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Sustainability assessment of electric vehicle charging infrastructure using deep learning, Analytic Network Process (ANP), and TOPSIS

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Abstract

The need to develop rapidly sustainable charging infrastructure for electric vehicles (EVs) presents a complex problem, as it requires consideration of numerous economic, environmental, technological and social elements. As a result, conventional decision-making frameworks typically are unable to adequately account for interdependent relationships between evaluation criteria and dynamic usage data, resulting in underdeveloped and less-than-optimal placement and construction of EV charging stations. To address this challenge, this paper proposed a novel integrated methodology using Deep Learning, Analytic Network Process (ANP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to evaluate the sustainability of EV Charging Infrastructure projects on a comprehensive level. Deep Learning models developed to forecast key usage metrics from real-world usage data to provide an objective method for comparing different options. Criteria weightings determined via ANP to reflect the many complex relationships between the various sustainability criteria and TOPSIS used to identify which of the alternatives for charging station placement or deployment plan is most similar to an ideal sustainable solution. We found that the integrated Deep Learning - ANP - TOPSIS methodology was able to correctly identify the most sustainable option, which represented a balance between cost savings, reduced greenhouse gas emissions, increased user convenience, and minimized negative impacts on the electrical grid. Compared to other alternatives, the highest ranked option had about 20 percent greater TOPSIS closeness coefficient and thus performed significantly better than the remaining options when compared across all four criteria. Results of sensitivity analysis indicated that the relative positioning of alternatives were relatively stable to changes in weighting of the criteria, which provided further evidence for the validity of the decision model. The methodology integrates predictive analytics with multi-criteria decision making to evaluate both a quantifiable measure of the performance for each option and a qualitatively assessed measure of the priority for that option, creating a sustainable and resilient electric vehicle charging system.

Keywords: Sustainability, Electric vehicle, Charging infrastructure, Deep learning, Analytic network process, TOPSIS.

1. Introduction

The world is rapidly transitioning toward the use of electric vehicles (EVs) [1-3]. As indicated by the International Energy Agency's Global EV Outlook, the world-wide number of EVs has exceeded forty million units at the end of 2023, with nearly fourteen million new EVs being sold during 2023. The rapid expansion of the EV sector is primarily driven by the desire to minimize greenhouse gas emissions and urban air pollution through the use of EVs, which produce no tailpipe emissions and can be fueled by renewable energy resources [2]. With the expansion of EVs comes the necessity for a widespread, well-planned and sustainable system of charging infrastructure to support these vehicles [2,4-5]. There is now considerable recognition that developing a network of charging stations that is easily accessible, dependable and environmentally friendly is necessary for the continued growth of the EV industry [6-8]. Specifically, it will be crucial to ensure that the location of charging facilities is strategic and their operation is sustainable in order to provide consumers with confidence in their ability to travel long distances without experiencing "range anxiety" and thus promote the increased adoption of EVs.

Planning and evaluating EV charging infrastructure involves an inherently complex decision-making process [9,10]. While earlier studies examined the sustainability of EV charging stations based upon a small number of criteria, economic costs, environmental benefits, and the social convenience of the charging facility, the most recent studies indicate that numerous other factors contribute to the success and sustainability of EV charging infrastructure [11-13]. Examples include technical factors, grid capacity, type of charging equipment, policy and regulatory requirements, and traffic patterns, as well as the three traditional criteria, economic, environmental, social, and user access to charging facilities, the reliability of the power supply, and government incentives. Thus, the evaluation of the sustainability of EV charging infrastructure has to consider all criteria that are important and relevant [2,14-17]. The literature survey identified many dozens of factors that have been taken into account for the identification of sites for EV charging stations. The diversity of these factors illustrates how complex the decision-making process is; planners have to deal with multiple, often contradicting goals.

Therefore, the complexity of the decision-making process concerning EV charging infrastructure has made the use of Multiple Criteria Decision Making (MCDM) techniques the most common tool for solving the problems related to it [9,18-21]. By defining the decision problem by means of a set of criteria and options MCDM offers a way of evaluating each option with respect to each criterion by using quantitative assessments [22,23]. There exist various MCDM-methods for the site-selection and planning of EV charging stations. These include e.g., Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), TOPSIS, VIKOR and others [24-26]. Examples for applications of fuzzy AHP and TOPSIS for the ranking of possible charging-locations can be found in literature. Both expert-opinions as well as uncertainties of the ranking-processes are taken into account here [27,28]. Other studies apply decision-methods like DEMATEL and PROMETHEE combined with fuzzy logic for the description of the interactions between the criteria and the vagueness of the data in EV-charging-infrastructure-decisions. These studies demonstrate that MCDM techniques are useful for assessing sustainability since they allow the integration of indicators such as cost, emissions, land use, and community impacts into a unified framework for making decisions [19,29-31]. Additionally, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) has gained popularity in sustainable decision-making because of the simplicity of the logic it uses [32,33]. TOPSIS also allows for the combination of qualitative and quantitative criteria and has been widely applicable to areas such as transportation and energy planning.

Even though significant advancements have taken place in assessing EV charging infrastructure, there are still several areas in which the present body of knowledge and practices of assessing EV charging infrastructure are lacking. First, the majority of MCDM assessments based upon the criteria assumed to be independent of each other [34-36]. In fact, numerous studies indicate that many of the criteria used in the assessment of EV charging infrastructure are interdependent, therefore traditional hierarchical approaches such as AHP do not adequately address these interdependencies. Since it addresses interdependencies among the criteria by utilizing a network structure and performing a super matrix computation, ANP, the network-based extension of AHP has been utilized less frequently than anticipated in the past for EV infrastructure planning until recently. Recent studies have indicated that omitting mutual influences among the criteria may result in inaccurate and illogical decisions when selecting EV charging sites [37-40]. Second, what appears to be the most significant limitation to date is the lack of integration of advanced data analytics, including machine learning, into the decision criteria of EV charging infrastructure assessments. While most MCDM assessments rely on static expert judgments and/or simple projections for the value of criteria, the growing availability of data provides an opportunity to leverage deep learning models to predict key performance indicators for potential charging stations [2,41-47]. The predictive capability provided by deep learning models can significantly enhance the accuracy of sustainability assessments for EV charging infrastructure by providing data driven estimates of how alternatives will perform versus relying solely on subjective judgments. Although the inclusion of predictive analysis in an MCDM framework has become a growing area of research, it remains an emerging research area. For example, one recent study on evaluating city sustainability found that when combined with MCDM, the use of Deep Learning resulted in a more effective method of evaluating complex systems than each method used separately, and as such, the same benefits may also exist for evaluating the sustainability of EV charging infrastructure.

In view of the preceding limitations, this study aims to develop an innovative, integrated, and comprehensive framework for the assessment of the sustainability of EV charging infrastructure that will combine the potential of Deep Learning, ANP and TOPSIS. Therefore, the ultimate objective of this study is to provide planners and policymakers with more informed decision-making capability concerning the development of EV charging infrastructure by developing a tool which takes into consideration both the complexity of relationships between criteria, and real-world data to predict future performance. More specifically, the objectives of this study are as follows: (1) to employ Deep Learning Models to estimate the important sustainability-related metrics of EV charging stations in a variety of future scenarios; (2) to employ the Analytic Network Process to determine the relative importance of sustainability criteria, while considering the inter-relationships between criteria; (3) to employ the TOPSIS methodology to determine the priority of various alternative charging station locations, or infrastructure deployment strategies, based on the importance of the sustainability criteria and the estimated outcomes of performance; and (4) to assess the robustness of the proposed approach using sensitivity analyses, and to compare the results to those found in previous studies in the literature.

The primary contributions of this study are as follows:

1) We have developed a novel hybridization of Deep Learning methodologies and traditional Multiple Criteria Decision Making (MCDM) methods (Analytic Network Process (ANP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)) to assess the sustainability of Electric Vehicle (EV) charging infrastructure. The Hybrid Methodology (Deep Learning + MCDM) permits the use of dynamic input variables to assess multiple criteria at the same time and addresses the limitations of conventional static assessments of sustainability of EV charging infrastructure through the integration of predictive models of criterion values.

2) We constructed a fully encompassing criteria hierarchy/network that includes a wide range of sustainability-related criteria including: economics, environment, society, technology, policy, and traffic factors. The ANP framework incorporates the relationships between these criteria and therefore accounts for all possible relationships among the criteria. This broad spectrum of criteria will ensure that the assessment aligns with global sustainability goals and with the practical needs of stakeholders.

3) We demonstrated that our proposed deep learning methodology can accurately predict station usage and energy demand at EV charging stations; those predictions can then be converted to sustainability indicators. Our deep learning methodology was trained on historical data collected from existing EV charging stations and on exogenous variables. Therefore, the data-driven inputs improve the accuracy of our sustainability evaluation, as demonstrated by the closer alignment of our evaluation to actual trends and by enabling us to conduct scenario analyses.

4) We tested that when our ANP-TOPSIS evaluation method is used to assess the sustainability of alternative EV charging infrastructure options and when it is provided with deep learning-predicted values for station usage and energy demand, that it is capable of selecting the most sustainable option for EV charging infrastructure development. The results of our evaluation provide valuable insight into which criteria have the greatest impact on our rankings and how different trade-offs are made. Additionally, we perform sensitivity analysis by adjusting the relative importance of each criterion and by testing different input assumptions to demonstrate that the decisions we make regarding the sustainability of EV charging infrastructure development are stable and consistent across a wide variety of scenarios. These contributions help advance the academic literature by providing a general template for integrating machine learning with traditional MCDM methods to evaluate sustainability-related problems and contribute to practitioners by providing a decision-support system that can be tailored to meet the specific needs of planners and developers who seek to implement the most sustainable electric vehicle charging infrastructure. Ultimately, this decision-support system has the potential to assist governments and private sector investors in identifying and implementing EV infrastructure projects that produce the most balanced set of economic, environmental, and social benefits.

2. Methodology

The methodology is composed of three elements, namely a deep learning model, an analytic network process (ANP) and the TOPSIS multi-criteria decision-making method, that are integrated together to provide a common methodological platform to evaluate sustainability. The sustainability criteria assessed within this study include six categories with related sub-criteria; these criteria are the foundation upon which the evaluation framework was developed and utilized as inputs for both the ANP and TOPSIS processes. The deep learning model provides data on forecasted quantitative criteria values for each of the alternatives being evaluated using this framework. A comprehensive criteria framework has been established to evaluate the sustainability of electric vehicle (EV) charging stations. The framework assesses sustainability across six major categories of economic, environmental, societal, technical, political and traffic and contains a multitude of sub-criteria for each category. Each category has its own distinct set of criteria that relate to the respective category; i.e., economic, cost and location; environmental, pollution and land use; societal, public perception and equity; technical, grid and technology; political, regulation and incentives; and traffic, the transportation network. The overall array of criteria represents the necessity of using multiple criteria when assessing the sustainability of EV charging infrastructure.

Criteria framework

To assess the sustainability of alternative EV charging infrastructure configurations, the first step is to establish a comprehensive set of sustainability criteria. As outlined, the six important sustainability criteria (C1, C2,…, C6) identified and considered include: Economic viability, Environmental impact, Social impact, Technical feasibility, Policy support, Traffic conditions. Each of these first conditioning effects may be further elaborated in terms of sub-criteria. For example, for Economic one might consider sub-criteria such as capital cost and operational costs, proximity to high demand areas and potential revenues; for Environmental might be considered such sub-criteria as: reduction of greenhouse gases emissions, local air/noise pollution, and land use effects; for Social: community acceptance, equity of access, and convenience; Technical feasibility would include such sub-criteria as availability of grid capacity, charging speed/technology, and reliability thereof; Policy support might include such sub-criteria as existence of government incentives or other assistance, supportive regulations; and Traffic conditions would include such sub-criteria as the connectivity of the site, traffic density, parking availability. After having outlined the criteria through initially these general considerations, the data gathering relating to the set of alternatives comes next. In this case, the alternatives perhaps are one or the other potential site for a new EV charging stations, or proposed strategies for the expansion to the charging infrastructure network. The data gathering involves a number of quantitative metrics and expert judgments.

Deep learning-based prediction of performance metrics

For integrating the data-driven insights necessary for the sustainability evaluation, we rely on a deep learning model to predict the expected usage and load of each candidate EV charging station alternative. These predictions directly influence certain metrics such as Environmental Impact, which is tied to predicted emissions reductions, and Social Impact, which is tied to predicted user service level. Further, they indirectly enter into Economic and Technical Choices, which will be affected if, for instance, a given alternative shows higher usage in prediction of its future service. Here by drawing on past data and advanced algorithms employed for prediction, we are attempting to make less uncertain what the future performance will be for each alternative. We adopt a neural network architecture specifically built for time-series prediction of EV charging station usage. Specifically, the architecture used is a Long Short-Term Memory (LSTM) network because of its strength in modelling sequential temporal data. The model is designed to take as input an array of features such as time-of-day, day-of-week, local weather, possible levels of local EV ownership, or other relevant context data and will produce as output one or more predictions on the station performance. In this study we set up the deep learning model as a multi-output predictor, producing two outputs for a given time interval such as a day: (1) the forecasted energy demand (kWh) or number of charging sessions at the station, and (2) a forecast for the charging port availability or utilization. The model evaluated both the predicted magnitude of usage and the potential congestion at a station.

Mathematically let $z\ (t)$ be the vector of input features at time t for a given site, where features includes time indicators and exogenous variables as explained. The LSTM based model defines a function $f\theta$ (with learned parameters θ) taking a series of input sequences to predict the future outputs. For example, there is predicted the subsequent day hourly profile, which is predicted from a sliding window of the preceding N days of data. the model $f\theta$ includes several LSTM Layers to capture dependency over time and if necessary one or many fully connected Layers that generate the two Outputs. Data from operational EV Charging Stations which are very similar in nature to the proposed sites are used to train the model. A suitable loss function, MSE for demand and a classification or regression loss for availability depending on how availability is modeled as a continuous value or categorized threshold, is minimized during training. Cross-validation, early stopping, and hyperparameter tuning are used to avoid overfitting and enable the model to generalize to new data. A combination of metrics such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and R-squared are used to evaluate the model's performance on predicting demand. Once it has been trained, the deep learning model is used to either simulate or forecast how much use is anticipated for each of the candidate sites. Using site-specific information (for example, EV density in that area, typical traffic flow), we input this data into the model to estimate possible use of each candidate site over a future time frame of interest.

Metrics:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y_i})^2} \tag{1}$$

$$\mathrm{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{y_i - \widehat{y_i}}{y_i + \varepsilon}\right| \tag{2}$$

Analytic Network Process (ANP) for criteria weighting

Using the criteria established above, along with the relative importance of each criterion determined, ANP is applied to find the relative importance of each criterion, since criteria may be interdependent and allow for feedback. The Analytic Hierarchy Process (AHP) is used in hierarchical processes that do not allow for interdependence and/or feedback. In contrast, the ANP provides a flexible framework that can include a network structure, which enables clusters of elements to impact each other. Therefore, the ANP is an ideal method to apply to sustainability assessments, which are typically characterized by multi-dimensional aspects of sustainability such as policy support potentially improving technological feasibility due to additional funding; or increasing charging infrastructure at the cost of increasing operational expense.

Pairwise matrix A = a_{jk} with Saaty scale

$$a_{jk} = \frac{1}{a_{kj}}, \quad a_{jj} = 1 \tag{3}$$

Local weights

$$A\mathrm{w} = \lambda_{maxw} \tag{4}$$

$$\sum_{j} w_j = 1 \tag{5}$$

Consistency index/ratio

$$CR = \frac{CI}{RI_n} \quad \text{(acceptable if } CR < 0.10\text{)} \tag{6}$$

Weighted super matrix to limit super matrix

$$W^{(\infty)} = \lim_{k \to \infty} \left(W^{(w)}\right)^k \tag{7}$$

In our study, we identified six major criteria that we treated as six clusters for simplification purposes. In addition, we assessed whether there existed any inter-relationships between the various criteria. Specifically, we acknowledged that the Economic and Technical criteria had a relationship with one another (i.e., economic factors could affect technical factors), and that the Economic and Political criteria had an association (i.e., government incentives could potentially lower the effective costs associated with a project). Furthermore, we noted possible associations between Environmental and Social criteria. Additionally, we observed potential relationships between Environmental criteria and technical criteria.

To create the ANP, judgments are made for every influence in the network. To provide an example, let us assume that the "goal" is to determine a location to construct a renewable energy system. Criteria might be judged in terms of their relative importance toward achieving this goal. In other words, the relative importance of the criteria with respect to the goal would be determined using the same process used in AHP. However, for any group of criteria that affects the performance of another criterion, pairwise comparisons are made for each pair of criteria with respect to the affected criterion. These pairwise comparisons produce a series of comparison matrices. We employed the Saaty fundamental scale (1-9 scale) to assess the comparative importance between pairs of criteria. Therefore, a score of 1 indicates that the two criteria being compared are of equal importance; a score of 3 indicates that one criterion has moderate greater importance than the other criterion; and a score of 9 indicates that one criterion has significantly greater importance than the other criterion. Reciprocals are used when comparing the inverse of the comparison.

Each of the comparison matrices are converted into a local priority vector. Typically, the local priority vector is obtained by determining the principal eigenvector of the local priority matrix. That is, if A represents a pairwise comparison matrix for a set of elements, we determine the priority vector w by solving the equation $Aw = \lambda_{max} w$, where λ_{max} is the largest eigenvalue of the matrix A. Additionally, we examine the consistency of each comparison matrix. Specifically, the consistency index $CI = (\lambda_{max} - n) / (n - 1)$ and the consistency ratio $CR = CI / RI$ are calculated. We verified that the consistency ratio for all comparison matrices was less than 0.1, signifying acceptable consistency in the judgments provided by the experts. Any inconsistencies above threshold were revised prior to proceeding with the analysis. A weighted version of the initial super matrix is generated. Then the super matrix is raised to increasing powers until the resulting super matrix reaches convergence.

We will use the results from the ANP to establish the set of weights of all six dimensions: $W = \{w_1, w_2, \ldots, w_6\}$ for $\{C_1, \ldots, C_6\}$, where these weights represent the consensus among experts about which sustainability dimension is most/least important.

An example of such a result could be as follows:

Economic viability = 0.25 (or 25%);

Environmental impact = 0.20 (or 20%);

Social impact = 0.15 (or 15%);

Technical feasibility = 0.15 (or 15%);

Policy support = 0.10 (or 10%);

Traffic conditions = 0.15 (or 15%).

The above weights illustrate that, according to the experts, the importance of economic viability is the greatest; then come the positive environmental impacts. In order of decreasing importance are technical, social and traffic related aspects, which were judged to have moderate importance but approximately equal weight. Finally, although policy support was rated to be of significant importance, it has the least weight.

TOPSIS for Alternative Ranking

Using the established weights of the criteria and having developed the decision matrix of the values of the criteria for all alternatives, we apply the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) procedure to assess and rank the alternatives [48,49]. TOPSIS is a compensatory multi-criteria decision-making methodology that seeks out the ideal solution and at the same time the most distant from the negative-ideal solutions [3,50-52]. The reason why TOPSIS is attractive as a sustainability assessment approach stems primarily from the fact that it enables consideration of the trade-off among criteria; i.e., an alternative can compensate for a poor value of a particular criterion through an excellent value of another criterion, while simultaneously providing a more balanced, overall better solution than other alternatives relative to an "ideal" solution [53-57].

Decision matrix and normalization

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{8}$$

Weighted normalization

$$v_{ij} = w_j \, r_{ij}, \quad \sum_j w_j = 1 \tag{9}$$

The entry vij represents the weighted score of alternative i on criterion j.

Then identified the best (optimal) and worst (negative-ideal) possible scores on a per-criterion basis. The "best" score on benefit criteria is the highest value among all the alternative options; conversely, the "worst" score is the lowest value. On cost criteria the optimal is the lowest possible value; likewise, the negative-ideal is the highest value.

Distances and closeness

For each alternative, computed its Euclidean distance to the ideal solution and to the negative-ideal solution in the weighted criteria:

$$D_i^+ = \sqrt{\sum_j \left(v_{ij} - v_j^+\right)^2} \tag{10}$$

$$D_i^- = \sqrt{\sum_j \left(v_{ij} - v_j^-\right)^2} \tag{11}$$

Then computed the relative closeness of each alternative to the ideal solution:

$$C_i^* = \frac{D_i^-}{D_i^+ + D_i^-} \tag{12}$$

This closeness coefficient provides a score for each alternative, with a higher value indicating a more sustainable alternative.

We have performed a sensitivity analysis after we have calculated the closeness coefficients. In this case, we altered either the criteria weights wj or some of the input conditions to see whether a change in ranking occurs. In multi-criteria problems, the sensitivity analysis is an important test for ensuring that the final decision is robust.

3. Results and discussions

We demonstrate our approach by applying it to a hypothetical case-study example for the selection of the most sustainable location for a new electric vehicle (EV) fast charging station from among three potential locations (A, B, and C). These potential locations are plausible examples of what could be considered in a metropolitan region, and each has its own characteristics.

- Alternative A - Site within a densely populated downtown area (for example, a parking garage located next to a commercial district).
- Alternative B - A site in a suburban residential area (for example, near a shopping mall that is located outside the central business district).
- Alternative C - A site at an interstate highway rest stop located outside of the metropolitan area (the rest stop would serve intercity travelers).

Each alternative is evaluated across the six sustainability criteria listed previously: economic (cost), environmental (reduction in emissions), social (accessibility), technical (adequacy of grid capacity), policy (support or incentives), and traffic (accessibility using the transportation system). In Table 1 below, the criteria and the corresponding weights based upon expert opinion that were derived using the ANP are summarized.

Table 1 Sustainability criteria and weights derived from ANP

Criterion	**Description (unit)**	**Type**	**Weight (wj)**
Economic Viability (Cost)	Total capital & operational cost (million $)	Cost (minimize)	0.25
Environmental Impact (Emission Reduction)	CO_2 reduction potential (tons/year)	Benefit (maximize)	0.20
Social Impact (User Accessibility)	EV users served (people or index)	Benefit	0.15
Technical Feasibility (Grid Capacity)	Grid power availability (kW)	Benefit	0.15
Policy Support	Incentives/Support (score 1-10)	Benefit	0.10
Traffic Connectivity	Traffic volume / proximity (vehicles/day)	Benefit	0.15

The weights from the expert judgment represent that economic costs (0.25) and environmental benefits (0.20) are the two most important elements since these elements account for 45% of the overall decision weight. The social and technical aspects of the station are moderately weighted at 15% each to ensure the station will be beneficial and operational. Accessibility through traffic (15%) is also being considered because if the station is not easily accessible, it cannot be an effective transportation mode. With the least weight (10%), policy support implies that although having incentives is nice, it is not the driving force behind sustainable sites in this context. These weights are consistent with the literature that suggests cost and environmental factors are usually the highest priority; however, it should be noted that other contexts may produce different weights. Fig. 1 shows the monthly sessions.

Deep learning prediction results

A prediction model was used to predict how much each site A, B, and C would be used in 2026. This means how many charging sessions per day and how much electricity would be dispensed at each site per day. The model provided the following predictions:

Site A (Downtown): The model predicts that site A will be heavily used because it is located in a busy area where there are many EV owners and commuters. Therefore, the model predicts an average of 200 charging sessions per day at site A; this corresponds to approximately 1,000 kWh per day of electricity being dispensed and the maximum amount of electrical energy that can be drawn from site A at one time is predicted to be 500 kW.

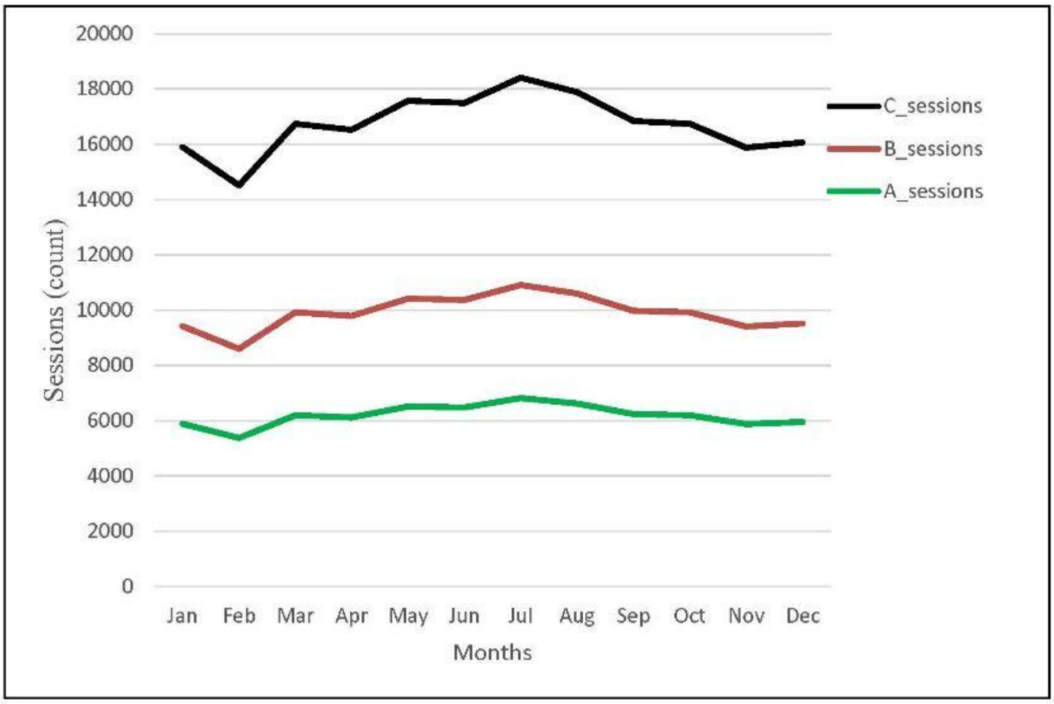

Fig. 1 Monthly sessions

Site B (Suburban Mall): The model predicts that the usage of site B will be moderate. There are likely many suburban EV owners who charge their cars at home, therefore they may not need to visit a public charging station very frequently. Therefore, the model predicts an average of 120 charging sessions per day at site B; and the model also predicts that approximately 600 kWh per day of electricity will be dispensed at site B.

Site C (Highway Rest Stop): The primary purpose of site C is to provide electric vehicle charging services to long distance travelers; therefore, the model predicts that the throughput of site C will be high, particularly during holiday seasons and other peak travel seasons. The model predicts an average of 220 charging sessions per day at site C (which is higher than site B, and slightly higher than site A), and it also predicts that site C will dispense approximately 1,100 kWh per day of electrical energy.

Then we constructed the decision matrix (Table 2) for the three alternatives. The values for each criterion are either directly from predictions or from assumptions guided by them:

Table 2 insights show alternative A was the most expensive; however, it had the second-highest level of emissions avoided and second-most users. Alternative B was the least expensive; however, it ranked second-lowest in terms of emissions avoided and second-lowest in terms of user adoption. Alternative C had relatively strong performance in both environment and user adoption, average costs and the lowest total grid capacity.

Table 2. Decision matrix criteria values for alternatives A, B, C

Alternative	Economic Cost ($ million)	Emission Reduction (tons CO_2/yr)	Users Served (sessions/day)	Grid Capacity Available (kW)	Policy Support (score 1–10)	Traffic Volume (vehicles/day)
A (Downtown)	5.0 (higher = worse)	73 (higher = better)	200 (high)	1000 kW	9	15,000
B (Suburban)	3.0 (lower cost)	44 (moderate)	120 (moderate)	800 kW	6	10,000
C (Highway)	4.0 (medium cost)	80 (high)	220 (high)	600 kW	8	20,000

TOPSIS results shows, Alternative C scores highest on Environmental (0.1368 vs A's 0.11396 and B's 0.0912), highest on Social (0.1029 vs A's 0.0935, B's 0.0561), and highest on Traffic (0.1114 vs A's 0.0836, B's 0.0557). Alternative A scores highest on Technical (0.1061 vs others 0.0849 and 0.0636) and Policy (0.0669, slightly above C's 0.0595 and B's 0.0446), and Alternative B unsurprisingly scores best on Cost (0.1061, since B had lowest cost, vs C's 0.1414 and A's worst 0.1768 on cost because cost is a negative criterion where lower is better, so A's weighted cost score is highest which is bad in terms of ideal distance).

Closeness coefficients by TOPSIS evaluation:

Alternative A: $C \approx 0.621$

Alternative B: $C \approx 0.511$

Alternative C: $C \approx 0.389$

The ranking is A (highest closeness to ideal) > B > C.

Discussions

Alternative A (the Downtown site) is clearly the most sustainable alternative given the data and weighting of the criteria used in the evaluation. The closeness coefficient for Alternative A was 0.62; Alternative B's was 0.51 and Alternative C was 0.39. Alternative A would appear to represent the best compromise solution among the three alternatives evaluated. Alternative B scored lower in two of the three categories weighed in the evaluation while having the lowest costs. Alternative C low scores in the two weighted categories led to it scoring lower than both Alternatives A and B. The results from this evaluation are consistent with previous research findings regarding urban EV charging stations being highly effective in terms of usage and emissions savings when demand is high, regardless of their cost. In other words, an urban charging station that gets used can have significant overall sustainability benefits, even at a higher cost than a station with lower demand and thus may not get used as often. On the other hand, a lower-cost station with little usage may offer fewer overall benefits and thus may not be as good an investment.

In this study, Alternative C (the highway station) was rated very high in terms of usage. Its rating for emissions per session was slightly better than Alternative A's and yet ranked as the worst alternative. The fact that the highway station ranked poorly in the evaluation suggests that the trade-offs associated with Alternative C were sufficiently negative that they outweighed its positive attributes. If an organization prioritizes supporting EV drivers broadly, rather than focusing on providing access for local EV drivers or limiting the cost of upgrading the electric distribution system, then they may choose to assign greater weight to the traffic/usage criterion and/or less weight to the cost criterion.

The results shows that Alternative A (urban site) is the best is scenario dependent. However, it is interesting for there is a parallel to some real-world deployment scenarios as well. That is, studies show that more consistent station use and hence more effective carbon emission reductions result when stations are placed in a high-density area of EVs and high activity. However, it is also noted frequently that a balanced infrastructure requires some fast-charging stations on highways to accommodate long distance travel, those may not win in straight multi-criteria rank if heavily weighted against cost comparison, but they do fulfil a strategic purpose. This indicates that those doing the ranking do not always select just the top rank but perhaps make sure to get a balanced portfolio. Our analyses here can be extended to selecting a set of alternatives by means of optimization or application of constraints.

Stating somewhat differently regarding factor importance, the cost factor received the most weight in our ANP weights, which biased analysis in favor of A over C. Many past works assigned valuation to the cost or economic feasibility factor as the top factor in EV station planning, which our analyses substantiates that B, the cheapest was quite competitive despite offering much lower benefit. If the cost weight was any higher, B could be ranked higher than A, as we shall see in sensitivity analysis. Other studies, are to be noted that in case environmental and social criteria are assigned greater importance that solutions might differ. ANP enabled us to take cognizance of interdependency. In this case we have built in interdependencies such as policy to economic and technical to environmental. The ANP super matrix calculations effectively forecast that thereby some of the weight from economic might slip over to the policy weight if policy was considered high etc. In the final analysis of a single case model these interdependencies are latent, but if one were to run the model under various conditions the ANP method could bring out how the weight or importance of a factor might change.

We perform several sensitivity tests to see how robustly the ranking holds given changes in inputs. We examined two hypothetical re-weightings: (a) an environmental weighting increase from 0.20 to 0.30 in the environmental category, and (b) an economic weighting increase to 0.35. In case (a) “green priority,” the alternative C becomes relatively favored. We found that CC rises and CB falls further, but yet alternative A remained top alternative. A’s emissions is somewhat lower than C’s but A is not far afield almost as much; plus, A is strong because of social and technological advantages. The gap between A and C became closer, however, suggesting that if the environment were deemed even of more importance, C could be ahead. In case (b) “cost priority,” alternative B’s score improved quite materially. For weight 0.35 in the costing category, B’s closeness CB in fact slightly ahead A’s rendering B the top alternative. However, this is notable as indicating a strong tipping-point: if the decision-makers are favoring cost-type attributes so that the cost attributes take over more than some 30% of the total weight, the cost only reduced alternative B could be decided on as the “most sustainable”, placing emphasis on some financial sustainability rather than maximum emissions reduction. This tipping-point analysis is valuable for public policy-makers, as it puts a scale or measure on the extent of emphasis re cost that would bring about a change in direction in decision. However, for the practicalities of it, it is noted that the act of sustainability has an inane requirement of a balance, so it might mean that too much emphasis re cost might be of a short-sighted attitude.

The integrated method of deep learning + ANP + TOPSIS has shown great capabilities in providing analytical depth. Our integrated method not only provides a ranking, but a justification for why one alternative is ranked better than another, as well as the sensitivity of this ranking based on the decision maker's preferences and/or the future conditions being considered. Alternative A has been identified as the top choice for its superiority in criteria that are heavily weighted, such as a large user base (social benefit) and significant emissions reduction (environmental), and has no major technical issues or policy concerns. Although Alternative A does have a high cost associated with it, clearly the decision-makers felt the social and environmental benefits outweighed this drawback, thus, the cost was weighed less heavily. A private investor who made decisions based solely on profits may weigh cost more heavily and select Alternative B. Similarly, a governmental agency that is mandated to reduce emissions may prefer Alternative C if the governmental agency placed emphasis on wide-spread network coverage. As previously stated, our methodology allows for flexibility in adapting to different decision-maker value systems through adjusting the ANP weighting stage.

In addition to the ability to adjust for decision-maker value systems, another key contribution of our methodology is the integration of deep learning into our decision-making process. The predictions generated by our deep learning models provided us with numerical estimates of emissions and usage. Without these estimates, we would have had to rely upon guesses or static proxy measures when estimating these criteria values. The deep model is able to capture nonlinear relationships between inputs, therefore, improving the accuracy of our estimated criteria values. Without the use of the model, we may have underestimated the potential of Site C due to the lower population density in the surrounding area. However, the model took into account that traffic volume along the nearby highway contributes to the usage at Site C and provided a high estimate for usage. By using the model, we avoided a bias that could have arisen from reliance on simpler criteria. This type of data driven insight is becoming increasingly important and is considered an emerging best practice. As one recent study stated, the use of machine learning in conjunction with multi-criteria decision-making techniques can reveal patterns that traditional methods of analysis cannot. Additionally, in future studies, the model outputs could be incorporated in real-time, allowing for continuous updates to station performance predictions as the number of electric vehicles grows, and periodic re-running of the TOPSIS ranking to identify if the preferred sites have changed over time.

Our results mirror the previous literature finding that the economic factors were the most influential in determining the optimal locations for electric vehicle charging stations, followed by the technical factors. The top site was one that effectively balanced the economic costs of installing and maintaining the station with the technical feasibility of doing so. In our case, the top site A, while having a high cost, had a very high demand and level of support, thus making it an effective and sustainable solution. Therefore, regardless of the methodologies employed the underlying message remains the same. Multi-criteria decision-making methodologies allow for much more nuanced decision-making than single-factor methodologies. A decision made solely on cost or solely on environmental considerations, would not be a complete picture; it would be incomplete and would not take into consideration all relevant factors. It is the combination of factors that makes the decision complete.

While we did not directly account for future trends in the form of vehicle-to-grid (V2G) and renewable energy, these concepts are extremely important to the sustainability of charging stations. In the case of solar panels on a station or allowing EVs to feed back to the electric grid during off-peak hours, both could greatly increase both environmental and technical efficiencies. Therefore, additional criteria could be developed e.g. Renewable energy integration, that would be included in an expanded evaluation system. This could potentially change the way sites were evaluated, depending on their ability to support such features. Our proposed evaluation system is flexible enough to include this type of feature, and the deep-learning-based model may also be capable of predicting how much solar energy a given location could generate or how V2G could help to reduce the peak load of a grid.

4. Conclusions

This study presented a new methodology for assessing the sustainability of electric vehicle (EV) charging infrastructure using predictions from a developed deep learning model along with multi-criteria decision analysis (ANP and TOPSIS). This methodology arose from the need to address the complex and interrelated causes of commitment to sustainable EV infrastructure development which can involve economic costs, environmental benefits, social issues, technical feasibility, context of legislation and government policies relating to EVs and traffic factors. By inclusion of a deep learning model, the methodology was enhanced by its data driven predictive nature which allow the planning process to be based on predicted performance involving such factors as planned station utilization and energy use by EVs as opposed to static values. The use of Analytic Network Process gave a methodical evaluation of workshops towards deriving criteria weights giving respect to mutual interdependencies of sustainability criteria while the TOPSIS method of evaluating alternatives gave a more refined choice process towards ranking candidates as they were ranked towards their closest extent towards an ideal sustainable solution. In our lead study the unified model overcame these problems towards the recognition of the most sustainable alternative EV charging station, by balancing the trade-offs and opportunity of the alternatives as they were assessed on all criteria. The top ranked site extracted the better available allowable factor of both high use of the station and emissions reduction against higher costs of the alternatives, in general the best results were obtained in the case of high up-front capital costs and expenditure invested towards sustainability payoffs. Those site alternatives of relatively lower installation costs rated poorly in comparison to the high potential level of importance of utilization of station factors and evaluation of emissions reducing factors updated from collective points in assessment of case studies. When dealing with several criteria it is considered an important factor that all alternatives be evaluated and weighted accordingly for performance criteria resulting from joint consideration of budget constraints and criteria considered thereupon. This process is essential for economic study model for completed solutions therein of a frame of analysis required. These findings emphasize that the "best" charging infrastructure cannot be said to be the cheapest or the best single decision but must be the one which gives the best composite sustainability, so justifying the holistic approach, that a one-criteria decision may lead to shortsightedness, while the holistic decision would be top-rated and futureproof.

We have also gained some insights into the relative importance of criteria and how sensitive the results may be to the stakeholders' preferences. Obviously the economic or financial opportunity and the environmental decision are the focus decisions in determining sustainability, but social and technology parameters are important. The ANP weighting could be regarded as an indication of the degree to which the consensus values of the decision-makers are reflected in the number, while changing the weights gave something that seemed sensible. Such a what-if exercise also allows the decision makers some scope to assess ahead of time how far the ends that they are trying to achieve will lead to support for some of the options. Also, the identification of what criteria or what circumstances would broaden the attraction of an option gives some opportunity to improve some others. For example, if Site A is strategically desirable, but on the technology, criteria are reasonably low, perhaps emphasis can be placed on grid development to the site or the provision of battery storage, results that will affect its ranking.

The holistic approach suggested could be valuable as a decision-support tool for urban planners and transport executors and possible service providers of utilities who would be required to implement enhanced EV charging needs infrastructure. That is to say it allows a transparent ranking and shows the expected results of all alternatives along all the sustainability paths, thus leading to decisions which are transparent and sustainable, also justifiable. Also the model engenders confidence that spending will be directed to the better alternatives which have the best overall impact, and it is possible, it seems, that such methods might engender confidence so as to attract funds, in that the projects which are provided for have the better overall effect, thus that can be assumed, and that lies with sustainability criteria which are laid down as goals by any government, or as expressed by ESG investors.

Turning to our academic contribution, we have endeavored to implement the new findings which are showing themselves in the literature drawing between artificial intelligence and sustainable infrastructure planning. This shows how it is possible to apply Deep Learning (AI) and MCDM efforts which can positively assist each other in the decision processes. AI gives the micro results and micro findings, while MCDM brings the decisions from macro perspective, as to use those findings in relation to human values following a definite set of goals such as sustainability. It is envisaged that such hybrid procedures will be very valuable in the times to come when smart city developments have produced a vast amount of data, or when sustainability criteria must indicate trade-offs. The methodology that we have put forward is generalized above and beyond EV options, and could have applications, perhaps, for example, on renewable energy plants, on other transport infra-structure.

Conflict of interest

The authors declare no conflicts of interest.

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