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Impact of Two-Way Communication of Traffic Light Signal-to-Vehicle on the Electric Vehicle State of Charge

AMAL ALTURIMAN AND MAAZEN ALSABAAN

Department of Computer Engineering, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia

Corresponding author: Maazen Alsabaan (malsabaan@ksu.edu.sa)

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ABSTRACT Given the ongoing concerns on the emissions of greenhouse gases that contribute to global warming, the electric vehicle is considered as a promising technology solution for the reduction of these emissions in the transportation sector. Despite the numerous advantages of electric vehicles, the limited driving range is one of the prominent drawbacks that need to be addressed. Since the driving range is related to the battery's state of charge, which is, in turn, related to power consumption, there is a need to minimize the vehicle power consumption. Increased speeds and accelerations lead to a decrease of the state of charge. In this paper, we utilized vehicular networks that allow traffic light signals to communicate with approaching vehicles to avoid unnecessary high speeds and accelerations at an isolated intersection. This communication can be bidirectional, that is, from the vehicle to the traffic light signal, and vice versa. This enables the traffic light signal to adapt its green duration according to vehicular information and then send back its information to vehicles that in turn adapt their speeds based on the received information. We propose an optimization model that determines the optimum green duration and optimum vehicular speed, which ensures that the vehicle will cross the traffic light signal with maximum battery's state of charge. The analytical results indicate that the proposed approach which is adaptive in both speed and traffic light signal can achieve an improvement of the state of charge compared to other two approaches, which are adaptive in either speed or traffic signal.

INDEX TERMS Intelligent transportation systems, electric vehicle, state of charge, power consumption, vehicle-to-traffic light signal communication, traffic light signal-to-vehicle communication, optimization.

NOMENCLATURE

C_L	TLS cycle (Green, yellow, and red) length (s).
L_g	Time remaining to switch from green to yellow (s).
N_g	Light cycles that will be completed before passing the TLS if a packet is sent when the TLS is green.
d_{OD}	Distance from the origin and the destination (m).
d	Distance between the vehicle and the TLS after receiving a packet from TLS (m).
d_{TLS}	Distance from origin to the TLS (m).
L	Distance between the vehicle and the destination at the time of receipt of a packet from TLS (given from GPS) (m).
h_{min}	Minimum safe distance headway between the vehicle and the TLS (m).
rh_{min}	Required time for the vehicle to be h_{min} away from the TLS (s).
M	Time of the vehicle to comfortably decelerate from S_{max} to S_R (s).
D	Packet delay (s).
δ	Deceleration rate (kph/s).
Acc	Maximum acceleration rate = 3.6 m/s^2.
$v_k(t_k)$	Vehicle's speed at time t_k ($k = 2, 4, 6, 7, 9$, and 10).
$na_k(t_k)$	Vehicle's deceleration at time t_k ($k = 2, 6$, and 9).
$a_k(t_k)$	Vehicle's acceleration at time t_k ($k = 4, 7$, and 10).
α_2	Required time to decelerate from S_{max} to S_R.
α_6	Required time to decelerate from S_R to S_x.
α_9	Required time to decelerate from S_R to 0.
β_4	Required time to accelerate from S_R to S_{max}.
β_7	Required time to accelerate from S_x to S_{max}.
β_{10}	Required time to accelerate from 0 to S_{max}.

I. INTRODUCTION

The global increase of greenhouse gas (GHG) emissions is a source of major concern because it contributes to global warming. The transportation sector is one of the major sources of GHG emissions. For example, in 2016, approximately 26% of GHG emissions originated from the transportation sector in the United Kingdom alone [1]. These emissions are largely related to the combustion of fossil fuels, which are used in conventional vehicles. One of the applicable solutions for reducing GHG emissions is the use of electric vehicles (EVs) since they are based on batteries instead of fossil fuels. Therefore, EVs including battery, hybrid, and plug-in hybrid electric vehicles [2], are considered as an environmentally friendly option. Consequently, the number of EVs are rapidly increasing worldwide, which is projected to reach 140 million by 2030 [3].

However, the high cost, long charging time, and limited driving range are some of EVs' drawbacks that still challenge manufacturers and researchers. The limited driving range is related to many factors, such as the battery's SOC, power consumption, and driving behavior [4]. The SOC for EVs is similar to the fuel gauge of conventional vehicles. It is defined as a percentage of the remaining battery capacity relative to the its full capacity [5]. Thus, in order to address the EVs' driving range drawback, there is a need to minimize power consumption. The vehicular networks in association with adaptive traffic light signal (TLS) could play a significant role in the achievement of this goal.

Vehicular network technology is one of the pillars of intelligent transportation systems (ITSs). These networks aim to allow communication between vehicles themselves as well as between vehicles and road infrastructures (e.g., roadside unit, TLS) to improve safety and efficiency of traffic. The communications use dedicated, short range communications (DSRC), which are based on a wireless communication technology intended for exclusive use in vehicular networks. It is based on the IEEE 802.11p standard for the physical and medium access control layers, and on the IEEE 1906 standard for the upper layers. In United States, DSRC operates on a 75 MHz spectrum in the 5.9 GHz frequency band [6]. The dedicated spectrum is divided into seven channels. One of the channels is considered as a control channel to support safety applications of vehicular networks. The remaining six channels are considered as service channels to support other applications.

One of the most useful vehicular network applications is the adjustment of the timing of TLSs to suit traffic conditions. TLSs are devices responsible for controlling traffic flow at road intersections. They can be operated with three control strategies: pretimed, actuated, and adaptive. The pretimed strategy uses fixed and predefined timings, which are derived from historical data regardless of the current traffic demand. Unlike this strategy, the actuated and adaptive strategies take into account the current traffic demand for the determination of their timing accordingly. The main difference of the actuated and adaptive strategies is the use of a set of predefined parameters (e.g., unit extension of green light) in the case of the actuated strategy, whereas the adaptive depends completely on the current real-time traffic. The split cycle offset optimization technique (SCOOT) [7] and sydney coordinated adaptive traffic system (SCAT) [8] are the most well-known TLS adaptive control systems. They use detectors on the road to collect real time traffic data. Recently, owing to the advances in wireless communications, vehicular networks are used in adaptive TLS to collect real time traffic data as an alternative to detectors.

In this study, we evaluate the effects of two-way communications between EVs and an adaptive TLS on the SOC of the EVs using vehicular networks at an isolated intersection. The TLS has the ability to adjust its green light duration (T_g) based on the received information from EVs via vehicle-to-traffic light signal (V2TLS) communications. Similarly, the EVs have the ability to adjust their speed to the recommended value (S_R) based on the TLS' information that is fed back to them via traffic light signal-to-vehicle (TLS2V) communications. These T_g and S_R values are ensure that the EVs will cross the TLS with maximum SOC.

The main contributions of this study can be summarized as follows:

- Study of the benefits of two-way communication between an EV and a TLS on maximizing the SOC of the EV
- Study the possible scenarios of an EV approaching a TLS, and show the need of optimization in achieving the maximum SOC
- Develop an optimization model with the objective function of maximizing the SOC for EVs approaching an isolated traffic intersection

The rest of this study is structured as follows: Section II presents related work of the V2TLS and TLS2V communications. Section III defines the problem. Our system models, including the SOC estimation, communication, traffic, and mobility models, are described in Section IV. Section V reviews our methodological approach. The optimization model is presented in Section VI. Section VII presents the results and discussion. Finally, Section VIII outlines the conclusions of this study.

II. RELATED WORKS

Many research efforts have been conducted aiming at the utilization of the interaction between vehicles and TLSs through vehicular network technology. They have achieved various of objectives including the increase of the throughput or decrease of the vehicular energy consumption, waiting time, queue length, and congestion or number of stops at red lights at intersections. This section presents some of the existing literature in this field classified into two categories according to the communication directions, namely, (1) V2TLS, and (2) TLS2V.

A. VEHICLE-TO-TRAFFIC LIGHT SIGNAL (V2TLS) COMMUNICATION

In this type of communication, a TLS adapts its timing based on the received information from the approaching vehicles. Li *et al.* in [9], presented a self-adaptive traffic light control system, using V2TLS communications. The system allowed the traffic light controller to determine either the extent of the time or the switching scheme of the light according to the proposed algorithm. The algorithm depended only on speed information that was received from each vehicle at an intersection. Compared to the traditional pretimed traffic light control system, the proposed system led to decreased traffic congestion and environmental pollution at the intersection. Zaho *et al.* in [10] proposed a dynamic traffic signal timing optimization strategy using V2TLS communication. The strategy aimed to reduce the energy consumption of all the vehicles that were considered in this study, including conventional and electric. Owing to the optimal traffic signal timing, positive results in the reduction of energy consumption at an intersection had been obtained.

Unlike other prior studies, the published studies in [11]–[16] considered the interaction among vehicles based on the use of vehicle-to-vehicle (V2V) communication in addition to V2TLS communication. An adaptive traffic light system has been proposed in [11]. The system used the vehicular information to estimate the traffic density, and then determined the cycle length based on that density using Webster's formula. The simulation results proved the superiority of the adaptive traffic light system in reducing the total average delay by 28.3%, and the fuel consumption and CO_2 emissions by 3.6%, compared to the pretimed traffic light system. Since the system depends only on the traffic density and does not consider the vehicle's position relative to the intersection, this may lead to an increase in the delay when the traffic that is near the intersection has a lower density. To address this problem, Kwatirayo *et al.* [12] have proposed another adaptive traffic light control (ATLC) algorithm which took into account the distance between the vehicle and the intersection in addition to the density. In the ATLC algorithm, the TLS calculates the weights along the flow directions and adapts the green light duration for the direction that has the highest flow weight. The flow weight is inversely proportional to the distance from the vehicle to the intersection. If the distance is large, the weight is low. Using real data traffic collected in a nine-year period at an intersection in the city of Moncton, the ATLC reduced the average delay by 28.35% compared to the system proposed in [11]. In addition, it has excelled in decreasing the average delay and travel time compared to the pretimed TLS.

The oldest arrival first (OAF) is an adaptive traffic light control algorithm that was proposed in [13]. The authors formulated traffic signal timing as a job scheduling problem. The algorithm divided vehicles into equal-sized platoons according to their speed and location. The platoon size refers to the time required by all vehicles to pass through the intersection. Each platoon was considered as a job, which can be scheduled using the oldest job first OJF algorithm for optimizing the schedule of the TLS. In light and medium traffic loads, OAF is the most effective algorithm in reducing the vehicular delay at the intersection compared to pretimed TLS. For cased with low-waiting times and high-throughput, a scheduling algorithm referred to as intelligent traffic light controlling (ITLC), was proposed in [14]. It has outperformed the OAF by 25% and 30% in terms of decreasing the delay time per vehicle and increasing the throughput at the intersection, respectively. The ITLC ensures that all existing vehicles in the ready area during the data gathering phase have the ability to cross the intersection, without exceeding the maximum green time.

A real time adaptive signal phase allocation algorithm has been proposed in [15]. The algorithm used the location and speed information of connected vehicles to solve the two-level optimization problem by minimizing the queue length and the total vehicular delay. Furthermore, the authors have proposed another algorithm named estimation of location and speed, whereby the speed and location of the unequipped vehicle were estimated. In the case where the penetration rate of connected vehicles was high, this proposed algorithm led to the reduction of the total delay by 16.33% compared to the actuated control algorithm.

Direct communication between each individual vehicle and TLS typically increases the waiting time at the intersection, as a result of the communication overhead. Therefore, Chang and Park [16] have proposed a traffic signal control algorithm with grouping. Vehicles waiting for the green light exchange their information via V2V communication. They then divide themselves into groups based on their direction. Each group elects one of the vehicles as a leader to be in charge of sends the intersection information to the traffic light controller. Accordingly, the traffic light controller allocates a suitable signal cycle length using the queue proposed length-based algorithm. This led to minimizing the average delay time and total queue length at the intersection.

B. TRAFFIC LIGHT SIGNAL-TO-VEHICLE (TLS2V) COMMUNICATION

Contrary to previous communication schemes, TLS2V communication enables the TLS to send its information, such as the current light state, the remaining time for the switch to the next light, etc., to approaching vehicles. Thus, the vehicles can take appropriate actions according to the received information. The green light optimal speed advisor (GLOSA) systems, is one of the systems that using this communication kind. They help vehicles determine the optimal driving strategy by suggesting the optimum speed for crossing the TLS during a green light period. It is noteworthy to state that the potentials and limitations of GLOSA have been previously studied [17]. Based on the results of this study, the systems elicits respective reductions in CO_2 emissions, trip time, and number of stops, up to 11.5%, 7%, and 6%, at light traffic scenario. Another study that aims to save fuel and reduce emissions is presented in [18]. The study considers the gear choices and distance between a TLS and a vehicle as the main effective factors. Based on the delivered TLS information via TLS2V communication, the driver can choose the suitable gear that should lead to fuel savings and emission reductions. As shown by the simulation results, the reductions reached up to 22% for fuel consumption and up to 80% for monoxide (CO) emissions for this single vehicle.

Alsabaan *et al.* in [19] used V2V communication as well as the economical and environmentally friendly geocast (EEFG) protocol in TLS2V communication. In this work, vehicles adapted their speeds based on TLS information to cross an intersection with minimum fuel consumption and CO_2 emissions. An optimization model was developed to achieve the maximum reduction of fuel consumption and CO_2 emissions. Moreover, the authors have proposed heuristic expressions that calculate a recommended vehicular speed to achieve a value near the optimum. Alsabaan et al. in [20], used real traffic data for urban and suburban intersections in the city of Waterloo in order to assess the EEFG feasibility in real scenarios. The real data was calculated in both the peak and lowest volume hours of a day. According to their simulation results, the EEFG protocol has proved its ability to save fuel and decrease CO_2 emissions in urban and suburban intersections. Djahel *et al.* [21] had proposed an architectural model to make the vehicle able to determine its collaborative decision, in an effort to reduce the congestion, vehicle delay, and avoid stopping at the intersection. The collaborative decisions include the maintenance of the current vehicular speed, acceleration, deceleration, or lane changes. The exact decision type depends on the received information from the TLS and neighboring vehicles. A distinct reduction in the average vehicle travel time was achieved in this model.

In comparison to the cited publications listed above that deal with conventional vehicles, a few studies have been conducted to reduce the energy consumption of EVs using TLS2V. Tielert *et al.* [22] presented an analytical study to prove if the TLS2V communication has the impact in relation to energy saving for EVs equal to its impact in fuel saving for conventional vehicles or not. The vehicles use the TLS information to calculate their optimized trajectory, and then adapt their speed based on the appropriate strategy. The simulation results indicate that EVs can benefit from TLS2V in saving up to 20% more energy than conventional vehicles. Another study focused on the improvement of the energy efficiency of EVs at signalized intersections using TLS2V [23]. An eco-driving model and several control strategies were proposed. The model used real time TLS information and offered advice to help drivers drive at appropriate speeds. The results showed that EVs with the eco-driving model significantly outperformed the ones that did not use TLS2V by at least 8.01% and up to 54.07% in terms of energy saving.

As an attempt to achieve further improvements in reducing energy consumption at the intersections, a sub-optimal strategy had been proposed in [24]. Vehicles in this work received the information from many successive TLSs, which exist at the upcoming intersections. According to the TLSs information, the strategy was able to define the most energy efficient path. As a result, a speed is suggested to the drivers in order to avoid stopping at the intersections during travel.

The aforementioned studies were based on one-way communications. To the best of our knowledge, very few studies have considered two-way communications [25], [26], however, they have not considered EVs. Moreover, the study in [25] have not guaranteed optimality. Unlike these studies, we consider herein EVs with the two-way communications (V2TLS and TLS2V). Furthermore, we will propose an optimization model that guarantees the optimality of maximizing the battery's SOC in EVs.

III. PROBLEM DEFINITION

This study aims to utilize vehicular network technology and adaptive functionality of TLS to reduce the effect on the SOC of EVs approaching a TLS. Vehicular networks are used to facilitate the interaction between EVs and TLS. This interaction helps the TLS to adapt its timing according to the EVs information, and helps at the same time the EVs to adapt their speeds according to the TLS timing information to maximize the SOC. Since the TLSs at the intersections are one of the causes that make the vehicles increase their speeds and accelerations on a frequent basis, a study of the impact of the speed and acceleration on the SOC of EVs is critical.

TABLE 1. Electric vehicle parameters.

Description	Symbol	Value
Vehicle mass	m	1380 (kg)
Vehicle frontal area	A	2.5 (m^2)
Rolling resistance coefficient	μ_{rr}	0.02 (−)
Drag coefficient	C_d	0.02 (−)
Air density	ρ	1.2 (kg/m^3)
Initial SOC	SOC_0	80 (%)

The impact of both speed and acceleration on the SOC of EV can be studied using a SOC estimation model, as discussed in Subsection IV-A below. In this study, we consider a first generation plug-in hybrid Toyota Prius electric vehicle (XW30) that is driven with electric motor only (EV mode) with battery capacity C_{bat} equal to 23400 (A.s). The other vehicular parameters are shown in detail in Table 1 [27]. In regard to the study of the impact of the speed, the acceleration is specified to assume a constant value (e.g., 0 kph/s). Hence, the SOC is calculated using various speed values. As illustrated in Fig. 1, the SOC decreases as speed increases. In contrast, to study the impact of acceleration, the speed is specified to have a constant value (e.g., 30 kph/s). The SOC is then calculated with various acceleration values. The SOC of EV decreases as acceleration increases, as shown in Fig. 2.

Consequently, avoiding or completely reducing unnecessary EVs increases in speed and acceleration as they approach a TLS are needed to save their SOC. In this study, we develop an optimization model that can define the optimum values of

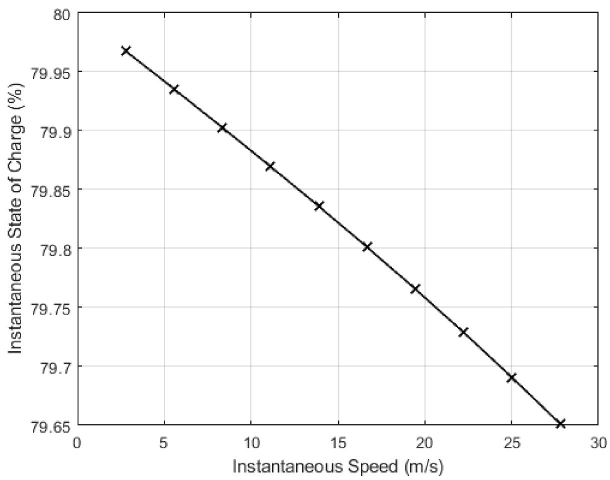


FIGURE 1. Impact of speed on the SOC of EV.

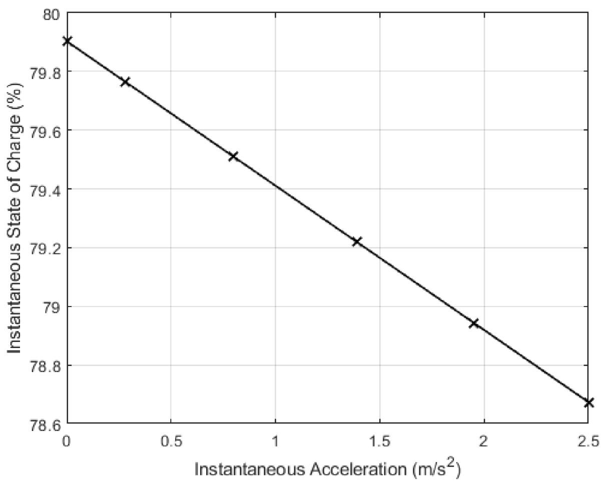


FIGURE 2. Impact of acceleration on the SOC of EV.

the green light duration (T_g^*) of a TLS and the recommended speed (S_R^*) of an EV that approaches the TLS. The optimum values help the EVs to cross a signalized intersection with a maximum SOC.

IV. SYSTEM MODEL

In this section, we discuss our system model that includes the SOC estimation, communication, traffic, and mobility models.

A. SOC ESTIMATION MODEL

We use a microscopic SOC estimation model to calculate the SOC level instantaneously. According to the power consumption model proposed in [28], the SOC estimation model uses the following equation to calculate the power consumption through the discharge time,

$$P = \sum_{t=1}^{T} P_t \tag{1}$$

where $P_t = v \times F_{te}$. Additionally, P is the total power consumption, T is the discharge time, and P_t is the instantaneous power consumption at time t. Furthermore, v is the velocity and F_{te} is the tractive effort, which denotes the force that propels the vehicle forward. This force is defined as the sum of various forces, including the rolling resistance (F_{rr}), aerodynamic drag (F_{ad}), hill climbing (F_{hc}), and acceleration (F_a) [29]. These can be calculated as follows,

$$F_{rr} = \mu_{rr} \times m \times g \tag{2}$$

$$F_{ad} = \frac{1}{2} \times \rho \times A \times C_d \times v^2 \tag{3}$$

$$F_{hc} = m \times g \times sin(\alpha) \tag{4}$$

$$F_a = m \times a \tag{5}$$

where μ_{rr} is the rolling resistance coefficient, m is the vehicle mass (kg), g is the acceleration owing to gravity (9.81 m/s^2), ρ is the air density (kg/m^3), A is the vehicle's frontal area (m^2), C_d is the drag coefficient, and a is defined as the vehicle's acceleration (m/s^2). Hence, the SOC estimation model can be calculated as follows [28],

$$SOC_{T+1} = SOC_0 - \frac{P}{C_{bat}} = SOC_0 - \frac{\sum_{t=1}^{T} P_t}{C_{bat}} \tag{6}$$

where SOC_{T+1} is the SOC after a discharge time T in (%), and SOC_0 is the initial SOC in (%). Correspondingly, C_{bat} is the battery capacity in (A.s).

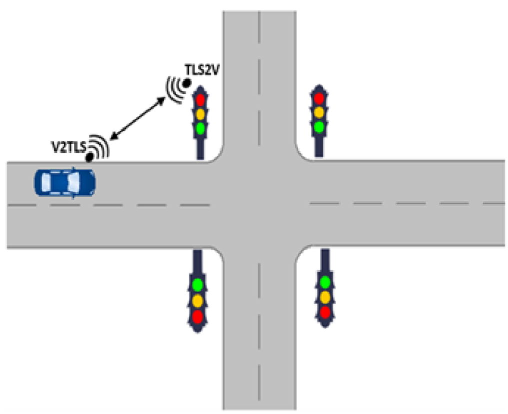


FIGURE 3. System model.

B. COMMUNICATION MODEL

In our communication model, EVs are considered as mobile nodes and TLSs as fixed nodes. They can interact with each other using two-way communications V2TLS and TLS2V, as shown in Fig. 3. In order to allow this interaction, we assume that the EVs are equipped with an on-board unit (OBU), which is a device responsible for communication in vehicular networks. Moreover, they are equipped with an application unit (AU), which is a device responsible for run applications and communication with OBU in wired or wireless configurations. To give the EVs the ability to determine their locations and the TLS locations, we assumed that each

AU is equipped with position data and an electronic road map. Furthermore, the TLSs are equipped only with the OBU. Additionally, an ideal communication channel was assumed in this study, where the packets arrive at the EVs and TLSs without delays.

C. TRAFFIC MODEL

An isolated signalized intersection on a suburban environment under low traffic demand conditions is the target in this study. We consider the intersection uses an adaptive TLS model that has three states: green, yellow, and red. The duration of yellow (T_y) and red (T_r) lights are set to be fixed, but the duration of green (T_g) light is changeable within a limited range from minimum (T_{gmin}) to maximum (T_{gmax}). Conversely, the road speed is limited by minimum (S_{min}) and maximum speed (S_{max}). Changing lanes and exceeding the limits of road speed are not considered in this study.

D. MOBILITY MODEL

The EV movement depends on the car-following microscopic traffic flow model [30]. We use the car-following behavior that has been used in the INTEGRATION traffic simulator [31]. The EV travels at the free flow speed before reaching the minimum safe distance headway (h_{min}) between itself and a TLS, especially when the TLS state is yellow or red. In contrast, the EV should be decelerated when the distance headway reaches h_{min}. The h_{min} is calculated as follows [31],

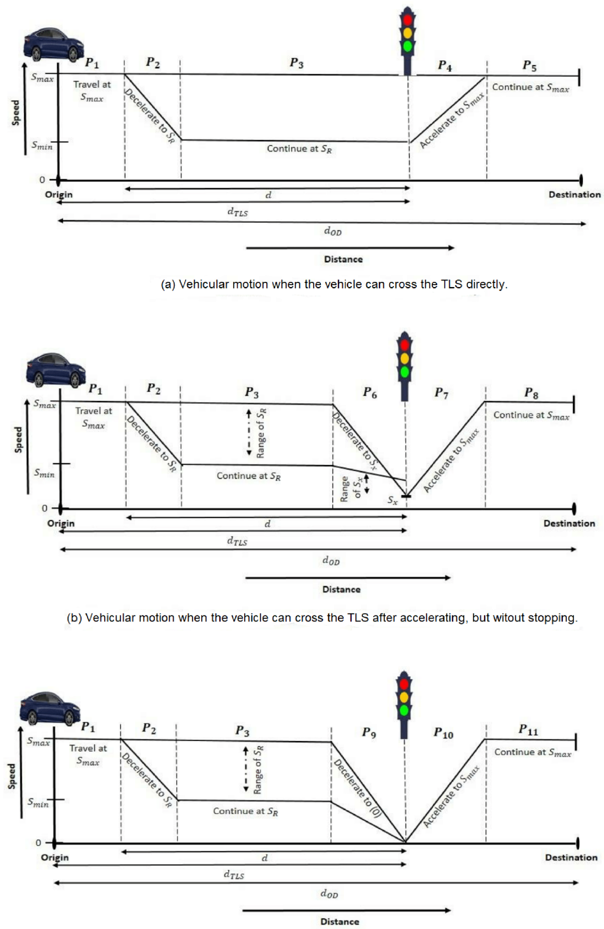
$$h_{min} = (\frac{S_{RF} + S_{RL}}{2}) \times (\frac{S_{RF} - S_{RL}}{\delta}) \quad (7)$$

where S_{RF} is the speed of the EV itself, S_{RL} is the speed of the leading EV. In the case where the EV is the closest to the yellow or red TLS, S_{RL} equals zero. Finally, δ is the deceleration rate.

V. METHODOLOGICAL APPROACH

Generally, the SOC for the EV's battery is affected by the vehicle's speed, as explained in Section III. Furthermore, since the TLSs constitute one of the reasons that lead to changes in the vehicular speed at intersections, there is a need to control both the EV speed and the TLS timing, which will in turn help maximize the SOC. Accordingly, we develop an optimization model to achieve a maximum SOC for an EV when it approaches a TLS. The model determines the optimum EV speed S_R^* and the optimum TLS green light duration T_g^*, such that the EV will be enabled to cross the intersection with maximum SOC. To calculate the SOC, we used the SOC estimation model that was discussed in Subsection IV-A. Three possible scenarios could occur when an EV approaches a TLS during its travel from the origin to the destination, as shown in Fig. 4 (The d_{OD}, d_{TLS}, and d notations were defined in the nomenclature section).

1) The vehicle crosses the TLS directly without decelerating or stopping, as shown in Fig. 4(a)



(a) Vehicular motion when the vehicle can cross the TLS directly.

(b) Vehicular motion when the vehicle can cross the TLS after accelerating, but witout stopping.

(c) Vehicular motion when the vehicle has to stop at the TLS.

FIGURE 4. Practical scenarios for an EV approaching a TLS.

2) The vehicle crosses the TLS after decelerating, but without stopping, as shown in Fig. 4(b)
3) The vehicle stops at the TLS as shown in Fig. 4(c)

In all scenarios, the vehicular speed is assumed to equal S_{max} before it receives a packet from a TLS and after it crosses the TLS. Each scenario contains a sequence of actions. For example, in the first scenario, the vehicle decelerates from S_{max} to S_R as a first action, and then continues at S_R until it crosses the TLS. Finally, it accelerates to S_{max} again and maintains the speed until it reaches its destination. In contrast, the vehicular needs to decelerate from S_R to S_X speed in the second scenario, and from S_R to a zero speed in the third scenario before it crosses the TLS. The S_X is the minimum speed that the vehicle can reach before it starts accelerating to S_{max}.

For each scenario, the measures of effectiveness are divided into sections (P_i), which refer to the vehicular power consumption at state i, where $i = 1, 2, \ldots, 11$ as illustrated in Fig. 4. The definition and calculation of each P_i are as follows (all notations were previously defined in the nomenclature section).

P_1: Total power consumption for the time interval when the vehicle's speed equals S_{max}, before it sends and receives a packet to or from the TLS.

$$P_1 = F_{te} \times S_{max} \times T_B \tag{8}$$

where F_{te} was previously defined in Subsection IV-A, and since the $F_a = 0$, $F_{te} = F_{rr} + F_{ad} + F_{hc}$. Whereas $T_B = \frac{d_{TLS}-d}{S_{max}}$, which is the time interval of the vehicle when it travels at S_{max}, before it receives a packet from the TLS.

P_2: Total power consumption during the deceleration time from the current speed S_{max} to the recommended speed S_R, after the vehicle has received a packet from the TLS.

$$P_2 = \sum_{t_2=1}^{\alpha_2} F_{te}(t_2) \times v_2(t_2) \times \frac{na_2(t_2)}{\delta} \tag{9}$$

where $\alpha_2 = \lceil \frac{S_{max}-S_R}{\delta} \rceil$, $t_2 = 1, 2, \ldots, \alpha_2$ s,
$F_{te}(t_2) = F_{rr} + F_{ad} + F_{hc}$,
$v_2(0) = S_{max}$, $v_2(t_2) = \max(v_2(t_2-1) - na_2(t_2), S_R)$,
and $na_2(t_2) = \min(\delta, v_2(t_2-1) - S_R)$.

The deceleration distance from S_{max} to S_R is called d_{dec_2}. Using the SUVAT equation of motion, $d_{dec_2}(t_2) = v_2(t_2) + 0.5 \cdot na_2(t_2)$. As a result,

$$d_{dec_2} = \sum_{t_2=1}^{\alpha_2} d_{dec_2}(t_2) \times \frac{na_2(t_2)}{\delta} \tag{10}$$

P_3: Total power consumption for the time interval when the vehicle's speed equals S_R, before it reaches the TLS.

$$P_3 = F_{te} \times S_R \times T_{TLS} \tag{11}$$

where $F_{te} = F_{rr} + F_{ad} + F_{hc}$. As for T_{TLS}, which is the required time need by the vehicle to reach the TLS, it varies depending on the vehicle's scenario.

For scenario 1, $T_{TLS} = \frac{d-d_{dec_2}}{S_R}$
For scenario 2, $T_{TLS} = \frac{d-d_{dec_2}-d_{dec_6}}{S_R}$
For scenario 3, $T_{TLS} = \frac{d-d_{dec_2}-d_{dec_6}-d_{dec_9}}{S_R}$

Both (d_{dec_6}) and (d_{dec_9}) will be defined and calculated in P_6 and P_9, respectively.

P_4: Total power consumption during the acceleration time from S_R to S_{max} after crossing the TLS.

$$P_4 = \sum_{t_4=1}^{\beta_4} F_{te}(t_4) \times v_4(t_4) \times \frac{a_4(t_4)}{Acc} \tag{12}$$

where $\beta_4 = \lceil \frac{S_{max}-S_R}{Acc} \rceil$, $t_4 = 1, 2, \ldots, \beta_4$ s,
$F_{te}(t_4) = F_{rr} + F_{ad} + F_{hc} + m \times a_4(t_4)$, $v_4(0) = S_R$,
$v_4(t_4) = \min(S_{max}, v_4(t_4-1) + a_4(t_4))$,
and $a_4(t_4) = \min(Acc, S_{max} - v_4(t_4-1))$.

The acceleration distance from S_R to S_{max} is referred to as d_{acc_4}. Using the SUVAT equation of motion, $d_{acc_4}(t_4) = v_4(t_4) + 0.5 \cdot a_4(t_4)$. As a result,

$$d_{acc_4} = \sum_{t_4=1}^{\beta_4} d_{acc_4}(t_4) \times \frac{a_4(t_4)}{Acc} \tag{13}$$

P_5: Total power consumption for the time interval when the vehicle's speed equals S_{max}, until it reaches its destination.

$$P_5 = F_{te} \times S_{max} \times (\frac{L - d - d_{acc_4}}{S_{max}}) \tag{14}$$

where $F_{te} = F_{rr} + F_{ad} + F_{hc}$.

P_6: Total power consumption during the deceleration time from S_R to S_x before crossing the TLS.

$$P_6 = \sum_{t_6=1}^{\alpha_6} F_{te}(t_6) \times v_6(t_6) \times \frac{na_6(t_6)}{\delta} \tag{15}$$

where $\alpha_6 = \lceil \frac{S_R-S_x}{\delta} \rceil$, $t_6 = 1, 2, \ldots, \alpha_6$ s,
$F_{te}(t_6) = F_{rr} + F_{ad} + F_{hc}$, $v_6(0) = S_R$,
$v_6(t_6) = \max(v_6(t_6-1) - na_6(t_6), S_x)$,
and $na_6(t_6) = \min(\delta, v_6(t_6-1) - S_x)$, $S_x = S_R - \delta \cdot T_{dec}$.

T_{dec} is defined as the time interval during which the vehicle has to decelerate prior to the instant the TLS becomes green. However, the vehicle will accelerate when the TLS switches to green before it stops. There are two equations to calculate it, as follows.

Case 1: The TLS light continues to be the same during the time at which the distance between the vehicle and TLS is less than h_{min}, and irrespective of whether the light is green, yellow or red.

$$T_{dec} = max(((N_g - 1) \cdot C_L + L_g + T_y + T_r - D) - (rh_{min}), 0)$$

Case 2: The TLS light switches from green to yellow during the time at which the distance between the vehicle and TLS is less than h_{min}.

$$T_{dec} = max(((N_g - 1) \cdot C_L + L_g + T_y + T_r - D) - (r_{h_{min}}) - (B - rh_{min}), 0)$$

where B is either the duration of the green light T_g if $N_g = 1$, or the durations of the last cycles plus current T_g if $N_g > 1$.

In both T_{dec} cases, N_g and rh_{min} will be calculated as follows.

$$N_g = max(\frac{\frac{d-d_{dec_2}}{S_R} - (L_g - M)}{C_L}, 1),$$
$$rh_{min} = (\frac{d - d_{dec_2} - h_{min}}{S_R} + M)$$

P_7: Total power consumption during the acceleration time from S_x to S_{max} after crossing the TLS.

$$P_7 = \sum_{t_7=1}^{\beta_7} F_{te}(t_7) \times v_7(t_7) \times \frac{a_7(t_7)}{Acc} \tag{16}$$

where $\beta_7 = \lceil \frac{S_{max}-S_x}{Acc} \rceil$, $t_7 = 1, 2, \ldots, \beta_7$ s,
$F_{te}(t_7) = F_{rr} + F_{ad} + F_{hc} + m \times a_7(t_7)$, $v_7(0) = S_x$,
$v_7(t_7) = \min(S_{max}, v_7(t_7-1) + a_7(t_7))$,
and $a_7(t_7) = \min(Acc, S_{max} - v_7(t_7-1))$.

The acceleration distance from S_x to S_{max} is called d_{acc_7}. Using the SUVAT equation of motion, $d_{acc_7}(t_7) = v_7(t_7) + 0.5 \cdot a_7(t_7)$. As a result,

$$d_{acc_7} = \sum_{t_7=1}^{\beta_7} d_{acc_7}(t_7) \times \frac{a_7(t_7)}{Acc} \quad (17)$$

P_8: Total power consumption for the time interval at which the vehicle's speed equals S_{max}, until it reaches its destination.

$$P_8 = F_{te} \times S_{max} \times (\frac{L - d - d_{acc_7}}{S_{max}}) \quad (18)$$

where $F_{te} = F_{rr} + F_{ad} + F_{hc}$.

P_9: Total power consumption during the deceleration from S_R to zero, when the vehicle has to stop at the TLS.

$$P_9 = \sum_{t_9=1}^{\alpha_9} F_{te}(t_9) \times v_9(t_9) \times \frac{na_9(t_9)}{\delta} \quad (19)$$

where $\alpha_9 = \lceil \frac{S_R - 0}{\delta} \rceil$, $t_9 = 1, 2, .., \alpha_9$ s,
$F_{te}(t_9) = F_{rr} + F_{ad} + F_{hc}$, $v_9(0) = S_R$,
$v_9(t_9) = \max(v_9(t_9 - 1) - na_9(t_9), 0)$,
and $na_9(t_9) = \min(\delta, v_9(t_9 - 1))$.

As for the stopping time (T_s), there are two equations to calculate according to the state of the TLS light during the h_{min} time interval, as mentioned in P_6.

$$\textit{For Case 1}: T_s = \max(0, T_{dec} - \frac{S_R}{\delta})$$
$$\textit{For Case 2}: T_s = \max(0, T_{dec} - \frac{S_R}{\delta_2})$$

where $\delta_2 = \frac{S_R}{\frac{S_R}{\delta} - (B - rh_{min})}$. It is worth noting that $\delta_2 > \delta$, that denotes the result relevant to the case where the light switches from green to yellow during h_{min} in case 2, whereby the required distance that makes the vehicle capable of stopping at the TLS will be less than h_{min}. Therefore, the vehicle needs to increase its deceleration rate to stop at the TLS.

P_{10}: Total power consumption during the acceleration from zero speed to S_{max} after crossing the TLS.

$$P_{10} = \sum_{t_{10}=1}^{\beta_{10}} F_{te}(t_{10}) \times v_{10}(t_{10}) \times \frac{a_{10}(t_{10})}{Acc} \quad (20)$$

where $\beta_{10} = \lceil \frac{S_{max} - 0}{Acc} \rceil$, $t_{10} = 1, 2, .., \beta_{10}$ s,
$F_{te}(t_{10}) = F_{rr} + F_{ad} + F_{hc} + m \times a_{10}(t_{10})$, $v_{10}(0) = 0$,
$v_{10}(t_{10}) = \min(S_{max}, v_{10}(t_{10} - 1) + a_{10}(t_{10}))$,
and $a_{10}(t_{10}) = \min(Acc, S_{max} - v_{10}(t_{10} - 1))$.

The distance associated with the acceleration from zero to S_{max} is called $d_{acc_{10}}$. Using the SUVAT equation of motion, $d_{acc_{10}}(t_{10}) = v_{10}(t_{10}) + 0.5 \cdot a_{10}(t_{10})$. As a result,

$$d_{acc_{10}} = \sum_{t_{10}=1}^{\beta_{10}} d_{acc_{10}}(t_{10}) \times \frac{a_{10}(t_{10})}{Acc} \quad (21)$$

P_{11}: Total power consumption for the time interval when the vehicle's speed equals S_{max}, until it reaches its destination.

$$P_{11} = F_{te} \times S_{max} \times (\frac{L - d - d_{acc_{10}}}{S_{max}}) \quad (22)$$

where $F_{te} = F_{rr} + F_{ad} + F_{hc}$.

VI. OPTIMIZATION MODEL

In order to guarantee the optimality in our study, we developed an optimization model to determine the optimum TLS green light duration T_g^* and the optimum speed S_R^* of the approaching vehicles. The model contains an objective function and a set of constraints as follows.

A. OBJECTIVE FUNCTION

The objective function of this optimization model is maximized the battery's SOC for an EV that approaches an isolated signalized intersection. Thus, the objective function of the model can be formulated as,

$$\textit{Maximize } SOC_0 - \frac{P}{C_{bat}} \quad (23)$$

Since SOC_0 and C_{bat} are constant values, and since the power consumption P is variable, we needed to minimize P which achieves the maximization of SOC. Consequently, the objective function of the model can be reformulated as,

$$\begin{aligned} &\textit{Minimize } P \\ &\textit{where } P = \sum_{i=1}^{3} P_i + (1 - x) \cdot [(1 - y) \cdot \sum_{i=4}^{5} P_i \\ &\qquad + y \cdot \sum_{i=6}^{8} P_i] + x \cdot \sum_{i=9}^{11} P_i \end{aligned} \quad (24)$$

P is a function of the decision variables of our model, which include S_R, T_g, x, and y. P_i is the measure of effectiveness, where $i = 1, 2, .., 11$ that has been defined previously in Section V. Symbols x and y, are binary variables that are considered as the selectors of the model. They are used to select which measures of effectiveness P_i should be calculated depending on the scenario of vehicular motion.

B. CONSTRAINTS

The objective function of our optimization model is subject to the following constraints:

1) Recommended speed (S_R) limitation

$$S_{min} \leq S_R \leq S_{max} \quad (25)$$

2) Green light duration (T_g) limitation

$$T_{gmin} \leq T_g \leq T_{gmax} \quad (26)$$

3) Selectors

a) x is a binary value that depends on the T_s value to determine if the vehicle will have to stop at the TLS or not

$$x = \begin{cases} 1 & \text{if } T_s > 0, \text{ it will stop} \\ 0 & \text{if } T_s \leq 0, \text{ it will not stop} \end{cases} \quad (27)$$

This is equivalent to
$T_s - \mathtt{M}_{big}(x-1) > 0$, and $T_s - \mathtt{M}_{big}x \leq 0$, where $\mathtt{M}_{big}$ is constant with a large value [32].
b) y is a binary value that depends on the T_{dec} value to ascertain if the vehicle will have to decelerate shortly before the TLS switches to the green light and then it accelerates after switching without stopping or not.

$$y = \begin{cases} 1 & \text{if } T_{dec} > 0, \text{ it will decelerate} \\ 0 & \text{if } T_{dec} \leq 0, \text{ it will not decelerate} \end{cases} \quad (28)$$

Similarly, this is equivalent to
$T_{dec} - \mathtt{M}_{big}(y-1) > 0$, and $T_{dec} - \mathtt{M}_{big}y \leq 0$

4) Positivity constraints
x and y are binary: $x, y \in \{0, 1\}$, S_R is positive as shown in the first constraint, and T_g is positive as shown in the second constraint.

VII. RESULTS AND DISCUSSION

This section presents the analytical results of the proposed approach named adaptive TLS and speed compared with two other approaches referred to as adaptive TLS and adaptive speed. The adaptive TLS and speed is the approach that determines the green light duration T_g of the TLS to be optimal, according to the received information from approaching vehicles using V2TLS communication. Furthermore, in this approach, the vehicular speed is able to change to the optimal value, according to the received information from the TLS using TLS2V communication. In the adaptive TLS approach, only V2TLS communication is used to adapt the T_g value of the TLS to become optimal based on the received information from the approaching vehicle. It is assumed that the vehicle travels at S_{max} during its entire trip duration. In regard to the adaptive speed approach, only TLS2V communication is used to adapt the vehicular speed to be optimal speed based on the received information from the TLS. The pretimed TLS is considered in this approach and has a fixed time cycle with $T_g = 45$s, $T_y = 5$s and $T_r = 50$ s.

In our study, we assumed that an EV travels along a straight direction toward an isolated TLS without turning left or right. The distance from the origin to the destination equals 2.5 km, whereas the distance between the TLS and the destination equals 0.7 km. In contrast, the distance between the vehicle and the TLS at the time of receiving a packet from the TLS (d) varies and equals (0.5, 1, 1.2, 1.5, and 1.7 km). The rest of the parameters are determined in Table 2 and they have been defined previously in the nomenclature section. To solve the optimization model, an exhaustive search is used with an increment of 0.1 km/h, within a speed range from S_{min} to S_{max}, and an increment of 1 s in regard to the duration of the green light from T_{gmin} to T_{gmax}.

1) $d = 0.5$ km
At $T_g < 44$ s and $d = 0.5$ km, the vehicle will stop at the TLS as in scenario 3 (discussed in section V) at all of the S_R values except for S_{max}. Stopping occurs at some T_g values, but it differs from S_R to another, for example at $T_g = [30 - 43\ s]$ when $S_R = 40$ km/h and at $T_g = [30 - 41\ s]$ when $S_R = 43$ km/h. Conversely, if $T_g \geq 44$ s, the vehicle will cross the TLS directly as described in scenario 1, for all possible values of S_R. This means that at the S_{max} speed and at all the T_g values, the vehicle will cross the TLS with maximum SOC. Therefore, the $S_R^* = S_{max}$ and T_g^* achieves all the possible values of T_g. As shown in Table 3, the maximum SOC becomes equivalent in all approaches as a result of the direct crossing of the TLS at S_{max} at all possible T_g values.

2) $d = 1$ km.
At $d = 1$ km, the vehicle can cross the TLS directly as in scenario 1 in two cases. First, in the subsequent cycle of the TLS, when $T_g = 30$ s, and when the vehicle travels at S_{min}. Second, in the current cycle, when $T_g = 60$ s and the vehicle travels at S_{max}. In the rest of the cases, the vehicle has to either decelerate as in scenario 2, or stop, as in scenario 3. In the two cases that are related to scenario 1, since the vehicle that travels at S_{min} has to accelerate to S_{max} after crossing the TLS unlike the case at which it travels at S_{max} the maximum SOC can be achieved when the vehicle travels at S_{max} and $T_g^* = T_{gmax}$. In regard to the adaptive speed approach, at all possible S_R values, the vehicle will stop at the TLS. Since the SOC decreases at increasing speed as mentioned in Section III, S_{min} attains its optimum speed in the adaptive speed approach. For this reason, our approach has outperformed the adaptive speed approach, whilst the maximum SOC in the adaptive TLS approach and our approach are equal, as noted in Table 4.

3) $d = 1.2$ km.
At $d = 1.2$ and for speeds larger than 47.9 km/h, only the vehicular deceleration or complete stop cases will occur at different Tg values. In contrast,

TABLE 2. Main parameters used in the study.

Parameter	Value	Parameter	Value
S_{max}	60 (km/h)	T_y	5 (s)
S_{min}	40 (km/h)	T_r	50 (s)
T_{gmax}	60 (s)	D	0 (s)
T_{gmin}	30 (s)	δ	-5 (kph/s)
L_g	T_g (s)		

TABLE 3. Comparison results at $d = 0.5$ km.

Adaptive approach	Maximum SOC(%)	S_R^*(km/h)	T_g^*(s)	Vehicle scenario
TLS	50.18	60	30-60	1
Speed	50.18	60	45	1
TLS and speed	50.18	60	30-60	1

TABLE 4. Comparison results at d = 1 km.

Adaptive approach	Maximum SOC(%)	S_R^*(km/h)	T_g^*(s)	Vehicle scenario
TLS	50.18	60	60	1
Speed	41.32	40	45	3
TLS and speed	50.18	60	60	1

TABLE 5. Comparison results at d = 1.2 km.

Adaptive approach	Maximum SOC(%)	S_R^*(km/h)	T_g^*(s)	Vehicle scenario
TLS	42.70	60	30-60	3
Speed	45.97	41.1	45	1
TLS and speed	47.43	47.9	30	1

TABLE 6. Comparison results at d = 1.5 km.

Adaptive approach	Maximum SOC(%)	S_R^*(km/h)	T_g^*(s)	Vehicle scenario
TLS	48.93	60	30	2
Speed	48.13	51.3	45	2
TLS and speed	50.14	59.3	30	1

TABLE 7. Comparison results at d = 1.7 km.

Adaptive approach	Maximum SOC(%)	S_R^*(km/h)	T_g^*(s)	Vehicle scenario
TLS	50.18	60	30-41	1
Speed	49.88	57.8	45	1
TLS and speed	50.18	60	30-41	1

S_R = 47.9 km/h is the highest speed that allows the vehicle to cross the TLS in accordance to scenario 1 at T_g = 30 s. Since high S_R values are needed to achieve low accelerations to S_{max} after crossing the TLS and then higher SOC, the optimum values are $S_R^* = 47.9$ km/h and $T_g^* = 30$ s. The results in Table 5 justify the improved performance of our approach. Our approach yields the best performance owing to the fact that the vehicle stops at all T_g values in the adaptive TLS approach, so it has the lowest SOC as a result to the high acceleration after the TLS switches to the green again. Furthermore, in the adaptive speed approach, the highest speed that is allowed to cross the TLS is 41.1 km/h. It is requiring higher acceleration after crossing the TLS compared with 47.9 km/h which is the optimum speed in our approach.

4) $d = 1.5$ km.
The optimum speed at $d = 1.5$ km is $S_R^* = 59.3$ km/h and the optimum green light duration is T_g^* = 30 s. These values allow the vehicle to execute scenario 1 with the highest SOC. If $S_R > S_R^*$, the vehicle has to decelerate at some T_g values and stop at others, and the SOC will thus decrease. Our approach has achieved an improvement in SOC at d = 1.5 km, as it can be observed in Table 6. When only the adaptive TLS approach is used, the vehicle can cross the TLS after decelerating or stopping. The maximum SOC in this approach can be achieved at $T_g = 30$ s, where the vehicle will be decelerated for a short time compared with other T_g values. In regard to the case where only the adaptive speed approach is used, the vehicle can cross the TLS after very simple decelerate with maximum SOC at SR=51.3 km/h, which is less than the optimum speed in our approach.

5) $d = 1.7$ km.
At this distance, SOC will be the maximized when the T_g values range from 30 s to 41 s, and the vehicle travels at S_{max} because it will be crossing the TLS without decelerating or stopping. Similar to the case where d = 1km, the maximum SOC in our approach and the SOC in the case of the adaptive TLS approach are equal. In addition, they are better than the adaptive speed approach, as shown in Table 7.

Based on the optimization model results, the maximum possible SOC of the EV that is considered in this study is 50.18%. In all the three approaches, this value can be attained when the EV travels at S_{max} and crosses the TLS directly as in scenario 1. In the cases that the EV needs to traveling at a speed less than the S_{max} to cross the TLS directly, the maximum SOC be less than 50.18%. At these cases, the EV has to accelerate its speed after crossing the TLS to be S_{max}, which in result decrease its SOC as mentioned in Section III. Similarly, in the cases that the EV travels in accordance to scenario 2 or 3, the maximum SOC be less than 50.18% in all three approaches. As noted in Fig. 5, our approach has succeeded in maximizing SOC when d=1.2 and 1.5 km. For the cases where d=1 and 1.7 km, the SOC state is equal to the state of the adaptive TLS approach. Additionally, the SOC states will be equal with both approaches when $d = 0.5$km.

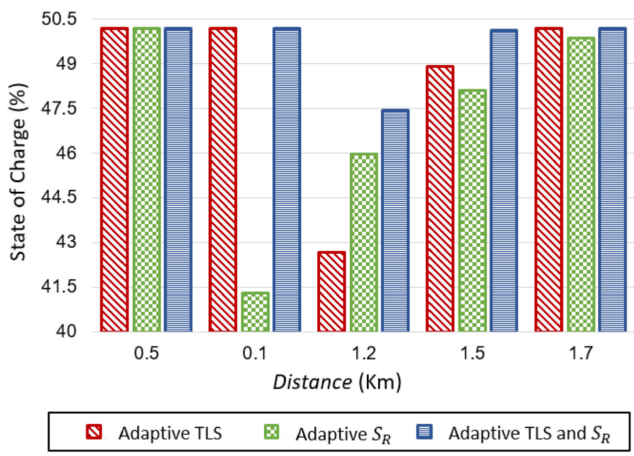


FIGURE 5. EV state of charge vs. distance d in the cases of the three adopted approaches.

VIII. CONCLUSIONS

In this study, we have evaluated the impact of the two-way communication between an adaptive TLS and the approaching EVs (V2TLS and TLS2V)in regard to their SOC of their batteries. Furthermore, we have developed an optimization model with the objective function of maximizing SOC of EVs at isolated signalized intersections. To achieve this objective, the model determined the optimum EV speed S_R^* and the optimum TLS green light duration T_g^*, which help to avoid undesirable acts, such as stops, unnecessary high speeds, and high accelerations as much as possible, when the vehicle approached the TLS. Three approaches were considered herein with different cases of communication between a TLS and the EVs. First, an adaptive TLS and speed approach, which allows the adaptation of the TLS green time duration based on the received EV information via the V2TLS. It also allows the adaptation of the EV speed based on the received TLS information via TLS2V. The second approach was an adaptive TLS, that allows adaptation of the TLS green time duration only based on the received EV information via the V2TLS. The third approach was an adaptive speed, that allows the adaptation EV speed only based on the received TLS information via the TLS2V. The results show that the adaptive TLS and speed approach achieves the highest SOC compared with the adaptive speed approach for the most distances d that have been studied herein. In contrast, compared with the adaptive TLS approach, the adaptive TLS and speed approach achieves the highest SOC at some distances and the same SOC at other. In the future work, we will improve this optimization model to consider the interaction among vehicles via vehicle-to-vehicle communication. Furthermore, we will extend it to be comprehensive model that include all vehicles types.

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AMAL ALTURIMAN received the B.S. degree in networking and telecommunication systems from Princess Nourah Bint Abdul Rahman University, Riyadh, Saudi Arabia, in 2014. She is currently pursuing the M.Sc. degree in computer engineering with King Saud University, Riyadh. Her current research interests include wireless communications, vehicular networks, and intelligent transportation systems.

MAAZEN ALSABAAN received the B.S. degree in electrical engineering from King Saud University (KSU), Saudi Arabia, in 2004, and the M.A.Sc. and Ph.D. degrees in electrical and computer engineering from the University of Waterloo, Waterloo, ON, Canada, in 2007 and 2013, respectively. He was the Chairman of the Department of Computer Engineering, KSU, from 2015 to 2018, where he is currently an Assistant Professor. He serves as a Consultant in different agencies and received many grants from KSU and King Abdulaziz City for Science and Technology. He has a publication record of eight journal papers, and most of them are published in prestigious IEEE journals. His current research interests include surveillance systems, vehicular networks, green communications, intelligent transportation systems, and cybersecurity. He is an Associate Editor of the *Circuits, Systems and Computers Journal*.