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RESEARCH ARTICLE

Integrated Multi-Criteria Model for Long-Term Placement of Electric Vehicle Chargers

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ABSTRACT Based on the global greenhouse gas (GHG) emissions targets, governments all over the world are speeding up the adoption of electric vehicles (EVs). However, one of the key challenges in designing the novel EV system is to forecast the accurate time for the replacement of conventional vehicles and optimization of charging vehicles. Designing the charging infrastructure for EVs has many impacts such as stress on the power network, increase in traffic flow, and change in driving behaviors. Therefore, the optimal placement of charging stations is one of the most important issues to address to increase the use of electric vehicles. In this regard, the purpose of this study is to present an optimization method for choosing optimal locations for electric car charging stations for Campus charging over long-term planning. The charger placement problem is formulated as a complex Multi-Criteria Decision Making (MCDM) which combines spatial analysis techniques, power network load flow, traffic flow models, and constrained procedures. The Analytic Hierarchy Process (AHP) approach is used to determine the optimal weights of the criteria, while the mean is used to determine the distinct weights for each criterion using the AHP in terms of accessibility, environmental effect, power network indices, and traffic flow impacts. To evaluate the effectiveness of the proposed method, it is applied to a real case study of Qatar University with collected certain attributes data and relevant decision makers as the inputs to the linguistic assessments and MCDM model. The Ranking of the optimal locations is done by aggregating four techniques: Simple Additive Weighting Method (SAW, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Grey Relational Analysis (GRA), and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE-II). A long-term impact analysis is a secondary output of this study that allows decision-makers to evaluate their policy impacts. The findings demonstrate that the proposed framework can locate optimal charging station sites. These findings could also help administrators and policymakers make effective choices for future planning and strategy.

INDEX TERMS Analytic hierarchy process, charger, electric vehicle, load flow multi-criteria decision making.

I. INTRODUCTION

The future increase in electric vehicles (EVs), as part of sustainability goals, requires effective planning strategies for EV deployment. The success of this transition depends on the ability to provide adequate power to the EVs charging demand. The adaptation of EVs can significantly contribute to reducing CO2 emission levels and can be further enhanced with renewable energy distributed generation and battery energy storage systems. However, the increased demand may cause stress on the power network and may lead to grid instability [1]. Methods of planning for EV charging infrastructure and its charging impact on the electrical network are found in several research papers. For instance, state-of-the-art EV

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TABLE 1. Problem objectives/attributes and solution methods for the EV charging placement problems.

Ref.	Objectives/Site Alternatives								Solution method				
	Economic	Vehicle to grid (V2G)	Technology (solar, storage, renewables, etc.)	Electrical power network	Geographic condition	Point of interests	Environment	Society	Multi-Objective Optimization	Metaheuristic techniques	Hybrid algorithm	Iterative pack-and-cover (IPAC)	Multi-Criteria
[12]	✓									✓			
[13]	✓	✓		✓						✓			
[14]			✓	✓						✓			
[15]	✓			✓	✓					✓			
[16]	✓		✓	✓	✓					✓			
[17]	✓		✓	✓							✓		
[10]	✓				✓		✓	✓					✓
[18]					✓	✓		✓					✓
[19]			✓	✓	✓				✓				
[2]	✓		✓	✓					✓				
[20]	✓									✓			
[21]				✓	✓	✓						✓	
[22]	✓						✓	✓					✓
[23]	✓		✓	✓	✓					✓			

charging technologies, placement and sizing methods, and impacts are reviewed in [1]. Also, other properties of EV chargers such as solar-powered EV chargers and vehicle-to-grid (V2G) technology can increase the benefits of EV chargers by reducing the charging energy burden on the grid and minimizing power losses [2].

The rapid development of EVs is promising that the future of modern transportation will be for EVs. However, the exact time for the full replacement of conventional vehicles is conditional on solving the issues related to charging, safety, and the demand for power which is amplified during the fast charging mode [3]. The most common problem with the implementation of EVs is the late development of EV charging stations (EVCSs) compared with the estimated future demand for the application. Also, installing electric vehicle charging stations in a power system without a suitable framework may cause an undesirable effect on the network performance or user preference because of several reasons. Overestimating the number of EVs can cause grid violations, and underestimation of the number of EVCSs can risk EV users' convenience. Concentrating charging stations in a specific area, from both technical and economic perspectives, can escalate local overloads' risk and business competition.

Higher education is a key contributor to society's efforts in achieving sustainability goals through initiating transformational projects [4]. Universities worldwide are supporting the energy transition to achieve global carbon neutral and are committed to supporting the growth of electric vehicle up take [5]. Many universities worldwide start by initiating electric vehicle infrastructure projects to promote EV adoption in communities [6] and [7]. A survey on preferences of early EV adopters in the EU and the US shows that they are between 18 and 34 of age, are interested in technology, and are well-educated [8] and [9].

In this context, as a means of enabling the deployment of charging stations within universities, this research aims to create an integrated planning model that incorporates the placement of EVCSs within the traffic and power networks. Most of the previous studies have focused on urban as well as city-size projects and have not been applied before for campus EV charging [10]. This will affect the placement problem which depends on the motivation of journeys and also project objectives which are linked to the university's transportation strategy and sustainability goals. Thus, the problem is developed based on campus charging behavior and infrastructures, such as charger locations, parking congestion or utilization, user parking durations, distance from campus gates, existing chargers, walking distances to buildings, bus stops, and cafeteria, which are specific for a campus charging problem. The proposed integrated model follows a multi-level execution of systems including campus EV adoption dynamic system, traffic flow, and power network load flow. The final solution solves the charger placement for different time periods.

A. CHARGER STATION PLACEMENT PROBLEM & OBJECTIVES

The EV charging infrastructure is a complex problem that has been extensively researched in the literature as reviewed in the recent comprehensive study in [11]. The author categorizes the charging station problem under facility location problems (FLP). The studies in the literature covering the FLP problem varied according to the charging demand models, game theory approaches decision variables, uncertainty, time-dependency, and solution methods. Most of the studies either cover the economic costs of the EV charger including the investment, operation, and maintenance costs, Table 1.

The study in [19] optimizes minimizing the investment cost of the distributed power system and its operation while maximizing the annually captured traffic flow considering different types of charging stations. Another study relies on demand response incentives and proposes a cost-based optimization technique [12].

Other solutions cover only the electrical objectives such as line loss reduction. The study in [14] optimizes simultaneously the locations of EVCS and distributed renewable resources (DRRs) considering loss minimization. Another study in [2] considers solar-powered electric vehicle charging stations with a cost function to minimize the power network objectives; voltage variations, stability, and line losses, using different optimization methods. The study did not consider the geographical benefit or traffic density of the selected sites.

The authors of [20] consider the economic benefit in time for the sizing and sitting of EVCs through net present values and lifecycle cost where the model considers the traffic flow and power grid network. Also, a useful charging placement method in [21] considers project budget, charging demand, and station waiting times simultaneously with knapsack packing constraint and a set covering constraint. These studies have a wider range of objectives compared to [20], [12], and [15], but at the same time are including more objectives will make the problem more difficult to solve.

B. EV CHARGER PLACEMENT IN THE LITERATURE

The EV charging station placement solution methods either solve an optimization problem to give an ‘‘exact’’ solution or near the optimal solution ‘‘Heuristic’’ solutions. The approaches consider different sets of decision variables and constraints. Most studies in the literature consider multi-objective optimization methods considering different objectives [12]. Other approaches include Metaheuristic techniques, such as the genetic algorithm used in [13] and [14], particle swarm optimization in [15], and the hybrid optimization algorithm in [16] and [17]. The previous techniques and objectives require modeling real-world systems to predict the required data for optimization. The benefits and drawbacks of the majority of heuristic optimization are the need for a sizable amount of computational and storage resources. This is the biggest obstacle to its application in a real-time setting.

The Multi-Criteria Decision Making (MCDM) is another type of classification for the EV charger placement problem which deals with multiple, complicated and conflicting criteria. The EV charger placement problem is considered a complicated multi-criteria decision-making problem in many studies [10]. According to the literature, there are two types of MCDM problems; the problem can be Multi-Objective Decision Making (MODM) or Multi-Attribute Decision Making (MADM). MODM methods solve for the previously described which involve optimization techniques [12], [10]. While MADM problems reflect the fuzzy nature of real-world problems as opposed to precision and have been seen to be far-reaching in real-life decision-making [18], [19], and [20].

The classifications of MADM studies are based on the different evaluation criteria and the selection method. In [18], the MADM method is used for the placement of EV chargers for mega-size projects such as cities and countries. In a significant number of cases, the problem of charging stations' location is connected with determining their number, taking into account the intensity and motivation of journeys and the technical parameters connected with the process of battery charging. The studies in the literature, therefore, are classified according to their decision objectives or attributes in EV charging placement problems, see Table 1.

In summary, the limitations of the above studies, are clear where MODM methods can cover a fewer number of objectives compared with the MADM methods, in Table 1. For instance, the study in [22] introduces the prospective of sustainability considering economic growth, social development, and environmental protection. Other studies consider the optimum EVCS location combined with photovoltaic (PV) and battery energy storage (BES) [23].

The proposed solution is developed based on campus charging behavior, and accordingly, six objectives are covered; environmental, economic, accessibility, proximity to the user power network, and system reliability, see Figure 1. This paper also investigates the impact of the proposed MCDM method on the power grid and traffic flow over a long-term period for future prediction, which has not been properly addressed in the literature.

The MCM method and normalization techniques both affect the results of the MCDM [24]. We compare the results of 16 case studies which include 4 normalization techniques and 4 MCDM methods. The final ranking is the aggregated solution of all the cases using the Borda method and statistic techniques [25], which are applied to evaluate alternative locations for charging stations of EVs. The challenging issue in MCDM problems is the concern about its reliability for real-world applications as the real data is variable and stochastic. Instead of having a single solution, this paper extends the MCDM problems into a constrained problem which allows the decision-maker predict the long-term impact of their decision. Power system and traffic flow have been applied to the MCDM attribute calculations for model validation and decision-makers evaluations.

The proposed method allows the planner to set different constraints and for the decision maker to select the final plan based on the long-term output of the suggested technique. The MCDM techniques have not been applied for EVCSs placement for campus size over long-term analysis. It allows us to determine interdependency among the criteria/factors and reflect relative relationships within them [31]. In the proposed methodology, the MCDM has been used to evaluate criteria weights in the decision process by utilizing these pairwise comparisons.

C. CONTRIBUTION AND ORGANIZATION

With the motivations stated above, this paper proposes a long-term planning model which integrates the MCDM methodology consisting of the decision-making model, analytic hierarchy process (AHP), load flow, and spatial and traffic flow models, to optimally locate campus charging

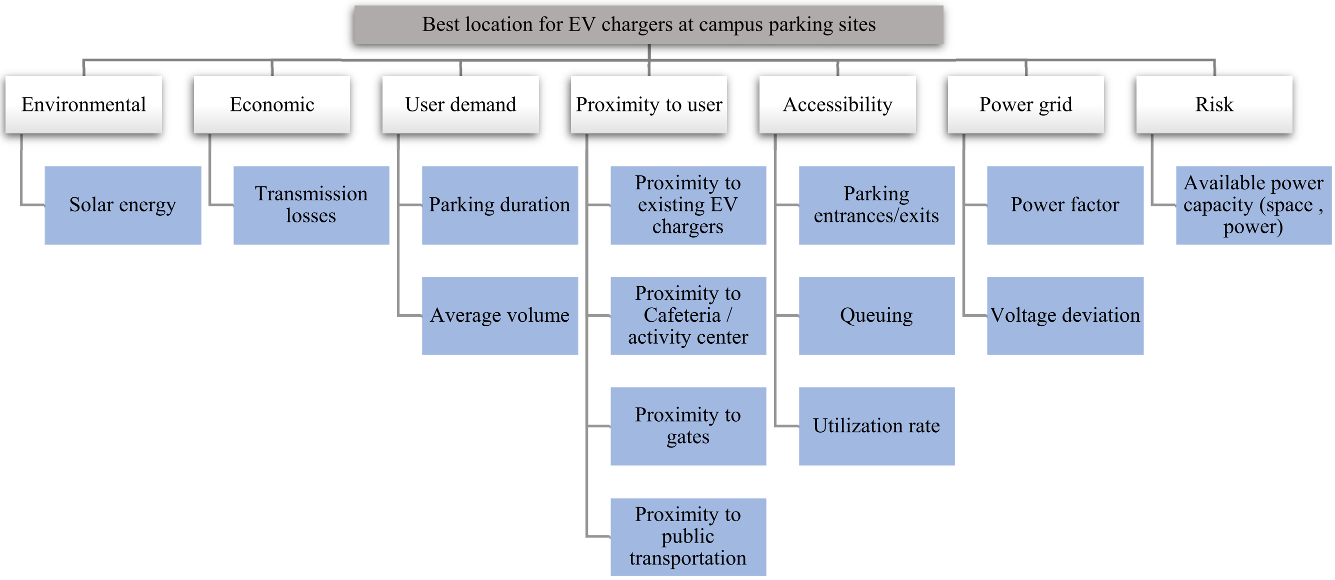

FIGURE 1. Objectives of the proposed EV placement problem specific for campus EV chargin.

stations for EVs over a long-term project. This research aims to develop a novel optimization technique for searching the optimal placement of these required chargers over the potential location. The problem considers the limitation of the number of parking slots, power system capabilities and constraints, extra driving costs, solar energy potential, location attractiveness, and traffic congestion. The main goal of this research is to address the staging plan of EV deployment at a campus by determining the best locations for EV chargers every year, taking into account multiple objectives. The secondary goal of this study is to evaluate the impact of EV charger installation on both the traffic flow and the power network. Finally, to determine the factors that may have a significant impact on the total decision of charging station placement, we conducted a sensitivity analysis on the constraints and found that the site selection is very sensitive to the traffic flow and policy constraints.

The main contributions of this study are threefold:

1) Formulating the dimensions affecting the placement decision problem for EV charger placement for campus EV chargers.
2) The placement problem model is integrated for long-term prediction where the traffic and power network models are interdependent and are re-evaluated every year after each charger placement solution for impact analysis and traffic flow prediction.
3) A real-life case study for Qatar University is chosen as a validation for this research, and the linguistic assessments of actual decision-makers are inputs to obtain the weights of this problem.
4) Demonstrate the potential advantages of the proposed EVCS site selection framework in analyzing policy impact on the placement problem through simulation.

II. PROBLEM FORMULATION

This paper takes into account the predicted number of chargers at a campus and then determines the best locations for the EV chargers every year. The solution to the placement problem is to find the ranking of the potential locations, which is the primary research question of this paper, see Figure 2. The secondary results include the impact effect of the charger installations on both the transportation and power network over the years.

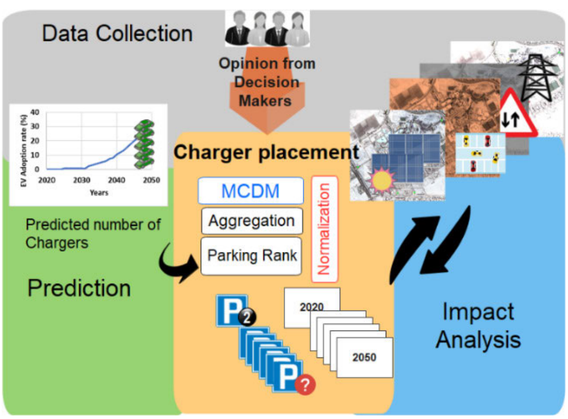

FIGURE 2. Illustration of the problem and proposed framework.

Figure 3 illustrates the building blocks used in solving the charger placement problem. This study takes into account site properties which are the decision criteria, defined in Figure 1; environmental, economic, accessibility, user demand, proximity-to-user, power grid, and risks. Then different multi-criteria methods are followed to rank the EV charger potential locations, which are; Simple Additive Weighting (SAW); Technique for Order Preference by

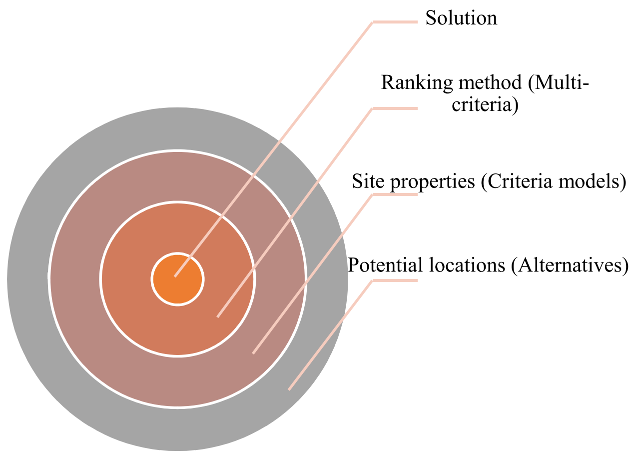

FIGURE 3. **The EV charger placement problem.**

Similarity to the Ideal Solution (TOPSIS); Grey Relation Analysis (GRA): Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE). This section defines the aggregation models and sub-models involved in obtaining site properties and the final solution.

A. AGGREGATION MODELS OF ALTERNATIVES

This study presents several important methods that have more high potential for solving decision-making problems in the production environment:

1) SIMPLE ADDITIVE WEIGHTING (SAW)

SAW chooses the alternative A_i^* with the maximum weighted average outcome [25]. The Performance indicator Q_i of the i-th alternative, in (1), was determined as the entire standardized estimations of the attributes r_{ij} with the weight w_j of the j-th criteria:

$$Q_i = \sum\nolimits_{j=1}^{n} w_j \cdot r_{ij}, \tag{1}$$

where $\sum_{j=1}^{n} w_j = 1$ and r_{ij} are the normalized values of the decision matrix.

2) TOPSIS (TECHNIQUE FOR ORDER OF PREFERENCE BY SIMILARITY TO IDEAL SOLUTION)

TOPSIS determines the performance indicator of the i-th alternative Q_i, a homogeneous function by (2) to (5);

$$Q_i = \frac{S_i^-}{S_i^+ + S_i^-}, \tag{2}$$

where,

$$v_{ij} = r_{ij} \cdot w_j,\ S_i^+ = d(v_{ij}, v_j^+),\ S_i^- = d(v_{ij}, v_j^-), \tag{3}$$

$$v_j^+ = \{\max_i v_{ij} \left| if\ j \in C_j^+;\ \min_i v_{ij} \right| if\ j \in C_j^-\}, \tag{4}$$

$$v_j^- = \{\min_i v_{ij} \left| if\ j \in C_j^+;\ \max_i v_{ij} \right| if\ j \in C_j^-\}, \tag{5}$$

S_i^+ and S_i^- are the distances d between the ideal and anti-ideal objects respectively. Whereas, the alternative A_i in the n-dimension attributes space, is defined in one of the L_p-metrics. The TOPSIS ranking result depends on the choice of distance metric.

3) GRA (GREY RELATION ANALYSIS)

GRA evaluates the effectiveness of alternatives in two groups with respect to ideal and anti-ideal objects. The sequence of calculations is as follows:

Step 1: Define two sets of attributes i.e., ideal and anti-ideal, by (6);

$$r_j^{(1)} = \begin{cases} \max\limits_i (r_{ij}), & if\ j \in C_j^+ \\ \min\limits_i (r_{ij}), & if\ j \in C_j^- \end{cases},$$
$$r_j^{(2)} = \begin{cases} \min\limits_i (r_{ij}), & if\ j \in C_j^+ \\ \max\limits_i (r_{ij}), & if\ j \in C_j^- \end{cases} \tag{6}$$

Step 2: Determine the matrix of deviations of normalized values from the ideal and anti-ideal, by (7);

$$V_{ij}^{(1)} = \left| r_j^{(1)} - r_{ij} \right|, \quad V_{ij}^{(2)} = \left| r_j^{(2)} - r_{ij} \right| \tag{7}$$

Step 3: Determine the matrices and the gray relational coefficient, by (8) and (9);

$$g_{ij}^{(1)} = \frac{\min\limits_i \left(\min\limits_j V_{ij}^{(1)}\right) + \beta \cdot \max\limits_i \left(\max\limits_j V_{ij}^{(1)}\right)}{V_{ij}^{(1)} + \beta \cdot \max\limits_i \left(\max\limits_j V_{ij}^{(1)}\right)} \tag{8}$$

$$g_{ij}^{(2)} = \frac{\min\limits_i \left(\min\limits_j V_{ij}^{(2)}\right) + \beta \cdot \max\limits_i \left(\max\limits_j V_{ij}^{(2)}\right)}{V_{ij}^{(2)} + \beta \cdot \max\limits_i \left(\max\limits_j V_{ij}^{(2)}\right)} \tag{9}$$

Step 4: Determination of the indicator performance for the alternative Q_i, by (10) and (11);

$$Q_i = Q_i^{(1)} / Q_i^{(2)}, \tag{10}$$

$$Q_i^{(1)} = \sum_{j=1}^{n} g_{ij}^{(1)} \cdot \omega_j,\ Q_i^{(2)} = \sum_{j=1}^{n} g_{ij}^{(2)} \cdot \omega_j \tag{11}$$

4) PROMETHEE (PREFERENCE RANKING ORGANISATION METHOD FOR ENRICHMENT EVALUATIONS)

This method starts with setting the preference function for two objects for each criterion $H_j = (d_{is}, p, q)$. As a rule, they have two parameters: p - indifference threshold, which reflects the fact that if the difference of dis values of two alternatives I and s is unimportant, then objects by criterion j are equivalent. If the difference in the threshold value p is exceeded, a preference relation is established between the objects. If the difference in threshold q is exceeded, the preference function corresponds to the "strong preference" of variant i over variant s with respect to the j criterion. With the difference of d_{is} in the interval from p to q, the preference function is less than 1, which corresponds to a "weak preference". The choice of the preference function is determined by the decision-makers. Some types of functions are preferred $H(d)$ and are presented in Table 2.

TABLE 2. Preference functions for PROMETHEE-II.

Function	Threshold	Formula
Usual	No threshold	$f(x) = \begin{cases} 1, x > 0 \\ 0, x \le 0 \end{cases};$
U-shape	q threshold	$f(x) = \begin{cases} 1, x > q \\ 0, x \le q \end{cases};$
V-shape	p threshold	$f(x) = \begin{cases} x/p, x \le p \\ 1, x > p \end{cases};$
Level	p and q threshold	$f(x) = \begin{cases} 0, x \le p \\ 0.5, p < x < q \\ 1, x \ge q \end{cases};$
Linear	p and q threshold	$f(x) = \begin{cases} 0, x \le p \\ (x-p)/(q-p), p < x < q \\ 1, x \ge q \end{cases};$
Gaussian	s threshold	$f(x) = 1 - exp\left(-\frac{x^2}{2s^2}\right);$

The second step is to calculate the difference in the values of the criteria for the two objects and calculate the preference indices V in (12) and (13). Finally, is to determine the preference factors by (14) and (15).

$$d_{is} = a_{ij} - a_{sj}; H_j = H_j(d_{is}, p, q,), \quad (12)$$

$$V_{is} = \sum_{j=1}^{n} w_j \cdot H_j - [m \times m]matrix \quad (13)$$

$$\Phi_i^+ = \sum_{s=1, s\neq i}^{m} V_{is}; \Phi_i^- = \sum_{s=1, s\neq i}^{m} V_{si}; \quad (14)$$

$$Q_i = \Phi_i^+ - \Phi_i^-. \quad (15)$$

B. CRITERIA MODELS AND CONSTRAINTS

This section explains the models included in the proposed approach, in Figure 4, including the power system, traffic system, and spatial model. These models are simulated to find the impact of EV charger installation on both the traffic flow and the power network for the annual EV charger installations.

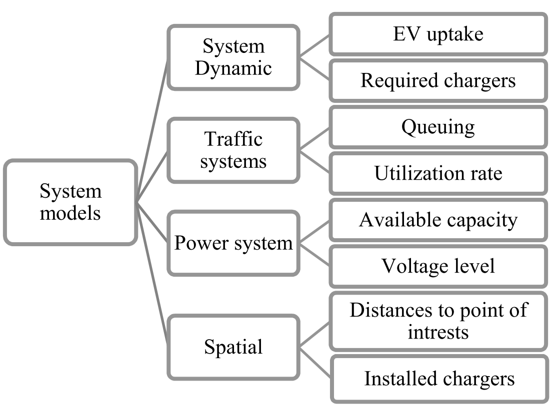

FIGURE 4. Models included in the study.

1) EV CHARGER NUMBERS AND DEMAND MODEL

Accurately modeling an EV infrastructure planning framework requires EV adoption to be known [26]. Forecasting is necessary for EV production planning, policy-making, power generation, and supply equilibrium. Multiple methods for EV forecasting have been proposed by these studies in [26] and [28]. In [29], a system dynamics model combined with optimization is proposed for obtaining the optimum amount of EV infrastructure for charging with solar PV projects. The same system-dynamics model is used to obtain annually the number of installed chargers on campus to be used as the input to the EV charger placement problem model proposed in this study.

2) POWER SYSTEM AND LOAD FLOW

A power system can be modeled by knowing the loads, cable lengths and impedances, and transformer sizes as shown in Figure 5. The basic tool for electrical system analysis is the power flow analysis which is used to determine the performance of the system. The load flow involves finding the node voltages, line currents, and system losses, which are necessary for optimization for network planning which in the process involves repeating the load flow for multiple iterations. When applying the optimization, the efficiency of the load flow technique is taken into consideration. The classification and comparison of load flow techniques have been addressed in [30]. The popular backward-forward sweep (BFS) approach has been used to determine the performance indices in the proposed study [31].

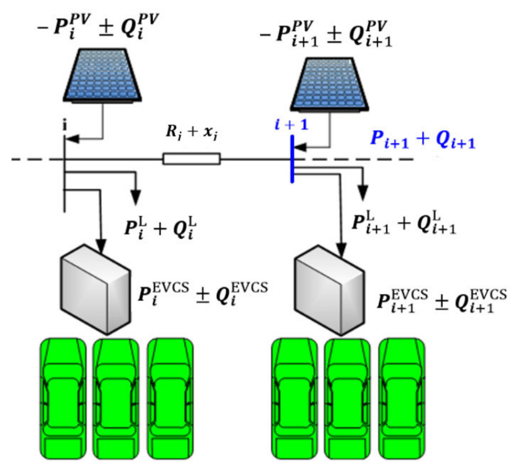

FIGURE 5. Series impedance line and bus model – power system model.

A distribution line illustrated in Figure 5 shows the effective active power P_i and reactive power Q_i flowing in the branch 'j' through the line resistance R_j and reactance x_j from node 'i' to node '$i+1$'. The active power and reactive power are calculated by (16) and (17);

$$P_i = P_{i+1}^T + R_j \frac{\left(P_{i+1}^{T2} + Q_{i+1}^{T2}\right)}{i+1} \quad (16)$$

TABLE 3. SEA standard for EV charging stations [33].

Charging level	Voltage	Type of connection	Usage/location	Expected power	Charging time (16 kWh)
Level 1	120 VAC	On-board Single-phase	Home and Office	1.44 kW (15A) 1.92 kW (20A)	11 hours 8 hours
Level 2	208 VAC 240 VAC	On-board Single-phase	Residential Outlet	3 kW (16A) 6 kW (32A)	5.5 hours 2.75 hours
			Commercial outlet	15.5 kW (80A)	1 hour
Level 3	480 VAC 600 VDC	off-board three-phase	Commercial Fast Charging Station (FCS)	50 kW 100 kW 250 kW	20 min 10 min 4 min

$$Q_i = Q_{i+1}^T + x_j \frac{(P_{i+1}^{T2} + Q_{i+1}^{T2})}{i+1} \tag{17}$$

where P_{i+1}^T and Q_{i+1}^T are the total active and reactive power at the node '$i+1$' formulated in (18) and (19);

$$P_{i+1}^T = P_{i+1} + P_{i+1}^L \tag{18}$$
$$Q_{i+1}^T = Q_{i+1} + Q_{i+1}^L \tag{19}$$

Considering the EVCS and PV implementation in the system, the total power equations are modified into (20) and (21);

$$P_{i+1}^T = P_{i+1} + P_{i+1}^L + P_{i+1}^{EVCS} - P_{i+1}^{PV} \tag{20}$$
$$Q_{i+1}^T = Q_{i+1} + Q_{i+1}^L + Q_{i+1}^{EVCS} - Q_{i+1}^{PV} \tag{21}$$

The voltages magnitude and phases at each node are calculated using (22) and (23);

$$V_{i+1} = \sqrt{\left[V_i^2 - 2\left(P_i R_j + Q_i x_j\right) + (R_j^2 + x_j^2)\frac{(P_i^2 + Q_i^2}{V_i^2} \right]} \tag{22}$$

$$\delta_{i+1} = \delta_i - \tan^{-1}\left(\frac{(Q_i R_i - P_i x_j)}{\left[V_i^2 - (P_i R_j + Q_i x_j)\right]} \right) \tag{23}$$

The line losses in the power system is calculated by (24);

$$P_{Loss} = I^2 R \tag{24}$$

The potential locations a_i^n follow a set of constraints. Once any of the constraints are violated the alternative is not considered in the problem. The power system's physical boundaries impose constraints on the voltage magnitudes and phase angles for all bus voltages as in (25) and (26);

$$V_{min} \leq V_{bi} \leq V_{max} \tag{25}$$
$$\delta_{min} \leq \delta_{bi} \leq \delta_{max} \tag{26}$$

Power system adequacy is essential for the installation of EVCSs. The currents in the power lines must not exceed the thermal limitation (27);

$$I_i \leq I_{max} \tag{27}$$

The available power capacity P_i^{max} and S_i^{max} at the parking area for EV charging defines the allowable number of chargers that can be installed on site $\sum a_i^n$, in (28) and (29);

$$P_{EVCS} \times \sum a_i^n < P_i^{max} \tag{28}$$

$$S_{EVCS} \times \sum a_i^n < S_i^{max} \tag{29}$$

The number of maximum chargers depends on the rating of the charges P_{EVCS} and S_{EVCS} which is different according to the charger type, see Table 3.

3) TRAFFIC FLOW MODELING

The traffic model involves two main criteria to be calculated; the utilization rate of the parking area and the queuing at the entrances. This will allow the Decision Maker (DM), such as the project investors or planners, to evaluate the congestion and usability at a specific site compared with others. The traffic flow model reflects the congestion of a site by the measurement of queuing in meters. The utilization rate measures how the parking area is being used with reference to its capacity. First, a traffic study is necessary to collect the site's parking data such as the peak number of parked vehicles, the average number of vehicles, peak hour, available parking spaces, number of entrances and exits, and number of lanes for exits and entrances. The parking turnover is high; therefore, data collection on the number of parking vehicles is for every 30 minutes from 6:00 am to 3:00 pm.

The capacities of the roads P_{lane} accessing the parking site is the number of vehicles per hour that can enter the parking area, and it depends on the entry type such as free-flow uncontrolled, controlled, etc., (see Table 4).

The average queuing, $Q_{average}$, and 95$^{\text{th}}$ percentile of the vehicles' queuing, $Q_{95\%}$, at the entrance of a parking site is determined by the capacity ratio p, which in turn is calculated using the maximum number of parking vehicles $n_{vehicles}$ and the number of entrance lanes n_{lane}. Calculating queuing is by (30) to (32), is based on 7 meters per vehicle [32].

$$Q_{average} = \frac{p^2}{1-p} \tag{30}$$
$$Q_{95\%} = \frac{p}{1-p} \tag{31}$$
$$p = \frac{n_{vehicles}}{n_{lane} \times P_{lane}} \tag{32}$$

The utilization U_rate of a parking area, in (33), is measured by the peak number of vehicles $n_{vehicles}$ and the parking area capacity PA_{max}.

$$U\_rate = \frac{n_{vehicles}}{PA_{max}} \tag{33}$$

TABLE 4. Entry Lane capacities for car parks [32].

Entry type	Lane capacity (vehicle/hour)
Free-flow access into distributor road/structure (no parking spaces immediately after access, i.e. ramp distribution after several levels of car park)	800
Free-flow access	580
Lifting-arm barrier without ticket issue (i.e. loop etc.)	550
Lifting-arm barrier with ticket issue (i.e. push button etc.)	360
Lifting-arm barrier with ticket issue (i.e. slot-based etc.)	235
Lifting-arm barrier with ticket issue (i.e. no slot - RFID etc.)	380

New trip generation: adding a new service on land use will generate new trips, which are specifically dedicated to that service.

Therefore, a generated trip affects the utilization rate and queue at the parking area. EV chargers are introduced as a new service for land use (parking), and currently, this service is still a new concept and not mature enough that there are no specific trip generation rates for it. A similar service to an EV charger is a gas station. The only difference is a gas station can provide other amenities too such as a car wash, vehicle services ATM, and washrooms. According to the currently applicable trip generation and parking rates guide in Qatar [34], [35], a single fuel point in a gas station attracts 18 new trips every hour on a weekday at lunchtime (LT). For the sake of comparison, an EV point development requires a parking service and a road network, where the deployment of 100% EV will have new trips (Tr_{new} =18).

A trip generation rate for an EV charging station is influenced by the average parking duration per hour at the site, and a successful EV plug-in is based on the availability of the charger. A parking area with an average 30 minutes parking duration will serve two vehicles per hour, the rest of the vehicles attracted to the site will stay and park in the location. Therefore, the EVCS affects the maximum parking capacity at the parking area, while the extra parking generated by the charging service will affect the queue length by increasing $n_{vehicles}$ by $\Delta n_{vehicles}$ in (34) and (35) respectively.

$$N_{EV\_plug_{in}} = n_{EVCS} \times \frac{d_{parking}(minutes)}{60\ minute/hour} \quad (34)$$

$$\Delta n_{vehicles} = (A_{EV}\% \times Tr_{new}) - N_{EV\_plug_{in}} \quad (35)$$

Though placing EV chargers at high parking occupancy sites may guarantee charger usage, it will start causing congestion at a point of higher utilization rates. To present this effect in the traffic model, a constraint of maximum utilization is set for all sites. The traffic indices (queuing, parking utilization rate, and parking volume) change with time, adoption rate, and the number of chargers.

4) THE SPATIAL MODEL

Spatial modeling relates to the position, area shape, and size of the parking areas. The spatial data are representing the geographical location of a place presented by location and shape. Spatial tools allow for obtaining the relationship among geographical locations such as distances. Three spatial data are stored in GIS: (i) geometric data, (ii) thematic component, and (iii) link identification (ID). The spatial model implemented for the EVCS application has a thematic component, which provides the attributes of data such as the name of the parking area and the measurements in Figure 6. The steps followed for building this model are the following:

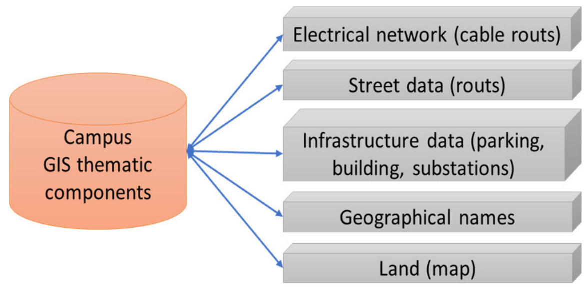

FIGURE 6. Illustration of a GIS spatial model showing the thematic components of the EVCS placement problem.

Step 1: Define the reference coordinate system according to the country and the satellite reference for the location of the institute/campus.

Step 2: Create shape files for; (i) car parks, building rooftops, parking slot shadings, (ii) gate locations, (iii) substation locations, (iv) routing for internal streets, (v) cable routing, and (vi) point of interests; attractive locations such as nearest to public transportation, nearest to the gates, nearest to activity centers, most active building, etc.

Step 3: Using the shape file area measurement tool, measure the areas for solar power installation. For instance, the buildings near every parking area have a rooftop area and the parking lot shading are potential surfaces for solar installation with power generation in an area. The total area A_i^T, in (36), solar PV generation is the sum of both building A_i^r and the shading area A_i^p, shading area is approximately 12 square meters per parking slot.

$$A_i^T = A_i^r + A_i^p \quad (36)$$

Step 4: Calculate the potential solar power generation; the total generation of a PV array E_A in kWh for a whole year is calculated using the Peak Sun Hour (PSH) approach, in (37). Where $(PSH)_i$ is the value PSH for day i, and P_o is the nominal array power under the standard test conditions (STC) [36]. The annual energy injected into the grid E_{Grid} depends on the capacity factor CF, in (38). The capacity

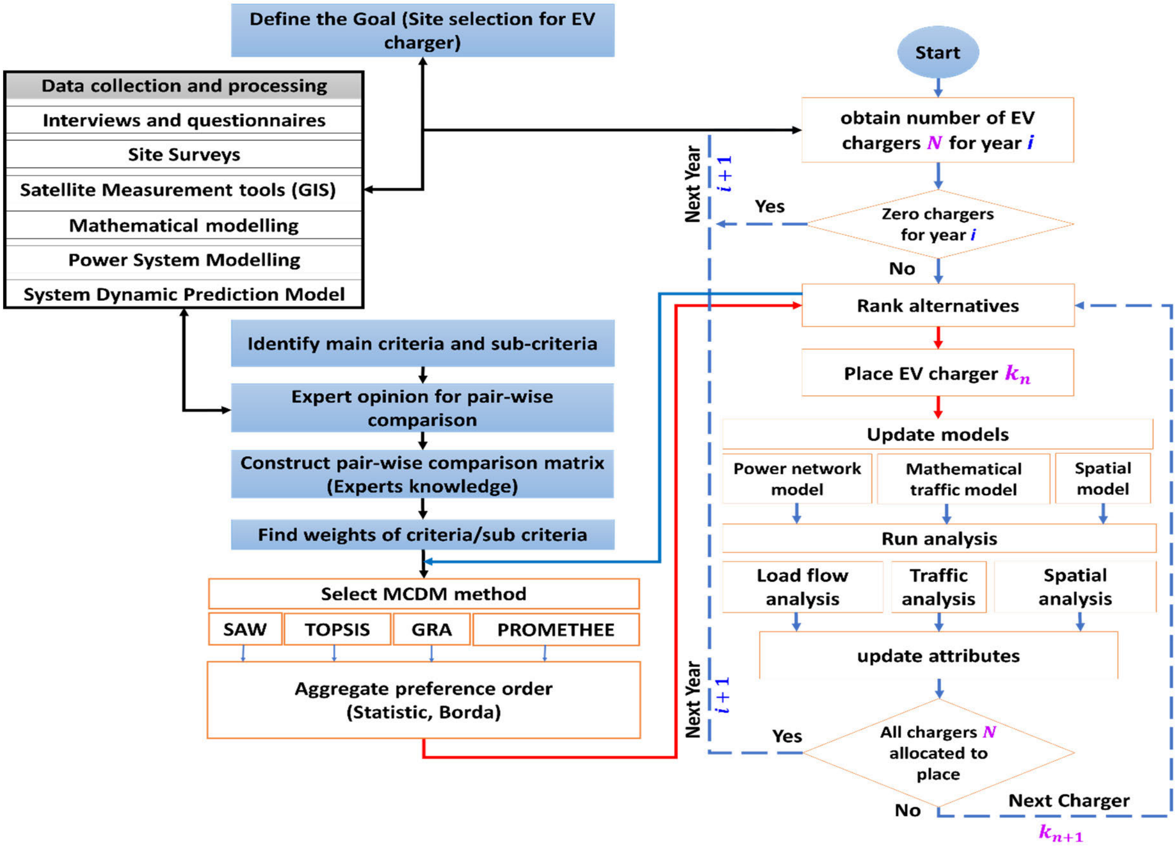

FIGURE 7. Methodology for placement problem.

factor of commercial PV projects depends on system configuration (fixed tilt or single-axis tracking angle) and the installation location (irradiance level). In the USA, for example, low irradiance areas have an average CF of 12.9% (Seattle, WA), and in higher irradiance, the average CF is 19.5% (Daggett, CA). The MENA region (Kuwait) has an average daily global irradiance of 5.319 kWh/m^2, and the capacity factor is 19.5 % [37]. Similar to Kuwait, the global solar radiation in Qatar is 5.5 kWh/m^2, and therefore the same CF is considered [38].

$$E_A = \sum_{i=1}^{365} (PSH)_i P_o \tag{37}$$

$$\mathrm{E_{Grid}}\left[\frac{\mathrm{kWh}}{\mathrm{yr}}\right] = CF \times \mathrm{P_o}\,[\mathrm{kW}] \times 8760[\frac{\mathrm{h}}{\mathrm{yr}}] \tag{38}$$

Step 5: Using ArcToolbox, perform spatial analysis to obtain distances: distance to gates, distance to point of interest, and distance to a substation that is nearest to the car park power source.

There is a minimum number of chargers a_{min} and maximum allowable chargers a_{max} at a specific site constrained by the civil infrastructure and vehicle spaces, see (39);

$$a_{min} \leq a_i^n \leq a_{max} \tag{39}$$

The restriction on the number of chargers per location is bound by the number of parking lots NP_i available at each site i. The maximum capacity for a specific site depends on the parking location capacity factorized by the adoption rate $r_{adoption}$ of that year represented by (40).

$$\sum a_{max} < r_{adoption} \times NP_i \tag{40}$$

Increasing the number of chargers per site will affect the decision by updating the evaluation criteria presented by the average volume, utilization rate, and queuing.

III. PROPOSED METHODOLOGY

Finding the suitable approach for selecting the optimum location of an EV charger depends on the objectives and criteria included in the decision maker's perspective and goals. The more questions and discussions, the better the understanding of the model objective and the decision-making.

This will create a basis for selecting what type of data the researcher or planner requires for comparison between the alternatives. This information is necessary to develop all the models defined in the previous section. The potential locations for EV charger installations are referred to as alternatives a_i. The quantified attributes of each location related to the power system, traffic model, and special model are referred to as criteria C_j. Figure 7 summarizes the main steps that are necessary for modeling the integrated MCDM problem for EV charger placement at campuses and universities. These steps are as follows:

(1) *Define the project goals and objectives:* when the university or research institution is the primary decision maker for its infrastructure projects, goals are based on the university's strategic plan which follows the overall country's strategy. For the EV placement problem, prioritizing the potential sites is based on the ranking of the objectives and criteria.
(2) *Define the potential sites (alternatives) and associated attributes:* an easy way to do this is by asking: Why is it hard to select a specific site for EV chargers? At a charging point, do I want to serve a greater number of users with less parking duration, or a smaller number of users for longer periods? Are the chargers installed to promote EV uptake? Is the infrastructure compensated for the additional civil works and cable laying or are the costs taken into account? This step includes defining the type of attributes (data), data collection method, variability to change, correlation with other measurements, etc. Multiple models are integrated to update the attributes, and these subsystems may include the power system, demand, accessibility, emissions, traffic flow, etc. The sub-models have different data sets for each site which are classified into criteria. The approach allows for expansion where other subsystems can be added and the same approach can be applicable.
(3) *Identify which criterion is more important than another with the help of experts and decision-makers:* in this context, a multi-criteria decision-making matrix is leveraged which can handle flexibility between different objectives (criteria). Experts are chosen from a single camp or firm and asked which alternative is important compared to the other alternatives using the linguistic terms of fundamental scale for AHP [39].
(4) *Solve for the EV placement:* obtaining the solution starts by integrating all the data collected and models into the process in Figure 7. At a specific year n, there is a number of required chargers K_n required for installation. The EV placement problem compares or ranks the different locations for every EV charger obtained. For year n, the proposed method solves for the location of each charger individually and then evaluates its effect on the integrated systems (power system, traffic, etc.) models. The attributes are updated after each EV placement solution provided that all constraints are not violated. An alternative is omitted from the selection filed when an attribute violates a set of constraints.
(5) *Sensitivity Analysis:* reaching a unified solution by employing four MADM methods simultaneously instead of selecting the best method for the situation. Aggregation methods rank the alternatives with four different MADM methods; SAW, TOPSIS, GRA, and PROMETHEE-II which include statistical ordering techniques; statistics, and Borda. The statistics method ranks the alternatives based on the mean ranking, the Borda method ranks based on the number of times an alternative "wins" in the voting. After aggregation, a partially ordered set is constructed to realize the orderings of the alternatives [25].

MADM methods are decision-making support tools used on a finite set of alternatives in the presence of several, usually conflicting criteria. Of the many multi-criteria decision-making methods described in the literature [25], [39], [42], this study presents several important methods that have more high potential for solving decision-making problems in the production environment: Simple Additive Weighting (SAW); Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS); Grey Relation Analysis (GRA): Preference Ranking Organisation METHod for Enrichment Evaluations (PROMETHEE).

A. DESIGNING OF THE MCDM MODELS

The solution structure of these methods is based on the performance analysis of alternatives and includes the following steps:

i. The approach begins with the definition of the goal, scenarios (alternatives), and criteria for evaluating alternatives. A complex problem is divided into a multi-level hierarchical structure of goals, criteria, attributes, and alternatives (Ai, i = 1, 2, ….., m). This is an integral part of the analytic hierarchy process proposed in [39].
ii. Structuring the multiple-choice criteria into a hierarchy and evaluating the relative importance of these criteria. $(C_j, w_j, j = 1, 2, \ldots.., n)$.
iii. Evaluation of the performance of alternatives $(a_{ij})_{mxn}$, in the context of the selected criteria. This step involves collecting data according to the given criteria and scenario. The datasets are a decision matrix — evaluations of alternatives in the context of the selected attributes.
iv. Transformation of attribute values to a single dimensionless scale – normalization $(r_{ij})_{mxn}$.
v. Selection of an aggregation model of alternatives and selection of a preferred (optimal) alternative.

The MCDM ranking model for each alternative Ai determines the value of Qi — an indicator of efficiency, based on which the ranking of alternatives is carried out and subsequent decision-making is carried out. A feature of the multi-criteria choice is the diversity of the design of the models. The design of the model consists of choosing a set of alternatives and criteria, methods for determining the weight of criteria, methods for evaluating the performance of alternatives, methods for normalizing the decision matrix, methods for aggregating alternatives, and additional model parameters.

B. DETERMINATION OF CRITERIA WEIGHTS

The weight of the criteria is the most powerful determinant of ranking. Criteria weights were determined using a multi-step procedure for constructing a hierarchical criteria structure, pair-wise comparison of criteria (attributes or sub-criteria) at each level of the hierarchy, and using the maximum

TABLE 5. Saaty rating scale for AHP [39].

Number of rating	Verbal judgment of preferences
1	Equally
3	Moderately
5	Strongly
7	Very
9	Extremely
2, 4, 6, 8	Medium value above pairwise comparison

TABLE 6. Arithmetic mean of random matrix consistency indexes [39].

n	1	2	3	4	5	6	7	8	9	10	11
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51

eigenvector method for the pair-wise comparison matrix P. Decision makers compare all elements of the same level in pairs from the point view of their priority weights based on their own experience and knowledge. The principle of eigenvalues of the pair-wise comparison matrix P is used to ensure the consistency of the judgments made. The calculation formula has the form in (41);

$$P \cdot w - \lambda_{\max} \cdot w = 0 \tag{41}$$

where P is the pair-wise comparison matrix, w is a vector of weights and $\lambda_{\max}$ is the maximum eigenvalues of matrix P. To unify the procedure for measuring the weight of each element in a pair-wise comparison, a standardized rating scale is used Table 5.

For each pair of criteria, the best option is awarded as a score according to Table 4, while the score of the other option in the pair depends on the reciprocal of this value. The total number of comparisons is $n(n\text{-}1)/2$.

To check the consistency of the expert's assessments, when forming the matrix of paired comparisons, the coefficient of consistency (CR), in (42), is used;

$$CR = \frac{CI}{RI} \tag{42}$$

where CI is the consistency index which is calculated by (43);

$$CI = \frac{(\lambda_{max} - n)}{n - 1} \tag{43}$$

RI is a random index given in Table 6, if the CR value is 0.1 or less, then pair-wise comparisons are considered to have acceptable consistency. However, if the value is greater than 0.1, then the ratio values indicate inconsistent judgments in which the result is unreliable.

C. EVALUATION OF THE PERFORMANCE OF ALTERNATIVES (A_{IJ})MXN IN THE CONTEXT OF THE SELECTED CRITERIA

Estimates of alternatives in the context of criteria can be numerical, rating, or linguistic variables. All estimates require translation into a single measurement scale for subsequent aggregation into integrated productivity. If it is required to evaluate the value of an alternative according to the criteria of the lower hierarchical level, a weighted average, in (44), is used;

$$a_{ij} = \sum\nolimits_{k=1}^{p} w_{jk} \cdot b_{ik} \tag{44}$$

D. NORMALIZATION METHODS

In the design of the MCDM model, we use four different linear normalization methods that have the greatest application in solving practical problems. The linear transformation, in (45), has the following form;

$$r_{ij} = \frac{a_{ij} - a_j^*}{k_j} \tag{45}$$

The parameters of the normalization methods are presented in Table 7. To normalize the cost attributes C_j^-, the ReS algorithm proposed in [24] is used which involves two steps:

1) Normalization of all criteria by (45),
2) Renormalization of the cost criteria $j*$ by (46);

$$\tilde{r}_{ij*} = -r_{ij*} + r_{j*}^{\max} + r_{j*}^{\min}, \quad \forall j^* \in C_j^- \tag{46}$$

IV. IMPLEMENTATION OF CASE STUDY

A. QATAR UNIVERSITY CAMPUS

We apply our model to a real-world case educational institute, Qatar University (QU), which is one of the high-ranked universities in the Middle East located on the northern outskirts of Doha. The country has a rapid economic development and unsurprising, the adoption of electric vehicles is projected to increase in the coming years [43]. Awareness is one of the high contributing factors affecting EV uptake and Universities are the first to adopt EV chargers and has a higher adoption rate than the countries' general adoption [29]. Nationwide, already there is an Electric Vehicle Strategy prepared by the Ministry of Transport [43]. As for QU, investigating new technologies as well as addressing sustainable environments are part of its research priority. For the case study, there are 32 parking areas and 6,116 available parking spaces at QU [44]. The geographical locations of the

TABLE 7. Basic linear methods for normalization of decision matrix.

Non-displacement	With displacement		
Max	**Max-Min**	**dSum**	**Z-score**
$k_j = a_j^{max}$	$k_j = a_j^{max} - a_j^{min}$	$k_j = \sum_{i=1}^{m}(a_j^{max} - a_{ij})$	$k_j = std_i(a_{ij}) = s_j$
$a_j^* = 0$	$a_j^* = a_j^{min}$	$a_j^* = a_j^{max} - k_j$	$a_j^* = mean_i(a_{ij}) = \bar{a}_j$

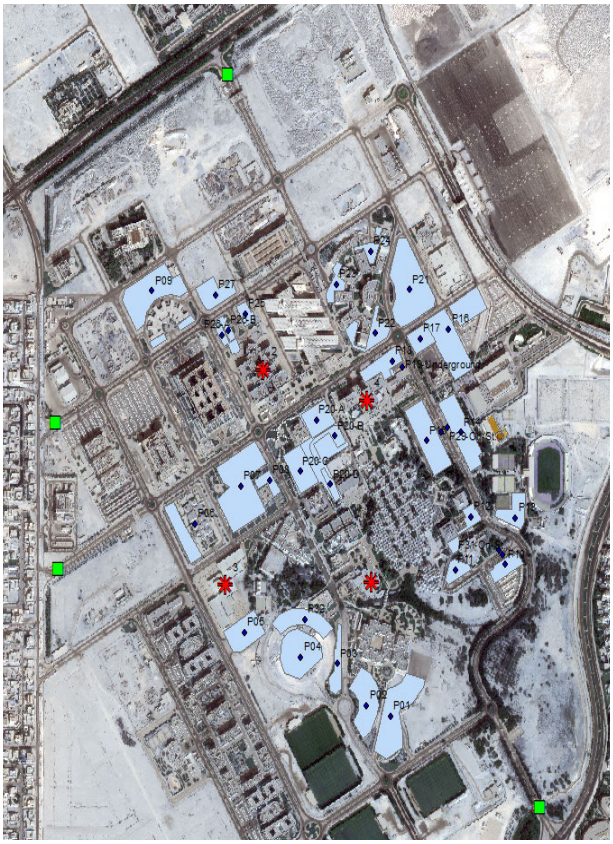

FIGURE 8. Qatar university campus with 32 parking locations (blue), bus transportation hubs (red) and gates (green).

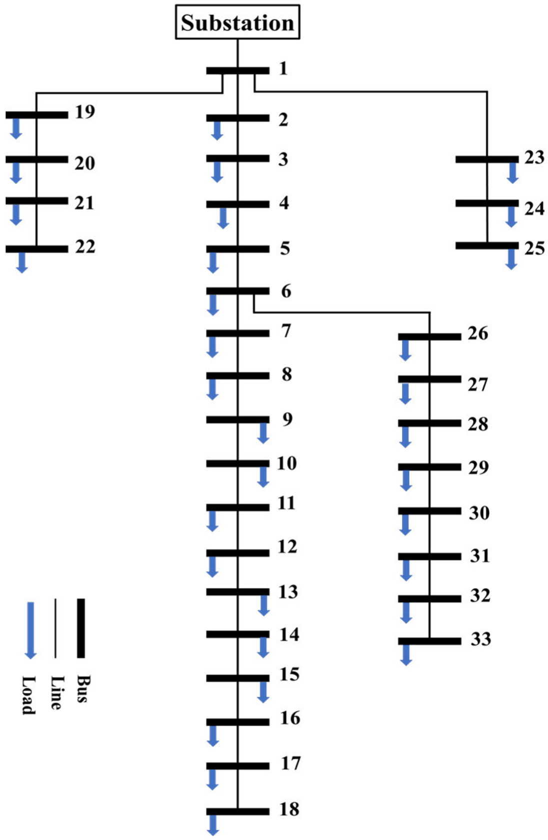

FIGURE 9. IEEE-33 bus system.

alternative sites for installing the EV chargers are the available 32-parking areas P_i (alternatives are A_1 to A_{32}) shown in Figure 8. The characteristics for each parking location are obtained during a specific peak traffic time for Qatar University, which is 11 am to noon. This peak time reflects the maximum occupancy of the parking areas in QU, and power system peak power is considered. The problem does not reflect seasonal variation or daily variation. It considers worst-case scenario because the priority is to provide power system security and reliability.

The IEEE-33 bus system is implemented for the evaluation of the proposed method, in Figure 9. There are 32 potential locations for the installation of EV chargers (Bus2 to Bus33), and when a violation occurs at a certain bus, it becomes no longer one of the potential site locations for an EV charger and the location is removed from the alternative list. The number of chargers per year to be installed is based on the system-dynamic model in [29]. The type of charger 6.6 kW is implemented in the study. For every year, the numbers of chargers required are plotted in Figure 10. For the case study, the years considered are from 2020 to 2050 which start at adoption 0% to 33%, the adoption rate is predicted through system dynamics for QU case study [29], see Figure 11.

B. TWO-LEVEL CRITERIA STRUCTURE FOR THE PROBLEM OF PLACING AN ELECTRIC VEHICLE CHARGER ON CAMPUS

Unlike most studies in the literature that place EV chargers in cities and urban areas, this issue is addressed by placing EV chargers on campus. This is reflected in such evaluation

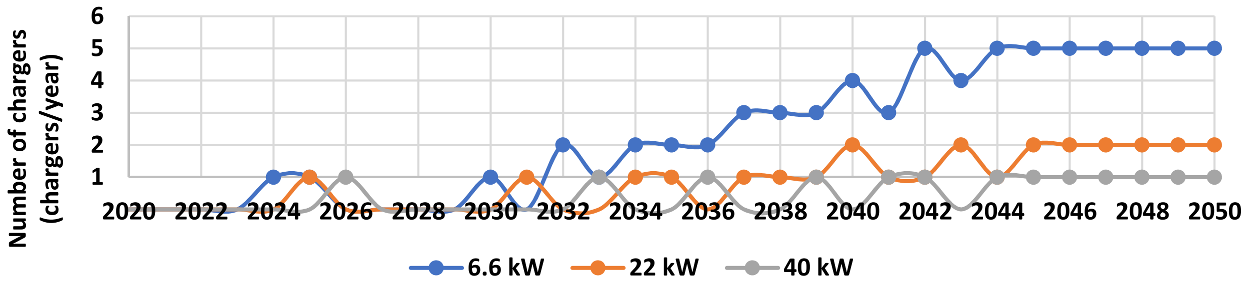

FIGURE 10. Required number of chargers per year.

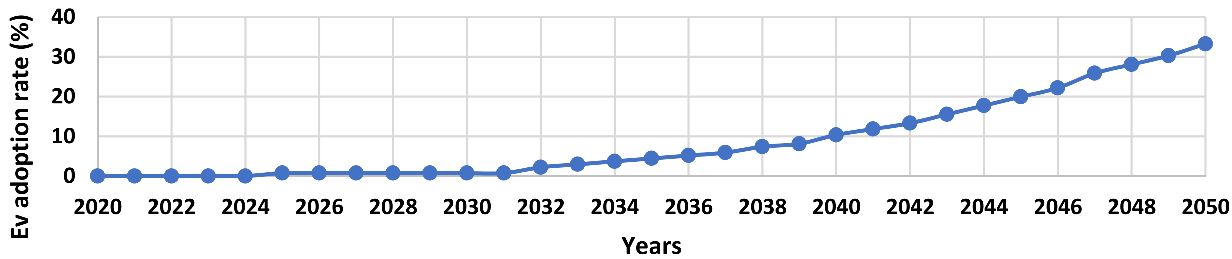

FIGURE 11. EV adoption rate for the case study, predicted through system dynamics [29].

criteria as driving and parking behavior, campus traffic and infrastructure, etc. Consistently equipping parking spaces on the university campus with chargers is determined in accordance with the ranking of parking spaces within the selected criteria system. The authors propose a two-level system of criteria, consisting of twelve lower-level criteria, combined into five groups of synthetic upper-level criteria, used for the final assessment of the priority of parking spaces, see Table 8. The top-level criteria for the campus are economy, affordability, user behavior, energy factors, and proximity to the user.

The lower-level criteria have a specific dimension, and each of the 32 parking lots located on the university campus is evaluated against these criteria. In accordance with the research methodology presented in Section III the values of the indicators in Table 9 are subject to normalization for the possibility of further aggregation of the indicators into an integral index (or the possibility of performing algebraic operations with values of different dimensions). The normalization method has some influence on the rating of alternatives, however, for multicriteria tasks, there is no criterion for choosing a normalization method. In our study, four popular linear normalization methods are used, as presented in Table 7. Accordingly, the decision maker has 4 possible options.

The experts consider the set goals of the initiator of the EV infrastructure project which is in this case QU. New transportation-related projects in QU are set based on the goals that follow the QU strategy which adopts the National strategy. The transportation plan follows a transportation master plan (TMP) which aims to:

- Implement sustainable transportation systems and practices
- Improve internal walkability and accessibility

Therefore, the decision-makers of QU will follow the TMP goals while considering and evaluating the potential locations for the EV charger site infrastructure-related projects.

Matrices of paired comparisons were obtained based on the opinions of experts using the Saaty fundamental scale (Table 5). The experts selected to build the model belong to the same camp or firm, in this case, QU, where experts with different work experiences can judge differently according to different criteria [31].

The case study decision makers are made up of experts in the transport system, the environment, and the electricity system. In addition, they hold a Master's or Ph.D. degree with at least 10 years of experience in their field. The panelists are asked to complete the pairwise comparison matrix (Table 10 and Table 11) based on their judgments of the various alternatives. They are asked which alternative is important compared to other alternatives, using the linguistic terms in Table 5. After determining the judgment of experts, firstly, the consistency of the pair-wise matrix is tested, and through the sequential procedure and the weights of the AHP are determined, in Table 10 and Table 11.

TABLE 8. **Hierarchical structure of criteria-based estimates of the problem of placement of an electric vehicle charger on a campus.**

Dimension	Evaluation criteria	Explanation	Cost/Benefit
Economic Criteria (D1)	Transmission losses (C1.1)	• The transmission losses in the system measured in kW. • Line losses increase as the substation is further away from the parking area.	Cost
	Extra driving loss (C1.2)	• The distance to EVCS from the nearest gate • The extra driving cost is an economic presentation of the burnt fuel, GHG emission or time loss.	Cost
Accessibility (D2)	Number of entrances (C2.1)	• Measured by the number of entrances to the parking area. • If the charger is easy to access, it will attract users and benefit sustainability goals.	Benefit
	Queuing (C2.2)	• It is the capacity of the parking site and the capacity of the street measured in meters. • It is the flow into the parking site • If there is a long queuing then drivers will not want to charge on campus.	Cost
	Utilization rate (C2.3)	• The ratio of the site demand and the site capacity • As the utilization rate increase the queuing increase as well which is an undesirable cost that reflects congestion.	Benefit
User demand (D3)	Parking duration (C3.1)	• Demand reflects how drivers are going to utilize the parking site measured by parking duration (minutes)	Benefit
	Average volume (C3.2)	• It is the average number of vehicles parked during the day • reflect the site-specific behavior of the users. • The average capacity reflects how the parking area is being used throughout the day and not just during the peak hour. • This measure allows us to compare the importance of the parking area in terms of attractiveness and serving other buildings.	Benefit
Energy (D4)	Solar energy potential (C4.1)	• Quantitative calculation of the free area for solar power generated measured in square meters. • Solar energy is an energy factor that increases the economic, environmental, and electrical benefits by reducing consumption costs, reducing GHG emissions, and reducing the burden on the power network.	Benefit
	Available capacity (C4.2)	• The available power at the bus dedicated for the EVCSs measured in kW. • To select the best location considering the power system's physical constraints.	Benefit
	Voltage level (C4.3)	• The voltage level from the load flow analysis measured in per unit. • To select the best location considering the voltage constraints.	Benefit
Proximity to user (D5)	Public transportation	• The proximity of important locations to the users • The distance from the car park to the public transportation measured in meters.	Benefit
	Current EVCSs (C5.2)	• The car park has a number of charging stations measured in numbers.	Benefit

After obtaining the weights, the experts are involved in evaluating the results based on the project goal and objective. The results show that the criterion, with the dominant effect on the site selection of the EV charger in this case study, is "Accessibility", which agrees with the TMP of the campus.

For each of the five groups of synthetic criteria of the upper level, it is necessary to calculate the weighted average values of the indicator u_{ij}, by (47), using the normalized values of the indicators r_{ij}, of the alternatives (parking) according to the criteria of the lower level w_{jk}:

$$u_{ij} = \sum_{k=1}^{n_j} w_{jk} \cdot r_{i,p_j+k-1}, \quad \forall i = 1, \dots, m, \ \forall j = 1, \dots, n \tag{47}$$

where n_j is the number of indicators in the j-th group (j = 1,..., n), pj is the serial number of the first indicator in the j-th group with continuous numbering.

For example, $j = 2$;

$$u_{i2} = (w_{21} \cdot r_{i3} + w_{22} \cdot r_{i4} + w_{23} \cdot r_{i5}), \quad n_2 = 3, p_2 = 3, \quad \forall i = 1, \dots, m$$

As a result, the criteria normalized values of indicators are converted into indicators of a synthetic type, or into weighted average additive values of indicators of various initial measurements. Therefore, synthetic values u_{ij} are subject to re-normalization to eliminate the priority of individual top-level synthetic criteria during aggregation. As before, we will use four popular methods of linear normalization. As a result, we obtain a matrix of normalized values of attributes of synthetic criteria $V = (v_{ij})$, $v_{ij} = \text{Normk}(u_{ij})$, $i = 1, \dots, m$, $j = 1, \dots, n$, $(m = 32, n = 5)$.

Figure 12 shows graphs of normalized attribute values for each of the 5 synthetic criteria using 4 normalizations. Synthetic values were obtained for average weights for 3 experts of the second level (Table 10). The displacement in the range of normalized values relative to each other for different normalization methods is a consequence of different transformations and has some effect on the ratings of alternatives obtained in different models. This fact is the basis for considering alternative models using various normalization methods.

TABLE 9. Values of indicators for 32 parking lots in the context of the selected system of criteria.

a_{ij}	C_1		C_2			C_3		C_4			C_5	
	C1.1	C1.2	C2.1	C2.2	C2.3	C3.1	C3.2	C4.1	C4.2	C4.3	C5.1	C5.2
i \ j	1	2	3	4	5	6	7	8	9	10	11	12
P01	12.240	1.9	2	4	0.678	58	221	29470	515	12.622	716.934	0
P02	51.791	2	1	2	0.616	54	165	28774	500	12.444	666.609	0
P03	19.901	1.4	1	1	0.426	107	29	26374	490	12.349	551.43	0
P04	18.699	2.2	1	1	0.137	120	42	14957	485	12.256	541.859	0
P05	38.249	2.1	1	5	0.694	61	120	15098	465	12.023	537.229	0
P06	1.915	0.9	2	0	0.006	39	1	2064	460	11.979	547.267	0
P07	4.838	0.7	3	2	0.419	60	223	24633	455	11.917	448.384	0
P08	4.181	0.95	1	1	0.663	60	55	5487	435	11.838	406.182	0
P09	3.561	1.5	4	1	0.203	180	89	5273	345	11.764	883.374	0
P10	0.554	1.8	2	1	0.586	50	75	25884	330	11.753	766.772	0
P11	0.881	2.1	1	5	1.105	30	84	25260	310	11.734	612.591	0
P12	2.666	1.5	1	3	0.727	80	64	15441	245	11.657	638.684	0
P13	0.729	1.2	1	1	0.297	120	38	28136	225	11.628	785.071	0
P14	0.357	1.5	2	4	0.662	25	219	47979	210	11.610	631.831	0
P15	0.281	1.7	2	14	0.788	60	287	11126	195	11.593	526.6	0
P16	0.252	1.6	2	2	0.308	46	120	12373	170	11.567	725.668	0
P17	0.053	1.5	1	1	0.319	140	15	4314	160	11.560	639.805	0
P18	0.161	1.4	1	2	0.825	160	66	46211	515	12.616	535.98	0
P19	0.832	1.4	1	2	0.254	30	48	47519	510	12.570	547.083	0
P20	0.101	1.2	3	0	0.282	45	148	14168	505	12.562	397.103	0
P21	0.044	1.3	5	0	0.163	50	81	1427	505	12.553	383.117	0
P22	3.182	0.75	2	0	0.353	50	41	563	495	12.399	369.715	0
P23	5.144	0.9	1	0	0.364	120	16	875	485	12.314	566.876	0
P24	1.287	1.5	1	1	0.243	45	17	28344	480	12.272	759.798	0
P25	2.601	1.3	1	1	0.660	30	31	29220	460	11.998	633.918	0
P26	3.329	1.2	2	1	0.808	25	97	27780	460	11.966	630.775	0
P27	11.301	1.1	1	2	0.285	40	59	2501	450	11.821	728.869	0
P28	7.833	1.6	1	0	0.842	180	16	245	440	11.717	572.623	0
P29	3.896	1.6	1	0	0.652	90	15	293	435	11.672	739	0
P30	1.594	1.6	1	0	0.929	50	13	24516	380	11.619	753.211	0
P31	0.213	1.6	1	0	1.083	20	13	24492	360	11.608	468.479	0
P32	0.013	2.2	2	2	0.688	45	165	4264	360	11.604	214.732	0

TABLE 10. Pairwise comparison matrix and weight of sub-criteria of three experts. Second level of the hierarchy.

	Expert 1			*Expert 2*			*Expert 3*		
	C_{11}	C_{12}		C_{11}	C_{12}		C_{11}	C_{12}	
	1	3		1	9		1	9	
w_{1k}	0.25	0.75		0.1	0.9		0.1	0.9	
					Average value of three experts		0.15	0.85	
	C_{21}	C_{22}	C_{23}	C_{21}	C_{22}	C_{23}	C_{21}	C_{22}	C_{23}
	1	1	1/5	1	1	1/3	1	1	1/3
	1	1	1/5	1	1	1/3	1	1	1/3
	5	5	1	3	3	1	3	3	1
w_{2k}	0.143	0.143	0.714	0.2	0.2	0.6	0.2	0.2	0,6
					Average value of three experts		0.181	0.181	0.638
	C_{31}	C_{32}		C_{31}	C_{32}		C_{31}	C_{32}	
	1	3		1	9		1	9	
w_{3k}	0.25	0.75		0.1	0.9		0.1	0.9	
					Average value of three experts		0.819	0.181	
	C_{41}	C_{42}	C_{43}	C_{41}	C_{42}	C_{43}	C_{41}	C_{42}	C_{43}
	1	2	2	1	7	7	1	3	6
	1/2	1	1	1/7	1	1	1/3	1	2
	1/2	1	1	1/7	1/1	1	1/6	½	1
w_{4k}	0.5	0.25	0.25	0.778	0.111	0.111	0.667	0.222	0.111
					Average value of three experts		0.648	0.194	0.157
	C_{51}	C_{52}		C_{51}	C_{52}		C_{51}	C_{52}	
	1	5		2	1		1	3	
w_{5k}	0.167	0.833		0.667	0.333		0.25	0.75	
					Average value of three experts		0.361	0.639	

Next, synthetic indicators are aggregated using one of four methods (SAW, TOPSIS, GRA, PROMETHEE, Section II, taking into account the weighting coefficients of the top-level criteria from (Table 8). Thus, the study uses 64 models, including 4 normalization methods, 4 aggregation methods, and 4 different estimates of the weight

TABLE 11. Pairwise comparison matrix and weight of criteria of three experts. Top level of the hierarchy.

	Expert 1					*Expert 2*					*Expert 3*				
	C_1	C_2	C_3	C_4	C_5	C_1	C_2	C_3	C_4	C_5	C_1	C_2	C_3	C_4	C_5
	1	1/9	1/3	1/3	1/3	1	1/9	1/2	1/4	1/2	1	1/6	1/3	1	1/3
	9	1	7	3	7	9	1	5	3	5	6	1	9	6	3
	3	1/7	1	1/5	1	2	1/5	1	1/3	1	3	1/9	1	1/2	1/5
	3	1/3	5	1	5	4	1/3	3	1	3	1	1/6	2	1	1/2
	3	1/7	1/1	1/5	1	2	1/5	1	1/3	1	3	1/3	5	2	1
w_j	0.046	0.535	0.08	0.259	0.08	0.052	0.524	0.094	0.235	0.094	0.065	0.537	0.08	0.097	0.221
	Average value of three experts														
w_j	0,054	0,532	0,085	0,197	0,132										
$\sigma(w_j)$	0.010	0.007	0.008	0.087	0.078										

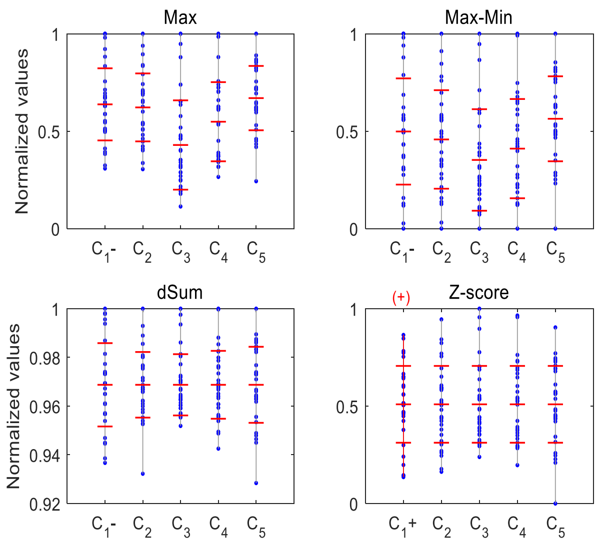

FIGURE 12. Normalized values of attributes for each of the 5 synthetic criteria. Normalization method according to Table 4. The red bars on the graph define the mean and standard deviation in the data (m$\pm\sigma$).

coefficients of the top-level criteria (3 experts and an average of experts).

C. RANKING OF THE ALTERNATIVES

Within each of the 64 models, ranking is performed based on the ordering of alternatives in descending order of the integral indicator Qi, defined by (1), (2), (10), (11), and (15). An example of ranking alternatives for 16 models (the weights of the top-level criteria are fixed as an average value for 3 experts) is presented in Table 12.

When determining the overall rank based on the results of the analysis of all models, we use two approaches. This is the Borda method and statistical. Borda's method involves processing the voting results of a certain group of voters [25]. In our case, one of the 64 models that determine the ranking of alternatives is used as voters, as shown in the example in Table 12. Accordingly, the alternative with rank 1 gets weight 32, rank 2 gets weight 31, and so on. Table 13 shows the counting of "votes" according to the Borda method. In total, the first five ranks were given to car parks P18, P31, P30, P26, and P11.

The statistical approach involves choosing the best alternative on average. Figure 13 shows the distribution of alternatives by the number of "wins". This number determines the number (proportion) of cases where the alternative had one of the ranks from 1 to 5. The combined result of the number of "wins" for the four options in Figure 13 is presented in Table 14. Priority parking numbers are highlighted in the table in color. The ranking result coincides with the Borda-method.

D. DECISION-MAKING GROUP BACKGROUND

The development project goals at universities are set based on the strategy of the project initiator, which adopts the country's strategy. Similarly, the transportation master plan also follows the same strategy, and therefore the decision maker on campus will follow these goals while deciding on the criteria preferences of the related projects. There is no single correct answer when it comes to choosing the locations of the EV chargers as a definite solution for all projects. This is because each country has a different set of development goals and different financing mechanisms. For the case study of Qatar and other oil-producing countries in the gulf region, the economic feasibility of the project has the least priority than the sustainable development goal such as electrification of the transportation sector and renewable energy generation.

For the purpose of this research, decision-makers from the university's academic faculty, Research Dean, Management, and from the Ministries, have been interviewed to show their preferences regarding which criteria are more important than the other, comparing between five main domains in the campus EV charger project; economic, accessibility, demand, energy, and proximity.

E. LONG-TERM EVCS PLACEMENT FOR INFRASTRUCTURE PLANNING

According to the procedure in Figure 7, the attributes of the criteria are updated according to the impact of placing the EV charger into the models, then the procedure is repeated for the rest of the chargers at that year and similarly for all required years. First, the number of chargers for each year is

TABLE 12. Numbers of the alternatives (parking lots) with ranks 1-32 in 16 models (SAW, TOPSIS, GRA, PROMETHEE combined with Max, Max-Min, dSum, Z normalization methods).

	SAW				TOPSIS				GRA				PROMETHEE			
Rank	Max	M-M	dSum	Z	Max	M-M	dSum	Z	Max	M-M	dSum	Z	Max	M-M	dSum	Z
1	18	18	30	18	31	31	30	31	18	18	18	18	18	18	31	31
2	30	31	18	31	11	11	31	30	31	31	31	31	31	31	30	18
3	31	30	31	30	30	30	26	11	30	30	30	30	30	11	18	30
4	11	11	26	26	18	26	28	26	11	11	28	26	11	30	28	11
5	26	26	28	11	26	18	18	18	26	26	26	11	26	26	26	26
6	28	28	25	28	28	28	11	28	14	28	25	28	28	28	25	28
7	14	1	29	1	1	1	29	1	28	1	29	1	14	1	29	1
8	1	14	10	14	14	14	25	14	1	14	1	14	1	14	10	14
9	25	25	1	10	25	25	10	10	10	10	10	10	25	25	9	10
10	10	10	11	25	10	10	8	25	25	25	2	25	10	10	1	25
11	2	2	2	2	12	12	2	29	12	2	11	2	9	2	11	9
12	12	12	3	29	29	32	32	12	2	12	9	12	2	9	2	2
13	29	29	8	12	2	29	1	32	7	7	3	29	12	12	3	29
14	7	7	9	7	32	2	12	2	29	29	8	7	7	7	23	12
15	9	9	14	9	8	8	14	8	9	9	7	9	29	29	7	7
16	3	8	23	8	5	5	3	5	8	8	23	8	3	8	14	3
17	8	5	12	3	7	7	20	7	3	3	14	3	19	3	19	8
18	5	3	7	5	15	15	22	9	5	5	13	5	13	5	8	5
19	13	15	13	13	3	9	23	21	13	15	12	20	8	19	13	19
20	15	32	20	20	9	3	7	20	15	20	19	13	5	15	24	13
21	19	20	24	32	20	21	21	3	19	13	20	19	15	20	12	20
22	32	13	22	23	19	20	9	15	32	19	24	23	23	23	20	23
23	24	23	19	21	13	22	5	22	20	23	22	21	24	13	22	21
24	23	19	21	19	22	19	13	19	24	32	21	32	20	21	21	15
25	20	21	5	24	21	23	24	23	23	21	5	22	32	32	27	24
26	16	24	32	15	23	13	17	13	16	22	27	24	16	22	5	22
27	17	22	27	22	24	16	19	16	22	24	32	15	17	24	16	32
28	22	16	17	16	16	24	16	24	21	16	17	16	22	16	17	16
29	21	17	16	17	17	17	27	17	17	27	4	17	21	17	6	17
30	27	27	4	27	27	27	4	27	27	17	16	27	27	27	4	27
31	4	4	6	4	4	4	6	4	4	4	6	4	4	4	32	4
32	6	6	15	6	6	6	15	6	6	6	15	6	6	6	15	6

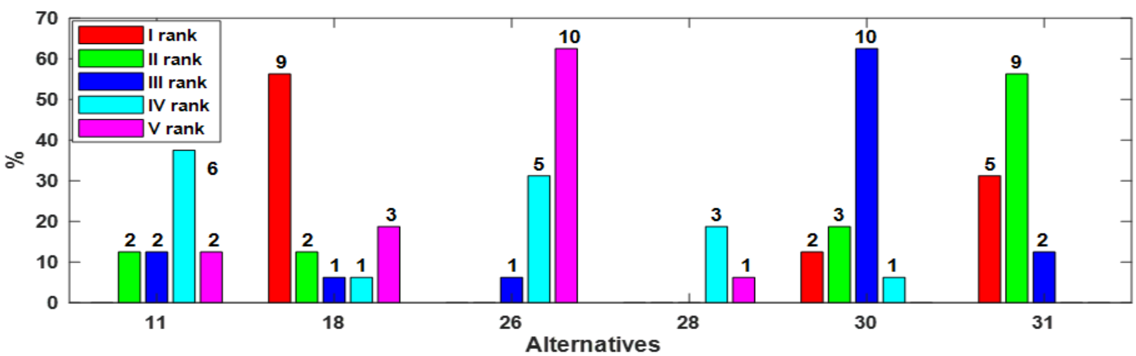

FIGURE 13. Distribution of alternatives by the number of "wins".

obtained from Figure 10, then the best sites for installations are obtained as shown in Figure 14 and Figure 15. The first years between 2020 to 2032 show years with no charger installations, this is because of the lower EV adoption rate in those years, see Figure 11. Other factors can be implemented into the model in future studies such as the new bus services, buildings, substations, roads, gates, and entrances, which consequently affect their relevant models and attributes. The long-term plans for EV charger site selection over 31 years, Figure 14 and Figure 15 describe how to place the predicted number of EV chargers from Figure 10. For instance, the first 6 chargers are installed at A30, the next 2 chargers at A31, and so on.

The placement plan is constrained by the maximum number of allowed chargers per site equal to the adoption rate at that specific year, see Figure 14 and Figure 15, and Table 15. The constraints of maximum number of chargers per site and the maximum allowed utilization rate (1.2) are met.

F. IMPACT ANALYSIS

While placing the EV chargers into the power network, a parallel operation of the impact analysis checks for any

TABLE 13. Borda-method ranking.

	Expert 1		*Expert 2*		*Expert 3*		Total		*Average*	
Rank	#Park	Count	#Park	Count	#Park	Count	#Park	Count	#Park	Count
1	P31	506	P31	500	P30	508	**P18**	1494	P18	499
2	P18	499	P18	500	P18	495	**P31**	1471	P31	493
3	P30	471	P30	481	P31	465	**P30**	1460	P30	486
4	P11	464	P26	456	P26	458	**P26**	1363	P26	455
5	P26	449	P11	434	P28	448	P11	1332	P11	446
6	P28	434	P28	423	P11	434	P28	1305	P28	438
7	P1	421	P14	398	P10	396	P1	1212	P1	401
8	P25	398	P1	396	P1	395	P25	1139	P25	388
9	P2	373	P25	389	P29	384	P10	1126	P10	380
10	P14	348	P10	383	P9	364	P14	1083	P14	373
11	P10	347	P2	348	P25	352	P2	1035	P29	342
12	P29	325	P29	312	P14	337	P29	1021	P2	341
13	P12	315	P7	304	P12	320	P12	931	P12	311
14	P8	283	P12	296	P2	314	P7	847	P9	290
15	P3	282	P3	278	P8	274	P9	823	P7	284
16	P7	282	P9	275	P7	261	P8	819	P8	279
17	P5	253	P8	262	P13	247	P3	788	P3	263
18	P19	237	P19	226	P3	228	P5	661	P5	218
19	P32	211	P5	205	P23	211	P20	578	P13	192
20	P20	209	P20	204	P5	203	P13	566	P20	191
21	P23	191	P13	199	P20	165	P23	555	P19	183
22	P9	184	P32	197	P16	158	P32	554	P32	183
23	P15	161	P21	159	P21	151	P19	531	P23	182
24	P22	159	P23	153	P32	146	P21	431	P15	146
25	P24	141	P24	139	P24	144	P15	424	P21	141
26	P21	121	P22	128	P15	139	P24	424	P22	132
27	P13	120	P15	124	P22	129	P22	416	P24	131
28	P27	71	P16	87	P17	105	P16	311	P16	86
29	P16	66	P17	78	P27	88	P27	207	P17	73
30	P17	57	P27	48	P19	68	P4	124	P27	62
31	P4	48	P4	44	P4	32	P17	91	P4	37
32	P6	22	P6	22	P6	29	P6	73	P6	22

TABLE 14. Total statistics of ranks for the parking alternatives.

#Parking	*Rank*					#Parking	*Rank*					#Parking	*Rank*				
	#1	#2	#3	#4	#5		#1	#2	#3	#4	#5		#1	#2	#3	#4	#5
P1	0	0	0	0	0	P11	0	4	13	10	9	P21	0	0	0	0	0
P2	0	0	0	0	0	P12	0	0	0	0	0	P22	0	0	0	0	0
P3	0	0	0	0	0	P13	0	0	0	0	0	P23	0	0	0	0	0
P4	0	0	0	0	0	P14	0	0	1	0	0	P24	0	0	0	0	0
P5	0	0	0	0	0	P15	0	0	0	0	0	P25	0	0	0	0	0
P6	0	0	0	0	0	P16	0	0	0	0	0	P26	0	0	2	18	25
P7	0	0	0	0	0	P17	0	0	0	0	0	P27	0	0	0	0	0
P8	0	0	0	0	0	P18	25	4	7	5	3	P28	0	0	4	3	10
P9	0	0	0	0	0	P19	0	0	0	0	0	P29	0	0	0	0	1
P10	0	0	0	0	0	P20	0	0	0	0	0	P30	15	9	27	13	0
												P31	15	43	6	0	0
												P32	0	0	0	0	0

violations in the power network. The results show that the voltages at all busses do not exceed the 10% margin set in this problem, see Figure 16. Installing 77 chargers increases the line losses by 20% in 2050 compared with the losses in 2020 (base case without chargers).

Also, there is a direct impact of policy on the placement of the EVCSs, for instance, changing the constrained utilization from 1 to 0.8 affects the projection of the future utilization rate till the year 2050. It is important to highlight that even if a parking site had been removed from the set of alternatives,

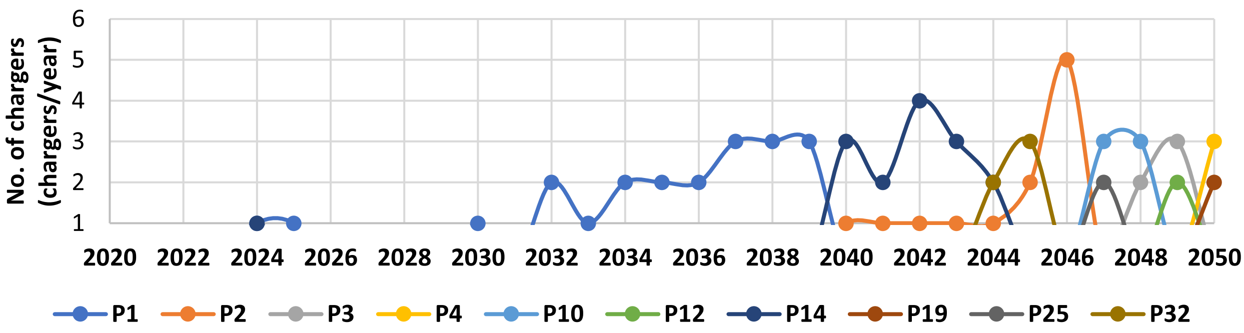

FIGURE 14. EV charger sitting for long-term project (Utilization rate<0.8).

TABLE 15. Effect of maximum utilization constrain on predicted utilization rate at final year (2050).

Site	Base UR	Site Capacity	No constrain	Constrains UR<1	Constrains UR<0.8
P1	0.68	326	0.68	**1.29**	1.06
P2	0.62	268	0.62	1.04	0.88
P3	0.43	68	0.43	0.51	0.87
P4	0.14	306	0.14	0.14	0.20
P5	0.69	173	0.69	0.69	0.69
P6	0.01	172	0.01	0.01	0.01
P7	0.42	532	0.42	0.42	0.42
P8	0.66	83	0.66	0.66	0.66
P9	0.20	438	0.20	0.24	0.20
P10	0.59	128	0.59	0.59	0.87
P11	1.11	76	1.11	1.11	1.11
P12	0.73	88	0.73	0.73	0.86
P13	0.30	128	0.30	0.30	0.30
P14	0.66	331	0.66	0.70	0.93
P15	0.79	364	0.79	0.79	0.79
P16	0.31	389	0.31	0.31	0.31
P17	0.32	47	0.32	0.32	0.32
P18	0.83	80	**6.29**	**1.43**	0.83
P19	0.25	189	0.25	0.25	0.32
P20	0.28	524	0.28	0.28	0.28
P21	0.16	496	0.16	0.16	0.16
P22	0.35	116	0.35	0.35	0.35
P23	0.36	44	0.36	0.36	0.36
P24	0.24	70	0.24	0.24	0.24
P25	0.66	47	0.66	0.66	0.91
P26	0.81	120	0.81	1.16	0.81
P27	0.29	207	0.29	0.29	0.29
P28	0.84	19	0.84	0.84	0.84
P29	0.65	23	0.65	0.65	0.65
P30	0.93	14	0.93	0.93	0.93
P31	1.08	12	1.08	1.08	1.08
P32	0.69	240	0.69	0.69	0.81

the attraction remains increasing with the increasing adoption rate which will affect the utilization rate of the chargers, seen in Table 15. Thus, the placement plan is sensitive to the utilization constraint, as illustrated in Figure 14 and Figure 15

V. FUTURE WORK

In our review, we have assumed that each attribute value was known, and that value was unique. But we recognize that the information available to the DM is often highly uncertain, especially in research and development decision-making. There are various ways of representing the decision-makers uncertainty. The simplest way is to use expected values for each attribute value and then treat the problem as one of certainty choice. A second and more computationally demanding procedure is to use an interval or range of values rather than a point estimate of attribute values. Some

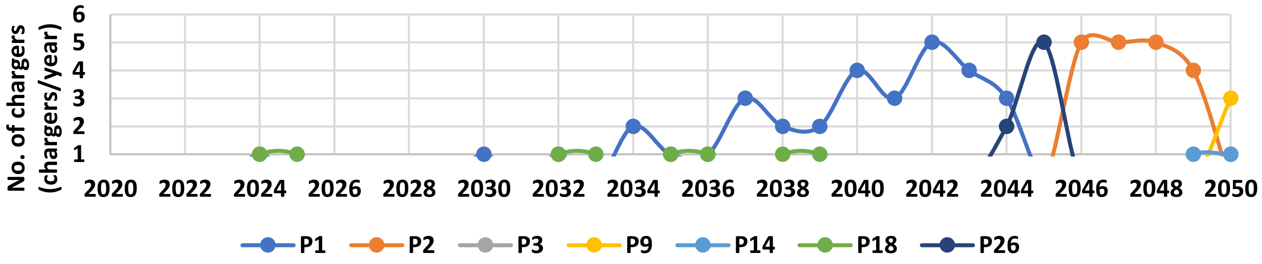

FIGURE 15. EV charger sitting for long-term project (Utilization rate<1).

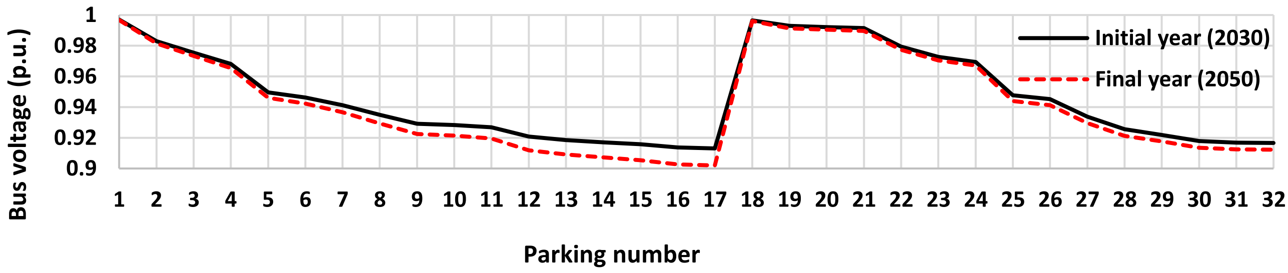

FIGURE 16. Voltage level at each bus from impact analysis results for years 2020 and 2050 (UR <0.8).

MADM methods such as dominance, disjunctive, conjunctive, and lexicographic method may somehow be modified to treat problems with uncertainty in attribute values, but the extension to other methods becomes computationally too cumbersome to be effective. A third and most complex way to account for attribute value with uncertainty is by introducing probability distribution. A recent approach is to apply fuzzy set theory to MADM methods aiming to overcome these difficulties [45]. Bellman and Zadeh have shown its applicability to MCDM studies [46]. Many efficient MADM methods are waiting for accommodation to the attribute value uncertainty.

VI. CONCLUSION

This paper solves the electric vehicle charger placement for a campus-size EV infrastructure planning. First, the dimensions affecting the placement problem are defined and presented mathematically through the Analytic Hierarchy Process (AHP) approach. The problem is solved by 4 Multi-Alternative Decision Making (MADM) methods; SAW, TOPSIS, GRA and PROMETHEE-II. The final ranking is the aggregated solution of the different case studies.

The solution is validated with two aggregating methods; the Borda method and statistical analysis which show similar results. The proposed model can be used for long-term planning. The sites for all future EV chargers are chosen. Also, the proposed model is constrained by both the power and traffic networks.

The impact analysis shows that after placing a charger in a parking area, the congestion increases with the increase in EV adoption. This can lead to undesired traffic congestion at the charger site. In this paper, we proposed finding the impacts of traffic flow while choosing the charger location and setting up the traffic constraints.

Finally, policy makers affect the transportation strategic plans which have a direct effect on the decision-makers who are responsible for assessing the AHP linguistic assessment of the charger placement problem. The findings demonstrate that the proposed framework can locate optimal charging station sites. These findings could also help administrators and policymakers make effective choices for future planning and strategy.

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