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QoE-based Assignment of EVs to Charging Stations in Metropolitan Environments

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***Abstract*—With the recent advances in battery technology enabling fast charging, public Charging Stations (CSs) are becoming a viable choice for Electric Vehicles (EVs). However, the distribution of EVs relies on strategic assignment of EVs to CSs. EVs drivers' Quality of Experience (QoE) is an significant impact factor that should be considered to find the optimal assignment of EVs to CSs. In this context, a novel framework to find the optimal assignment of EVs to CSs has been proposed based on optimization of QoE. Our proposed approach considers the travel time of EVs towards CSs taking into account the distance between EVs and CSs, the impact of congestion level on the roads resulted from the Internal Combustion Engine Vehicles (ICEVs) and EVs, queuing time at the CSs, and the time required to fully charge the EVs battery when connected to any charging slot at a CSs. The adjacency between the different zones in a city environment is also considered in order to minimize the potential number of CSs for each EVs. Specifically, the assignment problem is formulated as Mixed Integer Nonlinear Programming (MINLP), and a heuristic solution is developed using the Genetic Algorithm (GA) technique. The performance evaluation in realistic metropolitan environment attests the benefits of the proposed CSs assignment framework considering range of charging metrics.**

***Index Terms*—Electric vehicle assignment, Charging station, travel time, congestion level, queuing time, adjacency relation.**

I. INTRODUCTION

INCREASING energy demand, oil prices, environmental concerns, such as climate change and air pollution have made electric vehicle (EVs) a desirable solution for a new sustainable transportation system. At the same time, various factors, such as the technological innovation in electric drivetrain and battery efficiency, have helped to dramatically increase the EVs penetration in recent years in metropolitan areas [1], [2]. Using charging slots at home is an alternative for the users of EVs but it takes too much time (6 to 8 hours) for each charging process. Therefore, high voltage fast charging stations (CSs) are the best solution to increase the satisfaction of EVs users, because EVs batteries can be recharged at least 12 times faster [3].

The high penetration rate of EVs in urban areas is mainly depend on the presence of wide range of CSs to allow EVs drivers to charge their vehicle batteries during their daily trips [4], [5]. In addition, the optimal assignment of EVs to the available CSs in urban areas is an important factor that affects not only the adoption of EVs but also increase EVs users' satisfaction in terms of reducing the time to reach these CSs [6]. Moreover, EVs' batteries can provide the electricity grid's auxiliary storage capacity, further increasing the incorporation of renewable energy conversion technologies into the national electrical grid. Notwithstanding all these advantages, the spread of the market for electric vehicles is still somewhat below expectations [7]. This can be attributed to a variety of factors, such as financial matters (e.g. car and battery cost), EVs usability, which involves concerns of the EVs drivers on the range and the lack of spread and availability of the EVs charging slots, especially in urban areas, which is considered one of the most challenges and restrictions to the spread of the EVs [8], [9].

To the best of our knowledge, the existing literature in this field did not take into account the EVs drivers' QoE. It refers to the EVs driver satisfaction in terms of the travel time considering any possible charging during the journey. It depends on parameters including distance between locations of EVs and CSs, traffic congestion level on the roads, the queuing time at CSs as well as the time required to charge the EVs battery when connected to the charger and the rated power of the chargers installed at CSs. Our proposed approach is unique in that sense, as we take into account the influence of all these parameters on finding the optimal assignment of EVs to CSs. Furthermore, we consider the maximum number of EVs that assign with each CSs in our approach, the technology that is used in each connector, and the variety of the traffic circumstances. We argue that all of these metrics have a significant impact on the decision of assignment EVs to CSs.

The contributions of this work are list as follows;

- A novel model for assignment of EVs to CSs in urban areas is proposed in this paper. The proposed model considers the EVs drivers' QoE in terms of

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the travel time of EVs to reach CSs, the queuing time at CSs, also the time needed to charge the EVs battery when plugged into charger. The effect of road congestion level caused by both ICEVs and EVs was considered in this work. The results show the impact of congestion level on the travel times which in turn affects the EVs drivers' QoE.
- Our model takes into account the influence of the urban traffic circulation of EVs between adjacent zones on determining the optimal assignment of EVs to CSs in metropolitan areas.
- An optimization technique for selecting the optimal assignment of EVs to CSs has been introduced in this paper. The problem is formulated as Mixed Integer Nonlinear Programming (MINLP) problem. The GA technique has been utilized to solve this problem based on real world datasets. The Nonlinear objective function of the proposed approach is set as minimizing the total charging time of EVs.
- A critical performance evaluation in realistic traffic environment with a range of EV charging scenarios.

This paper is organized as follows. The recent works in this area will be discussed in detail in Section II. The assignment problem formulation and optimization model are presented in Section III. Section IV shows the numerical results of our proposed approach. Concluding remarks and future work are summarized in Section V.

II. Literature review

The problem of assigning EVs to CSs has been investigated from different perspectives in the literature, such as the overall energy consumption of EVs to reach CSs [10], EVs battery state of charge (SoC) [11], EVs user's charging cost as well as the shortest distance that EVs travels to reach CSs [12].

In [13], scheduling assignment of EVs to CSs has been presented as an optimization model. The scheduling assignment problem was formulated as linear programming (LP) problem. In this model the assignment of EVs must be solved inline with the constraints that are related to the status of CSs, the traffic conditions, EVs conditions, etc. The proposed approach was demonstrated considering two modes. The first mode is assignment of EVs to CSs under normal circumstances (roads without traffic jam and slops, driving without using electrical accessories, etc.), and the second mode is under disturbed circumstances. A new solution for the distributed dynamic assignment of a set of EVs to a network of CSs has been introduced in [14]. To solve this problem, the authors have proposed a quantized consensus algorithm that the network of CSs autonomously performs in order to reach a consensus about the assignment of the EVs to CSs. Two different setups for systems were considered and some consensus algorithms based on the solution of integer linear programming (ILP) problems were proposed.

In [15], an assignment rescheduling technique of mobile CSs has been proposed, where the assignment of EVs to the mobile CSs have been rescheduled dynamically. To minimize the expenses of charging EVs, the assigned EVs tp some mobile CSs can be switched to other CSs, while the locations of CSs were chosen based on minimizing the cost of charging EVs. Furthermore, the rewards of assigned EVs to minimize the expenses of EVs that have not assigned are demonstrated. Simulation results validated the outstanding efficiency and robustness of mobile CSs. In [16], an optimization approach for optimal assignment and scheduling of EVs to CSs was proposed. This approach was presented as an integrated platform to increase the interaction between different system entities, such as EVs, energy providers and CSs. The method of communication between EVs and the platform was ensured through the use of strengths in information and communication technologies, Geo-positioning techniques and web services. The remaining energy status of EVs, CSs is updated by the information received from the platform.

A stochastic decentralized algorithm to assign the most convenient CSs to EVs that need charging has been introduced in [17]. The authors used various utility functions to characterize the potential various priorities of EVs users, such as the preference to minimize charging times, charging costs, or the distance between the locations of EVs and CSs. In terms of the total time required for charging, they have studied the impact of the queuing time and travel time in the proposed scheme. However, they did not study the influence of the congestion level on the streets, and also the charging time at CSs in the presented algorithm. To illustrate this approach, they generalized the concept of a simple CSs to comprise the potential of supplying other loads in addition to EVs, and take advantage of locally produced energy from renewable sources. A muli-agent hierarchical approach for EVs charging stations trading and energy scheduling taking into account the constraint of mobility in the network of transportation and the system constraint of in the network of energy distribution was proposed in [18]. The problem has been modeled as a separated profit driven entities, where CSs schedule their operations based on different periods, which can be resolved by the agents of traffic operators. An auction method with constrained shared information has been incorporated, in order to manage the market of electricity according to the bids and offers of submitted CSs. In this study, a new technique based on four stage solution has been introduced to solve the problem of trading and power scheduling of CSs.

In [19], the authors have modeled the problem of assignment EVs to CSs in a certain geographical area. The energy requirement is communicated before the departure time and reduce the EVs drivers disutility in parking at charging stations away from their travel destination. The main difficulty in this paper is that the authors could not capture the disutility function of EVs user effectively due to the constraints of behaviour recognition of drivers. In [20], an integrated scheme aiming to determine the conditions of traffic and the EVs assignment of charging service that partly need to be charged during EVs drivers' trips. A specific feature of the proposed system is the assumption that the demand of the charging service has a probability density function that varies with the origin and destination pair.

In [21], a new methodology for managing a dynamic

EVs population has been proposed. The scheme consists of a queuing model that captures various states of EVs from the point of requesting the charging service until their departure was built. The Lyapunov method is used in order to analyze the queuing performance at CS. The assignment policy of EVs aimed to enhance EVs users' convenience by reducing the time required from the moment of requesting the charging service until arriving at CS. A new online assignment model for charging EVs has been introduced in [22] and integrated into the problem of fast-charging station (FCS) location. The aim was to minimize the total EVs idle time during charging process for dynamic ride-sharing facilities. The authors have incorporated the proposed online assignment policy with a bi-level optimization-simulation approach in order to optimize the number of FSC locations under stochastic EVs user demand, where the waiting time of EVs at FCS was considered as a multi-server queuing model with a stochastic charging demand of EVs and the heterogeneous specifications of CSs. A greedy based charging station reservation strategy has been suggested considering local statistics at charging station and travel distance based arrival time estimation in traffic environment [23]. It is majorly based static traffic information sharing using vehicular traffic network environment. Some other recent charging station optimization strategies have considered cost centric economic aspect of the charging stations optimization [24]–[26].

III. QoE oriented assignment for EVs to Charging Stations

This paper proposes a novel model to find the optimal assignment of EVs to CSs in metropolitan environment, based on EVs users' quality of experience (QoE). Travel time on the road networks including congestion level on the roads and the distance between the locations of EVs and CSs, as well as the total expected time inside the CSs which mainly depends on queuing time and the time required to fully charge EVs battery have been considered in this paper. The notations used in this paper are listed in Table I. In addition, parameters and variables are explained where they are first used. As shown in Fig. 1, we assume that the EVs which are represented by black vehicles are randomly distributed in zone k, where zone k has only one port with each adjacent zone. It assume that EVs in the same zone use different routes to reach the port between two adjacent zones. We do agree that the assumption is little strict in terms of independent charging decision made by EV drivers. However, it is highlighted that the assumption considers that any charging decision within the same zone will have approximately similar QoE due to the similar traffic scenario and their impact. It is expected that the due to the on-road connectivity of near by charging station zone, EV driver will prefer nearby zones with better QoE recommended by the proposed framework. Finally, all EVs that arrive to port (t^{kj}) take the same route to reach CS_u^j in zone j. The red arrow shows the direction of the EVs movement from zone k to zone j. We assume that the EVs can only be charged in the adjacent zones and also will not select any CSs at the same zone (k).

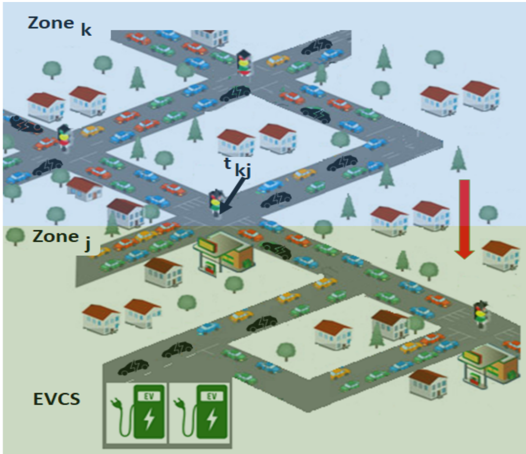

Fig. 1. An Illustrative example of EVs movement to CSs in adjacent zone

Any pair of zones are considered as adjacent if they have a geographical borders with each other. The adjacency set G_u represents exactly which zones have borders with zone j.

It is clarified that the central controller system has information about those EVs and their state of charge which are subscribed to the proposed framework. However, information related to traffic scenario, and their impact on mobility, adjacency of the charging stations, and their on-road connectivity is also considered to be available to the central controller system. The problem will be modeled and solved as shown in the following sections. In the Genetic Algorithm (GA) based solution, standard crossover, and mutation operation are adapted in the proposed framework which is detailed in [27].

A. Major Entities in Modeling

In this section, the attributes of EVs, CSs and the zones of the study area will be defined as shown below. Each parameter that has been introduced in our approach will be discussed in the next sections.

1) EVs: Define the EVs set as $\mathcal{N} = \{1, ..., i, ..., N\}$. The cardinality of $\mathcal{N}$ is N, i.e., there are N EVs in the investigated area. EV_i^k in $\mathcal{N}$ has one attribute: (p^i), where p^i is the position (coordinates) of EV_i^k.

2) CSs: Define the CSs set as $\mathcal{M} = \{1, ..., u, ..., M\}$. The cardinality of $\mathcal{M}$ is M, i.e., there are M CSs in the investigated area. CS_u^j in $\mathcal{M}$ has one attribute; b^u which is the location of the CS_u^j.

3) Zones: Define the Zone set as $\mathcal{Z} = \{1, ..., j, ..., Z\}$. The cardinality of $\mathcal{Z}$ is Z, i.e., there are Z postcode zones in the study area. The model of a postcode zone j is represented by (c^j, pop^j, g^j), in which c^j represents the ICEVs population in zone j, pop^j represents the EVs population in zone j, and g^j is the adjacency relation between zone j and other zones in the study area.

B. Travel Time Estimation

Two important factors should be taken into consideration in terms of travel time: the total distance between the current location of EV_i^k and CS_u^j in the adjacent zone, and the congestion level, i.e., traffic condition on the road. Therefore, the travel time relies on the length

TABLE I. MAIN NOTATIONS AND THEIR DESCRIPTIONS

Notation	Description
EV_i^k	The EVs with global index i in zone k.
$\mathcal{N}$	EVs set, in which each EV_i^k has one attribute; p^i, which is the EV_i^k location.
N	The total number of EVs in the study area.
CS_u^j	The CSs with global index u in zone j.
$\mathcal{M}$	CSs set, in which each CSs has one attribute; b^u, which is the CS_u^j position.
M	The number of CSs in the study area.
$\mathcal{Z}$	The set of the zones in the study area.
Z	The number of zones in the study area.
$T_{i,u}$	The total time of charging EV_i^k starting from movement towards CS_u^j until departure.
$\tau_{i,u}$	The travel time of EV_i^k to reach CS_u^j.
ℓ	The linear coefficient of the travel time function.
$d_{i,u}$	The total distance between the current location of EV_i^k and the location of CS_u^j.
$\delta_{i,u}$	The traffic condition, i.e., congestion level on the road which EV_i^k takes to reach CS_u^j per peak hour.
t^{kj}	The port of zone k with an adjacent zone j.
μ_i, Ψ_i	The latitude and longitude of EV_i^k, respectivelly.
$x_{i,u}$	A binary decision variable shows that EV_i^k selects CS_u^j for charging per peak hour.
$V_{i,t^{kj}}$	The number of ICEVs that share the same road with EV_i to reach t^{kj}.
$\zeta_{i,t^{kj}}$	The capacity of the road in zone k that EV_i uses to reach t^{kj}.
N^k	The total number of EVs in zone k.
q_u	The queuing time at CS_u^j per peak hour.
η_u	The number of chargers at CS_u^j.
r_u	The maximum number of EVs that can be charged by a charger in CS_u^j per hour.
ρ_u	The charging time of EVs at CS_u^j.
G_u	The number of adjacent zones for CS_u^j.
D_i	The number of adjacent zones for EV_i^k.
Γ	The maximum time of charging EV_i^k.
λ_u	The maximum number of EVs allowed to be assigned to CS_u^j.
β	The threshold value that shows the difference between the best fitness value of the current generation and the best fitness value in previous iterations.

and capacity of the road that EV_i^k takes to reach CS_u^j, and also the traffic congestion level on the road. In general, more vehicles on the road lead to higher congestion level. The greater the road capacity, the lower the level of traffic congestion on the roads. The EVs travel time (τ) is calculated as follows:

$$\tau_{i,u}(X) = \ell \times d_{i,u} \times \delta_{i,u}(X). \tag{1}$$

where $\tau_{i,u}$ represents the travel time of EV_i^k to reach CS_u^j, X is the associated matrix that shows the assignment of EVs to CSs, ℓ is the linear coefficient of the travel time function [28], $d_{i,u}$ denotes the total distance between the current location of EV_i^k and CS_u^j, and $\delta_{i,u}$ is the congestion level on the road that EV_i^k takes to reach CS_u^j. Knowing that the EVs that come from zone k use the same road inside zone j to reach CS_u^j. EVs move under the same route conditions (length, capacity and congestion level) in zone j. Here is the travel time matrix structure (N×M), that shows the travel time for the each EV_i^k with each CS_u^j. Knowing that τ = 0 if CS_u^j is not adjacent to the EV_i^k and also if they are in the same zone ($k = j$). Each line in the following matrix, shows how the travel time is calculated. To achieve this, the EV will be assigned to only one CS a time. The GA keeps trying to assign each EV to the optimal CS, until it is terminated. Consequently, this matrix is considered as the associated matrix, that shows the relation between all available EVs and CSs in the study area.

$$\mathbf{A} = \begin{pmatrix} \tau_{1,1} & \tau_{1,2} & \cdots & \tau_{1,M} \\ \vdots & \vdots & \ddots & \vdots \\ \tau_{N^1,1} & \tau_{N^1,2} & \cdots & \tau_{N^1,M} \\ \tau_{N^1+1,1} & \tau_{N^1+1,2} & \cdots & \tau_{N^1+1,M} \\ \vdots & \vdots & \ddots & \vdots \\ \tau_{N^1+N^2,1} & \tau_{N^1+N^2,2} & \cdots & \tau_{N^1+N^2,M} \\ \tau_{N^1+N^2+1,1} & \tau_{N^1+N^2+1,2} & \cdots & \tau_{N^1+N^2+1,M} \\ \vdots & \vdots & \ddots & \vdots \\ \tau_{N^1+N^2+N^3,1} & \tau_{N^1+N^2+N^3,2} & \cdots & \tau_{N^1+N^2+N^3,M} \\ \vdots & \vdots & \ddots & \vdots \\ \tau_{\sum_{k=1}^{Z-1} N^k+1,1} & \tau_{\sum_{k=1}^{Z-1} N^k+1,2} & \cdots & \tau_{\sum_{k=1}^{Z-1} N^k+1,M} \\ \vdots & \vdots & \ddots & \vdots \\ \tau_{\sum_{k=1}^{Z} N^k,1} & \tau_{\sum_{k=1}^{Z} N^k,2} & \cdots & \tau_{\sum_{k=1}^{Z} N^k,M} \end{pmatrix}_{N \times M}$$

The distance $d_{i,u}$ between the current location of EV_i^k and CS_u^j is calculated using haversine formula. The haversine formula is a very accurate technique of computing minimum distances between two points on the surface of a sphere using the latitude and longitude of the two points [29]–[31]. It is expressed in trigonometric function as shown in the following equation, where α is the central angle between two points on a sphere:

$$hav(\alpha) = sin^2(\frac{\alpha}{2}) \tag{2}$$

The distance between EV_i^k and CS_u^j is calculated in two stages as shown in eq.(3). The first stage from the current location of EV_i^k to the port of adjacent zone j. The second stage from the port between two zones to reach CS_u^j as illustrated in Fig. 1.

$$d_{i,u} = d_{i,t^{kj}} + d_{t^{kj},u} \tag{3}$$

where $d_{i,u}$ denotes the total distance between the location of EV_i^k and CS_u^j, $d_{i,t^{kj}}$ represents the distance from the location of EV_i^k to the port with the adjacent zone j, and $d_{t^{kj},u}$ is the distance between the port t^{kj} and CS_u^j.

The haversine of central angle (for instance $d_{t^{kj},u}$ / R) can be calculated using the following formula:

$$\begin{aligned} hav\left(\frac{d_{t^{kj},u}}{R}\right) &= hav\ (\mu_u - \mu_{t^{kj}}) + \\ cos(\mu_{t^{kj}})\ cos(\mu_u)\ &hav(\Psi_u - \Psi_{t^{kj}}) \end{aligned} \tag{4}$$

where $d_{t^{kj},u}$ is the distance along the surface of the earthly sphere from the port between zones (k and j) to the location of CS_u^j, $\mu_{t^{kj}}$, μ_u are the latitude of EVs at the port and CS_u^j, and $\Psi_{t^{kj}}$, Ψ_u are longitude, respectively. Fig. 2 shows how the spherical triangle is solved using haversine function, where R is the radius of the Earth which is known to be 6371 km, and $d_{i,u}$ is the distance along the surface of the earthly sphere. The haversine function finds only half of the angle α. The following equation shows how the distance from the port between zones k and j until CSs u, i.e., $d_{t^{kj},u}$, can be calculated by applying the inverse of the sin function:

$$\begin{aligned} d_{t^{kj},j} &= 2Rsin^{-1}\times \\ &\sqrt{hav(\mu_u - \mu_{t^{kj}}) + cos(\mu_{t^{kj}})cos(\mu_u)\ hav(\Psi_u - \Psi_{t^{kj}})} \\ &= 2Rsin^{-1} \times \\ &\sqrt{sin^2(\frac{\mu_u - \mu_{t^{kj}}}{2}) + cos(\mu_{t^{kj}})cos(\mu_u)sin^2(\frac{\Psi_u - \Psi_{t^{kj}}}{2})} \end{aligned} \tag{5}$$

The congestion level $\delta_{i,u}$ is resulted from the normal congestion caused by ICEVs, and the congestion caused by the EVs heading for charging. Only normal congestion is taken into account when EV_i^k moves from its location to reach the port with adjacent zones. However, from the port to the location of CS_u^j, both congestion are considered, taking into account the capacity of the road in both zones (k and j). Eq.(6) shows how the congestion level $\delta_{i,u}$ is calculated:

$$\begin{aligned} \delta_{i,u}(X) = (V_{i,t^{kj}}\ /\ (\zeta_{i,t^{kj}}\ \times\ \varphi))\ + ((V_{t^{kj},u} + \\ \sum_{i=1}^{N^k} x_{i,u})\ /(\zeta_{t^{kj},u}\ \times\ \varphi\ \times\ \varepsilon\ \times\ S_k\ \times\ S_j))) \end{aligned} \tag{6}$$

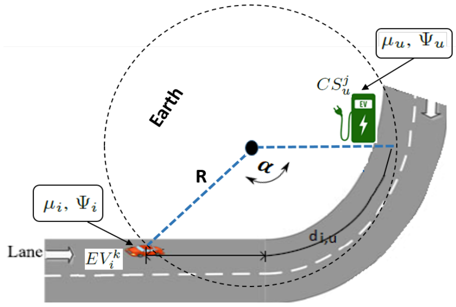

Fig. 2. Spherical triangle solved by the law of haversines.

where $V_{i,t^{kj}}$, $V_{t^{kj},u}$ represents the number of ICEVs in zone k and zone j that share the same route with EVs, respectively, $\zeta_{i,t^{kj}}$, $\zeta_{t^{kj},u}$ is the capacity of the roads in zones k and j, respectively, N^k represents the number of EVs in zone k that are needed to be charged, $x_{i,u}$ is a binary decision variable which indicates whether EV_i^k selects CS_u^j for charging, and φ, ε represents the proportion of ICEVs and EVs sharing the same roads with EVs per peak hour, S_k and S_j denotes the traffic flow level in the zone k and j respectively.

C. Queuing Time Estimation

Besides the travel time of the EVs, the queuing time inside CSs also influences the decision of assigning EVs to CSs. The queuing time at any CSs depends on the total number of EVs that reach this CSs for charging per peak hour, the number of chargers that have been installed in the CSs and also the charger technology, which mainly decides the number of EVs that can be charged per charger. The queuing time is calculated as follows:

$$q_u(X) = \sum_{f=1}^{G_u}\sum_{i=1}^{N^k} x_{i,u}/\ (\eta_u \times r_u \times \varepsilon \times Ch^r_{i,u}). \quad (7)$$

where q_u represents the queuing time at CS_u^j per peak hour, the indices f and i represent the number of adjacent zones of zone k (where the EV is located), and the total number of EVs in zone k, respectively. The associated matrix (X) shows the assignment of EVs to CSs, G_u represents the set of adjacent zones for CS_u^j, η_u denotes the number of chargers at CS_u^j, r_u is the maximum number of EVs charged per charger in an hour, ε denotes the proportion of EVs charge per peak hour, and $Ch^r_{i,u}$ is the charging rate of EVs. Here is the queuing time vector for CS_u^j, $\overrightarrow{Q} = \{q_1 \quad q_2 \quad q_3 \quad \dots \quad q_M\}$. It is clarified that the number of vehicles queued at charging stations, and their respective charging times, traffic conditions and their impact on mobility, and adjacency of different charging stations zones have been considered in the optimization problem for making recommendation to EVs for a particular charging station.

D. Charging Time Estimation

In addition to the travel time of the EVs to reach CSs location, and the queuing time at CSs, the charging time of EVs battery at a CSs is considered as an important factor that affects not only the time that the EVs user needs to stay at the CSs but also the total number of EVs that can be served by the CSs. The maximum number of EVs charged per charger is the main parameter that has an influence on charging time of EVs inside CSs. The rated power of the chargers varies in the range of 50 kW to 350 kW, depending on the charger technology and manufacturer [32], [33]. EVs chargers can basically be classified into three different charging levels of Electric Vehicle Supply Equipment (EVSE). Table II lists the differences between the three levels. The charging time for each CSs is calculated as follows:

$$\rho_u = 60/r_u. \quad (8)$$

TABLE II. Classification of EVs chargers [33]

EVSE Type	Power Supply	Charger Power	Charging Time Battery EVs (BEV)
Level 1 (AC Charging)	120 VAC 12 A to 16 A (Single Phase)	$\sim$ 1.44 kW to $\sim$ 1.92 kW	$\sim$ 17 Hours
Level 2 (AXC Charging)	208 $\sim$ 240 VAC 15 A $\sim$ 80 A (Single/Split Phase)	$\sim$ 3.1 kW $\sim$ 19.2 kW	$\sim$ 7 Hours (3.3 kW on-board charger) $\sim$ 3.5 Hours (6.6 kW on-board charger)
Level 3 (Combo Charging System or DC Charging)	200 $\sim$ 920 VDC (Max 500 A) (Poly Phase)	From 120 kW to 350 kW	$<$ 30 Minutes

where ρ_u is the charging time of a EVs at CS_u^j, and r_u is the number of EVs that can be served by this charger per one hour. $\overrightarrow{P} = \{\rho_1 \quad \rho_2 \quad \rho_3 \quad \dots \quad \rho_M\}$, is the vector of the charging time at CS_u^j.

Thus, the total time for EV_i^k that have been assigned to CS_u^j is calculated as the sum of the travel time $\tau_{i,u}(X)$ of EV_i^k, where X is the associated matrix that shows the relation between EVs and CSs, the queuing time q_u at CS_u^j, and the charging time inside a CSs ρ_u, as shown in the following equation:

$$T_{i,u}(X) = \tau_{i,u}(X) + q_u(X) + \rho_u. \quad (9)$$

It is highlighted that the estimation of charging time considers range of parameters including number of vehicles at charging stations, respective charging time, traffic scenario on the road and their impact on mobility, adjacency of charging stations nearby, and their on-road connectivity.

E. The Optimization Problem

To minimize the overall charging time of EVs, we determine the optimal assignment of EVs to CSs in urban environments. The following equation shows the corresponding optimization problem of our proposed approach:

$$\min_X \sum_{i=1}^{N}\sum_{u=1}^{M}(\tau_{i,u}(X) + q_u(X) + \rho_u) \times x_{i,u} \quad (10)$$

$$s.t. \sum_{u=1}^{D_i} x_{i,u} = 1, \qquad \forall i \in \mathcal{N} \quad (11)$$

$$\sum_{i=1}^{N} x_{i,u} \leq \eta_u \times r_u, \qquad \forall u \in \mathcal{M} \quad (12)$$

$$x_{i,u} \in \{0,1\}, \qquad \forall i,u \in \mathcal{N},\ \mathcal{M} \quad (13)$$

$$(\tau_{i,u}(X) + q_u(X) + \rho_u) \leq \Gamma, \quad \forall i,u \in \mathcal{N},\ \mathcal{M} \quad (14)$$

where N is the total number of EVs in the study area, M is the total number of CSs, EV_i^k is assigned to only one CSs from the set of adjacent zones (D_i) as shown in eq.(11). Constraint (12) indicates that the total number of EVs that are assigned to each CSs should not exceed the capacity of the CSs, $x_{i,u}$ is a binary decision variable with values {0,1} as shown in eq.(13), to indicate whether CS_u^j in zone j is selected by EV_i^k, $x_{i,u}$ is equal to 1 if the CS_u^j in zone j is selected by EV_i^k, otherwise it is equal to 0. The total time to charge EV_i^k should not exceed a certain threshold value (Γ) which is used as EVs drivers' QoE indicator as shown in eq.(14).

The objective function shown in eq.(10), and system constraints in Eqs.(11)-(14) form a MINLP problem, where the values of $x_{i,u}$ are constrained to be integer values {0,1}, and all constraints are linear terms. Finding the optimal assignment of EVs to CSs represent the solving of this optimization problem. In this work, GA is used to find the optimal assignment of EVs to CSs. Despite the high computational complexity of GA to solve this type of problems, it is considered as one of the most effective techniques that can be used to perform meta-heuristic search in very complex, multimodal landscapes, and large problems, and provide near optimal solutions for

TABLE III. FOUR CORNERS OF THE STUDY AREA

Corner	Longitude	Latitude
SE	54.965405	-1.537112
NE	55.021271	-1.565240
NW	55.015563	-1.750658
SW	54.968385	-1.711929

Algorithm 1 GA strategy to determine the optimal assignment of EVs to CSs

Input: $N, M, V_{i,t^{kj}}, V_{t^{kj},u}, \ell, \mu_i, \Psi_i, \mu_{t^{kj}}, \Psi_{t^{kj}}, \mu_u, \Psi_u, \zeta_{i,t^{kj}}, \zeta_{t^{kj},u}, N^k, \varepsilon, \varphi, \eta_u, r_u, G_u, D_i, \Gamma, \beta, \lambda_u$

Output : X^{opt}

begin:
GA generates an initial population $F^{(1)} = \{X_1^{(1)}, X_2^{(1)}, X_3^{(1)}, ..., X_Y^{(1)}\}$
K = maximum number of GA iterations
Y = size of F
for $i = 1$ to N **do**
  for $u = 1$ to M **do**
    Calculate $d_{i,u}$ using Eqs. (3)-(5)
  end for
end for
for $u = 1$ to M **do**
  Calculate ρ_u using eq. (8)
end for
set iteration ID s = 1
while s < K **do**
  for $n = 1$ to Y **do**
    for $i = 1$ to N **do**
      for $u = 1$ to M **do**
        Calculate $\delta_{i,u}(X_n^{(s)})$ using eq. (6)
        Calculate $\tau_{i,u}(X_n^{(s)})$ using eq. (1)
      end for
    end for
    for $u = 1$ to M **do**
      Calculate $q_u(X_n^{(s)})$ using eq. (7)
    end for
    set $l_n = 0$
    for $i = 1$ to N **do**
      for $u = 1$ to M **do**
        $l_n = l_n + T_{i,u}(X_n^{(s)})$, where $T_{i,u}(X_n^{(s)})$ is the total time as shown in eq. (9)
      end for
    end for
  end for
  $\overrightarrow{L} = \{l_1, l_2, l_3, ..., l_Y\}$
  $[b^{(s)}, idx_1] = min(\overrightarrow{L})$. This step calculates the minimum total time of the objective function as shown in eq. (10).
  $R^{(s)} = F_{idx_1}^{(s)}$
  $C = \{b^{(1)}, b^{(2)}, b^{(3)}, ..., b^{(s-1)}\}$
  $[B, idx_2] = min(C)$
  if $b^{(s)} < B$ **then**
    $X^{opt} = R^{(s)}$
  else
    $X^{opt} = R^{(idx_2)}$
  end if
  if $|B - b^{(s)}| \leq \beta$ **then**
    Return X^{opt}
    Break
  end if
  GA selects solutions from $F^{(s)}$, then implements crossover process to create new offspring
  GA applies mutation operator on a random solution
  s = s + 1
  GA updates $F^{(s)}$ subject to the constraints in Eqs. (11)-(14)
end while
Return X^{opt}

fitness or objective functions of optimization problems [34], [35], especially when the approaches using this technique prioritize the accuracy of the results rather than focusing only on the time required for implementation. Algorithm 1 explain the GA steps to determine the optimal assignment of EVs to CSs based on inheritance, mutation, selection and some other techniques. Fig. 3 shows the flowchart of our proposed approach.

F. Implementation Settings

To implement our optimization algorithm, a centric server is used, where all the required information should be stored on the server, and any changes on the environment should be updated on the server environment as well. A 95% confidence interval of the mean is a range with the lower and upper values in our approach. Following is the information that should be stored on this server in advance:

- EVs information includes; EVs's ID, coordinates, and to which zone its belong.
- CSs details includes; CSs's ID, location, η_u and r_u.
- Details of each zone includes; the borders of each zone, coordinates of the ports with adjacent zones, number of EVs, Number of ICEVs, and roads capacity of each zone.
- Study area characteristic includes; number of the zones, adjacency map between zones and the four corners which represents the investigated area.

The assignment of EVs to the optimal CSs is managed by the server which has all the information mentioned before. The implementation process on this server is done based on the objective function of this approach and all system constraints as introduced in Section III-E . A best choice of CSs for each EVs is determined by this server, and this requires every EVs that needs to be charged to communicate directly to this server in order to determine the optimal CSs as shown in Fig. 4, which illustrates an example of charging time process, starting from movement of EVs to reach CSs, then waiting in a queue until a charger is available for charging. Finally, the EVs leaves the CSs after its battery is fully charged.

IV. NUMERICAL RESULTS

A. System Base Scenario

The proposed model is applied to the city of Newcastle upon Tyne considering a total of seven post codes from NE1 to NE7. Fig. 5 shows detailed map of the study area with a length of about 11 km and a width of about 6 km. As shown in Fig. 5, the available CSs are distributed on main roads in different zones in the study area. The coordinates of the four corners of the study area is shown in Table III. Table IV shows the information for each zone in terms of ID, EVs population, ICEV population, the number and location of CSs at each zone, we assume 10 CSs in the study area as shown in Table IV. Table IX in Appendix section shows the adjacency relations between zones.

According to the statistics of Newcastle upon Tyne city council in the second quarter 2020, the population of the personal ICEVs in Newcastle upon Tyne has reached around 82,850 [36]. 5% EVs are assumed to be EVs. It is assumed that 10% of EVs population needs to be charged at peak hour. We assume that 10% of ICEV use the same road as EVs per peak hour, also we assume that the capacity of the road in the study area is the same. Table V presents the value of the study parameters used in the current base scenario.

Besides the impact of charging activities of EVs and movement of EVs between adjacent zones, the movement of ICEVs is also taken into account in our proposed model. The assignment problem will be solved based on minimizing the overall completion time of charging EVs batteries considering our objective function in line with the system constraints. The proposed approach has been performed in MATLAB environment R2019a.

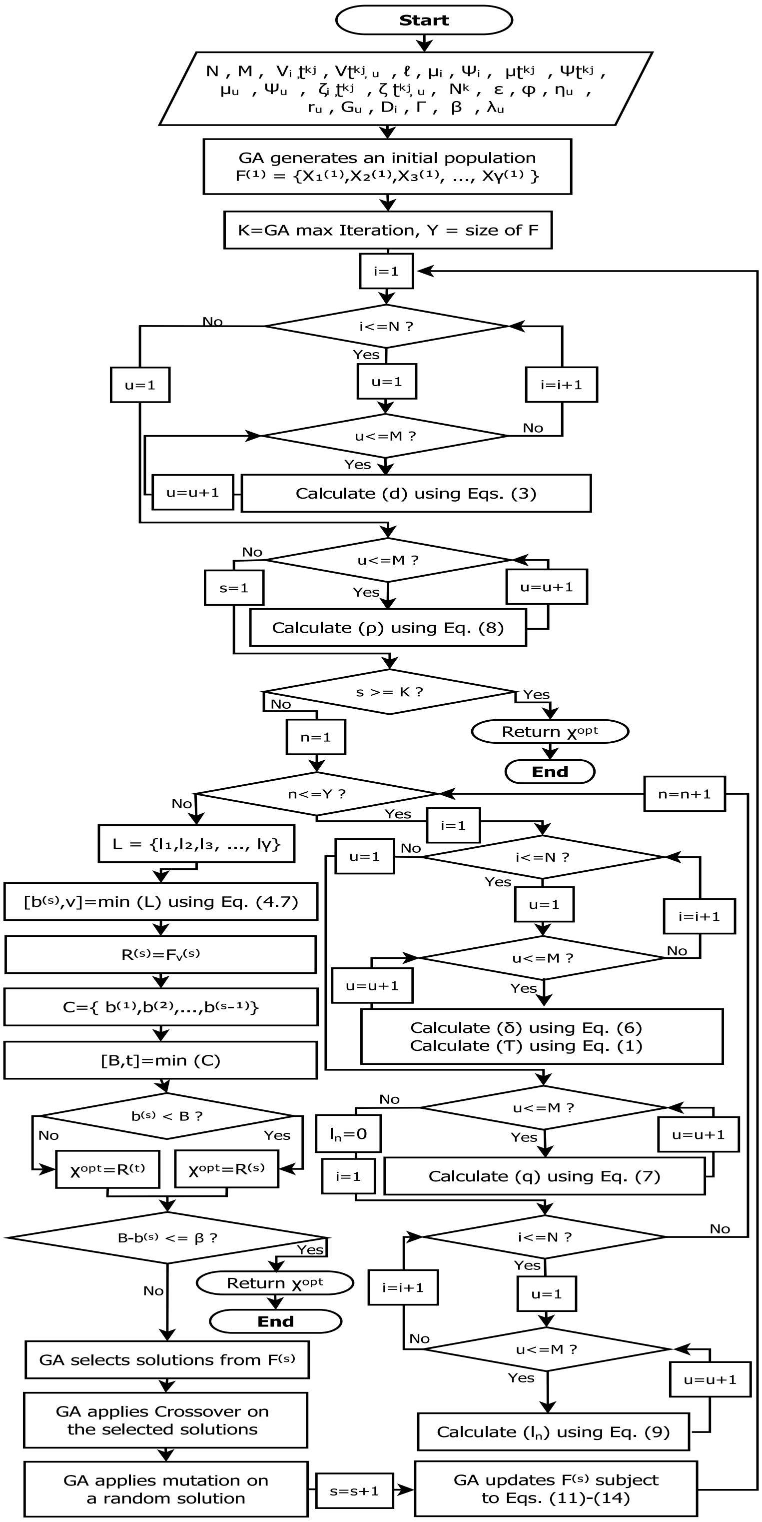

Fig. 3. Flowchart of the proposed approach.

B. Other Case Studies

More studies have been evaluated to demonstrate the advantage of the proposed approach in determining the optimal assignment of EVs to the available CSs in the study area. Moreover, the reason for implementing these different case studies is to show the importance and influence of these parameters on the decision of assigning EVs to the available CSs in the study area.

Four different case studies have been conducted as follows:

- Case A: With reduced congestion level on the road towards CS9 in NE3. We assume that the capacity of the road towards CS9 in NE3 is doubled, while the other CSs characteristics remain the same as the base scenario.
- Case B: With increased congestion level on the roads towards CSs in NE1. The road capacity towards CSs in zone NE1 is assumed to be reduced by a third, while the others CSs conditions remain the same as the base scenario.
- Case C: With increased ICEVs. We assume that the number of ICEVs that share the roads with EVs moving towards CSs in NE1 is increased to be the same as in NE5 while the road capacity towards these CSs remain the same as the base scenario. The condition of other CSs remain the same as the base scenario.
- Case D: Increased charging rate of connectors. We assume that the maximum number of EVs that can be charged per

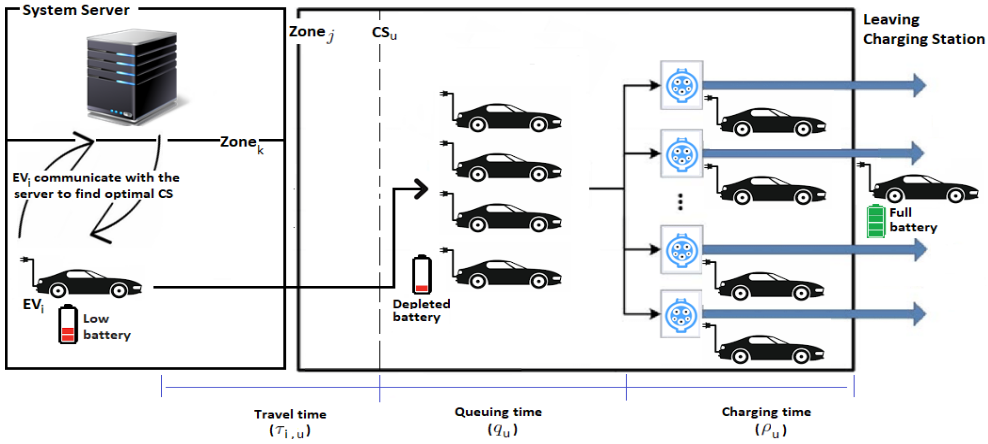

Fig. 4. Illustration of charging process completion time.

Fig. 5. Study area map

TABLE IV. ZONES INFORMATION

Zone ID	EVs Pop	ICEVs Pop	Zone CSs	CSs's Coordinates	
				Latitude	Longitude
NE1	67	1349	CS2 CS3 CS4	54.9740967 54.9792671 54.9749156	-1.6212623 -1.6098994 -1.595424
NE2	268	5362	CS6	54.988027	-1.613854
NE3	1123	22466	CS9	55.0072571	-1.619521
NE4	499	9977	CS1 CS7	54.97448 54.9862673	-1.644712 -1.6594208
NE5	1150	23000	CS8	55.0023349	-1.6754294
NE6	708	14154	CS5	54.988743	-1.581588
NE7	333	6662	CS10	55.009272	-1.57895

charger in CS1 and CS7 in NE4 to be 8 (r_1 and r_7=8) instead of 6 as assumed in other cases. The characteristics of other CSs remain the same.

- Case E: Future scenarios with increased EVs and ICEVs, in this case, we study the impact of increasing the number of EVs and ICEVs on the total time of charging EVs in Newcastle upon Tyne city in three different scenarios.

TABLE V. Base scenario parameters

Parameter	Value
N	415
M	10
V	8285
η_u	10
r_u	6
Z	7
ℓ	0.2
ζ	1590
Γ	120
λ_u	48
β	10

Then we present suggested solutions in order to reduce the charging time caused by increasing the density of vehicles in the study area in these three scenarios.

C. Result Analysis Discussion

In this section, we run experiments on the real data set from Newcastle upon Tyne city, results are presented in averages taken over 30 independent experiments. Error bars are used to represent the standard deviation obtained from these experiments.

Fig. 6 shows the comparison results between the base scenario and Cases A to D in terms of the assignment EVs to CSs. It can be seen in Fig. 6 that the CSs at zones NE1, NE2, NE4, NE6 and NE7 in the base scenario have received a large number of EVs, the reason for this is the proximity of these CSs to the location of the majority of EVs in the study area, and also the congestion level in these zones are less compared to the other zones, which in turn reduces the time for these EVs to reach CSs due to the low level of congestion on the roads. Another observation in this case is that the assignment of EVs to CS8 in NE5 has reached to the maximum number of EVs, although the congestion level in NE5 is very high due to the large number of ICEVs, and the reason behind this is that the location of EVs in NE3 is very close to CS8 in NE5. In addition, the EVs need to travel a long distance within a high congestion level in NE3 to reach other available adjacent CSs in NE2, NE4 and NE7. It can be observed that the EVs in the adjacent zones of NE3 has selected CS9 as shown in Fig. 6 in Case A, rather than selecting CS1, CS3 and CS5 as shown in the base scenario, and the reason behind this is that the the road capacity towards CS9 in NE3 is doubled which in turn led to reduce the congestion level in NE3 as we assume in this case. In Case B, when the road capacity towards CSs in NE1 is reduced by a third while the road capacity of other CSs remain the same as the base scenario, it can be observed that the total number of EVs that are assigned to CS3 is less compared to the total number of EVs that are assigned to CS3 in the base scenario as shown in Fig. 6, and this is due to the high level of congestion on the roads resulting from the low road capacity towards this CSs. The number of EVs that are assigned to CS2 and CS4 is almost the same as they are still the best CSs for EVs in NE4 and NE6, respectively.

The results obtained for Case C have shown the influence of the total number of ICEVs that share the same roads with EVs that are heading to charge at CSs in NE1, on the decision of assignment EVs to the optimal CSs. As shown in Fig. 6, the total number of EVs that were assigned to CS3, is reduced by more than a half compared to the base scenario. The main reason for this is the increased congestion due to the increase in the number of the ICEVs on the roads towards CS3. However, CS2 and CS4 in NE1 have the almost received the same number of EVs because they are still the best options for EVs in NE4 and NE6, respectively.

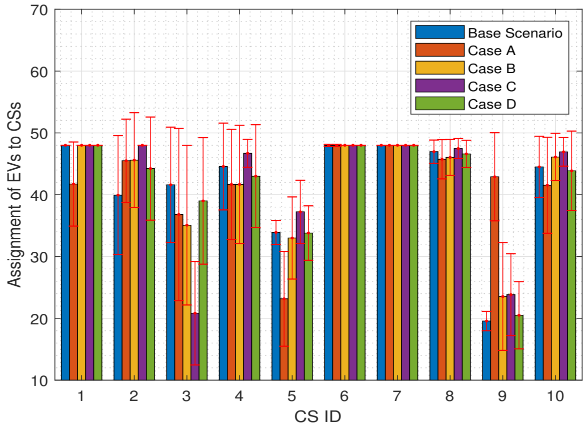

Fig. 6. Comparison between all cases in terms of EVs assignments

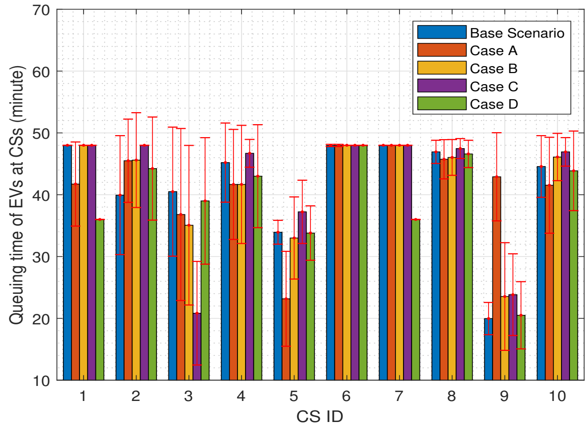

Fig. 8. Comparison between all cases in terms of queuing time

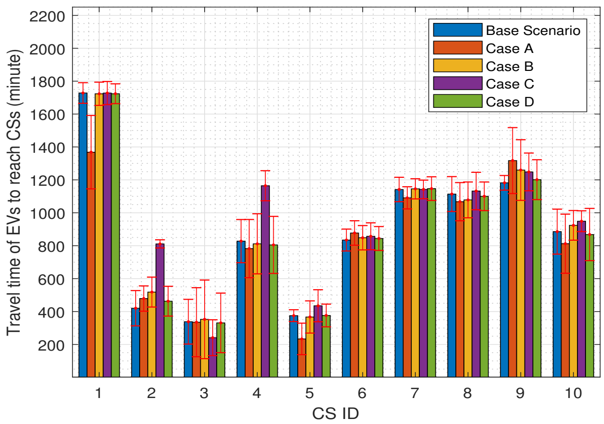

Fig. 7. Comparison between all cases in terms of travel time

In Case D, we assume that the maximum number of EVs that can be charged per charger in NE4 is increased to 8 instead of 6, which in turn reduce the queuing time and charging time inside CSs. As shown in Fig. 6, the assignment of EVs to CSs in Case D is remain the same as in the base scenario, and the reason for this is, of course, the assignment of EVs to CS1 and CS7 have reached the maximum number of EVs in the base scenario. We will discuss the significant impact of this assumption, when it comes to talk about the figures and discussion of queuing time and charging time.

Fig. 7 shows the comparison between the base scenario and Cases A to D in terms of the travel time of EVs to reach CSs in adjacent zones. Several factors were taken into consideration to calculate the travel time of EVs en route to CSs, i.e, congestion level, road capacity towards CSs, total number of EVs and ICEVs that share the same route with these EVs that are heading to charge. In the base scenario, as can be seen in Fig. 7, the travel time of EVs that move from NE5 to reach CS1 in NE4 is significant, and the reason behind this is the large number of ICEVs inside NE5 and also the long distance between the locations of EVs in NE5 and CS1 in NE4. EVs in NE5 can be charged in two adjacent zones NE3 and NE4. However, they have selected CS1 in NE4 although CS9 in NE3 is much closer to their locations, and this is because of the high congestion level in NE3 due to the large number of ICEVs in this zone, compared to the number of the ICEVs in NE4 as shown in Table IV. It is easy to notice that the travel time of CS9 in NE3 is very high even though the number of EVs that are assigned to CS9 is very few as shown Fig. 6, and this is due to the high congestion level in this zone. Another observation in the base scenario in Fig. 7, is that the travel time of EVs that are assigned to CS2, CS3 and CS4 in NE1 is very low, although the EVs assignment to these CSs has almost reached to the maximum number of EVs that allowed to be assigned to CSs, the reason for this is the low level of congestion in this zone, and the proximity of these CSs to the EVs locations.

It can be seen from Fig. 7, that the travel time of EVs that are assigned to CS9 in Case A is almost the same as in the base scenario, although the EVs assignment to CS9 has increased more than doubled, and also the number of ICEVs in this zone is very high, this is due to the assumption that the road capacity towards this CSs has doubled. Another observation in the results of Case A in Fig. 7, is that the travel time of EVs to reach CS1 and CS5 are decreased, and the reason for this is that some of EVs in NE5 and NE7 have selected CS9 rather than selecting CS1 and CS5, this has reduced the travel time because of the low number of EVs that are assigned to them. In Case B, we assumed that the capacity of the roads towards CSs in NE1 is reduced by a third. As shown in Fig. 7, the travel time of EVs to reach CS9 is slightly increased compared to the base scenario, and the reason for this is that some of EVs in NE2 moved to NE3 for charging rather than selecting CS3 in NE1 due to the high congestion level because the road capacity towards NE1 is reduced as we assumed in this case, and this is also the reason why the travel time for CS3 is reduced. It is easy to see that the travel time to reach CS2 and CS4 is increased, this is also because of the congestion level in NE1 which is increased due to the assumption in this case.

In Case C, as shown in Fig. 7, the travel time of EVs to reach CS2 and CS4 has increased compared to the base scenario, this is due to the increase in the number of ICEVs in NE1 as we assumed in this case which in turn increased the congestion level on the roads towards these CSs. It is observed in Fig. 7 that the travel time of EVs to reach CS3 is reduced, the reason behind this is that the number of EVs that are assigned to CS3 has dramatically decreased because of the increase in the congestion level in this zone which encouraged some of EVs in NE2 to select CS9 in NE3 rather than selecting CS3 in NE1 as shown in Fig. 6. In Case D, we assumed that the maximum number of EVs that can be charged by a charger per hour in CS1 and CS7 in NE4 is 8 rather than 6 as assumed in the other cases, i.e, r_1 and r_7 = 8. As shown in Fig. 7, it is observed that the travel time of EVs to reach CS1 and CS7 in Case D and base scenario is almost the same, and the reason for this is that in both cases the number of EVs that are assigned to CS1 and CS4 have reached to the maximum number of EVs. As mentioned before, the effect of this assumption will be noticed when we study the figures of queuing time, charging time and total time.

Fig. 8 shows the queuing time inside each CSs. As shown in eq. (7), the queuing time is calculated considering the number of EVs that are assigned to CS_u^j, the number of chargers at CS_u^j and the rated power of chargers. In the base scenario and Cases A to D, we assumed that the number of chargers at each CSs are the same, and the charger's rated power are the same for base scenario and Cases A, B and C, while it is different for

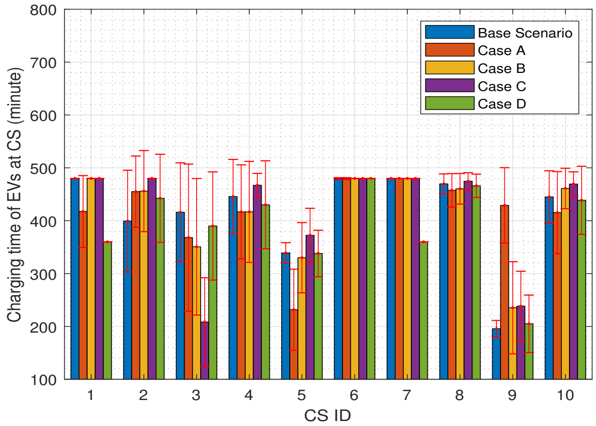

Fig. 9. Comparison between all cases in terms of charging time

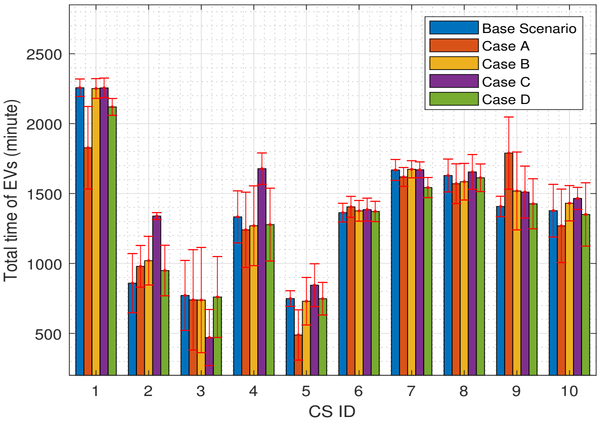

Fig. 10. Comparison between all cases in terms of the total time of EVs with each selected CSs

Case D as mentioned earlier. As shown in Fig. 8, the queuing time at CS1, CS2, CS4, CS6, CS7, CS8 and CS10 in all cases is more than the other CSs, and the reason behind this is that the number of EVs that are assigned to these CSs is more than the other CSs as shown in Fig. 6. Quite the contrary, the queuing time at CS3, CS5 and CS9 is less, this is because the number of EVs are assigned to these CSs is less as shown in Fig. 6. Another observation in Fig. 8, is that the queuing time for CS1 and CS7 in Case D is less than the base scenario although the number of EVs that are assigned to them is the same, and this is because of the assumption of this case that the charger rated power is higher. As a result, the waiting time for EVs inside these CSs will be shorter. It is also shown in Fig. 8, that the queuing time at CS9 in Case A is higher than the other cases in CS9, and this is because of the assumption in this case that the road capacity towards this CSs has doubled, which led to an increase in the number of EVs that are assigned to it, and thus an increase in queuing time inside it.

Fig. 9 shows the charging time of EVs that are assigned to each CSs. The charging time for each EVs inside CS_u^j is mainly depend on the number of EVs that can be charged by a charger in CS_u^j per hour as shown in eq. (8). As shown in Fig. 9, it is obvious that the charging time of EVs that are assigned to CS1 and CS7 in Case D is less compared to the other cases, although the number of EVs that are assigned to them is the same, the reason behind this is that the charger's rated power of CS1 and CS7 in Case D is higher than other cases in these CSs. As shown in Fig. 6 and Fig. 9, the CSs that received more EVs, the charging time is more, and the opposite is true for CSs that received fewer EVs. Therefore, the charging time at CS1, CS2, CS4, CS6, CS7, CS8 and CS10 in all cases is more than the other CSs.

TABLE VI. Comparison between the base scenario and Case D in terms of the total time

CSs ID	Base scenario		Case D	
	EVs	Charging Time(m)	EVs	Charging Time(m)
CS_1	48	2,256.897	48	2,119.686
CS_7	48	1,668.656	48	1,542.862
Total	**96**	**3,925.553**	**96**	**3,662.548**

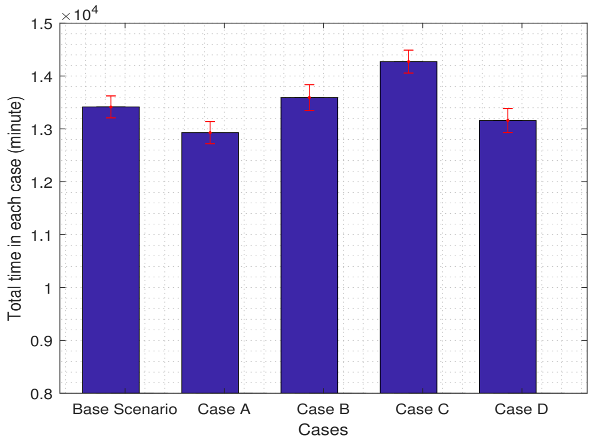

Fig. 11. Total time required to fully charge EVs based on proposed scenarios

Fig. 10 shows the total time of charging EVs with each selected CSs, starting from movement towards CSs until departure as shown in Fig. 4. The total time consists of travel time, queuing time and charging time at CSs. As shown in Fig. 10, CS1 has the highest total time compared to all CSs and in all cases, and the reason for this is that CS1 has almost reached the maximum number of EVs in the base scenario, and Cases B, C and D. Knowing that these EVs come from NE5, and as shown in Table IV, the number of ICEVs in NE5 is very high which increases the congestion level on the roads towards CS1 in NE4, also the distance that EVs need to move from NE5 to reach CS1 in NE4 is too long as shown in the study area map in Fig. 5. Another observation in Fig. 10, is that the total time of EVs that are assigned to CS2 and CS4 is low although the EVs assignment to these CSs has almost reached to the maximum number of EVs that allowed to be assigned to CSs, the reason for this is the low level of congestion in this zone the zones from which these EVs come, in addition to the proximity of these two CSs to the sites of EVs. As shown in Fig. 109, the total time of EVs that are assigned to CS1 and CS2 in Case D is the least compared to the others cases in these two CSs, and the reason for this is the assumption of this case that the chargers rated power in these CSs is higher than other cases. Table VI shows comparison between the base scenario and Case D in terms of the total time for charging EVs in CS1 and CS7.

Fig. 11 shows the total time of charging EVs that are assigned to the best choice of CSs for the base scenario and the other cases that have been proposed in order to demonstrate the efficiency of the proposed scheme. As shown in Fig. 11, it is obvious that the total time for Case A is less compared to the base scenario, and the reason behind this is the assumption in this case which is increasing the road capacity to the double towards CS9 in NE3. The number of ICEVs in this zone is large, and thus increasing the road capacity led to less congestion level on the road, therefore less travel time to reach CS9. In Case B, as shown in this figure, the total time is higher than the base scenario as shown in Fig. 11, and this is due to the decrease in the road capacity of CS2, CS3 and CS4 in NE1 by a third, which has resulted in an increase in the level of congestion on the roads leading to these CSs.

To demonstrate the influence of ICEVs on the congestion level and total time. In Case C, the number of ICEVs in NE1 was increased to be the same as in NE5 while the road capacity remain the same as in the base scenario. As a consequence, the

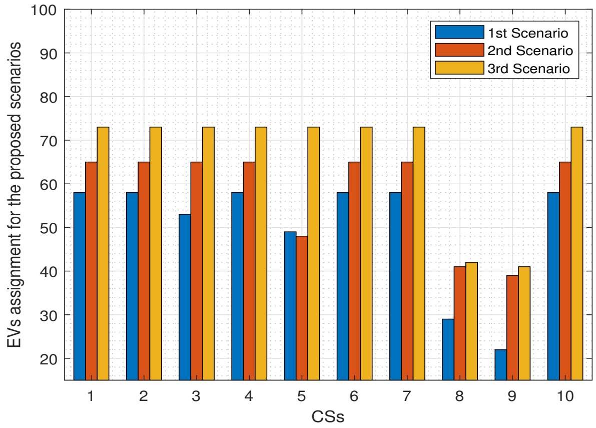

Fig. 12. EVs assignment for Case E

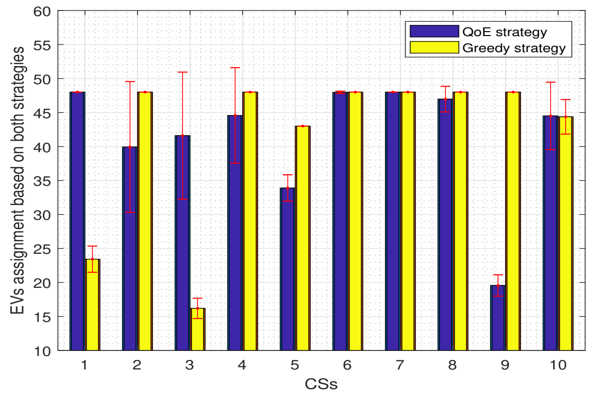

Fig. 14. Comparison between QoE strategy and Greedy strategy in terms of EVs assignment

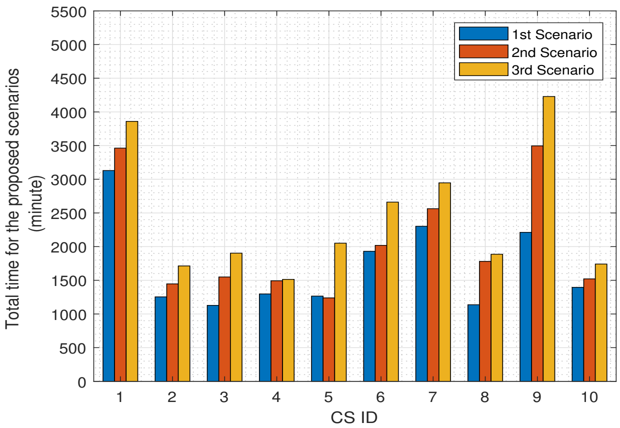

Fig. 13. Case E results in terms of the total time to charge EVs

total time for the EVs that are assigned to the CSs has increased compared to the base scenario as shown in Fig. 11. In Case D, the total time has decreased compared to the base scenario as shown in Fig. 11, and the reason for this is the increase in the maximum number of EVs can be charged per charger in CS1 and CS7 in NE4, as the charging time inside the CSs mainly depends on the rated power of charger.

Figs. 12 and 13 show the assignment of EVs to the optimal CSs as proposed for Case E, and also the total expected charging time for EVs which increased dramatically due to the increase number of vehicles in Newcastle upon Tyne as proposed in the three scenarios. Fig. 12 shows how the EVs are distributed to the available CSs based on the projection that the number of EVs and ICEVs will increase by 20% and 10% for the first scenario, 40% and 15% for the second scenario, 60% and 20% for the third scenario, respectively, compared to the current vehicle density in the study area. It is assumed that the values of λ_1, λ_2, λ_3, ..., λ_M = 58, 65 and 73 for the three proposed scenarios, respectively. In this case we also assume that the rest of parameters remain the same as in the base scenario.

Fig. 13 shows the total expected time for charging EVs based on the assumption in this case. It is obvious that the total time has increased dramatically, as shown in Fig. 13. To overcome the increase in total time for the three proposed scenarios, the following two suggested solutions have been proposed:

- Selecting most recent chargers which can serve more EVs within one hour r_u.
- Increasing the number of chargers η_u at each CSs.

In the first suggested solution, to minimize the overall charging time. We assume that the maximum number of EVs that can be charged per charger in CS_u^j is increased to 8 per hour, which means that r_1, r_2, r_3, ..., r_{10} = 8 instead of 6 as assumed in the previous three scenarios. The use of new technology and an advanced charger directly affects the total number of EVs that can be charged per hour. As a results, the total time of charging EVs has decreased. Table VII show the impact of the charger's rated power on reducing the total time of charging EVs for the three proposed scenarios.

In the second suggested solution, to minimize the overall charging time for the three proposed scenarios, the number of chargers will be increased to 12 for all CSs, i.e, η_1, η_2, η_3, ..., η_{10} = 12, instead of 10 chargers as assumed before. The increase in the number of chargers in the CSs affects directly the performance of the CSs in terms of the queuing time, as having a larger number of chargers reduces the overall charging time of EVs as shown in Table VIII. As shown in the previous figures, it is obvious that increasing the charger rated power as proposed in the first solution has more impact on the total time than increasing the number of chargers as proposed in the second scenario, and the reason behind this is that the chargers rated power affects the queuing time and also the charging time, while the number of chargers at CSs affects only on the queuing time inside the CSs.

D. A Comparison between QoE strategy and Greedy strategy

The comparison between the two strategies is done first based on the congestion level that is proposed in the base scenario, and then the congestion ratio is increased by 20%, 40%, 60%, 80% and 100% in order to see the impact of congestion level on the EVs driver's QoE. Fig. 14 shows the EVs assignment results for both strategies, It is observed that the number of EVs that are assigned to some CSs has changed. As shown in Fig. 14, CS9 in NE3 in greedy strategy has reached the maximum number of EVs compared to low number of EVs in the QoE strategy, and the reason for this is that the EVs in NE5 moved to NE3 for charging because of the proximity to the location of CS9 in NE3 and also ignoring the high congestion level in both zones, knowing that the NE3 and NE5 have the highest congestion level because of the high number of ICEVs in these zones compared to the other zones as shown in Table IV. Another observation in Fig. 14, is that the assignment of EVs to CS1 and CS3 in greedy assignment has decreased dramatically, and the reason for this is that the EVs in NE5 selected CS9 in NE3 rather than selecting CS1 in NE4, and the EVs in NE2 selected CS5 instead of CS3 in NE1, and the reason for this is the long distance between the locations of EVs and CSs.

Figs. 15 and 16 show the comparison between the QoE strategy and greedy strategy in terms of the travel time and the total time, respectively. It is easy to see in both figures that the travel time and total time have increased in greedy scenario, and the reason for this is that the congestion level on the road towards CSs has been ignored when assigning EVs to CSs, whereas the

TABLE VII. Total time of charging EVs at each CSs in Case E where $r_u = 6$ & 8 (minute)

CSs ID	First scenario		Second scenario		Third scenario	
	r_u		r_u		r_u	
	6	8	6	8	6	8
CS_1	3129.436263	2929.957268	3462.292027	3241.408114	3859.115391	3694.001159
CS_2	1254.219562	1094.37063	1447.10629	1271.255051	1713.51112	1529.7045
CS_3	1127.682654	825.5329969	1549.5048	1515.246455	1903.029848	1215.131903
CS_4	1297.453849	1359.746675	1493.08984	1157.926111	1513.397148	1886.994357
CS_5	1265.391947	880.5210802	1239.194264	1219.198678	2051.236573	1850.486573
CS_6	1930.784719	1528.256329	2018.615044	1834.006093	2660.624901	2465.614232
CS_7	2302.362157	2181.940581	2563.098152	2432.267806	2947.114222	2707.806859
CS_8	1137.250528	1396.896541	1780.957542	1711.818979	1886.901305	1497.118697
CS_9	2211.886189	2151.900653	3496.111945	3250.258396	4228.490812	4297.014697
CS_{10}	1395.503289	1253.178433	1521.501169	1342.022471	1741.338642	1541.407026
Total	**17051.97116**	**15602.30119**	**20571.47107**	**18975.40815**	**24504.75996**	**22685.28**

TABLE VIII. Total time of charging EVs at each CSs in Case E where $\eta_u = 10$ & 12 (minute)

CSs ID	First scenario		Second scenario		Third scenario	
	η_u		η_u		η_u	
	10	12	10	12	10	12
CS_1	3129.436263	3083.942266	3462.292027	3381.059848	3859.115391	3859.124833
CS_2	1254.219562	1222.939124	1447.10629	1450.238559	1713.51112	1803.638444
CS_3	1127.682654	1123.473499	1549.5048	1711.524658	1903.029848	1704.202567
CS_4	1297.453849	1374.07816	1493.08984	1382.053357	1513.397148	1690.162977
CS_5	1265.391947	983.1079562	1239.194264	1231.533765	2051.236573	2038.787622
CS_6	1930.784719	1675.865047	2018.615044	2008.467179	2660.624901	2652.549138
CS_7	2302.362157	2328.27438	2563.098152	2621.24549	2947.114222	2911.251208
CS_8	1137.250528	1489.607598	1780.957542	1540.156533	1886.901305	1589.396339
CS_9	2211.886189	2206.67613	3496.111945	3644.65523	4228.490812	4419.275512
CS_{10}	1395.503289	1401.002234	1521.501169	1508.48174	1741.338642	1733.263897
Total	**17051.97116**	**16888.96639**	**20571.47107**	**20479.41636**	**24504.75996**	**24401.65254**

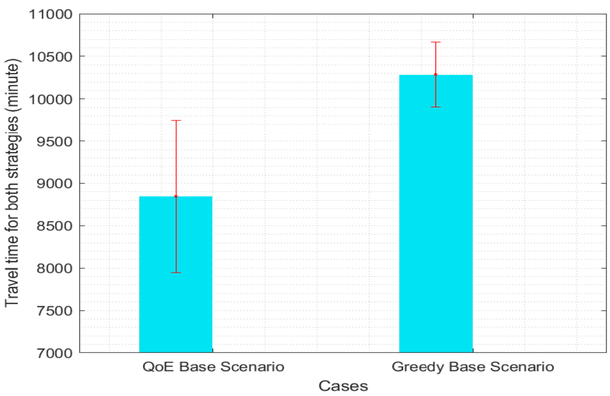

Fig. 15. Comparison between QoE strategy and Greedy strategy in terms of travel time

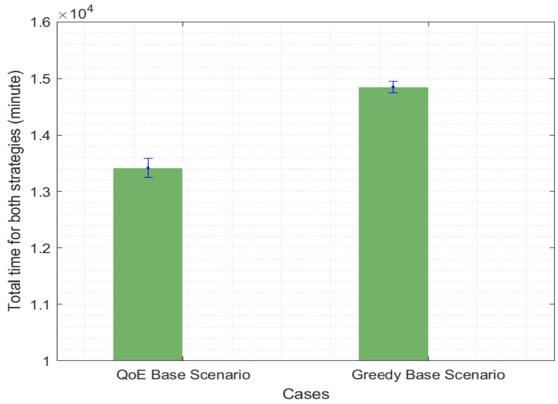

Fig. 16. Comparison between QoE strategy and Greedy strategy in terms of total time of charging EVs

only metric that has been considered is the distance between the EVs and the locations of CSs.

Figs. 17 and 18 show the comparison between the QoE strategy and greedy strategy in terms of the travel time and the total time, respectively, taking into consideration different percentages of the congestion's levels on the roads leading to the charging stations. It is obvious that the total time and travel time in QoE strategy is less compared to the greedy strategy, and the reason behind this is that in addition to the distance between the locations of EVs and CSs, the congestion level has also been taken into account in this strategy. Moreover, it is easy to notice that the relation between both the travel time and total time, and the congestion level is linear. The reason behind this is that the increase of the percentages of the different congestion levels that have been assumed in our experiments is linear.

E. A Comparison between QoE strategy and the Ant Lion Optimizer (ALO) technique

The comparison between the two QoE and ALO strategies was made based on the assumptions that have been proposed in the previous section (Section IV-C). Based on the experimental results, the difference of assigning EVs to the CSs in both techniques is small, and the reason behind this is that the both algorithms was working on assigning EVs to the optimal CSs

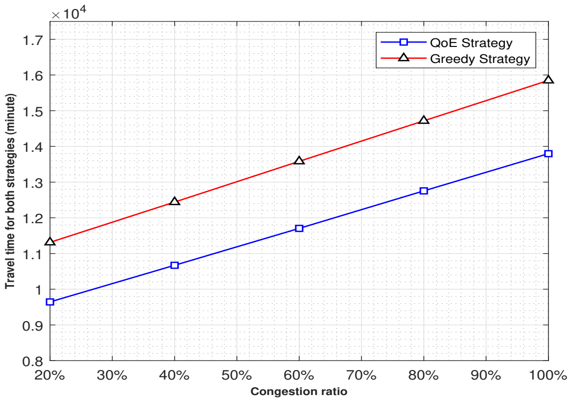

Fig. 17. Travel time required for EVs to reach CSs based on the proposed scenarios taking into account the differences in congestion ratio

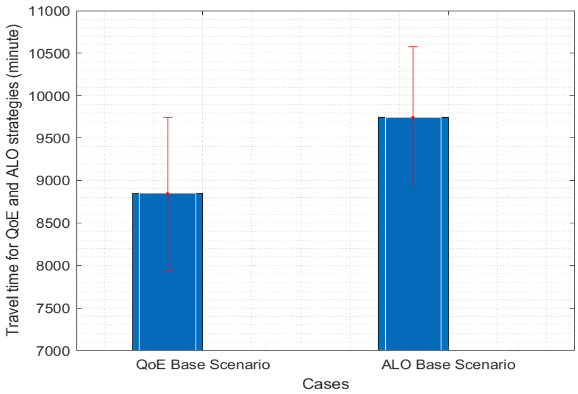

Fig. 19. Comparison between QoE strategy and ALO strategy in terms of travel time

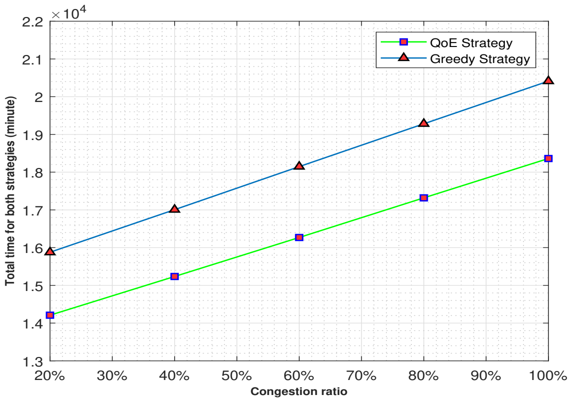

Fig. 18. Total time required to fully charge EVs based on the proposed scenarios taking into account the differences in congestion ratio

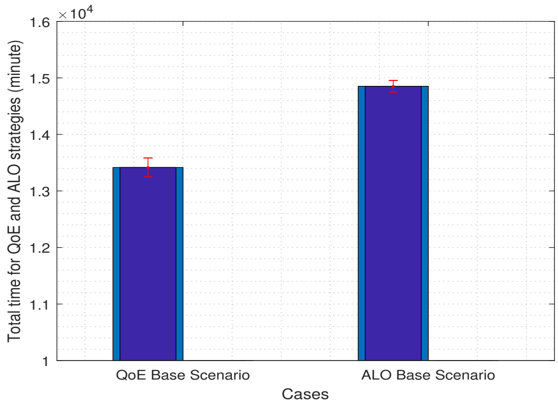

Fig. 20. Comparison between QoE strategy and ALO strategy in terms of total time of charging EVs

in the investigated areas, considering the same parameters and system constraints.

Figs. 19 and 20 show the comparison between the QoE the ALO strategies in terms of the travel time and the total charging time, respectively. It is easy to see in both figures that the travel time and total time have increased in ALO technique, and the reason for this is that the distribution of EVs to the available CSs in the study area using our proposed approach (QoE) is more accurate, which in turn directly affects the travel time and total charging time. Moreover, the ALO suffers from the slow speed of convergence and the local-optima stagnation for particular optimization problems. However, It is obvious that the travel time and total time of assigning EVs to CSs using the ALO is less compared to the greedy technique, and the reason for this is that the ALO considers all the parameters and system constraints, while the greedy technique ignores all of them.

Figs. 21 and 22 show the comparison between the QoE strategy and ALO strategy in terms of the travel time and the total time, respectively, taking into consideration different percentages of the level of congestion on the roads leading to the charging stations. It is easy to see that the total time and travel time in QoE strategy is less compared to the ALO strategy, and the reason behind this is that our proposed approach in more accurate, and also because of the main limitation on the ALO, i.e., slow convergence and local optima stagnation.

V. Conclusion and Future Work

A new optimization model dedicated to the problem of assignment of EVs to CSs in metropolitan environments has been introduced in this paper. The assignment of EVs to the best charging stations has been done considering the EVs user's QoE, in terms of the total completion time of charging EVs in the available CSs in the study area. Travel time towards CSs, travel distance, congestion level on the streets that resulted from both ICEVs and EVs, queuing time at the CSs, required time to fully charge EVs battery, chargers' technology, the maximum capacity of the CSs and the influence of the urban traffic circulation of EVs between adjacent zones have been taken into account in the proposed scheme. In this paper, the assignment problem has been formulated as MINLP problem, this is because the decision of selecting the optimal charging station is directly influenced by

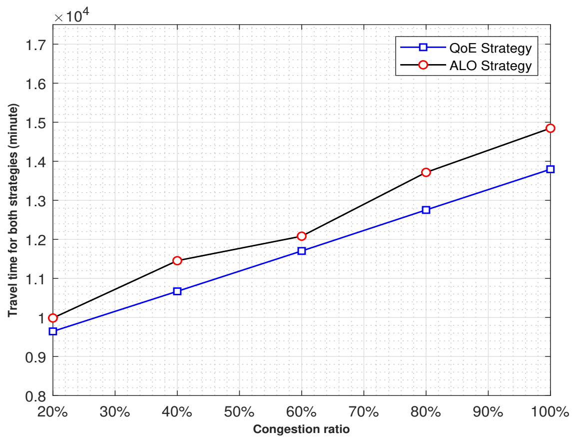

Fig. 21. Travel time required for EVs to reach CSs based on the proposed scenarios taking into account the differences in congestion ratio

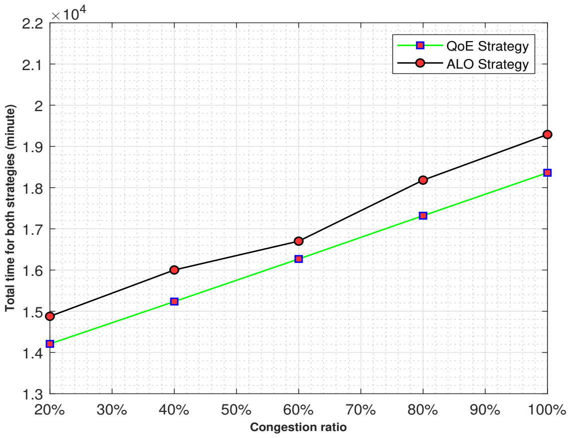

Fig. 22. Total time required to fully charge EVs based on the proposed scenarios taking into account the differences in congestion ratio

the interaction between the EVs and ICEVs in the investigated area. GA technique has been incorporated into this work in order to solve the MINLP problem. Additional metrics and constraints can be incorporated into this approach to determine the optimal assignment of EVs to CSs, such as the difference in elevation between the locations of CSs and EVs, the amount of energy consumption that EVs requires to reach CSs, the charging cost at CSs, etc. The proposed approach has been applied to different cases using real world datasets of Newcastle upon Tyne, United Kingdom. The results demonstrate the significance of the proposed approach. This approach is scalable so can be easily utilized to different geographical areas and different sample size.

More parameters and constraints related to the EVs can be considered in our work in near future. Moreover, deep learning (DL) techniques can also be utilized in order to solve the assignment problem.

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APPENDIX

TABLE IX. Adjacency relations between zones

Zone ID	Adjacent Zones	Zone Port Coordinates	
		Latitude	Longitude
NE1	NE2	54.982939	-1.612724
	NE4	54.975764	-1.626792
	NE6	54.976013	-1.589379
NE2	NE1	54.982939	-1.612724
	NE3	55.001376	-1.619571
	NE4	54.995152	-1.628682
	NE6	54.980327	-1.580731
	NE7	54.997546	-1.593246
NE3	NE2	55.001376	-1.619571
	NE4	54.989936	-1.656745
	NE5	55.00171	-1.667159
	NE7	55.006931	-1.601896
NE4	NE1	54.975764	-1.626792
	NE2	54.995152	-1.628682
	NE3	54.989936	-1.656745
	NE5	54.989939	-1.669187
NE5	NE3	55.00171	-1.667159
	NE4	54.989939	-1.669187
NE6	NE1	54.976013	-1.589379
	NE2	54.980327	-1.580731
	NE7	54.993012	-1.579443
NE7	NE2	54.997546	-1.593246
	NE3	55.006931	-1.601896
	NE6	54.993012	-1.579443

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