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Analysis of an Optimal Planning Model for Electric Vehicle Fast-Charging Stations in Al Ain City, United Arab Emirates

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ABSTRACT For the large-scale promotion of electric vehicles (EV), reliable fast-charging stations (FCS) demand high priority among EV users. However, unplanned locations of charging stations (CSs) and station capacity determination have adverse effects on the operation and the performance of power-distribution network. In this study, we developed an optimal FCS-planning model considering the aspects of EV users' convenience, station economic benefits, the impact on distribution systems and the effect on environment. A queuing-theory-based CS sizing algorithm that benefits EV users as well as improves CS capacity utilization was proposed. The proposed planning model was verified through a case study using real road network data by employing multi-objective binary and non-dominated sorting genetic algorithm. In addition, to evaluate the efficiency of the proposed sizing algorithm, sensitivity analyses for different EV penetration levels and station utilization were conducted. The simulation results show that the proposed CS-allocation model is beneficial in terms of achieving the satisfaction of EV users, cost savings, better station utilization, and less impact on power grids and the environment. Finally, to validate the effectiveness of the proposed planning model, a comparative study with one of the previous work on CS planning is also performed. The results demonstrate that the proposed charging station sizing method is highly efficient in optimizing EV users' satisfaction and for better station utilization.

INDEX TERMS Distribution network performance, environmental impact, fast charging station, optimal planning, queuing theory, station utilization.

NOMENCLATURE

CONSTANT PARAMETERS

B_{dr}	EV Battery Discharge Rate
B_{tc}	Maximum capacity of EV Battery
C_{ele}	Unit cost of electricity
P_{rated}	Rated power of a charger
SoC_{cri}	Minimum limit of state of charge
$SoC_{\max}$	Maximum limit of state of charge
P_{tow}	Price of hiring a tow truck service
N_{EV}	Total number of electric vehicles(EV)
$N_{\max}^{CS}$	Maximum allowable number of chargers at a station
A_c	Land area for one charger
C_{fixed}	Fixed cost of one charging station
AEF_{EV}	Average emission factor of the electric vehicle fuel mix
AEF_{ICEV}	Average emission factor of the gasoline/ diesel fuel
FE_{EV}	Fuel economy of an EV
FE_{ICEV}	Fuel economy of the internal combustion engine
η_{grid}	Efficiency of transmission/ distribution network
$\eta_{charger}$	EV charger efficiency
μ	Mean service rate at a station
λ	Average arrival rate

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$\rho_{\max}$	Maximum utilization rate
$W_t^{\max}$	Maximum waiting time
w_i	Weighting coefficient of objective function i

VARIABLES

$T_{\min}^i$	Minimum time for an EV to reach charging station i
$D_{\min}^i$	Minimum distance for an EV to reach station i
C_{access}^i	Station access cost
C_{land}^i	Land cost for charging station i
c^i	Number of chargers in station i
$c_{\min}^i$	Number of chargers in station i
$C_{operation}^i$	Operational cost of station i
$C_{installation}^i$	Installation cost of station i
N^{CS}	Number of selected charging station
ρ^i	Utilization rate of station i
β^i	Number of busy chargers at station i
P_0^i	Probability that station i is empty
P_{loss}^{base}	Base value of power loss
EP_{loss}^{CS}	Extra power loss
VSI^{CS}	Voltage stability index of charging station
VSI^{base}	Base voltage stability index
$\|V_i\|$	Voltage magnitude of "from" bus i
P_j	Real power of "to" bus j
Q_j	Reactive power of "to" bus j
R_i	Resistance of branch i
X_i	Reactance of branch i
$g_{i,j}$	Conductance of branch i–j
θ_i	Voltage angle of bus i
$V_i^{\min}$	Minimum value of bus voltage
$V_i^{\max}$	Maximum value of bus voltage
CE_{EV}	Total CO_2 emission from an EV

I. INTRODUCTION

Over the past decade, electric vehicles (EVs) have gained wide recognition in the international automobile market owing to their indispensable role in mending our planet toward a sustainable low-carbon future. According to the International Energy Agency, road vehicles accounted for 75% of the total CO_2 emissions of the transportation sector, which was 15% of the total global CO_2 emissions in 2018 [1]. In view of this fact, global stakeholders have fostered policies for promoting sustainable EV transportation as a mitigation measure for ceasing the greenhouse gas emissions of vehicle fleets. As the United Arab Emirates (UAE) is one of the most active and flourishing vehicle markets in the world, UAE energy strategy 2050 aims to develop a feasible environment in terms of air quality and increased reliance on clean energy by 2050 [2]. In this context, the UAE government has taken many initiatives to attract the public to use EVs, such as free assigned parking spaces, exemptions from electric vehicle registration and renewal fees, and setting up publicly accessible electric vehicle charging stations (CSs) across the country [3]. A previous study indicated that the availability of publicly accessible recharging points [4], particularly fast-charging stations (FCS), is the most important aspect concerning the widespread adoption of EVs owing to the range and charging anxieties of users. Besides, randomly positioned FCSs adversely affect the operation and configuration of power-distribution systems in terms of increased power losses, power quality decline, and voltage instability; this eventually requires distribution network upgrading [5]. The impact is severe in the case of level 3 fast charging, as more power is drawn from electrical grids compared with level 1 and level 2 charging [6]. Therefore, when designing an optimal planning model, a comprehensive study of the different factors influencing the allocation of CSs is essential for estimating the charger capacities and locations of CSs.

There are several important decision-making factors related to CS planning, such as impact on power and transportation systems, economic benefits, user convenience, and environmental concerns. Reference [7] investigated the factors influencing the CS planning and established a weight coefficient for each factor using the analytic hierarchy process (AHP). Their results showed that grid power loss and traffic congestion are key factors affecting the locations and capacities of CSs. Based on this, reference [8] proposed a multi-objective planning model that considered EV traffic flow and a power-distribution system for optimal CS placement in the city of Ontario and solved using multi-objective evolutionary algorithm (MOEA).This model could effectively reduce the power loss, voltage deviation, and travel distance to a CS. Similarly, a coordinated planning strategy for a coupled power-distribution system and transportation system that simultaneously minimize grid power losses and maximize EV traffic flow was presented [9] to determine the location and sizing for FCSs. The simulation results of these studies [8], [9] showed that transportation and distribution are two conflicting systems and that the power loss increases with an increase in EV traffic flow because more charging infrastructures would be needed to satisfy the charging demand. Reference [10] considered transportation cost, station build up cost, and grid power loss cost particularly harmonic power loss for optimal allocation of FCSs in a city of Malaysia, and solved using binary lightning search algorithm (BLSA). Some studies have evaluated the impact of fast charging on power-distribution networks in terms of the power loss and decline in voltage profile [11], [12]. Moreover, [13] critically assessed how the EV penetration levels affect distribution networks from the aspects of network investment and energy loss. Their study showed that with 60% penetration, the investment cost and power loss increased up to 15% and 40%, respectively, in off-peak hours. From the aforementioned studies, it can be concluded that if CSs are not properly allocated, the connection of EVs with distribution networks poses serious problems.

Nevertheless, most of the above-mentioned studies neglected significant aspects related to charging processes, such as the recharging time and waiting time, which may lead to station congestion. EV users expect FCSs to provide a function similar to that of traditional gas stations. However, charging consumes more time than refueling. This may result in station congestion and long waiting times, which can cause discomfort to EV users [14]. Various queuing theories have been employed to model the uncertainties associated with EV charging processes, with the M/M/c queuing model being the most widely accepted model. Reference [15] modeled a FCS as M/M/c queue for estimating the EV charging demand taking into account the EV traffic flow and real road network in New York city, while [16] adopted M/M/c queuing to predict the waiting time for station capacity optimization in the context of Guwahati city, India. Both studies [15], [16] assumed the EV charging time as a random variable. However, a more sophisticated approach was presented by [17], in which the charging time estimation considered the charging power and the arrival/departure SoC of an EV. In this study, FCS was modeled as a multi-class M/G/s queuing network, in which the waiting time was computed by considering the charging requirements for different EV models popular in the Spanish market. To ensure maximum customer satisfaction [18], [19] used the queuing theory to determine the optimal CS capacity that guarantee minimum waiting time for EV users. These studies highlighted the CS congestion issues from the perspectives of EV users. However, none of them discussed how the CS infrastructure could be optimally utilized during charging.

Some studies [20]–[22] analyzed the placement of CSs from the perspective of the economic benefits associated with CSs and the operational costs of power grids. Reference [20] developed an economic planning model for a coupled distribution and transportation network that considers the investment costs, substation costs, and the power loss costs associated with site selection for CSs. In addition, their model took into account the uncertainty of distribution networks in regard to estimating the charging load demand. Reference [21] developed an incentive policy for EV users to manage the EV charging process and proposed an optimal EV charging infrastructure planning model using genetic algorithm. In a related work, a cost-based model was presented in [22] to determine the CS locations and sizes using particle swarm optimization. The authors considered the minimization of the demand response cost, investment cost, and power loss cost as objective functions. However, they ignored the range anxiety concern and waiting time constraints affecting the convenience of EV users. Reference [23] formulated a bi-level CS-allocation model to maximize the station investment benefits while guaranteeing the satisfaction of EV users in regard to fast-charging service. Their study considered power flow and voltage limit as constraints for maximizing the investment benefits.

In addition to these factors, only a few studies optimized station locations from the perspective of sustainability. Reference [24] employed a fuzzy TOPSIS indexing method to allocate optimal CSs in Beijing city with priority given to the environmental impacts caused by CS installation, including vegetation losses, water destruction, and greenhouse gas (GHG) emissions.

From the above discussions, it is evident that past studies mostly focused on one or two factors such as technical performance of distribution networks [8]–[10], [16] benefits of EV users [17]–[19], [23] CS cost-effectiveness [20]–[23] and environmental impact [24]. However, in real-life scenarios, each of these factors is crucial when designing a CS placement model. In most of the previous studies, the sizing of CSs was optimized by taking into account the impact of EV charging on the power grid or waiting time of users in station. For instance, if too many fast chargers are built to minimize waiting time, FCS owners may face underutilization issues. Therefore, for station capacity optimization, the waiting time for EV users must go hand in hand with the utilization of CSs. To the best of our knowledge, no study has determined the station capacity in terms of CS utilization. Meanwhile, a similar study has not been conducted in the context of the UAE. Currently, over 300 CSs are available in different areas of the UAE. However, most of them are slow CSs that require excessive time for charging, which makes them inconvenient for most EV users. Therefore, a novel approach for the optimal placement and sizing of FCSs is urgently required in order to minimize the grid impact, environmental impact, and station economic burden while maximizing EV user satisfaction and station utilization. In this regard, the main contributions of this study can be summarized as follows:

1. This study introduces a multi-objective planning model for a FCS that addresses various aspects, such as the convenience of EV users (minimizing the CS accessibility and queuing time), station economy (minimizing the investment and operational costs), CS efficiency (maximizing the CS utilization), technical performance of distribution networks (minimizing the power loss and improving the voltage stability), and environmental impact (minimizing CO_2 emissions) simultaneously.
2. We develop a queuing algorithm to determine the optimal CS capacity that is beneficial for EV users as well as improving the efficiency of CSs, leading to minimum waiting time and maximum CS utilization.
3. Finally, the station-planning methodology is optimized using multi-objective (Pareto and scalarization based) binary genetic algorithms and is tested on the UAE road network. A larger number of EVs are expected to ply on the roads of the UAE in the future.

The rest of this paper is organized as follows. Section II addresses the main factors affecting CS planning. Then, in Section III, the design steps of CS sizing based on the queuing model are presented. Next the required Pareto and scalarization based multi-objective optimization functions for the placement problem is formulated in Section IV.

Sections V details the input parameters utilized to perform the case study in the city of Al Ain, UAE. Section VI analyze the performance of the proposed CS model under various circumstances. Finally, Section VII presents the conclusions of this study.

II. FACTORS AFFECTING THE LOCATION AND SIZING OF FCS

In the present work, four important factors, i.e., EV user convenience, CS economic benefits, distribution network technical performance, and environmental impact, were considered for optimizing the CS allocation model. The EV user convenience was measured in terms of the minimum travel time to access the CSs, whereas the distribution network technical performance was analyzed in view of real power loss reduction and voltage stability improvement. The environmental impact associated with the CS planning was related with the GHG emission reduction, particularly the CO_2 gas produced during EV usage.

A. EV USER CONVENIENCE

EV users always prefer the best route to access a CS. For most individuals, the best route would be one with the shortest travel time rather than the shortest distance from the origin to the destination point. Besides, the travel time can be more important for users, as EVs consume a considerable amount of ancillary energy for air conditioning and battery thermal management. Therefore, it is necessary to minimize the travel costs incurred in reaching CSs, which are based on the access time required to reach the CSs. In this work, access time (T_a) estimation was actualized using the Google Maps Distance Matrix application programming interface (API), which is a Google Maps service that provides travel distance and access time information for an origin–destination (EV location–CS location) pair while taking into account real-time road traffic data [25]. The estimated access time can be expressed as

$$T_a = \begin{bmatrix} T_{11} & T_{12} & \cdots & T_{1N_{CS}} \\ \vdots & \vdots & \vdots & \vdots \\ T_{N_{EV}1} & T_{N_{EV}2} & \cdots & T_{N_{EV}N_{CS}} \end{bmatrix} \tag{1}$$

$$T_{\min} = \begin{bmatrix} \min(T_{11}, T_{12} \cdots T_{1N_{CS}}) \\ \vdots \\ \min(T_{N_{EV}1}, T_{N_{EV}2} \cdots T_{N_{EV}N_{CS}}) \end{bmatrix} \tag{2}$$

Each row in the access time matrix (T_a) expressed in (1) provides the estimated time for an EV from a certain position to reach different CSs. Further, each row in the $T^i_{\min}$ matrix given by (2) represents the minimum time for an EV i to access the nearest CS. To predict how much longer a battery can continue to perform before it needs recharging, SoC estimation is essential. This helps EV users to foresee if a vehicle will switch off in the middle of a driveway before reaching a CS owing to lack of power. In such circumstances, the vehicle needs to be towed to the nearest CS, and the cost will depend on the towing distance.

Therefore, the estimated SoC to reach the nearest CS, SoC_{CS} can be stated as [10]

$$SoC_{CS} = SoC^i_{ini} - B_{dr} \times \frac{T^i_{\min}}{B_{tc}} \tag{3}$$

where SoC^i_{ini} denotes the initial SoC at the EV origin. In this study, the initial SoC was assumed to be a randomly distributed value that varies within 20%–80%. To extend EV battery life, SoC of less than 20% (SoC_{cri}) is not recommended during travel. B_{dr} is the battery discharge per unit time, and B_{tc} is the maximum battery capacity of an EV model. For simplicity, in this study, only one type of EV model, i.e., Nissan Leaf, with a 24-kWh battery was considered for analysis.

The station access cost (C^i_{access}) for an EV is represented as

$$C^i_{access} = C_{ele} \times B_{dr} \times T^i_{\min} \tag{4}$$

where C_{ele} is the per unit cost of electricity. Once SoC_{CS} is lower than the critical SoC (SoC_{cri}), an EV user has to depend on a tow truck service to pick up their EV to the nearest station. Furthermore, the cost for an EV j that cannot reach a CS when SoC_{CS} is less than SoC_{cri} can be expressed as

$$C^j_{tow} = P_{tow} \times D^j_{\min} \tag{5}$$

where $D^j_{\min}$ is the distance from the EV location to the nearest CS and P_{tow} is the price of hiring a tow truck service.

Therefore, the objective function for minimizing the total travel cost that sums up the station access cost and cost associated with the tow truck assistance can be expressed as

$$f_1 = \sum_{i=1}^{m} C^i_{access} + \sum\nolimits_{j=m-N_{EV}}^{N_{EV}} C^j_{tow} \tag{6}$$

B. STATION ECONOMIC BENEFITS

The initial investment required for CS setup and operation costs is the main contributor that affects station economy. To design an optimum CS location and sizing, it is necessary to minimize these costs. Both the installation and operational costs are a function of the number of fast chargers installed. The initial installation cost also depends on other costs, such as the fixed cost, land cost, and costs of other auxiliary equipment. The fixed cost represents the cost associated with the basic machinery and equipment necessary to establish a CS. The land cost for each station can vary depending on the site chosen for CS placement. In this work, we assumed that the installation of new EV charger equipment requires an area of 25 m^2 (A_c) with a clearance of 1 m between the chargers. The other auxiliary cost refers to the costs of essential equipment, such as distribution transformers and power cables, which are needed to set up a CS. Therefore, the overall installation cost of one CS can be expressed as

$$C^i_{installation} = C_{fixed} + (A_c C^i_{land} + C_{ch} P_{rated}) c^i + C^i_o \tag{7}$$

In (7), C_{fixed}, C^i_{land}, C_{ch}, and C^i_o denote the fixed cost, land cost, charger cost, and other auxiliary costs of the i^{th} CS, respectively. Here c^i represents the number of fast chargers equipped in a CS i, and P_{rated} indicates the rated power of a fast charger.

The operational cost depends on the cost of electricity per unit and the power demand at each CS. The expected power demand at a CS can be evaluated by multiplying the rated power of the charger and the expected number of busy chargers. The evaluation of the power demand from the queuing model makes the system more realistic, as some chargers may be idle in the off-peak hours. The mathematical formulation is explained in Section III.

$$C^i_{operation} = C_{ele} \times P^i_d \tag{8}$$

$$P^i_d = P_{rated} \times \beta^i \tag{9}$$

where β^i denotes the expected number of busy chargers in the CS 'i'.

Therefore, the objective function for minimizing the total station costs for all CSs can be expressed as

$$f_2 = \sum_{i=1}^{N_{CS}} (C^i_{installation} + (C^i_{operation}) \tag{10}$$

To meet the EV charging demand, at least one CS needs to be installed in the considered area, as described in (11).

$$0 < N^{CS} \leq N^{CS}_{\max} \tag{11}$$

where N^{CS} and $N^{CS}_{\max}$ represent the number of selected and candidate CSs, respectively.

C. TECHNICAL PERFORMANCE OF THE DISTRIBUTION NETWORK

The planning of CSs needs to consider reliable power delivery from power-distribution networks. Fast charging usually has a negative impact on power flow, voltage profile, and voltage stability [11], [26]. EV charging usually draws real power from electricity grids. Hence, in this work, two technical performance indicators, i.e., the real power loss index and voltage stability index were considered to minimize the effect of EV penetration on radial distribution systems.

1) POWER LOSS

A sample radial distribution system with one branch and two nodes is shown in Fig. 1. The total real power loss of the distribution system can be calculated by summing the power losses in all the branches, as given in (12). The power flow is computed using backward and forward sweep load flow [27] because the radial system has a high R/X ratio:

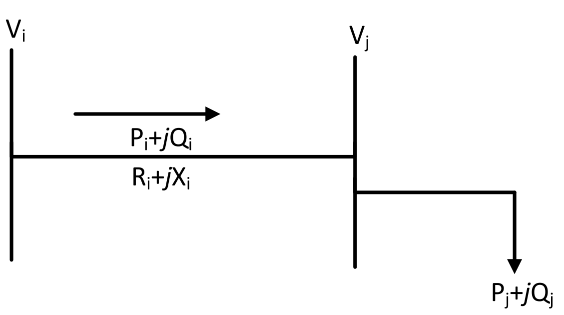

FIGURE 1. **Sample radial distribution system.**

$$P_{loss} = \sum_{\substack{i,j=1 \\ i \neq j}}^{n} g_{i,j}[V_i^2 + V_j^2 - 2V_iV_j\cos(\theta_i - \theta_j)] \tag{12}$$

where

$g_{i,j}$ Conductance of branch i–j
n Number of transmission lines
θ_i Voltage angle of bus i

Once the EV starts recharging, the power loss of the bus to which the FCS is connected increases, which creates extra power loss from the distribution system. Therefore, the active power loss index can be defined as the ratio of the extra real power loss occurring because of all the CSs to the actual power loss before the CSs are installed.

Therefore, the objective function for minimizing the active power loss can be expressed as

$$f_3 = \frac{EP^{CS}_{loss}}{P^{base}_{loss}} \tag{13}$$

where EP^{CS}_{loss} and P^{base}_{loss} denote the extra power loss values after the FCS allocation and the power loss before the CS allocation, respectively.

2) VOLTAGE STABILITY

Since fast charging severely affects voltage stability, it is essential to identify the optimal location and capacity for FCSs based on the voltage sensitivity. Voltage sensitivity index (VSI) is a parameter used for investigating the voltage stability of each bus in a distribution system. Under stable operating conditions, the VSI of each bus should be less than unity. A bus having a small VSI is called a weak bus. Conversely, a bus with a high VSI is less prone to voltage instability. Hence, VSI should be maximized to avoid voltage collapse in any system.

According to Fig. 1, the VSI at bus j can be calculated using (14) [28]:

$$VSI_j = |V_i|^4 - 4(P_jX_i - Q_jR_i)^2 - 4(P_jR_i + Q_jX_i)^2\,|V_i|^2 \tag{14}$$

where

$|V_i|$ Voltage magnitude of "from" bus i
P_j and Q_j Real and reactive power of "to" bus j
R_i and X_i Resistance and reactance of branch i

The objective function proposed in this work for minimizing the VSI, as defined in (15), is

$$f_4 = 1 - \frac{\sum_{j=2}^{N_{bus}} VSI^{CS}_j}{\sum_{j=2}^{N_{bus}} VSI^{base}_j} \tag{15}$$

Meanwhile, to maintain the voltage within standard limits, the acceptable voltage margins for every single bus are as follows:

$$V_i^{\min} \leq V_i \leq V_i^{\max} \tag{16}$$

D. ENVIRONMENTAL IMPACT

Compared with vehicles that run on gasoline or diesel, EVs have near-zero tailpipe emissions. However, their upstream emissions, which mainly come from the electrical energy consumed during the EV charging phase, cannot be neglected. In this context, it is important to consider the reduction of CO_2 emissions as an objective while determining the optimal CS location.

The carbon emissions related to EV charging mostly depend on two important factors: EV on-road energy consumption and the type of fuel mix used for electric power generation. Previous studies have proved that power plants fed by fossil fuels such as coal and natural gas have a higher CO_2 emission rate than renewable energy sources such as wind and solar energy [29]. Apart from the EV fuel consumption and fuel mix used for generation, such emissions also depend on other factors such as the losses associated with the transmission and distribution of electricity to the charging points of EVs and the efficiency of chargers. In light of these aspects, a mathematical formulation for estimating the total CO_2 emissions of an EV to travel from the EV origin to the CS destination can be computed as [30].

$$CE_{EV} = \frac{AEF_{EV} \times FE_{EV} \times D_i^{\min}}{\eta_{grid} \times \eta_{charger}} \tag{17}$$

where AEF_{EV} represents the average emission factor of the fuel mix, which is measured in kilograms of CO_2 emitted per kilowatt hour of electricity generated. FE_{EV} denotes the fuel economy of an EV, which characterizes the amount of energy consumed in kWh to travel a distance of 100 miles (kWh/100 mile). $D_i^{\min}$ denotes the distance corresponding to the minimum travel time for an EV i to reach a CS. In addition, η_{grid} represents the efficiency of the transmission/distribution network, which accounts for the energy lost during the electricity pathway from the generation point to the EV charging point. $\eta_{charger}$ denotes the charger efficiency, which takes into account the losses associated with the AC/DC converter in the EV charger.

Therefore, the objective function for minimizing the CO_2 emissions while charging an EV in a CS is defined as

$$f_5 = \sum_{i=1}^{N_{EV}} CE_{EV}^i \tag{18}$$

where CE_{EV}^i denotes the carbon emission for an EV i.

Furthermore, to investigate the environmental benefits of an EV with reference to internal combustion engine vehicles (ICEV), the emissions associated with the usage of ICEV for traveling the same distance as with an EV is calculated as

$$CE_{ICEV} = \frac{AEF_{ICEV} \times k \times D_i^{\min}}{FE_{ICEV}} \tag{19}$$

where AEF_{ICEV} represents the average emission factor of gasoline/diesel fuel, which defines the amount of CO_2 emitted per gallon of fuel burned; k represents the upstream emission factor, which defines the additional emissions associated with the production and processing of fuel; and FE_{ICEV} represents the fuel economy of the ICEV. Unlike EVs, the fuel economy of an ICEV is measured as the distance traveled for a gallon of fuel consumed (MPG), while the fuel economy of EVs is expressed as the fuel consumed for a fixed distance (kWh/100 mile). Finally, the difference between (17) and (19) provides the emission savings achieved by the electrification of vehicles.

III. CS SIZING BASED ON THE QUEUING THEORY

A CS can be considered a queuing system in which customers are represented by EVs, where reception corresponds to charging devices and providing service means charging. When an EV arrives at a station, if no charging devices are available, queuing and waiting occur, which frustrates EV drivers and creates congestion in the station. Thus, the proposed model adopts M/M/c queuing theory to determine the optimal number of chargers, that minimize the waiting time and ensure average station utilization [31].

Here the first M in the M/M/c queuing indicates inter arrival time of EV to the CS, that follows exponential distribution with mean time λ. The second M means the charging service time that follows an exponential distribution with mean rate μ and c denotes the number of chargers at the CS.

In order to characterize EV arrival and charging time, exponential distribution is considered here because of the following reasons. Firstly, in this work, EVs are exponentially distributed in the real road network and therefore we assume that EVs arrive at a CS randomly and is independent of each other. Moreover, the arrival rate to a CS was predicted by estimating EV traffic flow, initial SoC of the battery, maximum battery capacity and battery discharge rate. As mentioned in section II, the initial SoC is a random variable.

Secondly the charging time of EVs is also uncertain because charging duration of EVs is determined by different factors such as battery state of charge (initial and final), required charging level, and EV battery-charging characteristics. Therefore both the arrival and charging time are Poisson process. A Poisson process is a stochastic process, where the average time between events is known, provided that the exact timing of events is random.

With the above assumptions and criteria, the charging time required for an EV can be calculated from the piecewise linear SoC curve shown in Fig. 2. During the fast-charging process, the charging power typically starts at a high rate and then drops off as the battery SoC approaches its full capacity. As shown in Fig. 2, during charging, an EV attains SoC of 50% in the initial 10 minutes (min) and 75% in the next 5 min (15 min in total). Afterward, there is a drop in the charging rate. Note that battery full charge is achieved in the next 35 min (60 min in total), which is really time consuming. Therefore, to save time, we assume that all customers charge

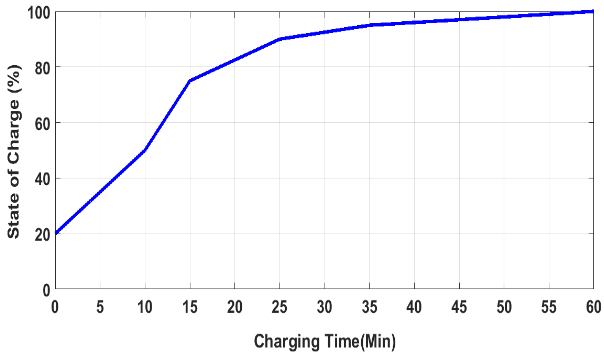

FIGURE 2. Fast-charging characteristics of an electric vehicle.

their EVs till an SoC of 85% is attained (SoC_{max}), which is the maximum possible value during a fast-charging session, and the rest of the charging can be done using an onboard charger at home.

Once the charging time is obtained, the number of EVs that can be served per unit time in a CS can be computed, and this defines the mean service rate (μ).

Based on the information on the EV arrival to a CS, the minimum number of chargers required in the i^{th} CS ($c^i_{\min}$) can be computed as

$$c^i_{\min} = \frac{\lambda^i \times c_{\max}}{N_{EV}} \tag{20}$$

where λ^i is the arrival rate at the i^{th} CS, $c_{\max}$ is the maximum allowable number of chargers, and N_{EV} is the total number of EVs considered for the FCS-planning model.

The minimum number of chargers ($c^i_{\min}$) calculated from (20) should meet the maximum utilization condition given by (21). If the initial chargers cannot satisfy the condition, the number of chargers is incremented until the utilization condition is met. Fig. 3 illustrates a flow diagram for obtaining the optimal sizing of FCSs as a queue model.

$$\rho_{\max} > \frac{\lambda^i}{c^i \mu} \tag{21}$$

Here, $\frac{\lambda^i}{c^i \mu}$ refers to the station utilization factor, i.e., it describes how well the CS i is utilized, which is denoted as ρ^i. This value depends on the arrival rate of EVs at a CS and the departure rate of EVs from the CS. Likewise, $\frac{\lambda^i}{\mu}$ denotes the expected number of busy chargers at a CS, and it is denoted as β^i. A high value of β^i indicates that most chargers are busy at all times.

The average number of EVs waiting in a queue for service is given by

$$L^i_q = \frac{(\rho^i c^i)^{c^i+1} \times P^i_0}{(c^i - 1)!(c^i - \rho^i c^i)^2} \tag{22}$$

where

$$P^i_0 = [\sum_{n=0}^{c-1} \frac{(\rho^i c^i)^n}{n!} + \frac{(\rho^i c^i)^c}{c^i!} \times \frac{1}{(1-\rho^i)}] \tag{23}$$

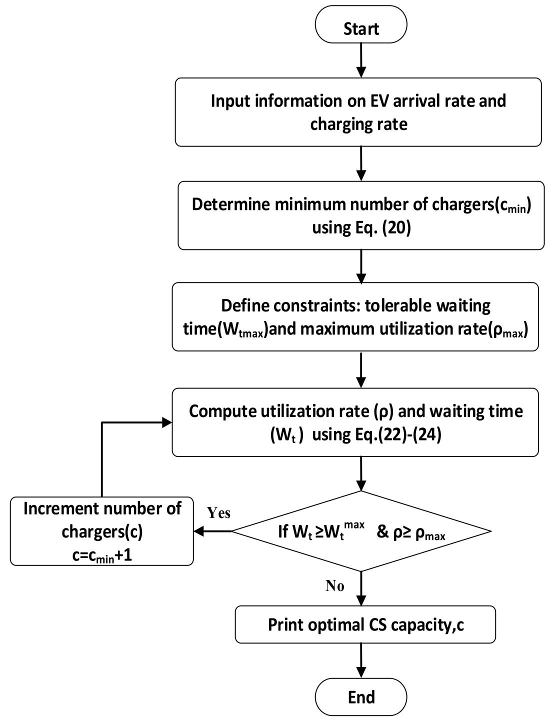

FIGURE 3. Framework for optimal charging station sizing.

In the above expressions, P^i_0 denotes the probability that CS is empty, with no EVs waiting for service. Therefore, the average waiting time for an EV user in the i^{th} CS can be formulated as

$$W^i_t = \frac{L^i_q}{\lambda^i} \tag{24}$$

To ensure adequate service quality for EV users, the waiting time should not exceed the tolerable waiting time $W_t^{\max}$ as expressed below:

$$W^i_t \leq W^{\max}_t \quad i = 1, 2, \ldots\ldots N^{CS} \tag{25}$$

IV. PROBLEM FORMULATION

In the present study, problem of identifying the optimal location and sizing of FCSs was developed considering various aspects, including the benefits of EV users, technical factors such as power loss and voltage stability, economic factors, and environmental factors. The FCS placement problem is formulated as follows. The location of charging station is considered as the decision variable in the model. Here the decision variable is a binary vector that contains n bits of 0s and 1s, where n represents the number of candidate charging station locations. A '1' in the binary vector indicate the presence of a CS in that location and '0' indicate no CS at that point. The CS decision variable, N can be expresses as

$$N = [l_{cs1}, l_{cs2}, l_{cs3} \ldots\ldots l_{csn}] \tag{26}$$

where l_{cs} indicates the charging station location.

In order to attain the optimal charging station location and capacity, the model has multi-objective functions to be minimized simultaneously. The objective functions of the planning model includes EV user travel costs (f_1), total station cost (f_2), power loss index (f_3), voltage stability index (f_4) and CO_2 emission (f_5). The formulation of objective functions and the constraints are detailed in sections II and III.

Since the present work solves the multi-objective CS allocation problem using two approaches, i.e. scalarization and Pareto based methods, the multi-objective functions can be expressed as follows.

$$F = w_1 f_{1n} + w_2 f_{2n} + w_3 f_{3n} + w_4 f_{4n} + w_5 f_{5n} \tag{27}$$

$$F = \min(f_1 + f_2 + f_3 + f_4 + f_5) \tag{28}$$

Subjected to constraints defined in (11), (16), (21) and (25).

Eqn. (27) represents multi-objective function corresponding to the weighted sum method. In the weighted sum method, the objective functions are summed up with varying weighting coefficients and this sum is optimized as a single objective function. Here a single optimal solution that simultaneously satisfies all the objective functions is obtained. In Eqn. (27) w_i denotes the weighting coefficient and f_{in} denotes the normalized objective function value where $i = 1, 2 \ldots 5$.

The selection of weighting coefficients depends on the importance given to a particular objective function and to ensure consistency for all objective functions, it is necessary to normalize these functions such that they have a value between 0 and 1. The normalized objective function is given by

$$f_{in} = \frac{f_i}{f_i^{\max}} \tag{29}$$

where $f_i^{\max}$ represents the maximum value of the function.

Eqn. (28) represents pareto based multi-objective function for the CS location and sizing problem. In this approach, a set of solutions known as Pareto-optimal solutions are obtained that satisfies all the objective functions, in which each solution obtained is unique and does not dominate over other solution.

A. OPTIMIZATION TOOLS

In the present work, binary genetic algorithm (BGA) was used to find the optimal solution for the FCS-planning model. The BGA is a stochastic search algorithm based on the

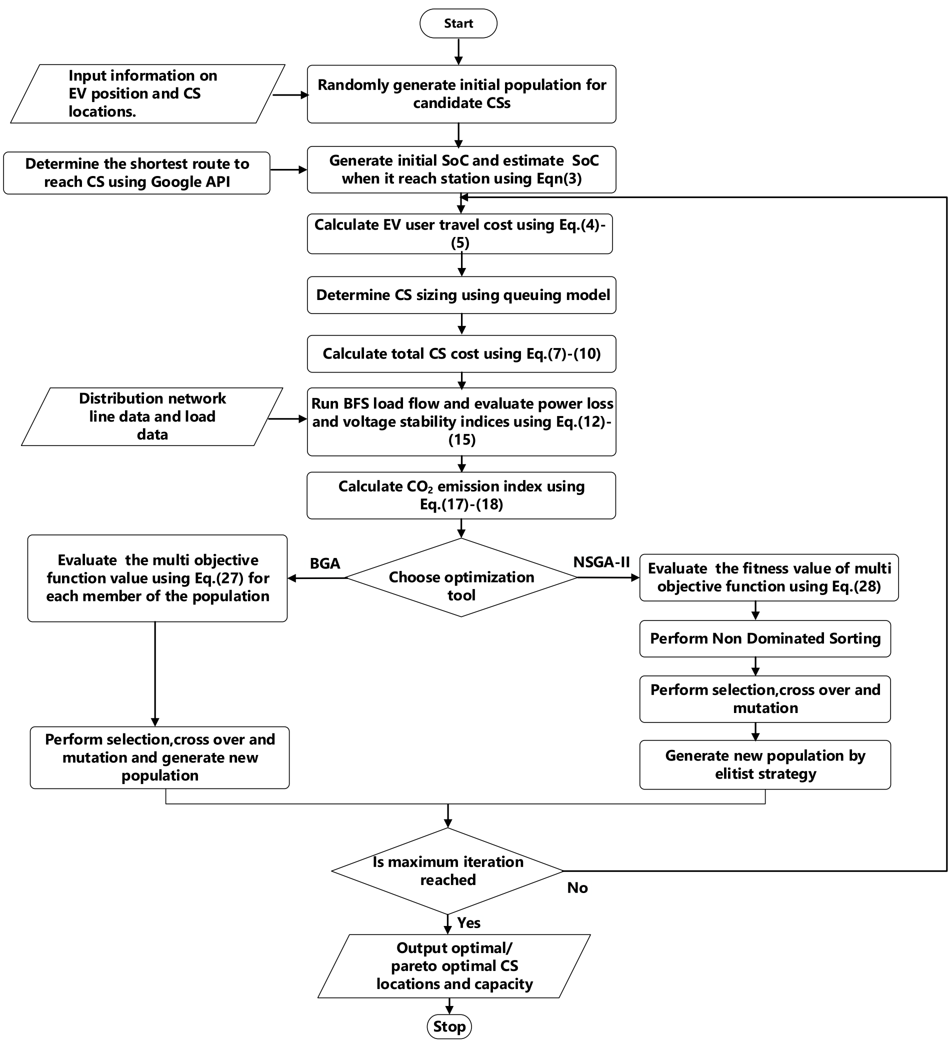

FIGURE 4. Framework for optimal CS allocation using BGA and NSGA-II.

concept of natural selection and genetics [32]. In the past, many authors have applied BGA for optimal sitting and sizing of EV CSs because of its ability to deal with both continuous and discrete variables and with linear and nonlinear objective functions compared with other evolutionary techniques [33]–[35]. For this reason, the proposed CS planning model chose BGA to solve the multi-objective optimization problem.

In order to compare the performance of CS planning model in multi-objective scenario, the problem is also solved using non dominated sorting GA (NSGA-II) [36]. NSGA-II is a prominent, fast sorting and elite multi-objective genetic algorithm. Unlike the single objective optimization technique like BGA, NSGA-II simultaneously optimizes each objective without being dominated by any other solution and provides multiple Pareto-optimal solutions in one single simulation run. A detailed description of BGA and NSGA-II are provided in references [33] and [36] and interested readers are encouraged to refer the above references.

Fig. 4 shows a flowchart for choosing the optimal location and capacity of EV CSs using BGA and NSGA-II. As described in Fig. 4, an initial population is randomly generated in which each individual in the population contains candidate CSs. Each individual represents the decision variable N defined in Eqn. (26). Once the CS locations are selected, the objective functions values are evaluated, and the station capacity is determined using the queuing algorithm shown in Fig. 3. Using the multi-objective function defined in Eqn. (27) and (28), individual fitness values are computed for BGA and NSGA-II accordingly. In NSGA-II, an additional process of non-dominated sorting is performed, where the crowding distance of individuals were calculated and sorted according to the crowding distance. Then, to obtain the new population set, the processes of selection, crossover, and mutation are performed in both optimization algorithms. However in NSGA-II, in addition to these procedures, elitist preservation strategy is used to create the next generation. The objective function evaluation process is continued until an optimal solution is obtained. Unlike BGA, NSGA-II outputs a set of pareto solutions instead of a single solution where the output corresponds to optimal CS location.

V. TEST SYSTEM

To verify the effectiveness of the methodology discussed in Section II and III, the CS model was tested for the city of Al Ain, UAE. Of the many gas stations exist in the city, 18 were chosen as candidate sites based on their potential charging demand. Fig. 5 shows the Al Ain city map with the candidate locations for the placement of the EV CSs; the study area is divided into different regions (R_1, R_2, R_3, R_4, and R_5) based on the population density. Accordingly, EVs are randomly distributed depending on the population density, as shown in Fig. 6. We assumed that there are more EVs in densely populated areas of, and hence greater charging demand. Then, the travel time data from the EV location to the CS were recorded using Google Distance Matrix API. Thus, the

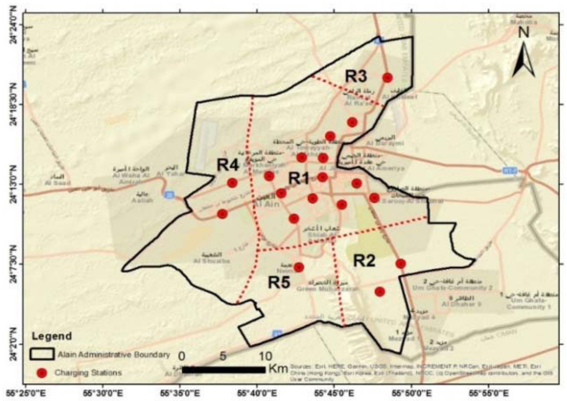

FIGURE 5. CS locations in different regions of the studied area.

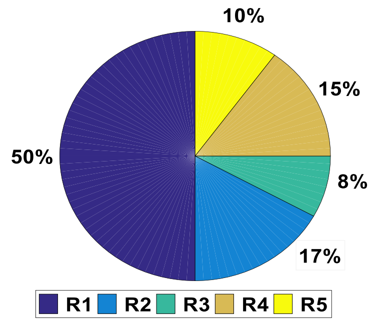

FIGURE 6. Regionwise distribution of the EV population in the studied area.

essential inputs needed to design the CS planning model were obtained; the parameters used for designing the proposed CS model are given in Tables 1, 2 and 3. Table 1 contains

TABLE 1. Electric-vehicle (EV)-related parameters.

Definition	Notation	Value
Number of EVs	N_{EV}	100
Battery discharge rate (kW/h)	B_{dr}	5.24
Maximum battery capacity(kWh)	B_{tc}	24
Critical value of EV SoC for charging	SoC_{cri}	0.2
Maximum SoC during charging (%)	$SoC_{\max}$	0.85
CO_2 emission factor of fuel mix ($kgCO_2$/kWh)	AEF_{EV}	0.47
Fuel economy of EV (kwh/100 mile)	FE_{EV}	30
Grid efficiency (%)	η_{grid}	92.98
Charger efficiency (%)	$\eta_{charger}$	95
CO_2 emission factor of gasoline (kg/gallon)	AEF_{ICEV}	8.887
Upstream emission factor	k	1.25
Fuel economy of ICEV (MPG)	FE_{ICEV}	35.5

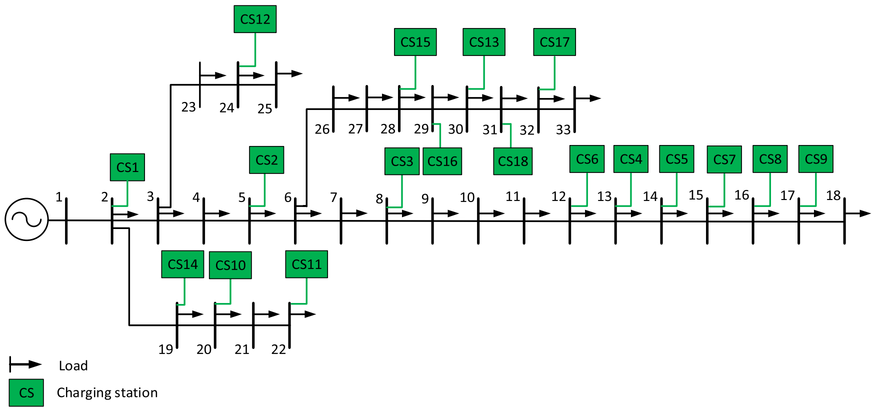

FIGURE 7. Single-line diagram of the test distribution system.

TABLE 2. CS-related parameters for the optimization.

Definition	Notation	Value
Fixed station cost (\$/station)	C_{fixed}	100
Land cost per unit area (\$/m^2)	C_{land}	15–55
Unit charger cost (\$/kW)	C_{ch}	0.06
Auxiliary cost per station (\$/station)	C_o	1000
Maximum number of stations	$N^{CS}_{\max}$	18
Maximum station utilization (%)	$\rho_{\max}$	85
Station service rate (EVs/h)	μ	4.5
Rated power of EV charger (kW)	P_{rated}	50
Electricity price for charging (\$/kWh)	C_{ele}	0.08
Maximum voltage limit (V)	$V^{\max}$	1.05
Minimum voltage limit (V)	$V^{\min}$	0.9

TABLE 3. Optimization tool design settings.

Definition	GA	NSGA-II
Maximum number of iterations	30	100
Population size	20	200
Mutation probability	0.05	0.05
Crossover probability	0.6	0.6

EV-related data, and the necessary data associated with the stations is listed in Table 2. To perform the CS allocation optimization problem, Table 3 lists the parameters related to BGA and NSGA-II algorithms.

Figure 7 shows a single-line diagram of the test distribution system with CSs connected to various buses. The total real and reactive power loads of the system before connecting the CSs were 3715 kW and 2300 kVAR, respectively, and the base case power loss was found to be 176.36 kW. The base values were $S_{\text{base}} = 1$ MVA and $V_{\text{base}} = 12.66$ kV.

VI. RESULTS AND DISCUSSION

The proposed algorithm for the optimal CS model was simulated using a BGA in a MATLAB environment. To evaluate the impact of CS installation in the studied area the simulation results were analyzed from the perspectives of the EV user satisfaction, economic benefits, technical performance of power grid, and environmental impact. Moreover to compare the performance of solution obtained from BGA, the CS model is also optimized using NSGA-II and the simulation results are compared in Table 4.

TABLE 4. Optimal CS-allocation scheme for the base case.

Optimal Solution	BGA	NSGA-II
Location	1,11,12,14	3,6,10,11,14,16
Size of CS	4,5,12,7	9, 3, 4, 5,5,5
User travel cost,f_1(\$)	8.5	7.68
Station cost,f_2(\$)	158663	288255
Avg. waiting time (min)	6.16	4.77
Avg. Station Utilization(%)	79.15	71.54
Extra power loss (kW)	31.65	57.63
Power loss (%)	17.94	32.67
Min. VSI	0.716	0.708
Total emissions(kgCO_2eq)	91.89	88.87
CO2 savings (kgCO_2eq)	86.34	83.51

A. BASE CASE STUDY

In this case, the optimum location and capacity were determined using the multi-objective function defined in (27).

All the five objective functions were given equal priority. Thus, the weighting coefficient (w_i) for each function was distributed as given below:

$$\sum_{i=1}^{5} w_i = 1 \tag{30}$$

$$w_1 = w_2 = w_3 = w_4 = w_5 = \frac{1}{5} \tag{31}$$

Fig. 8 summarizes the contribution of each objective function in determining the optimal sizing (capacity) and location of the CS for the base case study.

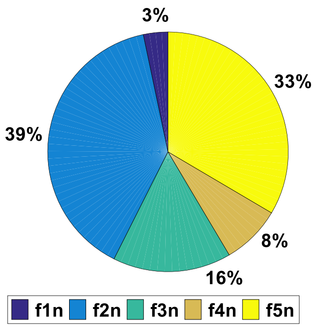

FIGURE 8. Contribution of objective functions in the base case study using GA.

It can be noted that among the five objectives, function f_{2n}, which is related to the station investment and operation cost, has the highest share (39%) of the total function value. This implies that the station cost is the most significant factor in the CS location decision-making process. The objective function f_{5n} indicates that the CO_2 emission reduction accounts for 33% and also plays a major role. The CO_2 emission from the EVs has a linear relationship with the CS location. As the distance from the EV to the destination CS increases, the emissions rapidly increase. Similarly, the objective functions f_{3n} and f_{4n} also have a notable share of the total function value, where f_{3n} and f_{4n} correspond to the total power loss and voltage stability index, respectively. However, f_{1n} which reflects the EV user travel cost, only contributes 3% of the total function value. This confirms that most EV users can access CS quickly. For example, according to (4), the lower the CS access time, the less is the EV user travel cost. The above results affirm that economic factors and environmental aspects mainly govern the optimal location and sizing problem.

Fig. 9 illustrates the frequency distribution of EVs with respect to the time taken by the EVs to reach CSs, obtained from BGA. The histogram reveals that 67% of the EVs can reach the CSs within 15 min, and only 5% of the EVs take more than 30 min to access the CSs, which in turn results in less travel cost.

Table 4 shows the optimal solutions obtained for the proposed CS planning model. For comparing the performance of proposed model under different optimization methods,

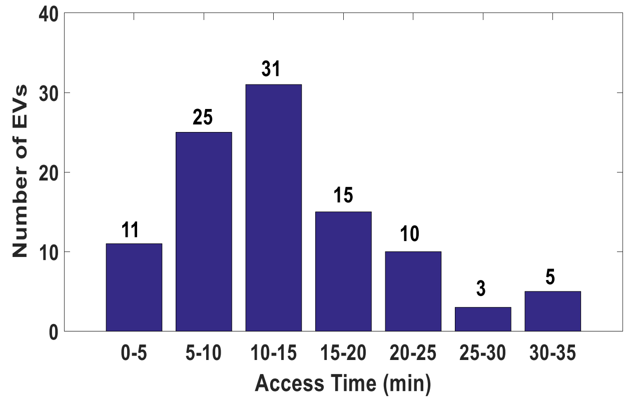

FIGURE 9. CS access time frequency distribution.

the problem is solved using both BGA and NSGA-II. Here, NSGA-II algorithm generated 3 non dominated optimal solutions. Since each of the solution is unique in nature, the decision maker finds difficult to choose the best compromise solution from the Pareto optimal set. Therefore in this work, a fuzzy set based approach is used to obtain the best compromise solution [37]. In the fuzzy decision making, each objective has an associated membership function and the solution that scores highest membership function value in the fuzzy set is chosen as the best solution. The best solutions obtained using BGA and NSGA-II is given in Table 4.

Using BGA, stations 12 and 14 located in region R_1, station 1 in R_2, and station 11 in R_5 were chosen as optimum locations with 12, 7, 4, and 5 chargers, respectively. Using NSGA-II, six charging station locations, namely stations 3, 14, and 16 in region R_1, station 6 in R_3, station 10, and 11 in R_5 were selected with 9, 3, 4, 5,5, and 5 chargers respectively. As expected, in both the solutions, R_1 has the highest priority for building a CS because of its high population, followed by R_2, R_3 and R_5. The station plan obtained using BGA has the station cost and travel cost as 158663 $ and 8.53 $ respectively. Whereas the optimum values of station cost and travel cost obtained using NSGA-II were 288255 $ and 7.68 $ respectively. In terms of station economic benefits, CS plan associated with BGA is the best whereas plan obtained using NSGA-II is best from EV users' point of view. However, the average waiting time obtained using BGA and NSGA-II is 6.16 min and 4.77 min respectively, which is not too long.

Such a planning model is expected to encourage more users to replace their conventional vehicles with EVs. Furthermore, the CS utilization in both the solutions was at an appreciable level of more than 70%, and the CS plan associated with BGA had the maximum, with the highest utilization rate being 79.15%. Fig. 10 illustrates the EV arrival rate for the CS plans given in Table 4. In the optimal plan obtained using BGA, station No.12 is the most engaged CS, as it serves 43 EVs per hour with 12 fast chargers resulting in better system utilization while keeping the waiting time minimum. Similarly, station No.3 is the busiest CS that serves 27 EVs per hour with 9 chargers, in the optimal plan obtained using

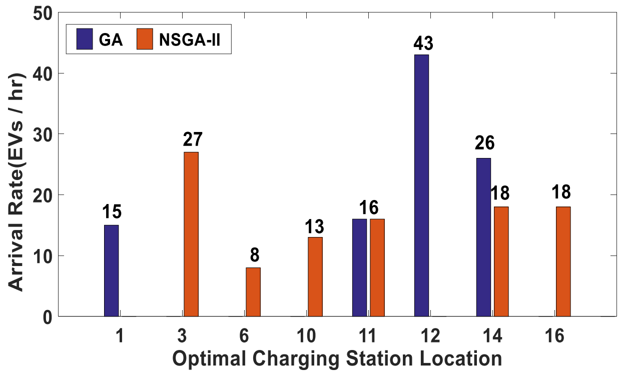

FIGURE 10. EV arrival rate for the base case study using GA and NSGA-II.

NSGA-II. These results verify that the proposed algorithm accurately determines the station capacity to balance the station utilization rate and waiting time, thereby benefiting both EV users and the CS owner.

In view of the technical performance of the distribution system, additional power loss occurred after the CS placement was 31.65 kW, which accounted for 17.94% of the initial power loss, implying that this BGA based CS model can be implemented without performing any network reconfiguration. The power loss associated with NSGA-II based CS plan was 51.63 % which accounted for 32.67% of the initial power loss. As seen from the power loss value and the voltage stability index value, BGA based plan is more acceptable than NSGA-II based plan. Fig.11 depicts the voltage profile of the buses for the optimal CS plans given in Table 4. The voltage profiles for both the plans are within the voltage limits defined in the optimization problem.

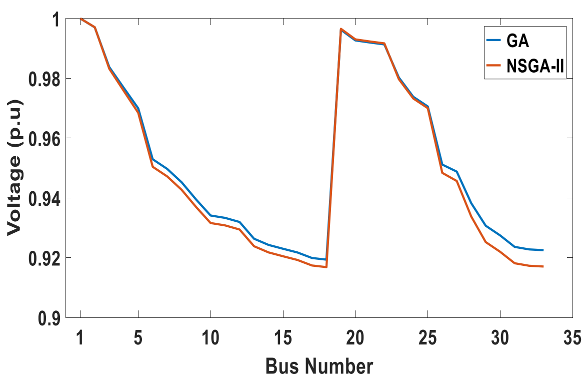

FIGURE 11. Bus voltage profile obtained for the base case study.

In terms of environmental impact associated with CS positioning, the amount CO_2 emitted from all the EVs were 91.89 kg CO_2/h for the BGA based plan. However, to travel the same distance, the emission from the ICEV was 178.23 kg CO_2/h, which is nearly two times higher than that of the optimized CS plan. A similar trend can be observed for the NGSA-II based plan. In addition, the emission savings by the use of EVs over conventional ICEVs are advantageous for the promotion of CS installation.

In general, the results indicate that the performance of the proposed CS model is acceptable from the aspects of EV user comfort, station economic benefits, power grid technical performance, and CO_2 emission reduction.

B. SENSITIVITY ANALYSIS

To assess the effect of variation of the input parameters on the performance of the proposed CS model, a sensitivity analysis was performed on the queuing model attributes, i.e., EV arrival rate (λ^i) and utilization factor ($\rho_{\max}$). Two scenarios were considered. In scenario 1, the EV arrival rate at each station was varied by increasing the number of EVs (N_{EV}) distributed in the road network, while in scenario 2, the utilization constraint increased upon holding other parameters, which is the same as in the base case study. The sensitivity analysis on queuing attributes is again optimized using multi-objective NSGA-II.

1) SCENARIO 1: EFFECT OF THE EV ARRIVAL ON THE CS PERFORMANCE

Here, two cases were studied with the following numbers of EVs $N_{EV1} = 200$ EVs/h and $N_{EV2} = 300$ EVs/h. Correspondingly, $\lambda^i_{N_{EV1}}$, $\lambda^i_{N_{EV2}}$ were modified. The effect of increasing the EV arrival rate for the optimal locations and sizing obtained from the base case was then analyzed. As the number of EVs arriving at each station increased, the number of optimal chargers attained in the base case could not meet the growing charging demand. Consequently, the queuing length became infinite, and hence the system sizing became unacceptable. In such circumstances, many EVs get rejected as the queue length increases beyond the station capacity. Fig. 12 shows the frequency of the EVs that get rejected at each station as the arrival rate increases to 200 and 300 EVs/h. Therefore, it is mandatory to re-optimize the problem to find the optimum locations and sizing that favor EV users, the station economy, distribution network performance, and CO_2 emission reduction.

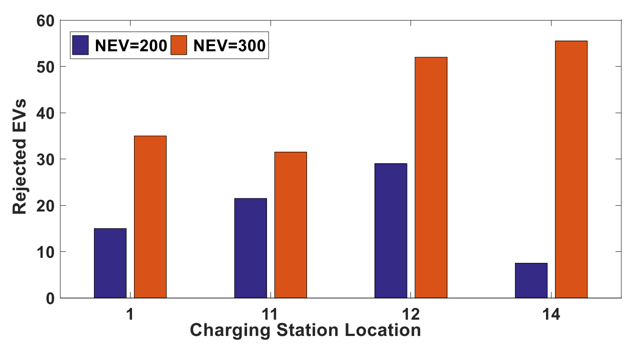

FIGURE 12. Number of EVs rejected from the selected CSs.

Fig. 13 illustrates the objective function values for cases 1 and 2 after re-optimizing using BGA. The figure shows that

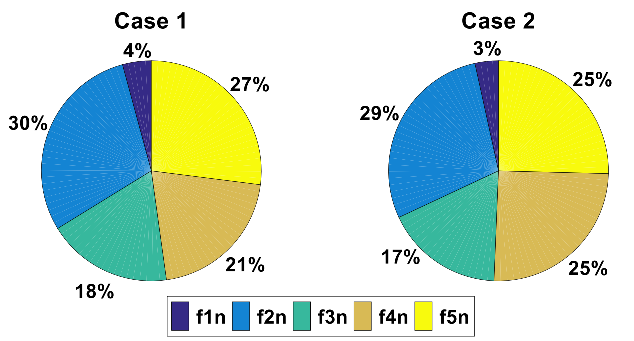

FIGURE 13. Variation of the objective function values under different EV arrival rates.

the value of the station cost function (f_{2n}) decreases as the number of EVs increases, which indicates that when the charging demand increases, the technical performance function (f_{3n} &f_{4n}) becomes more significant in the CS allocation problem. In cases 1 and 2, the power loss index and voltage stability functions together accounted for approximately 38% and 42%, respectively, which is much higher than that of the base case study (25%).

Table 5 presents the performance of the optimum CS allocation obtained using BGA under scenario 1, in comparison with the base case model, revealing the effect of the EV arrival rate. From the results, we can observe that as the EV arrival rate increases, the size of the CS has a general increasing trend with a slight variation in the CS location. Consequently, the average waiting time decreased to 2.77 and 2.45 min in cases 1 and 2, respectively, ensuring better service to EV users. Furthermore, the average station utilization was slightly improved to 79.72% and 80.38% in comparison with the station utilization in the base case. This result further highlights the relevance of the proposed approach in designing the optimal sizing of CSs from the aspect of EV users and station efficiency.

In terms of technical performance, the total real power loss increased to 96.33 kW and 135.67 kW, which are 54% and 76% of the initial power loss for cases 1 and 2, respectively. Moreover, the minimum voltage of the distribution network was within the acceptable limit for both cases, even though a slight drop occurred with respect to the base case study.

Concerning the environmental aspect, the CO_2 emission positively increased with the increase in the EV arrival rate. Compared with the base case, the total emissions in case 1 were two times higher, but case 2 did not follow a trend similar to that of case 1. For example, the emission rate in case 2 was less compared with that in case 1. This is because in case 2, the number of CSs increased from four to six, so that most of the EVs could reach the station in a short distance. Furthermore, as the EV penetration increased, the CO_2 emission savings owing to the electrification of vehicles increased according to Table 5. Such results provide valuable insights into emission reduction, which can be achieved by the proper installation of CSs.

Table 6 presents the optimum CS plan obtained using NSGA-II. Similar to the plans obtained in BGA, the power loss and CO_2 emission increases with the increase in the EV arrival rate but worse than BGA based plan. Besides, the average station utilization was improved to 79.23% and 80.72% in comparison with the station utilization in the base case plan obtained from NSGA-II. Thus we can conclude that solutions obtained by BGA are more acceptable for the EV users and in terms of technical performance of power network.

2) SCENARIO 2: EFFECT OF STATION UTILIZATION RATE ON CS PERFORMANCE

To further understand the importance of the utilization rate on the CS sizing, the maximum utilization constraint ($\rho_{\max}$) was varied from 0.85 to 0.95. The optimal number of chargers and other CS parameters obtained under this scenario are given in Table 7.

In BGA based plan, the station utilization improved from 79% to 89% compared to the base case plan, and this planning scheme resulted in the best utilization of the chargers, as most chargers are busy at all times. Similarly, in NSGA-II based plan, the station utilization improved from 71% to 86% compared to the base case plan. On the contrary, in both BGA and NSGA-II based plans, EV users have to wait for a long time in the queue, which creates discomfort. Further, from the viewpoint of the distribution network performance, the CS plan obtained by BGA offers the best solution because the power loss is 11.31 kW, which is the minimum value compared with all the optimal solutions discussed in this section. In NSGA-II based plan power loss is more than the base case plan. A similar trend was observed for the CO_2 emissions too. For example, for an increase in ρ by 0.1, the emissions increased by 25.5 kg and 5 kg in BGA and NSGA-II based plan respectively. Therefore, it can be concluded that the increase in the station utilization rate was advantageous from the CS economic aspect, but it negatively affected EV users and the environment. Moreover, the results confirm that both the optimization algorithms, BGA and NSGA-II are capable to solve complex problems on charging station placement and sizing.

Through the above sensitivity study, the impact of the arrival rate (EV penetration) and station utilization on the efficiency of the CS model were clearly evaluated.

C. PERFORMANCE COMPARISON OF PROPOSED CS MODEL WITH EXISTING MODEL

To validate the effectiveness of proposed charging station planning model, its performance was further compared with the LSA based CS allocation method presented in [10]. For both, existing model and proposed model, the simulation parameters and test system were taken similar to the base case study discussed in section VI. The optimum location

TABLE 5. Performance comparison of the base case scenario and scenario 1 using BGA.

Parameters	Base Case(BGA)	Scenario 1	
		Case 1(BGA)	Case 2(BGA)
Optimum location	1, 11,12,14	1, 4, 10, 12, 14	1, 4, 6, 10, 11, 14
Optimum size of CS	4, 5, 12, 7	8, 13, 6, 12, 14	12, 20, 7, 8, 13, 20
Avg. waiting time (min)	6.16	2.77	2.45
Avg. station utilization (%)	79.15	79.72	80.38
Extra power loss (kW)	31.65	96.33	135.67
Power loss percentage	17.94	54.62	76.92
Minimum Voltage (p.u.)	0.9193	0.9192	0.9190
Total Emissions ($kgCO_{2eq}$)	91.89	186.93	233.45
CO_2 savings ($kgCO_{2eq}$)	86.34	175.65	238.75

TABLE 6. Performance comparison of the base case scenario and scenario 1 using NSGA-II.

Parameters	Base Case(NSGA-II)	Scenario 1	
		Case 1(NSGA-II)	Case 2(NSGA-II)
Optimum location	3,6,10,11,14,16	4,6,11,14,18	1, 4, 7,10,14,17,18
Optimum size of CS	9, 3, 4, 5,5,5	15,3,5,23,7	12, 16, 10, 7, 21, 5,8
Avg. waiting time (min)	4.77	4.61	3.1656
Avg. station utilization (%)	71.54	79.23	80.72
Extra power loss (kW)	57.63	117.474	205.72
Power loss percentage	32.67	66.60	76.92
Minimum Voltage (p.u.)	0.9168	0.9182	0.9106
Total Emissions ($kgCO_{2eq}$)	88.87	205.1935	241.25
CO_2 savings ($kgCO_{2eq}$)	83.51	192.815	226.705

TABLE 7. Performance comparison of the base case scenario and scenario 2 using BGA and NSGA-II.

Optimal Solution	Base case (BGA)	Base case (NSGA-II)	Scenario 2(BGA)	Scenario 2(NSGA-II)
Optimum location	1,11,12,14	3,6,10,11,14,16	10,11,14	1,3,11,13
Optimum CS sizing	4,5,12,7	9, 3, 4, 5,5,5	8,5,11	4, 6, 4, 11
Extra power loss(kW)	31.65	57.63	11.31	81.8971
Avg. waiting time(min)	6.16	4.77	13.55	14.5915
Avg. station utilization (%)	79.15	71.54	89.43	86.24
Total Emissions($kgCO_{2eq}$)	91.89	88.87	117.38	94.239
CO_2 savings ($kgCO_{2eq}$)	86.34	83.51	110.31	88.55

and capacity were determined using the multi-objective BGA technique.

Table 8 exhibits the performance comparison of proposed CS model with existing model. As can be seen from the table, the existing model chose less number of chargers in each station without taking into account of charging station congestion issue. For example, the LSA based model chose 7 chargers in station No.12 to serve 35 EVs, thus resulting in long queue and the users has to wait an average of 50 minutes to get charged. Such a long queuing time is not

TABLE 8. Performance comparison of proposed CS model with existing model.

CS Model	Optimal location	Optimal sizing	Arrival Rate(EVs/hr)	Station utilization (%)	Waiting time (min)	Extra power loss(kW)
Proposed	1	4	15	83.33	10.15	31.65
	11	5	16	71.11	3.65	
	12	12	43	79.63	1.96	
	14	7	26	82.54	5.90	
Existing [10]	1	3	11	-	-	32.65
	2	1	1			
	10	3	12			
	11	2	8			
	12	7	35			
	14	5	25			
	18	2	8			

favorable for most EV users. A similar situation can be seen in Station no.14, where 25 EVs are served by 5 chargers which seem impossible. As a consequence, the queue length grows without bound and thus the charging system becomes unstable. From these results, we can conclude that proposed CS sizing algorithm outperforms LSA based method. Furthermore, additional power loss occurred in the existing method is slightly higher than the proposed model, though the number of chargers in each station is less compared to proposed model. This is because, the proposed method estimated CS load based on the concept of busy chargers (β) described in section III whereas existing method considered all the chargers to calculate the power demand in each station. The above comparative study, confirms the efficacy of proposed CS planning model in determining optimal CS placement and sizing that favors EV users, station operators, and distribution network performance.

In summary, the above results of the proposed planning model serve as a foundation for decision makers under different scenarios to implement CSs at any location. Moreover, this study model can provide detailed analyses of the effects of various parameters, such as the EV arrival rate and utilization rate, on the CS placement design from the viewpoint of EV users' satisfaction, CS economy, distribution network operators, and environmental concerns. Furthermore, the optimal station sizing considering the queuing model while taking into account the waiting and CS utilization is more beneficial in terms of the station economy savings and EV users' satisfaction.

VII. CONCLUSION

In the present study, a multi-objective planning model considering distinct factors such as EV user interests, economic benefits, technical merits, and environmental impact was proposed for the optimal allocation of FCSs. A novel queuing algorithm was used to determine the CS sizing that improves the cost savings and simultaneously satisfies EV users by providing acceptable waiting times for recharging EVs. Moreover, to make the planning model more realistic, a real-world road traffic system were used in this study. The simulation results have shown the significance of each factor in determining the optimum CS placement. In addition, the sensitivity analysis of the queuing parameters based on the proposed methodology was also discussed. The result shows that the proposed methodology is efficient in terms of achieving EV user satisfaction with reduced travel costs, and simultaneously the economic benefits of CSs are also realized, with improved CS utilization and without any congestion issue. To confirm the capability of proposed study, a comparative study with the previous work was carried out. The results proved that queuing based charging station capacity planning is essential to ensure adequate service to EV users and in the meantime to utilize the charging facilities efficiently as possible.

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