave life cycle greenhouse gas emissions and economic assessment. *Environ. Sci. Technol.* 52, 4 (2018), 2392–2399.

[81] Joshuah K. Stolaroff, Constantine Samaras, Emma R. O'Neill, Alia Lubers, Alexandra S. Mitchell, and Daniel Ceperley. 2018. Energy use and life cycle greenhouse gas emissions of drones for commercial package delivery. *Nat. Commun.* 9, 1 (2018).

[82] Dong Guo, Juan Wang, Jin B. Zhao, Feng Sun, Song Gao, Chun D. Li, Ming H. Li, and Chao C. Li. 2019. A vehicle path planning method based on a dynamic traffic network that considers fuel consumption and emissions. *Science of the Total Environment* 663 (2019), 935–943.

[83] Gaurav Gupta, Sreeja Kamishetty, and Praveen Paruchuri. 2018. A prioritized routing assistant for flow of traffic. In *Proceedings of the 2018 21st International Conference on Intelligent Transportation Systems (ITSC'18).* IEEE, 3627–3632.

[84] Miaomiao Cao, Qiqi Shuai, and Victor O. K. Li. 2018. Navigation-based traffic signal control in intelligent transportation systems. In *Proceedings of the 2018 IEEE Global Communications Conference (GLOBECOM'18).* IEEE, 1–7.

[85] André B. Campolina, Azzedine Boukerche, Max do V. Machado, and Antonio A. F. Loureiro. 2018. Fuel efficient routes using vehicular sensor data. In *Proceedings of the 16th ACM International Symposium on Mobility Management and Wireless Access.* ACM, 29–36.

[86] Timothy Searchinger, Ralph Heimlich, Richard A. Houghton, Fengxia Dong, Amani Elobeid, Jacinto Fabiosa, Simla Tokgoz, Dermot Hayes, and Tun-Hsiang Yu. 2008. Use of US croplands for biofuels increases greenhouse gases through emissions from land-use change. *Science* 319, 5867 (2008), 1238–1240.

[87] Jiwoon Ahn, Gicheol Jeong, and Yeonbae Kim. 2008. A forecast of household ownership and use of alternative fuel vehicles: A multiple discrete-continuous choice approach. *Energy Econ.* 30, 5 (2008), 2091–2104.

[88] Alan J. Miller. 1963. Settings for fixed-cycle traffic signals. *J. Operat. Res. Soc.* 14, 4 (1963), 373–386.

[89] Karl E. Stoffers. 1967. Scheduling of traffic lights-a new approach. *Transport. Res.* 2, 3 (1967).

[90] Thomas Urbanik, Alison Tanaka, Bailey Lozner, Eric Lindstrom, Kevin Lee, Shaun Quayle, Scott Beaird, et al. 2015. *Signal Timing Manual.* Washington, DC: Transportation Research Board.

[91] Javad Abdi, Behzad Moshiri, Baher Abdulhai, and Ali Khaki Sedigh. 2013. Short-term traffic flow forecasting: Parametric and nonparametric approaches via emotional temporal difference learning. *Neural Comput. Appl.* 23, 1 (2013), 141–159.

[92] Monireh Abdoos, Nasser Mozayani, and Ana L. C. Bazzan. 2013. Holonic multi-agent system for traffic signals control. *Eng. Appl. Artif. Intell.* 26, 5–6 (2013), 1575–1587.

[93] Javad Abdi, Behzad Moshiri, Baher Abdulhai, and Ali Khaki Sedigh. 2012. Forecasting of short-term traffic-flow based on improved neurofuzzy models via emotional temporal difference learning algorithm. *Eng. Appl. Artif. Intell.* 25, 5 (2012), 1022–1042.

[94] M. A. Wiering. 2000. Multi-agent reinforcement learning for traffic light control. In *Machine Learning: Proceedings of the 17th International Conference (ICML'00).* 1151–1158.

[95] Atulya Mahajan, Niranjan Potnis, Kartik Gopalan, and Andy Wang. 2007. Modeling vanet deployment in urban settings. In *Proceedings of the 10th ACM Symposium on Modeling, Analysis, and Simulation of Wireless and Mobile Systems.* ACM, 151–158.

[96] Simone Göttlich, Michael Herty, and Ute Ziegler. 2015. Modeling and optimizing traffic light settings in road networks. *Comput. Operat. Res.* 55 (2015), 36–51.

[97] Seyed Sajad Mousavi, Michael Schukat, and Enda Howley. 2017. Traffic light control using deep policy-gradient and value-function-based reinforcement learning. *IET Intell. Transport Syst.* 11, 7 (2017), 417–423.

[98] Dunn Engineering Asociates In association with Siemens Intelligent Transportation Systems, *Traffic Control Systems Handbook*. Federal Highway Administration Office of Transportation Management, Washington, D.C.
[99] K. Pandit, D. Ghosal, H. M. Zhang, C. Chen-Nee. 2013. Adaptive traffic signal control with vehicular ad hoc networks. *IEEE Trans. Vehic. Technol.* 62, 4 (2013), 1459–1471.
[100] N. Maslekar, J. Mouzna, M. Boussedjra, and H. Labiod. 2013. CATS: An adaptive traffic signal system based on car-to-car communication. *J. Netw. Comput. Appl.* 36, 5 (2013), 1308–1315.
[101] Kartik Pandit, Dipak Ghosal, H. Michael Zhang, and Chen-Nee Chuah. 2013. Adaptive traffic signal control with vehicular ad hoc networks. *IEEE Trans. Vehic. Technol.* 62, 4 (2013), 1459–1471.
[102] Theresa Thunig, Nico Kühnel, and Kai Nagel. 2019. Adaptive traffic signal control for real-world scenarios in agent-based transport simulations. *Transport. Res. Proc.* 37 (2019), 481–488.
[103] Avinash Mungur, Abdel Sa'D. Bin Anwar Bheekarree, and Muhammad Bilaal Abdel Hassan. 2018. Smart eco-friendly traffic light for mauritius. In *Future of Information and Communication Conference*. Springer, Cham, 475–487.
[104] Galang P. N. Hakim, Ahmad Firdausi, Mudrik Alaydrus, and Setiyo Budiyanto. 2018. Dynamic traffic light timing control system using fuzzy TOPSIS algorithm. *MS&E* 453, 1 (2018), 012–063.
[105] Ajinkya Khadilkar, Kunal Sunil Kasodekar, Priyanshu Sharma, and J. Priyadarshini. 2019. Intelligent traffic light scheduling using linear regression. In *Applications of Artificial Intelligence Techniques in Engineering*. Springer, Singapore, 329–335.
[106] Luis Cruz-Piris, Miguel A. Lopez-Carmona, and Ivan Marsa-Maestre. 2019. Automated optimization of intersections using a genetic algorithm. *IEEE Access* 7 (2019), 15452–15468.
[107] Gianluca Bianchin and Fabio Pasqualetti. 2018. A network optimization framework for the analysis and control of traffic dynamics and intersection signaling. In *Proceedings of the 2018 IEEE Conference on Decision and Control (CDC'18)*. IEEE, 1017–1022.
[108] Martin Pilát. 2018. Evolving ensembles of traffic lights controllers. In *Proceedings of the 2018 IEEE 30th International Conference on Tools with Artificial Intelligence (ICTAI'18)*. IEEE, 958–962.
[109] Chaogang Tang, Xianglin Wei, Mingyang Hao, Chunsheng Zhu, Rongcun Wang, and Wei Chen. 2018. Traffic signal phase scheduling based on device-to-device communication. *IEEE Access* 6 (2018), 47636–47645.
[110] Li Zhihui, Cao Qian, Zhao Yonghua, Tao Pengfei, and Zhuo Rui. 2019. Krill herd algorithm for signal optimization of cooperative control with traffic supply and demand. *IEEE Access* 7 (2019), 10776–10786.
[111] Jiangqun Wang, Ning Cao, and Guozhong Yao. 2018. Research on Model of Feasible Timing of Traffic Light for Intersection Control. In *Proceedings of the 2018 International Conference on Mechanical, Electronic, Control and Automation Engineering (MECAE'18)*. Atlantis Press.
[112] Zhenning Li, Qiong Wu, Hao Yu, Cong Chen, Guohui Zhang, Zong Z. Tian, and Panos D. Prevedouros. 2019. Temporal-spatial dimension extension-based intersection control formulation for connected and autonomous vehicle systems. *Transport. Res. C: Emerg. Technol.* 104 (2019), 234–248.
[113] Leena A. Abdalla, Reem M. Taha, Nejod S. Mohammed, and Niemah I. Osman. 2019. Reducing Delay and CO2 Emissions in Multi-lane Intersections using Vehicular Ad-hoc Networks. In *Proceedings of the 2019 International Conference on Computer and Information Sciences (ICCIS'19)*. IEEE, 1–6.
[114] Trung-Thanh Ngo, Thien Huynh-The, and Dong-Seong Kim. 2019. A novel VANETs-based traffic light scheduling scheme for greener planet and safer road intersections. *IEEE Access* 7 (2019), 22175–22185.
[115] Li Zhihui, Cao Qian, Zhao Yonghua, Tao Pengfei, and Zhuo Rui. 2019. Krill herd algorithm for signal optimization of cooperative control with traffic supply and demand. *IEEE Access* 7 (2019), 10776–10786.
[116] Jialang Cheng, Weigang Wu, Jiannong Cao, and Keqin Li. 2016. Fuzzy group-based intersection control via vehicular networks for smart transportations. *IEEE Trans. Industr. Inf.* 13, 2 (2016), 751–758.
[117] M. Bani Younes and Azzedine Boukerche. 2014. An intelligent traffic light scheduling algorithm through VANETs. In *Proceedings of the 39th Annual IEEE Conference on Local Computer Networks Workshops*. IEEE, 637–642.
[118] M. Bani Younes and Azzedine Boukerche. 2015. Intelligent traffic light controlling algorithms using vehicular networks. *IEEE Trans. Vehic. Technol.* 65, 8 (2015), 5887–5899.
[119] Libing Wu, Lei Nie, Samee U. Khan, Osman Khalid, and Dan Wu. [n.d.]. A V2I communication-based pipeline model for adaptive urban traffic light scheduling. *Frontiers of Computer Science*, 1–14.
[120] M. Bani Younes, Azzedine Boukerche, and Abdelhamid Mammeri. 2016. Context-aware traffic light self-scheduling algorithm for intelligent transportation systems. In *Proceedings of the 2016 IEEE Wireless Communications and Networking Conference*. IEEE, 1–6.
[121] M. Bani Younes and Azzedine Boukerche. 2018. An efficient dynamic traffic light scheduling algorithm considering emergency vehicles for intelligent transportation systems. *Wireless Netw.* 24, 7 (2018), 2451–2463.
[122] O. Voloch Barzilai, N. Hasgall, A. Lavi Steiner, and O. Ahituv. 2018. Traffic control in a smart intersection by an algorithm with social priorities. *Contemp. Eng. Sci.* 11, 31 (2018), 1499–1511.

[123] Haibo Mu, Yubo Song, and Linzhong Liu. 2018. Route-based signal preemption control of emergency vehicle. *J. Contr. Sci. Eng.* 2018 (2018), 1–11.

[124] Marcin Lewandowski, Bartłomiej Płaczek, and Marcin Bernas. 2017. Self-organizing traffic signal control with prioritization strategy aided by vehicular sensor network. In *Proceedings of the IFIP International Conference on Computer Information Systems and Industrial Management.* Springer, Cham, 536–547.

[125] P. Hunt, D. Robertson, R. Bretherton, and R. Winton. 1981. Scoot-a traffic responsive method of coordinating signals. Technical Report (1981).

[126] X.-H. Yu and Wilfred W. Recker. 2006. Stochastic adaptive control model for traffic signal systems. *Transport. Res. C: Emerg. Technol.* 14, 4 (2006), 263–282.

[127] P. Lowrie. 1982. SCATS: The sydney co-ordinated adaptive traffic system-principles, methodology, algorithms. In *Proceedings of the IEEE International Conference on Road Traffic Signalling.* 67–70.

[128] Ovidiu Tomescu, Ilona Madalina Moise, Alina Elena Stanciu, and I. Batros. 2012. Adaptive traffic light control system using ad-hoc vehicular communications network. *UPB Sci. Bull. Ser. D* 74, 2 (2012).

[129] Pitu Mirchandani and Larry Head. 2001. A real-time traffic signal control system: Architecture, algorithms, and analysis. *Transport. Res. C: Emerg. Technol.* 9, 6 (2001), 415–432.

[130] Nathan H. Gartner. 1983. *OPAC: A Demand-responsive Strategy for Traffic Signal Control.* No. 906. 1983.

[131] Christina Diakaki, Markos Papageorgiou, and Kostas Aboudolas. 2002. A multivariable regulator approach to traffic-responsive network-wide signal control. *Contr. Eng. Pract.* 10, 2 (2002), 183–195.

[132] Chin Kian Keong. 1993. The GLIDE system—Singapore’s urban traffic control system. *Transport Rev.* 13, 4 (1993), 295–305.

[133] Feng Zhu, H. M. Abdul Aziz, Xinwu Qian, and Satish V. Ukkusuri. 2015. A junction-tree based learning algorithm to optimize network wide traffic control: A coordinated multi-agent framework. *Transport. Res. C: Emerg. Technol.* 58 (2015), 487–501.

[134] Gaochao Wang, Yandong Hou, Yanyu Zhang, Yi Zhou, Ning Lu, and Nan Cheng. 2017. TLB-VTL: 3-level buffer based virtual traffic light scheme for intelligent collaborative intersections. In *Proceedings of the 2017 IEEE 86th Vehicular Technology Conference (VTC’17).* IEEE, 1–5.

[135] Yandong Hou, Gaochao Wang, and Yi Zhou. 2018. Virtual-grid based traffic control strategy with multiple intersections collaboration. *IEEE Access* 6 (2018), 40105–40119.

[136] Shiuan-Wen Chen, Chang-Biau Yang, and Yung-Hsing Peng. 2007. Algorithms for the traffic light setting problem on the graph model. In *Proceedings of the 12th Conference on Artificial Intelligence and Applications.* 1–8.

[137] Yi-Sheng Huang, Yi-Shun Weng, and MengChu Zhou. 2013. Modular design of urban traffic-light control systems based on synchronized timed Petri nets. *IEEE Trans. Intell. Transport. Syst.* 15, 2 (2013), 530–539.

[138] Carolina Tripp Barba, Miguel Angel Mateos, Pablo Reganas Soto, Ahmad Mohamad Mezher, and Mónica Aguilar Igartua. 2012. Smart city for VANETs using warning messages, traffic statistics and intelligent traffic lights. In *Proceedings of the 2012 IEEE Intelligent Vehicles Symposium.* IEEE, 902–907.

[139] Samah El-Tantawy, Baher Abdulhai, and Hossam Abdelgawad. 2013. Multiagent reinforcement learning for integrated network of adaptive traffic signal controllers (MARLIN-ATSC): Methodology and large-scale application on downtown Toronto. *IEEE Trans. Intell. Transport. Syst.* 14, 3 (2013), 1140–1150.

[140] Behnam Torabi, Rym Z. Wenkstern, and Robert Saylor. 2018. A self-adaptive collaborative multi-agent based traffic signal timing system. In *Proceedings of the 2018 IEEE International Smart Cities Conference (ISC2’18.* IEEE, 1–8.

[141] M. Bani Younes and Azzedine Boukerche. 2018. Toward a smooth vehicular traffic at round road-intersections. In *Proceedings of the 2018 IEEE Global Communications Conference (GLOBECOM’18).* IEEE, 1–7.

[142] Joshué Pérez, Vicente Milanés, Teresa De Pedro, and Ljubo Vlacic. 2011. Autonomous driving manoeuvres in urban road traffic environment: A study on roundabouts. *IFAC Proc.* 44, 1 (2011), 13795–13800.

[143] Efterpi Damaskou, Foteini Kehagia, and Magda Pitsiava-Latinopoulou. 2015. A review of roundabout safety performance in Europe and the USA. In *Proceedings of the 6th Hellenic Conference in Road Safety.*

[144] John M. Scanlon, Rini Sherony, and Hampton C. Gabler. 2016. Predicting crash-relevant violations at stop sign–controlled intersections for the development of an intersection driver assistance system. *Traffic Injury Prevent.* 17, 1 (2016), 59–65.

[145] M. Bani Younes and Azzedine Boukerche. 2019. Safety and efficiency control protocol for highways using intelligent vehicular networks. *Comput. Netw.* 152 (2019), 1–11.

[146] M. Bani Younes, Azzedine Boukerche, and Xiaoli Zhou. 2016. Traffic efficiency protocol for highway roads in vehicular network. In *Proceedings of the 2016 IEEE Global Communications Conference (GLOBECOM’16).* IEEE, 1–6.

[147] M. Bani Younes and Azzedine Boukerche. 2017. A vehicular network based intelligent lane change assistance protocol for highways. In *Proceedings of the 2017 IEEE International Conference on Communications (ICC’16).* IEEE, 1–6.

[148] M. Bani Younes and Azzedine Boukerche. 2018. Safety traffic speed recommendations for critical road scenarios using vehicular networks. In *Proceedings of the 2018 IEEE International Conference on Communications (ICC’18).* IEEE, 1–6.

[149] Gabriel R. Diniz, Felipe D. Cunha, and Antonio A. F. Loureiro. 2017. On the characterization of vehicular mobility. In *Proceedings of the 6th ACM Symposium on Development and Analysis of Intelligent Vehicular Networks and Applications*. ACM, 23–29.

[150] Maan Joseph, Xiaofeng Liu, and Arunita Jaekel. 2018. An adaptive power level control algorithm for DSRC congestion control. In *Proceedings of the 8th ACM Symposium on Design and Analysis of Intelligent Vehicular Networks and Applications*. ACM, 57–62.

[151] Rodolfo W. L. Coutinho and Azzedine Boukerche. 2018. Information-centric intelligent vehicular networks: Challenges and guidelines. In *Proceedings of the 21st ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems*. ACM, 7–8.

[152] Noura Aljeri and Azzedine Boukerche. 2018. Mobility and handoff management in connected vehicular networks. In *Proceedings of the 16th ACM International Symposium on Mobility Management and Wireless Access*. ACM, 82–88.

[153] André B. Campolina, Azzedine Boukerche, Max do V. Machado, and Antonio A. F. Loureiro. 2018. Fuel efficient routes using vehicular sensor data. In *Proceedings of the 16th ACM International Symposium on Mobility Management and Wireless Access*. ACM, 29–36.

[154] Maroua Gharam and Noureddine Boudriga. 2016. User mobility under LTE based VPN: QoS and handover management. In *Proceedings of the 14th ACM International Symposium on Mobility Management and Wireless Access*. ACM, 1–8.

[155] Seilendria A. Hadiwardoyo, Jean-Michel Dricot, Carlos T. Calafate, Juan-Carlos Cano, Enrique Hernandez-Orallo, and Pietro Manzoni. 2019. UAV mobility model for dynamic UAV-to-car communications. In *Proceedings of the 16th ACM International Symposium on Performance Evaluation of Wireless Ad Hoc, Sensor, and Ubiquitous Networks*. ACM, 1–6.

[156] Luis F. Urquiza-Aguiar, William Coloma Gómez, Pablo Barbecho Bautista, and Xavier Calderón. 2019. Comparison of traffic demand generation tools in SUMO: Case study: Access highways to quito. In *Proceedings of the 16th ACM International Symposium on Performance Evaluation of Wireless Ad Hoc, Sensor, and Ubiquitous Networks*. ACM, 15–22.

[157] Jovan Radak, Lukas Baulig, Dawid Bijak, Christian Schowalter, and Hannes Frey. 2017. Moving towards wireless sensors using RSSI measurements and particle filtering. In *Proceedings of the 14th ACM Symposium on Performance Evaluation of Wireless Ad Hoc, Sensor, and Ubiquitous Networks*. ACM, 33–40.

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