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

| Ref. | Economic | Vehicle-to-grid (V2G) | Technology (solar, storage, etc.) | Electrical power network | Geographic condition | Point of interests | Environment | Society | Multi-Objective Optimization | Heuristic optimization | Hybrid algorithm | Iterative pack-and-cover (IPAC) | Multi-Criteria |
|------|----------|-----------------------|-------------------------------|-------------------------|----------------------|-------------------|---------------|--------|-----------------------------|----------------------|----------------|----------------------------|----------------|
| [12] |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |
| [13] |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |
| [14] |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |
| [15] |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |
| [16] |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |
| [17] |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |
| [18] |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |
| [19] |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |
| [2]  |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |
| [20] |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |
| [21] |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |
| [22] |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |
| [23] |          |                       |                               |                         |                      |                   |               |        |                             |                      |                |                            |                |

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 cafeterias, 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 EVCSs 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 siting of EVCSs 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 EVCSs 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
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 effect of the charger installations on both the transportation and power network over the years.

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 determine 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 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
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:

$$Q_i = \sum_{j=1}^{n} w_j \cdot r_{ij},$$

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);

$$Q_i = \frac{S_{i-}}{S_{i+} + S_{i-}},$$

where,

$$v_{ij} = r_{ij} \cdot w_j, \quad S_{i+}^j = d(v_{ij}, v_{j}^+), \quad S_{i-}^j = d(v_{ij}, v_{j}^-),$$

$$v_{j}^+ = \{ \max_{i} v_{ij} \mid j \in C_{j}^{+}; \min_{i} v_{ij} \mid j \in C_{j}^{-} \},$$

$$v_{j}^- = \{ \min_{i} v_{ij} \mid j \in C_{j}^{+}; \max_{i} v_{ij} \mid j \in C_{j}^{-} \}.$$  

$S_{i+}^j$ and $S_{i-}^j$ are the distances of 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);

$$r_{ij}^{(1)} = \begin{cases} \max_i (r_{ij}) , & \text{if } j \in C_{j}^{+} \\ \min_i (r_{ij}) , & \text{if } j \in C_{j}^{-} \end{cases},$$

$$r_{ij}^{(2)} = \begin{cases} \min_i (r_{ij}) , & \text{if } j \in C_{j}^{+} \\ \max_i (r_{ij}) , & \text{if } j \in C_{j}^{-} \end{cases}$$

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

$$V_{ij}^{(1)} = |r_{ij}^{(1)} - r_{ij}|, \quad V_{ij}^{(2)} = |r_{ij}^{(2)} - r_{ij}|$$

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

$$s_{ij}^{(1)} = \frac{\min_i (\min_j V_{ij}^{(1)}) + \beta \cdot \max_i (\max_j V_{ij}^{(1)})}{V_{ij}^{(1)} + \beta \cdot \max_j (\max_i V_{ij}^{(2)})},$$

$$s_{ij}^{(2)} = \frac{\min_i (\min_j V_{ij}^{(2)}) + \beta \cdot \max_i (\max_j V_{ij}^{(2)})}{V_{ij}^{(2)} + \beta \cdot \max_j (\max_i V_{ij}^{(2)})}$$

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

$$Q_i = \frac{s_{ij}^{(1)}}{\sum_{j=1}^{n} \omega_j}, \quad Q_i^{(2)} = \frac{s_{ij}^{(2)}}{\sum_{j=1}^{n} \omega_j}$$

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

This method starts with setting the preference function for two objects for each criterion $H_j = (d_{ij}, p, q)$. 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 $d_{ij}$ 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 | \(f(x) = \begin{cases} 1, x > 0; \\ 0, x \leq 0 \end{cases};\) |
| U-shape  | \(q\) threshold | \(f(x) = \begin{cases} 1, x > q; \\ 0, x \leq q \end{cases};\) |
| V-shape  | \(p\) threshold | \(f(x) = \begin{cases} x/p, x \leq p; \\ 1, x > p \end{cases};\) |
| Level    | \(p\) and \(q\) threshold | \(f(x) = \begin{cases} 0, x \leq p; \\ 0.5, p < x < q; \\ 1, x \geq q \end{cases};\) |
| Linear   | \(p\) and \(q\) threshold | \(f(x) = \begin{cases} (x - p)/(q - p), p < x < q; \\ 1, x \geq q \end{cases};\) |
| 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, to determine the preference factors by (14) and (15).

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

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

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

\[
Q_i = \Phi_i^+ - \Phi_i^-; \quad (15)
\]

**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.

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].

A distribution line illustrated in Figure 5 shows the effective active power \(P_{i}\) and reactive power \(Q_{i}\) flowing in the branch ‘\(i\)’ through the line resistance \(R_{i}\) and reactance \(x_{i}\) from node ‘\(i\)’ to node ‘\(i+1\)’. The active power and reactive power are calculated by (16) and (17):

\[
P_i = P_{i+1}^T + R_i \frac{(P_{i+1}^{T+1} + Q_{i+1}^{T+1})}{i + 1} \quad (16)
\]

\[
Q_i = Q_{i+1}^T + x_i \frac{(P_{i+1}^{T+1} + Q_{i+1}^{T+1})}{i + 1} \quad (17)
\]
TABLE 3. SEA standard for EV charging stations [33].

| Charging level | Voltage | Type of connection | Usage/location                    | Expected power         | Charging time |
|----------------|---------|--------------------|-----------------------------------|------------------------|--------------|
| Level 1        | 120 VAC | On-board           | Home and Office                   | 1.44 kW (15A) 1.92 kW (20A) | 11 hours     |
|                |         | Single-phase       |                                   |                        | 8 hours      |
| Level 2        | 208 VAC | On-board           | Residential Outlet                | 3 kW (16A)            | 5.5 hours    |
|                | 240 VAC | Single-phase       |                                   | 6.6 kW (32A)          | 2.75 hours   |
| Level 3        | 480 VAC | off-board          | Commercial Fast Charging Station (FCS) | 15.5 kW (80A)   | 1 hour       |
|                | 600 VDC | three-phase        |                                   | 50 kW                 | 20 min       |
|                |         |                    |                                   | 100 kW                | 10 min       |
|                |         |                    |                                   | 250 kW                | 4 min        |

\[ Q_i = Q_i^{T} + \frac{(P_i^{T2} + Q_i^{T2})}{i+1} \] (17)

where \( P_i^{T} \) and \( Q_i^{T} \) are the total active and reactive power at the node ‘i + 1’ formulated in (18) and (19);

\[ P_{i+1} = P_{i+1}^{T} + P_{i+1}^{L} \] (18)

\[ Q_{i+1} = Q_{i+1}^{T} + Q_{i+1}^{L} \] (19)

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

\[ P_{i+1}^{T} = P_{i+1}^{T} + P_{i+1}^{L} + P_{EVCS}^{T} - P_{PV}^{T} \] (20)

\[ Q_{i+1}^{T} = Q_{i+1}^{T} + Q_{i+1}^{L} + Q_{EVCS}^{T} - Q_{PV}^{T} \] (21)

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

\[ V_{i+1} = \sqrt{V_{i}^{2} - 2(P_{i}R_{j} + Q_{i}X_{j}) + (R_{i}^{2} + X_{i}^{2})\left(\frac{P_{i}^{2} + Q_{i}^{2}}{V_{i}^{2}}\right)} \] (22)

\[ \delta_{i+1} = \delta_{i} - \tan^{-1}\left(\frac{(Q_{i}R_{j} - P_{i}X_{j})}{V_{i}^{2} - (P_{i}R_{j} + Q_{i}X_{j})}\right) \] (23)

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

\[ P_{Loss} = I^2R \] (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);

\[ V_{min} \leq V_{hi} \leq V_{max} \] (25)

\[ \delta_{min} \leq \delta_{hi} \leq \delta_{max} \] (26)

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

\[ I_{i} \leq I_{max} \] (27)

The available power capacity \( P_{max}^{EVCS} \) and \( S_{max}^{EVCS} \) 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);

\[ P_{EVCS} \times \sum a_{i}^{n} < P_{max}^{EVCS} \] (28)

\[ S_{EVCS} \times \sum a_{i}^{n} < S_{max}^{EVCS} \] (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 95th 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].

\[ Q_{average} = \frac{p^2}{1 - p} \] (30)

\[ Q_{95\%} = \frac{p}{1 - p} \] (31)

\[ p = \frac{n_{vehicles}}{n_{lane} \times P_{lane}} \] (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 \( PA_{max} \).

\[ U_{rate} = \frac{n_{vehicles}}{PA_{max}} \] (33)
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.

$$
N_{EV\_plugin} = n_{EVCS} \times \frac{d_{parking}(\text{minutes})}{60 \text{ minute/hour}}
$$

(34)

$$
\Delta n_{vehicles} = (A_{EV\%} \times Tr_{new}) - N_{EV\_plugin}
$$

(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:

**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 $A_i^{B}$ and the shading area $A_i^{P}$, shading area is approximately 12 square meters per parking slot.

$$
A_i^{T} = A_i^{B} + A_i^{P}
$$

(36)

**Step 4:** Calculate the potential solar power generation; the total generation of a PV array $E_i$ 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 $E_{\text{Grid}}$ depends on the capacity factor $CF$, in (38). The capacity

---

**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                          |

**FIGURE 6.** Illustration of a GIS spatial model showing the thematic components of the EVCS 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 \( 5.319 \text{ kWh/m}^2 \), and the capacity factor is 19.5% [37]. Similar to Kuwait, the global solar radiation in Qatar is \( 5.5 \text{ kWh/m}^2 \), and therefore the same \( CF \) is considered [38].

\[
E_A = \sum_{i=1}^{365} (PSH)_i P_o
\]

\[
E_{\text{Grid}} \left[ \frac{\text{kWh}}{\text{yr}} \right] = CF \times P_o [\text{kW}] \times 8760 \left[ \frac{\text{h}}{\text{yr}} \right]
\]

\[
\sum a_{\text{max}} < r_{\text{adoption}} \times N P_i
\]

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 
, 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 (\( A_i, i = 1, 2, \ldots, m \)). 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 \( (a_{ij})_m \), 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 \( (r_{ij})_m \).

v. Selection of an aggregation model of alternatives and selection of a preferred (optimal) alternative.

The MCDM ranking model for each alternative \( A_i \) determines the value of \( Q_i \) — 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):

\[ P \cdot w - \lambda_{\max} \cdot w = 0 \] (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 \( n(n-1)/2 \).

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:

\[ CR = \frac{CI}{RI} \] (42)

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

\[ CI = \frac{\lambda_{\max} - n}{n - 1} \] (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 (Aij)\_MAX 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:

\[ a_{ij} = \sum_{k=1}^{p} w_{jk} \cdot b_{ik} \] (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:

\[ r_{ij} = \frac{a_{ij} - a_j^*}{k_j} \] (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);

\[ \tilde{r}_{ij^*} = -r_{ij^*} + r_{j^*}^{\text{max}} + r_{j^*}^{\text{min}}, \forall j^* \in C_j^- \] (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].
TABLE 7. Basic linear methods for normalization of decision matrix.

| Non-displacement | With displacement | dSum | Z-score |
|------------------|-------------------|------|---------|
| Max              | Max-Min           |      |         |
| $k_j = a_{j}^{\text{max}}$ | $k_j = a_{j}^{\text{max}} - a_{j}^{\text{min}}$ | $k_j = \sum_{i=1}^{m} (a_{i}^{\text{max}} - a_{i})$ | $k_j = \text{std}_i(a_{i}) = s_{j}$ |
| $a_j^* = 0$      | $a_j^* = a_j^{\text{min}}$ | $a_j^* = a_j^{\text{max}} - k_j$ | $a_j^* = \text{mean}_i(a_{i}) = \bar{a}_j$ |

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

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
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.                       | Cost         |
|                 | Extra driving loss (C1.2)            | Line losses increase as the substation is further away from the parking area. |              |
|                 |                                      | 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. |              |
| Accessibility (D2) | Number of entrances (C2.1)           | Measured by the number of entrances to the parking area.                    | Benefit      |
|                 |                                      | If the charger is easy to access, it will attract users and benefit sustainability goals. |              |
|                 | Queuing (C2.2)                       | It is the capacity of the parking site and the capacity of the street measured in meters. | Cost         |
|                 |                                      | It is the flow into the parking site                                        |              |
|                 | Utilization rate (C2.3)              | If there is a long queuing then drivers will not want to charge on campus.  |              |
|                 |                                      | The ratio of the site demand and the site capacity                         |              |
|                 |                                      | As the utilization rate increase the queuing increase as 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                  | Benefit      |
|                 |                                      | 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. |              |
| Energy (D4)     | Solar energy potential (C4.1)        | Quantitative calculation of the free area for solar power generated measured in square meters. | Benefit      |
|                 |                                      | 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. |              |
|                 | Available capacity (C4.2)            | The available power at the bus dedicated for the EVCSs measured in kW.     | Benefit      |
|                 | Voltage level (C4.3)                 | To select the best location considering the power system's physical constraints. | Benefit      |
| Proximity to user (D5) | Public transportation               | The proximity of important locations to the users                         | Benefit      |
|                 | Current EVCSs (C5.2)                 | The distance from the car park to the public transportation measured in meters. |              |
|                 |                                      | 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 \( w_{jk} \):

\[
u_{ij} = \sum_{k=1}^{n_j} w_{jk} \cdot r_{ij} \cdot p_j + k-1, \]

\[
\forall i = 1, \ldots, m, \forall j = 1, \ldots, n \quad (47)
\]

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

For example, \( j = 2 \):

\[
u_{2i} = (w_{21} \cdot r_{i3} + w_{22} \cdot r_{i4} + w_{23} \cdot r_{i5}), \quad n_2 = 3, p_2 = 3, \quad \forall i = 1, \ldots, m
\]

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 \( V = (v_{ij}), \quad v_{ij} = \text{Normk}(u_{ij}), \quad i = 1, \ldots, m, \quad j = 1, \ldots, n, \quad (m = 32, \quad n = 5) \).

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.
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  |
|---|-----------|---|-----------|---|-----------|
|   | C1        | C2 | C3        | C4 | C5        | w1 |   |   | w2 |   |   | σ(w2) |
| 1 | 1/9       | 1/3| 1/3       | 1/3| 1         | 0.046| 0.054 | 0.052 | 0.524 | 0.094 | 0.235 | 0.094 | 0.065 | 0.537 | 0.08 | 0.097 | 0.221 |
| 9 | 1         | 7  | 3         | 5  | 1         |   |   |   |   |   |   |   |   |   |   |   |
| 3 | 1/7       | 1/5| 1         | 3  | 1         |   |   |   |   |   |   |   |   |   |   |   |
| 3 | 1/5       | 1/3| 1         | 3  | 1         |   |   |   |   |   |   |   |   |   |   |   |
| 1 | 1/3       | 1/1| 1         | 1/3| 1         |   |   |   |   |   |   |   |   |   |   |   |

Average value of three experts

|   |   |   |   |   |   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
|   | C1 | C2 | C3 | C4 | C5 |   |   |   |   |   |   |   |   |
|   | Max|    |    |    |    |   |   |   |   |   |   |   |   |
|   | Max-Min|    |    |    |    |   |   |   |   |   |   |   |   |
|   | dSum|    |    |    |    |   |   |   |   |   |   |   |   |
|   | Z-score|    |    |    |    |   |   |   |   |   |   |   |   |

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±σ).

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).

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

### TABLE 13. Borda-method ranking.

| Rank | Expert 1 | Count | Expert 2 | Count | Expert 3 | Count | Total | Count | Average | 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   | P31   | 1471  | P31     | 493   |
| 4    | P4       | 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      | 384   | P10      | 383   | P9       | 364   | P14   | 1083  | P14     | 373   |
| 11   | P10      | 347   | P2       | 348   | P25      | 352   | P2    | 1035  | P2      | 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      | 149   | P24      | 144   | P15   | 424   | P24     | 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 |
|----------|------|----------|------|----------|------|
| 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 0 |
| P10      | 0 0 0 0 0 | P20 | 0 0 0 0 0 | P30 | 0 0 9 27 13 |
|          |       |      |      | P31 | 15 43 6 0 0 |
|          |       |      |      | P32 | 0 0 0 0 0 |
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

![Image of Figure 14: EV charger sitting for long-term project (Utilization rate < 0.8).](image.png)

**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  | 0.69   | 240           | 0.69         | 0.69            | 0.69              |

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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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