Optimal Charging Scheme for Electric Vehicles (EVs) in SDN-based Vehicular Network, Scheduling, and Routing

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Abstract: **Recent development in Electric Vehicles (EVs) has provoked an important demand increase at charging points with different charging modes, (fast-charging or slow-charging). However, the power resources at charging points and parking spaces are limited, hence developing an optimisation scheme for charging is required. In addition, there is an essential need to satisfy the user preferences in terms of time and price. To this end, this paper develops an optimal charging scheme for EVs aiming to meet the user preferences in terms of time and price. Furthermore, the main objective of this paper is to avoid the overload at the charging points by minimising the service time in terms of (travelling time, charging time, and waiting time), as well as considering different charging fee. Using the proposed scheme, the EVs customers become able to charge their batteries at a specific charging point and at a specific time. This paper also exploits the Software-Defined Network (SDN) and Cloud computing, which allows real-time interactions between the user and the service provider. Besides, this paper introduces a flexible system model that allows EV customers to make suitable decisions to select a charging point where a novel charging scheme is proposed. In addition, an advanced scheduling and routing algorithm is proposed to reduce the time cost. A comprehensive simulation has been performed for the Bucharest city map use case. The results show that the proposed approach achieves optimal performance. Moreover, different charging fee mechanisms for multiple charging options are considered to maximise the income of the charging system. Finally, the results indicate that load balancing at different charging points is achieved. These findings underpin the main contribution of this work.**

Keywords—Electric Vehicles (EVs), charging coordination, optimisation, scheduling and routing.

I. Introduction

Electric Vehicles (EVs) have been widely used due to their potential for a green environment, which can reduce the emissions of CO2 significantly [1]. Recent statistics have revealed that the number of EVs is expected to grow exponentially and even expected to be more in the coming years. Therefore, EV technology is being developed and highly recommended for public transportation in many countries. For example, in China, there are more than 2.6 million EVs, while there are around 1.1 million EVs in the USA [2]. With this rapid growth of EVs, most EVs users are expected to charge their batteries at peak hour times [3], i.e., in the morning between (5 - 9 am) and in the evening between (4 - 8 pm). Specifically, there is an expectation to be high traffic during these periods. Besides, Smart Grid (SG) systems have been considered an essential part of the Internet of Vehicles (IoV) networks. This connection allows to collect and update important information related to the SG and delivers it to the EVs consumers. For instance, SG can monitor the charging point's status (e.g., available charging stations, energy consumption, queue length, a electricity prices), which are required in the IoV network. This cooperation between both technologies can be used to estimate the travel route/time from users' location to the charging point, which would avoid overload at a single charging point caused by the random charging scheme. In addition, a random charging scheme for EVs would increase power demand, which affects electric power generation, distribution, transmission, and networks [4]. Currently, SG infrastructure becomes widely used in most major cities, and because of the long waiting times at charging points, without an efficient optimisation scheme, the EVs charging operation can cause significant delays [5].

To solve such a problem of random charging patterns, it is very essential to utilise an optimal charging strategy for EV technology to manage their performance in real-time, where the interaction between EVs and charging points is existed [2]. On another hand, cloud computing services can handle and host many tasks that require high processing power [6]. Software-Defined Networks (SDNs) are considered a promising paradigm that has the potential to improve the scalability, flexibility, and reliability of vehicular networks. The main SDN concept in network architecture is to decouple the control plane from the data plane. Deploying SDN controller into the SG increases the flexibility and reliability of the IoV network and also decreases the development costs [7]. Therefore, the SDN-based cloud computing architecture provides interaction between EV customers and SG, in which the real-time data can be managed and analysed in a centralised or decentralised manner. By integrating the SG and renewable power generation technologies, charging stations became different from each other in their energy capacities, charging rates, charging fees, and charging modes fast-charging and slow-charging. The EVs may have different battery State of Charge (SOC) and charging or discharging operation requests. Therefore, the decision making for each EV charging demand has become challenging.

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The objective of this paper is to develop a new scheme that can reduce the overload of power demand over charging points while keeping the elasticity for customers to charge their EV batteries at any available resource. To this end, this paper tries to answer the research question of how to achieve an optimal charging scheme for an EV network that supports different charging modes (fast-charging or slow-charging) while minimising the service time (time cost), hence the traffic load at any charging point can be effectively reduced. Moreover, this paper investigates the problem of EV charging schedules and routes to find an optimised charging scheme. The proposed model functionality is based on SDN and cloud computing features, to enable real-time interaction between the user and the service provider.

Apart from state-of-the-art research, the original contributions of this paper can be summarised as the following:

1) We identify the requirements of EV charging strategy, and a new system model is proposed, considering the SDN-based cloud computing vehicular architecture.

2) The mathematical model for the EV routing and scheduling problems is developed. To this end, fuzzy logic control and Dijkstra's tools are exploited to solve the scheduling and routing problems. Consequently, an efficient algorithm is proposed aiming to minimise the service time, while considering the most relevant parameters that influence the charging operation, i.e., state of charge (SOC), charging mode, EV type, service time, charging fees, and available charging points.

3) A new simulation tool using the MATLAB program is developed to evaluate the proposed algorithm under different real-time scenarios. To this end, the Bucharest city map data as topology information is used in the evaluation. The performance of the proposed algorithm is compared with two different scenarios of charging distribution schemes: random scheme, First-Come-First-Serve (FCFS) scheme. The proposed scheme is named EV priority. Furthermore, the time of use (TOU) mechanism is applied in this work to calculate the charging fee.

The simulation results demonstrate that the proposed scheme achieves an optimal performance in comparison to other schemes. In particular, the results indicate that the proposed scheme provides better performance in terms of service time and can achieve an optimal solution in a large-scale network while the EVs customers' requirement has been satisfied. In addition, different charging fee mechanisms for multiple charging options are considered in this paper to maximise the income of the charging system. Finally, the results indicate that load balancing at different charging points is achieved. These findings underpin the main contribution of this work.

In this paper, the terminology for the entities appearing is introduced. Noting that the travelling time represents the duration for an EV customer to reach the charging point, based on the distance and vehicle speed. The waiting time represents the time for the EVs to wait in a queue, before charging starts. The charging time denotes the duration required for the EV battery to be fully charged. The service time is the total time duration of the charging service, which is defined as the sum of the above components. The SOC is the current energy state for the EV battery before the charging request. The routing term refers to the road route computing between two nodes, EV and charging point (considered as source and destination). Finally, the Time of Use (TOU) mechanism is applied in this work, which is defined as the charging fee (or charging price) that is variant in different periods within a single day. The detailed definition of the parameters is given in Table I.

TABLE I. LIST OF SYMBOLS

Symbol	Definition
M	Number of EVs
N	Number of available charging points in the city.
$T^{traveling}$	The total traveling time of an EV from its current position to the selected charging point.
$T^{waitting}$	The time duration for an EV waiting in the queue line, at charging point.
$T^{charging}$	The time duration for an EV to get its battery charged.
B^{SOC}	The SOC for an EV battery measured by the percentage of current energy amount.
B^{size}	The energy capacity of an EV battery measured in kwh.
D_{max}	The maximum distance that an EV can travel based on, based on its B^{SOC} and B^{size}.
V_v	The driving speed of an EV.
o	The charging option mode (o =1 is fast-charging, o =2 is slow-charging).
$\gamma_{c,t}$	The arrival rate represents the number of EVs which are arriving at charging point per time unit.
$L_{q,c}$	The queueing length of EVs at charging point at time moment t.
E_v	The energy consumption of an EV per unit of distance, assumed to be fixed for all EVs models (0.15KWh/km).
ϑ_c^o	The charging rate at a charging station measured in kw.
t	Time moment
$E_{charging}$	The energy amount demanded by an EV to be charged.
E_c^{supply}	The energy capacity of each charging point
$E_v^{request}$	The total energy demand by all EVs from charging point.
$D_{v,c}$	The distance between two nodes, vehicle position and charging point

The remainder of this paper is organised as follows: Section II summarises some previous works on EV charging scheduling and routing. Section III describes the architecture of the proposed system and develops a new mathematical model for EV charging strategy. Section IV, introduces the proposed algorithm for EVs charging scheme, aiming to minimise the charging time cost. The proposed algorithm is evaluated under three different scenarios. The simulation results and discussion are presented in Section V. Finally, the conclusion of this work is provided in Section VI.

II. Related Works

In this section, the state-of-the-art related works on charging and discharging strategies are discussed.

In a smart grid (SG) environment, the coordinated EV charging scheme can be achieved in two approaches: a *centralised* approach or a *decentralised* approach. Faddel *et al*. [8] discussed the impact of increasing the number of EV charging power demands in the SG environment. The results in [8] showed that charging the battery has become more challenging when low cost and high-density constraints are needed. Bayram and Papapanagiotou [9] addressed the impacts of uncoordinated EV charging operations on the power grid and discussed the advantages of EV charging management based on their related literature, which has been divided into two categories: centralised charging control, and decentralised charging control.

Luo et al. [10] proposed an optimal charging scheduling and routing strategy for various EV models, aiming at reducing the road traffic and smoothing the power load curve during peak hours. The authors have taken into account the total weight value of the power network, total EV number, EV request (charging or swap battery), traffic speed and charging point locations. The purpose of the work in [10] was to find a route with the minimum weight value to decrease the EV waiting time at the charging points and increase the charging system efficiency.

To solve the joint optimisation problem of routing and charging scheduling, a distributed algorithm has been proposed by Tang *et al*. [11] to minimise the complexity of the charging system operator and protect the privacy EVs customers. Mohammadi et al. [12] proposed a distributed cooperative charging scheme to coordinate plug-in electric vehicles (PEVs). Furthermore, Moghaddam *et al*. [5] proposed a routing solution for the EV customers to the charging point considering multiple charging mods slow-charging, fast-charging, and waiting time and charging fee. The solution of Moghaddam *et al*. [5] is based on Ant Colony Optimisation (AOC) meta-heuristic algorithm. The final decision between EV customer and system operator to select the charging point and select the charging mode was not clear in their proposed solution. Dijkstra's algorithm has been applied in multiple aspects to determine the short route by modelling the traffic network as well as weight directed graph. Similarly, Dijkstra's algorithm is used by Diaz-Cachinero *et al*. [13] to enhance the EV operational planning model and to find a model for the route and charging of an EV fleet for small-scale instances. The work in [13] formulated the problem as a Mixed-Integer Linear Programming (MILP). In [14], Park *et al*. proposed a charging point selection scheme based on the fuzzy logic controller algorithm to balance the load of EVs charging requests. The work in [14] considered the charging time, the charging speed, and the distance between the EVs current position and the charging point. The fuzzy logic controller is used to define the weighted value of each set of EVs and charging points. The simulation results demonstrated that the proposed scheme achieved a higher performance by reducing the average waiting time compared with the maximum weight-based and random scheduling schemes.

Hussain *et al*. in [15] discussed the charging scheduling operation between the EVs and parking lots. To this end, a fuzzy logic weight-based charging scheme (FLWCS) was proposed. The work in [15] focused on the optimal distribution of the power resources to the EVs, aiming to maximise the utilisation of the power grid. They have considered the EVs parameters such as SOC, the total EVs charging power, parking time at the charging point, and available power from the grid and correlated them as weighted values. The EVs charging operations are controlled by normalising the time at parking lots into time slots, based on the EVs inputs weight values. Fast-charging scheduling and management for electric buses was proposed by He *et al*. [16], considering charging power demand and charging time to address the problem of limited bus routing range. The work in [16] introduced a mathematical EV charging programming model and formulated it as a nonlinear, non-convex optimisation problem. At various times of the day, the charging points can adjust the fast-charging fees according to their operation status. In addition, adjusting the charging fee in real-time becomes an efficient method to control the number of charging EVs, especially at the peak-hour time. TOU is used in today's electricity market and it has been considered in [16][17] [18] and by Yang *et al*. in [19]. The aforementioned works have simplified the charging cost problem by considering the mechanisms of TOU electricity pricing. Liu *et al*. [17] considered the TOU fee mechanism to find the optimal decision for the low-battery level of EVs.

Besides, SDN and cloud computing technologies are considered in their work to enhance the vehicular network by proposing a deep reinforcement learning (DRL) based approach to solving the problem of fast-charging station (FCS) selection as well as EV routing planning. The main goal of [17] is to reduce the number of EVs charging while taking the available charging points and charging fee into account. Focusing on the intelligent routing of EVs that need urgent battery charging, Kosmanos *et al*. [18] proposed a dynamic wireless EV charging method using the existing city buses. The proposal was called "mobile energy disseminators (MEDs)", where the EVs buses have the ability to operate as mobile charging stations. The exchange of power between EVs can be enabled by an Inductive Power Transfer (IPT) process.

III. System Model

This section defines the system model and formulates the problems of scheduling and routing charging strategy. A random charging scheduling may cause overload over one charging point and increase the time delay of the charging service. With the increasing number of EVs, SG may have limited computing capacity and storage to manage the charging operation, while real-time demands and monitoring of the charging point are required. The proposed system model allows interaction between the SG and SDN-based cloud computing, to monitor and manage the charging operation. This paper assumes the charging points as a part of the SG as shown in Fig. 1. In the application layer, investing in the cloud features of large computing capacity and data storage can help the SG to manage the EVs request. This paper considers the charging point includes k number of charging stations and provides two charging modes (fast-charging, and slow-charging). Each charging point shares its status (e.g., idle charging stations, number of EVs in the queue, and charging fee) to the cloud via the SDN controller.

The EVs request to charge their battery from the SG via the SDN controller. The SDN controller communicates with EVs through Roade side Unit (RSU) in a real-time way, to collect their information and charging demand. Each EV sends a charging request as a profile, which includes the information: $EV^{profile}[User^{id}, B^{size}, B^{SOC}$,charging option o, position]. Where $User^{id}$ is the user identifier number. The SDN controller is responsible for running the algorithm to find the available charging point and scheduling the EVs in the cloud. More details about the algorithm solution are discussed in the next section.

When the EVs have low battery energy, their driving range is limited. The EVs will seek to find a shortest-distance route to an available charging point within their range. In order to solve the routing problem, the EV network as a weighted graph $G(N, E)$ is assumed, where N denotes a set of nodes, which are numbered from 1to 15, as shown in Fig. 2 where E denotes the number of edges. In particular, the nodes represent either a charging point indexing by c or the EV geographical position in the city indexing by s. The edges represent a road segment that connects two nodes. Moreover, each charging point has a limited number of parking spots for EV customers. The length of the queue at a charging point can be influenced by many factors, such as EVs arrival rates, charging fee, and service time. This study assumes several EVs with different requirements request to charge their batteries at a single time moment t. In particular, the arrival rate of EVs at a single charging point is considered to have an exponential distribution. The messages are forwarded between the EV, charging point, and SDN-Cloud platform, which can be summarised as:

- **Step 1:** The charging points are updating their resource information of available energy and parking space frequently to the cloud platform via SDN controller.
- **Step 2:** SDN controller receives the EVs profiles and runs the proposed algorithm to find the charging point within their range. After EV select the charging point, the shortest-distance route will be indicated.

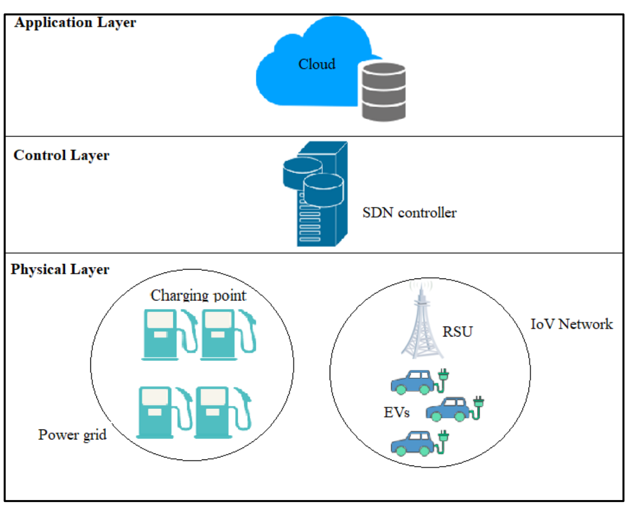

Fig. 1. Communication between SG and IoV network.

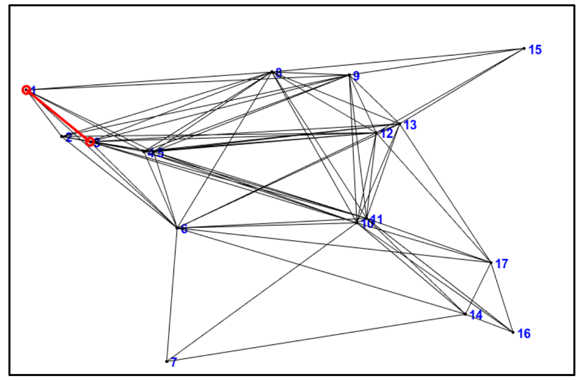

Fig. 2. The Design of EV graph network.

- **Step3:** The SDN controller then sends the EV profile need to be scheduled in the cloud platform.
- **Step 4:** Considering the time hour of the day, and the amount of energy demand, the calculation of charging fee for the EV customer is obtained.
- **Step 5:** When the EV user completes the charging service or in case of delay or service breakdown, the charging point will update this information to the system.

A. Mathematical Model

This subsection summarises the mathematical model on which the proposed model is used to determine the service time. The notations used in the mathematical model are summarised in Table I. The service time denotes the total time duration for an EV to be charged so can complete the trip, which can be calculated as:

$$T_{v,c}^{service} = T_{v,c}^{traveling} + T_{v,c}^{waiting} + T_{v,c}^{charging} \quad , (1)$$

where $T_{v,c}^{traveling}$ represents the time required for the EV to travel from one node to another, which can be obtained by:

$$T_{v,c}^{traveling} = \frac{D_{v,c}}{V_v}, \quad (2)$$

where $D_{v,c}$ is the distance between the current EV position s to the charging point c, and V_v represents the EV driving speed. Moreover, an EV should have enough energy to reach the charging point. The maximum distance D_{max} of an EV can travel adopted from [5] which can be defined as:

$$D_{max,v} = \frac{B^{size} B^{soc}(t)}{E_v} \quad (3)$$

where the E_v denotes the energy consumption of an EV battery per unit of distance (0.15KWh/km), B^{size} is the total battery capacity, and the B^{SOC} denotes the battery state of charge at the moment t. This proposed use M/M/S model, which is developed in [20], to estimate the waiting time for the EV customers at charging point c. When an EV sends a charging request and finds all the charging stations inside the charging point are busy, it must wait at the queue line. Therefore, the waiting time $T_{v,c}^{waiting}$ is:

$$T_{v,c}^{waiting} = \frac{L_{q,c}}{\gamma_{c,t}} \tag{4}$$

where $\gamma_{c,t}$ is the EVs arrival rate, influenced by peak hour time and charging fee. The queue length $L_{q,c}$ is an essential parameter that can be used to determine the waiting time at each charging point. In addition, the charging time for each EV is considered with the multi charging option o (fast-charging and slow-charging). Each option has a power rate. Unlike the previous related work in [17], which assumed that the power rate is fixed at each plug-in charger of one charging station, this work considers an adaptable power rate that depends on the user's demands. Therefore, the inspiration to calculate the charging time presented in [17], and has been modified based on this work requirements. As such, the charging time can be rewritten as

$$T_{v,c}^{charging} = \frac{B^{size}(\sigma - B^{soc}(t))}{\vartheta_c^o}, \tag{5}$$

where ϑ_c^o is the charging rate for each charging option, parameter σ denotes the expected battery of an EV to be fully charged, which is expected to be ($\sigma = 95\%$), and B^{size} denotes the total battery capacity size for an EV.

B. *Charging Fee*

This work applied TOU charging fee, which indicates the electricity price is variant for different periods within one day. There are three periods: regular $P^{regular}$, valley P^{valley}, and peak P^{peak}. The charging fee $F_{v,c}^o$ can be calculated according to the charging service period, and energy demand moment by EV plugs in to charge, which is given in (6).

$$F_{v,c}^o = \begin{cases} P^{regular} \\ P^{valley} \\ P^{peak} \end{cases} * E_{charging} \tag{6}$$

Noting that the conventional method of pricing considers only fixed price, which is given using the following equation.

$$F_{v,c}^o = P^{regular} * E_{charging} \tag{7}$$

IV. Problem Formulation

This section presents the problem formulation of the changing cost subject to some essential constraints. The objective of this work is to obtain an optimal charging scheme that achieves minimum time cost for the EVs charging service, aiming to bring satisfaction to the EVs customers by selecting the charging point c and determining the route at a certain moment t. Therefore, the proposed objective function of the cost function can be modelled as:

$$\mathbb{C} = [w_1 T_{v,c}^{traveling} + w_2 T_{v,c}^{waiting} + w_3 T_{v,c}^{charging}] + F_{v,c}^o \tag{8}$$

s.t.

$$T_{v,c}^{traveling} \le D_{max} \tag{9}$$

$$B^{size} B^{soc} + E_{charging} - D_{v,c} E_v = B^{size} \tag{10}$$

$$E_v^{request} < E_c^{supply} \tag{11}$$

where $w_1, w_2, and\ w_3$ are the weight coefficient values for three objectives: the travelling time, waiting time and charging time. The constraint in (9) represents the travelling time from the EV location to the charging point and should be less or equal to the maximum distance in (3). That means the EV battery should have enough energy to reach the charging point. The constraint in (10) shows that the EV battery should be fully charged based on their capacityB^{size}, to be able to complete their travel. The constraint in (11) indicates that the total energy demanded by the EVs customers should not exceed the total energy of the charging point.

V. The Proposed Algorithm

This section introduces the proposed **Algorithm** for EVs charging strategy, solving the routing, and scheduling problems. As shown in the previous section the proposed optimal charging scheme can be formulated as a conventual optimisation problem. However, the objective function (8) is Nonlinear Programming hard (NP-hard) problem, due to shortest-distance route discovery mechanisms. The proposed **Algorithm** is divided into two parts. In the first part, we use Dijkstra's algorithm, which is widely applied in the literature see, e.g., [21][18][22]. It can be used for solving the shortest-distance routing problem. According to the Dijkstra algorithm, the travelling time can be calculated by assuming the nodes to be the intersection of a road network, and the line of the graph to be the distance between nods, respectively. In the second part, fuzzy logic control is used to manage the load distribution of the network system. This allows converting multiple parameters to one, which is the weight value. The feature of fuzzy logic control is to consider multiple requirements of an EV customer and charging point, so it can reflect the priority of the EV to be scheduled. The parameters considered as input in this work are travelling time and waiting time from both the EVs and the smart grid sides, respectively, to compute the weight value w for each EV. The fuzzy input is converted to three different variables, the travelling time as *(short, medium, or long)* and the waiting time as *(short, medium, or long)*. The variables of the weight output value are *very-small, small, low-medium, high-medium, high, very-high}*. We have assigned a higher weight value to the close distance, and a shorter waiting time gradually based on the decision rules. For example, Rul1; IF the *travelling time* is *short*, and the *waiting time* is *short*, **THEN** *weight* is *very-high*. The centroid-based method is used for defuzzification, and the weight value *w* for each EV is calculated. The lower the time spent on EV charging operations, the greater the weight value to be assigned.

Algorithm: *charging scheduling and shortest-distance route selection*

Require: Graph of charging points, real-time information of Charging Points, EV profile;
Ensure: an optimal EV charging scheme
Set $EV^{profile}[User^{id}, B^{size}, B^{SOC}$, charging option o, position]
Initialise *(t, M)*, and Network Traffic;
t: certain moment, *M*: EV number;
Initialise :
for each *M* **do**
Calculate the *charging time.*
Calculate the D_{max} .
Find available charging points within EV range with their *waiting time*.

Calculate the *travelling time* for each available charging point.
if charging points satisfied (9) and (10) **then**
Make a **MATRIX** of *travelling time* and *waiting time* as **Fuzzy** input.
Fuzzy output calculates the *Max. Weight* value
scheduling the EV at a charging point with minimum time cost
else
The EV can not reach any charging point.
end if
Calculate $\mathbb{C}$ *using* (8)
Update the *waiting time* of charging point, **repeat** for all EVs
end for
Optimal charging scheme for each EV with minimum charging cost

VI. Simulation and Results

To evaluate the proposed **Algorithm** for the system model, this simulation assumes the graph reign of Bucharest city. Each charging point is assumed to be an M/M/S multi-server, which has several charging stations that can provide two different charging moods (fast-charging and slow-charging). This work only considers 10 charging points, and the short distances between them are taken from real measurements [23] (see Fig. 3). The initial waiting time for each charging point is assumed randomly, and the charging requests are considered to begin at 7:00 am as a rush-hour time in the city. Table II illustrates the set parameters of the charging points and the TOU charging fee adopted from [25] for different periods during the day. The above mentioned are considered benchmarks for the proposed charging scheme, and the MATLAB tools used for evaluating performance. We consider 50 EVs with an initial SOC of 20% and energy consumption of 0.15KWh/km. This simulation adopts different EV models from [26] such as BMW i3, Ford Focus, Tesla S, Mercedes B, and Honda Fit with energy capacities (42kWh), (23kwh), (60kwh), (28kwh), and (20kwh) respectively. The driving speed is assumed to be (60km/h) for all EVs consumers.

Three scenarios of charging distribution have been simulated and evaluated to examine the influence of the suggested algorithm. The first scenario is the traditional approach, in which EV charging requests are assigned randomly, where all EVs customers desired to select the nearest charging station without regard for any parameters. The second scenario depicts a method in which all EV charging requests are handled in the system and follows the FCFS scheme. In the third scenario, the proposed scheme is examined, where the main idea is to give a priority to the EV request, which has the lowest charging time. Finally, the TOU charging fee is applied for the second and third scenarios and compared with the regular charging fee given in (7).

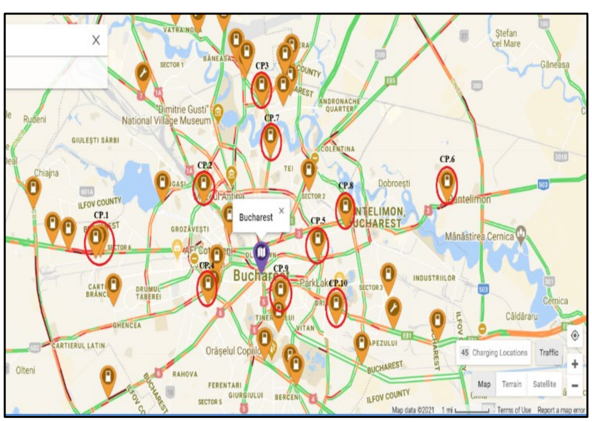

Fig. 3. Bucharest city map with charging points [26].

TABLE II. CHARGING POINTS PARAMITERS AND CHARGING PRICE.

Charging mode/rate		Fast-charging/ 50kw				Slow-charging/ 22kw					
TOU-charging fee	Regular period 00:00-06:00, 22:00-00:00	2.29 lei/kwh				1.53 lei/kwh					
	Valley period 06:00-08:00, 11:00-17:00, 20:00-22:00	4.30 lei/kwh				2.88 lei/kwh					
	Peak period 08:00-11:00, 17:00-20:00	5.86 lei/kwh				3.92 lei/kwh					
Regular fee		1.95lei/kw				1.45lei/kwh					
Charging point no.		1	2	3	4	5	6	7	8	9	10
Charging station no.		4	3	3	4	3	3	3	5	4	5

This simulation evaluates the waiting time, service time, weight values, and charging fee. The waiting time in this work represents the time of EV spent in the queue line before being charged. Fig. 4 compares the amount of time each EV takes to charge at the charging station. The results in Fig.4 show that when the traffic in the queue line above the charging station rises, the waiting time is increased. However, in comparison with the random load distribution in the first scenario, the proposed scheme provides higher performance in terms of waiting time at charging points. As a result, numerous EVs can be charged at the same time, hence reducing the time spent in line. Fig. 5 represents a comparison of different schemes based on the service time in hours as a function of the number of EVs. In particular, the proposed algorithm with the proposed scheme, which gives a priority weight to the EVs that have a minimum charging time, is compared with the random scheme and FCFS based scheme. The proposed algorithm is denoted by the red line.

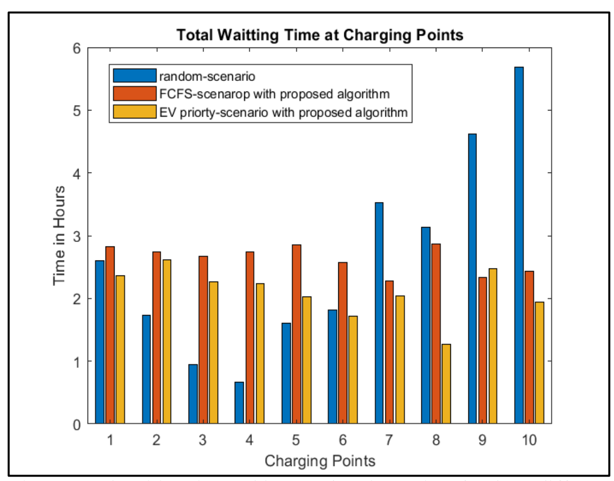

Fig. 4. Total waiting time subject to charging points for three different scenarios.

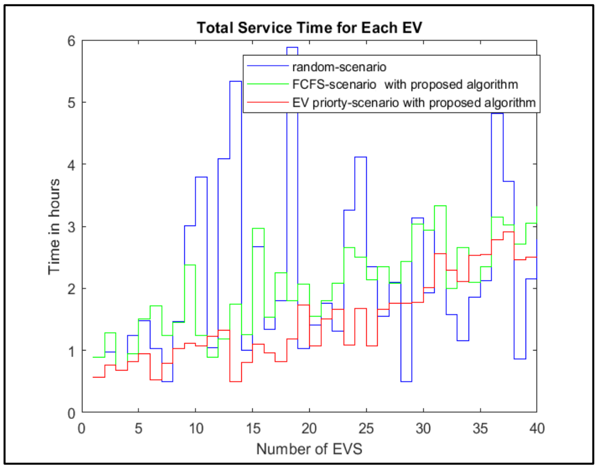

Fig. 5. Comparison of total service time for each EV.

The results show that the proposed approach achieves the lowest service time. This is because the proposed scheme has the ability to make an optimal selection to pick a charging point with a minimum amount of time cost. This is attributed to the use of Fuzzy logic control, which takes the waiting time into consideration. Another advantage of using the Fuzzy logic control is to give a weighted value to the EVs, which makes the normalization for the waiting time and travel time. The results also indicate that when the proposed algorithm is applied to the FCFS scheme, the performance of load distribution can also be minimized. This achievement is obtained since the proposed algorithm makes the FCFS scheme to focus more on the waiting time at the charging points. In the random scheme, the proposed algorithm gives priority to EVs that have a short charging time, so one charging point could serve much more EVs than others due to the charging mode. For example, one EV has around 20% SOC request for charging its battery with slow-charging mode. Therefore, around 2 hours is needed for the EV to be fully charged, while EVs with fast-charging mode could be charged in 20-30 minutes.

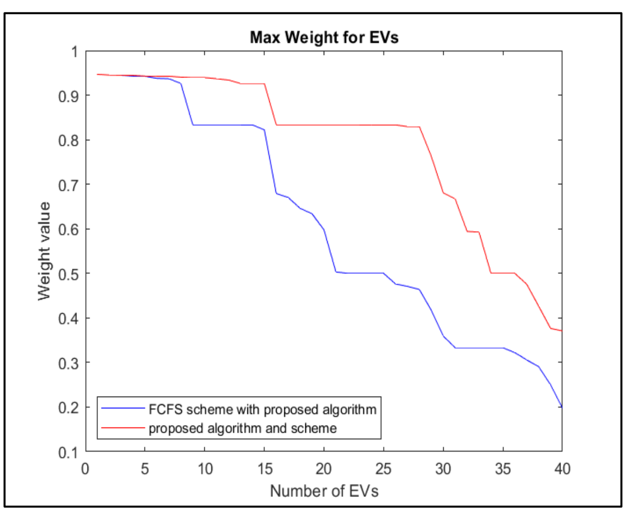

Fig. 6. Maximum weight value for each EV.

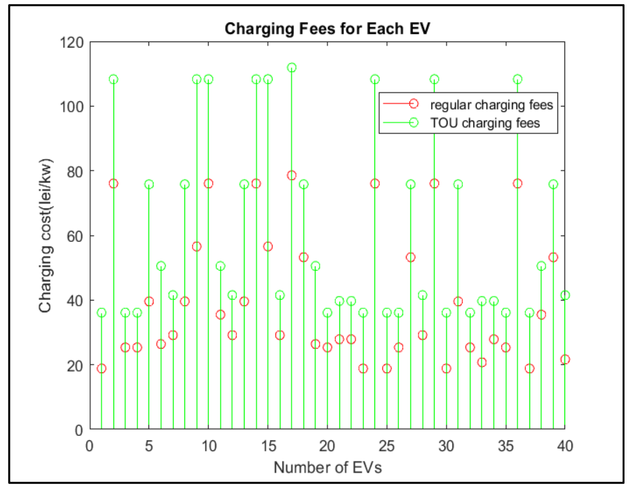

Fig. 7. Charging fee for each EV based on amount of power demand.

Although the results in Fig.5 show some fluctuations in the graphics due to the randomness of the simulation, the results demonstrate that the proposed approach still achieves the lowest service time when we take the average values across all the graphs.

Fig. 6 compares the FCFS scheme with the proposed algorithm and scheme at different maximum weight values. This comparison is given using the Fuzzy logic control at each EV consumer. The results in Fig.6 show that the proposed scheme using the Fuzzy logic controls provides the highest weight value.

Fig. 7 shows the simulation results of applying the TOU charging fee to the proposed scheme. The service providers can increase their profits with TOU mechanisms compared with the regular charging fee, especially at rush hour times when the traffic is high. This concept could also encourage EVs customers to charge their batteries in the evening when the traffic is low.

VII. CONCLUSION

This work addressed the problem of routing and scheduling charging strategies. To this end, we developed an optimal charging scheme for the EVs customers, which requests to charge their batteries with multiple charging modes. The queue theory using M/M/s model has been developed to estimate the waiting time at each charging point. In addition, this work exploited fuzzy logic control and Dijkstra's tools to solve the scheduling and routing problems. The proposed algorithm was employed to find the optimal charging scheme. Besides, the traffic power demand caused by many EVs that request to charge their batteries at one time moment at one charging point is reduced using the proposed algorithm. The proposed algorithm has been evaluated for charging load distribution in two scenarios: FCFS scheme, and EV priority scheme. Besides, the proposed scheme is compared with a random scheme. The simulation results showed that the proposed scheme provided better performance in terms of service time and can achieve the optimal solution in a large-scale network while the EVs customers' requirement has been satisfied. Future works aim to IoV network traffic road, and power load distribution from Smart Grid (SG) will be in consideration for the future work.

VIII. References

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