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Unsupervised Learning-Driven Charging Station Deployment: Optimizing Electric Vehicle Networks For Sustainable Development

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Abstract
The fast growth of the electric vehicles (EVs) makes the strategic implementation of charging facilities necessary in support of a sustainable transport ecosystem. The conventional methods of charging station's location typically take the position to be set beforehand without giving much consideration to the dynamic traffic patterns, the user behavior, and constraints in grid capacity. The paper suggests an unsupervised learning-based approach to optimal deployment of charging stations taking into consideration the clustering algorithms, dimensionality reduction techniques, and graph-based optimization to determine strategic points on which to place EV charging stations. Its methodology uses three tier methodology: data aggregation and pre-processing, unsupervised pattern discovery and multi-objective optimization. The framework employed is a K-means clustering with DBSCAN to perform spatial analysis, Principal Component Analysis (PCA) as a feature re- duction method and graphene neural networks to optimize network topology. It is experimentally validated on actual traffic data of metropolitan regions that the pro- posed UL-EVCD (Unsupervised Learning Electric Vehicle Charging Deployment) model reimbursement 23% of the coverage efficiency and 18% of the mean distance to the charging stations in comparison with traditional grid-based models. The framework also guarantees 94% grid stability and as much as possible integration of renewable energy towards a sustainable city development system.
Keywords: *Unsupervised Learning, Electric Vehicle Infrastructure, Charging Station Optimization, Sustainable Development, Clustering Algorithms, Smart Grid Integration*

1. INTRODUCTION

The preference the world has changed to a sustainable transportation model has improved the adoption of electric vehicles (EVs) and projections indicate that over 230 million additional EVs would be presently on the road in 2030 (more than 230 million) [1]. This paradigm shift has taken shape in the nature of new challenges of designing adequate charging facilities which are capable of accommodating mass implementation of EVs as well as ensuring grid stability that will lead to sustainable development. The traditional forms of charging station placement are also more often location based and are placed where it operates based on rudimentary demographic data or existing fuel stations grids and network systems that do not consider the dynamic nature of urban mobility, fluctuation of demand, and variation in terms of preference of behavior among users [2].
EV charging spatial location is a complex system optimization problem that involves the spatial analysis, time demand curves, and grid integration, and the need of user accessibility. Conventional paradigms of supervised learning rely on big defined datasets comprising of preset optimization purposes that are not always reflective of the fresh developments of EV usage and charging[3]. Besides, space patchiness of urban space, traffic and the multiculturalism of users of the space creates complex interdependencies that cannot be treated using traditional tools of analysis.
Unsupervised learning methods have been found to be very helpful in overcoming such issues and finding out unconscious patterns and structures in the large scale transportation and energy data without having any knowledge or pre-opted labels [4]. These techniques can distinguish natural groupings of charging demand, demonstrate reactionary crimes in traffic movement and indicate spatial connections that might not otherwise be noticeable by utilizing traditional analysis. Unsupervised learning can be used to draw informed suggestions in terms of optimal location of charging stations using clustering algorithms, dimensionality reduction algorithms, as well as anomaly detection algorithms. Still, the optimization problem in the implementation of the charging station is complicated by the fact that smart grid technologies and renewable energy sources are being combined. The characteristics of modern EV charging networks are that they are required to address grid capacity, peak demand control and integration of distributed energy capacity solar panels and energy storage units, among others [5]. This has necessitated a holistic approach combining infrastructure investment costs, user convenience, grid stability and environmental

sustainability as a goal.

This paper discusses these issues with an implication of a holistic method of unsupervised learning to optimize the deployment of EV charging stations. Its strategy involves the integration of several methods of unsupervised learning to analyze the traffic patterns and find optimal points to integrate with the current energy infrastructures in a sustainable way. The framework takes into account real-time traffic dynamics, charging trend within the past, grid capacity limits, and availability of renewable energy sources in a bid to come up with sound suggestions to be implemented to ensure the charging station locations contribute to sustainable development in the long run.

2. LITERATURE REVIEW

Chen et al. (2024) [6] reviewed an issue of optimization of EV charging stations input location through genetic algorithm methodology integrated with traffic simulation models. In their approach, they used the analysis of traffic flow, grid capacity limitation, and the degree of user comfort to declare the best places in urban areas. The paper has shown that strategic placement would minimize average waiting time by 31 percent and grid load distribution. The methods were however very dependent on predefined traffic models and were energy consuming in large-scale implementation cases.

Rodriguez et al. (2024) [7] suggested the use of machine learning to develop a charge demand prediction model on the basis of historical traffic flow and demographic variables in EV charging. They employed a strategy that involved the use of ensemble techniques that combined random forests and support machine to predict the charging needs within the various urban areas. It was able to predict demand with 87% accuracy and offered several determinants of charging behavior with the model. The paper emphasized the significance of changes in time and seasonal fluctuations in charging demand but left out the issue of the spatial optimization of charging station location.

Kumar et al. (2023) [8] examined how the process of locating optimal charging stations sites in smart cities is supported by the methods of clustering algorithms. They used a strategy of K-means clustering with spatial restraint to cluster high-demand areas and set strategic points of placement. The strategy put into consideration the population density, the amount of traffic and the availability of infrastructure. Raised coverage efficiency by 25 percent over random placement methods, but the experiment has been limited to a static traffic pattern and has not considered the grid integration factor.

Wang et al. (2023) [9] manages to work out a deep reinforcement learning strategy to control the deployment of charging stations based on the necessity to change over time. The framework employed the Q-learning algorithms in order to change the strategies of placing charging stations according to the real-time traffic patterns as well as changes in the demand of charging. Their model showed better performance dealing with changing environments and had a 19% decrease in the average distance that travelled to charging stations. Nevertheless, the method demanded large training data and computing power, which prevents its application in large scale. Thompson et al. (2022) [10] provided a detailed discussion of the optimization algorithm application in the integration of renewable energy in EV charging networks. Their test was aimed at optimizing the solar energy use without affecting grid stability and user satisfaction. The approach involved weather prediction systems, energy-saving application and load balancing algorithms in order to realize the deployment of sustainable charging infrastructures. Findings showed that there was a 34 percent increase in the use of renewable energy and a 22 percent decrease in peak grid demand, which showed that sustainable EV charging networks are possible.

Patel et al. (2022) [11] investigated using the graph neural networks in simulating the EV charging network topology and optimization of substation locations. Their method modeled charging stations and traffic intersections as the graph structure, which allowed the evaluation of the network connectivity and patterns of network flows. The model was able to identify the important nodes where to locate the charging stations in and also optimized the network topology to achieve high efficiencies. The paper has attained 28 percent improvement in coverage of a network as well as establishing the ability of graph-based methods to optimize the infrastructure.

Zhang et al. (2021) [12] explored the application of the unsupervised learning techniques in the user behavior analysis to understand the placement of EV charging stations. They used clustering algorithms in their methodology to determine different groups of users, according to charging patterns, travel patterns and demographic factors. The analysis showed that there are great differences in the preferences of the charging between various user groups and the need to plan

infrastructures individually. Findings revealed a 21% positive change in user satisfaction when taking into account behavioral patterns when determining the station locations.
Liu et al. (2021) [13] suggested a multi-criteria decision model to use in the deployment of sustainable EV charging stations. The strategy combined the environmental impact analysis, economic feasibility, and social acceptance measures to analyze the good places to have the charging stations. Their approach employed the use of fuzzy logic and analytic hierarchy process to address the uncertainty and contradicting goals. The re- search revealed that it is essential to keep in mind various stakeholders and sustainability criteria when making decisions in the infrastructure planning.

3. PROBLEM STATEMENT

Although the current EV charging infrastructure planning processes have made considerable improvements, there are various critical limitations likely to hamper the ideal deployment and sustainable development of the processes. The current supervised learning models have large population size of labeled data and predetermined optimization goals, both of which may not reflect the changing dynamics of EV adoption and pattern of user behaviors. A lot of existing systems are based on the fixed traffic models and demographic data which do not consider the real-time change in the charging demand, seasons, and newly appeared mobility trends, including ride-sharing and autonomous vehicles.
Moreover, the majority of current frameworks solve the problems of charging station placement and grid integration independently and provide sub-optimal solutions, which can fulfill specific goals but cannot result in global system efficiency. Absence of holistic solutions that can simultaneously take into account spatial optimization, temporal demands patterns, grid capacity limits, and integration of renewable energy source leads to non-use of charging networks, their overutilization or non-supportiveness of the infrastructure, based on environmental aspects.
Conventional ideas of clustering and optimization do not usually tackle the dimensions of high-dimensionality of some common urban mobility data, and as such cannot find complex patterns and relations in that sophisticated data to guide better placement decisions. Also, current strategies are usually centered on reducing the travel distance or increasing the coverage without sufficient attention to more extensive claims on sustainable development, such as the reduction of the carbon footprint, grid stability and long-term infrastructure resilience.
Another complication of future research that the existing research approaches fail to take into account is the need to incorporate renewable energy sources and energy storage mechanisms into the charging networks. The temporal lack of fit between the supply of renewable energy and the demand to charge batteries is not well modeled in most currently existing frameworks, which causes usage of clean energy resources to be suboptimal and have grid electricity being more depended on during peak demand.
To overcome these shortcomings, the paper will present a detailed unsupervised learning model that will identify concealed trends in the interaction of multi-dimensional urban mobility and energy data in order to streamline the amount of charging stations to be installed in efforts to achieve sustainable development. The framework will help to fill the gap between the spatial optimization, temporal demand model, as well as sustainable energy integration and provide scalable solutions to different urban manners.

4. METHODOLOGY

In the present research, the authors suggest a combined learning system to deploy optimal EV charging stations unsupervised that integrates several machine learning methods with the use of multi-objective optimization algorithms.

4.1 Data Acquisition and Preprocessing Layer

This layer reads data feed and processes them according to their nature. The structure of the framework is based on the extensive gathering of the information of various types such as traffic monitoring systems, available logs of the usage of charging stations, grid capacity data, and the profiles of the renewable energy generation. The preprocessing pipeline of data usage is based on the method of dimensionality reduction and filtering the noise to create the as-good inputs.

4.2 Multi-Source Data Integration

There are five major categories of data which are collected and integrated by the system:

- **Traffic Flow Data:** Traffic data obtained in real-time and historical trends in traffic the sensor of traffic monitoring, GPS tracking and data of mobile networks. This would involve vehicle density, speed profile, route preference during various time scales and geographical area.

- **Charging Behavior Data:** Previous charging session history in terms of duration, frequency, user date time and favorite charging location. This data gives data about the real EV user behavior and preferences when it comes to charging.
- **Grid Infrastructure Data:** Irradiation and wind formation data, together with capacity of these storage systems of different geographical locations. To this end, maximum utilization of renewable energy can be optimized with such information.
- **Renewable Energy Data:** The irradiation and wind formation as well as storage system capacity of various geographical sites. With such information, optimization of maximum use of renewable energy is possible.
- **Urban Infrastructure Data:** Network on road systems, building density, land use patterns of a particular area as well as the current energy infrastructure. These contextual data can be used to give the placements and accessibility analysis of the real constraint.

4.3 Data Preprocessing Pipeline

Algorithm-1 outlines the data preparation stages will be provided below:

Algorithm- 1 Multi-Source Data Preprocessing

Require: Raw data streams from multiple sources
1: *Data_cleaning* ← *remove_outliers* (*raw_data, threshold* = 3 × *std*)
2: *Temporal_alignment* ← *synchronize_timestamps* (*data_streams*)
3: *Spatial_interpolation* ← *interpolate_missing_locations* (*GPS_data*)
4: *Feature_extraction* ← *extract_relevant_features* (*cleaned_data*)
5: *Normalization* ← *min_max_scaling* (*feature_matrix*)
6: *Dimension_reduction* ← *PCA_transform* (*normalized_data, variance_ratio* = 0.95)
Ensure: Preprocessed feature matrix

4.4 Unsupervised Pattern Discovery Layer

This layer is used to detect the hidden patterns and structures in the preprocessed data using several unsupervised learning algorithms. The strategy is a combination of clustering algorithms, dimensionality reduction and anomaly detection used to identify an ideal zone with regard to placing charging stations.

4.5 Hierarchical Clustering Analysis

This framework uses a hierarchical clustering method which is a combination of the K- means clustering and DBSCAN to distinguish between natural clusters of high-demand locations and patterns of traffic flows. This hybrid scheme takes advantage of the reliance of K-means to identify the first clusters but it uses the DBSCAN capability to deal with irregular cluster shapes and spot outliers.

Algorithm-2 Hybrid Clustering for Demand Zone Identification

Require: Preprocessed spatial-temporal data matrix *X*
1: *Initial_clusters* ← *K_means* (*X*, $k = \sqrt{n/2}$)
2: **for** each cluster *c* in *Initial_clusters* **do**
3: *Refined_clusters* ← *DBSCAN*(*c, eps* = *adaptive_eps*(*c*), *min_samples* = 5)
4: *Merge_adjacent_clusters* (*Refined_clusters, distance_threshold*)
5: **end for**
6: *Demand_zones* ← *validate_clusters* (*Refined_clusters, minimum_size*)
Ensure: Identified demand zones with priority scores

Temporal Pattern Analysis

The system uses time series analysis that works unmonitored to define repeated patterns in the changing need of a charging service and traffic. This comparison makes use of auto encode and spectral coding to find out the temporal connection and peak time.

4.5.1 Spatial Relationship Discovery

The unsupervised learning methods represent by graphs, examine relationships between the location of the possible charging stations, established facilities, and the traffic flow methods. This study finds strategic location points which maximize the access and the network connectivity.

4.6 Multi-Objective Optimization Layer

The optimization layer combines the identified patterns with multi-objective optimization algorithms to identify the most suitable location of charging stations that can mitigate to various competing goals such as coverage maximization, the travel distance minimization, grid stability, and the renewable energy incorporation.

4.6.1 Objective Function Formulation

The framework optimizes four primary objectives:

Coverage Efficiency (CE): Maximizes the percentage of EV users within acceptable travel distance to charging stations:

$$CE = \frac{\sum_{i=1}^{n} w_i . I(d_i \leq d_{max})}{n}$$

where w_i indicates the weight of user i, d_i is the distance to be traveled for nearest charging station, and d_{max} is the maximum distance that is acceptable.

Grid Stability Index (GSI): This makes sure that charging station placement maintains electrical grid stability.

$$GSI = 1 - max\,(\frac{P_{peak} - P_{capacity}}{P_{capacity}}, 0)$$

where P_{peak} represents peak power demand and $P_{capacity}$ denotes grid capacity.

Renewable Energy Utilization (REU): Increases the amount of charging energy that comes from renewable sources:

$$REU = \frac{\sum_{t=1}^{T} min(RE_t, CD_t)}{\sum_{t=1}^{T} CD_t}$$

where RE_t is renewable energy availability and CD_t is charging demand at time t.

Infrastructure Cost Efficiency (ICE): Minimizes the total infrastructure investment per unit of service provided:

$$ICE = \frac{Service_{total}}{Cost_{infrastructure} + Cost_{operation}}$$

4.6.2 Multi-Objective Genetic Algorithm

The framework employs a modified NSGA-II (Non-dominated Sorting Genetic Algorithm II) enhanced with local search capabilities to solve the multi-objective optimization problem.

4.7 Sustainable Integration Analysis Layer

This layer assesses the sustainability implications of proposed deployments of charging stations, in the long perspective, taking into account the environmental impact and economic viability factors, as well as the social acceptance factor.

4.7.1 Environmental Impact Assessment

The system computes the potential of reduction of carbon footprint of each charging station setup based on the local energy mix, integration of renewable energy, and lifecycle emissions of charging infrastructure.

4.7.2 Economic Viability Analysis

A comprehensive economic model evaluates the financial sustainability of charging station deployments, including capital costs, operational expenses, revenue projections, and payback periods.

5 Experimental Validation

5.1 Dataset Description

The experimental validation is based on real world data in 3 metropolitan regions: San Francisco Bay Area, Amsterdam Metropolitan Region, and Singapore Urban District. The datasets contain data of traffic flow on 2,500 of the existing monitoring points, records of charging session at 15,000 charging stations in existence, grid capacity of local power plants, and renewable energy generation of 24 months.

San Francisco Dataset: This dataset consists of traffic data of 850 cameras, 5,200 charging stations that are currently in existence, and solar output across 1,200 installations. The sample is 9,000 square kilometers where urban, suburban and highway environments are ranged.

Amsterdam Dataset: It consists of traffic data of 680 sensors, 3,800 charging stations and wind generation data of 45 installations. The data is reflective of developed EV market with dense charging stations.

Singapore Dataset: The dataset includes features of 970 traffic monitoring stations, 2,100 charging stations, and full data on the integration of the environment of the public transport, which represents a smart city.

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5.2 Experimental Setup

The experiments investigate the UL-EVCD framework along with three baseline methods, namely, Random Placement (RP), Grid-Based Placement (GBP), and Genetic Algorithms Optimization (GAO). These approaches are tested using the same datasets and metrics of the performance in order to conduct an equal comparison.

5.3 Results and Analysis

Table-1 presents the comprehensive performance comparison across all experimental scenarios:

Table 1: Performance Comparison of Charging Station Deployment Methods

Method	Coverage Efficiency (%)	Avg. Travel Distance (km)	Grid Stability Index	Renewable Energy Utilization (%)
Random Placement	67.3	4.8	0.78	52.1
Grid-Based	74.8	3.9	0.82	61.3
GA Optimization	81.2	3.2	0.87	71.8
UL-EVCD	92.1	2.6	0.94	84.7

The performance of the experimental results proves that the UL-EVCD framework is more effective than the methods of basis in all the evaluation metrics. A 23-percent increase in effectiveness of coverage compared with genetic algorithm optimization and 37-percent improvement against grid-based approaches is obtained by the framework. The contribution compared to the optimum baseline method is the 18-percent cut in the average distance travelled to charge stations.

The stability analysis of grid stability indicates that the UL-EVCD framework will have a stability index of 0.94 therefore a good integration with existing electrical infrastructure. The rate of 84.7 in using renewable energy source is a significant step compared to the conventional means of doing the same and this has led to lower carbon emission and sustainable development objectives.

5.4 Scalability Analysis

The computational complexity analysis shows that UL-EVCD framework is efficient in respect of dataset size. The time required to process the number of potential locations of charging stations increases logarithmically, so the method is effective when a large-scale deployment of charging stations in a metropolitan area is required. The incremental processing architecture attributes memory requirements because they are fixed.

6 CONCLUSION AND FUTURE WORK

The paper gives an in-depth unsupervised learning model to maximize the deployment of electric vehicle charging stations overcoming limitations in the development of sustainable transportation infrastructure. The suggested UL-EVCD framework effectively combines several techniques of unsupervised learning methods with multi-objective optimization to find the best possible locations of charging stations that combine coverage efficiency, stability on the grid, use of renewable energy and economic feasibility.

Experimental validation indicates that there are considerable improvements on the current methods, including 23 percent coverage efficiency increase, decrease of an average travel distance by 18 percent and a utilization rate of 84.7 percent by renewable energy. Such findings suggest that the unsupervised learning approach could reveal the concealed features in urban mobility and energy data in large cities and contribute to the use of data in the infrastructure planning process.

The capability of the framework to have the 94% grid stability and to maximize the integration of renewable energy is a high input in the sustainable development agendas. The strategy promotes the overall shift toward sustainable transport systems and ideal utilization of the clean energy sources by maximizing the network of charging stations and maintaining the affordability and dependability of charging networks.

Future research directions, the framework is to be extended to support autonomous vehicle traffic patterns along with dynamic pricing to manage demand and integration with the vehicle-to-grid technologies. More efforts will be made on how to develop real-time adaptation to accommodate the changing mobility trends in the city and the expansion of the functions to rural and highway charging corridors optimization. Distributed processing might be made possible through integration of edge computing technologies to optimize processes in real-time in a large-scale deployment.

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REFERENCES

[1] International Energy Agency, "Global EV Outlook 2024: Towards a Net Zero Emissions Future," IEA Publications, Paris, France, 2024.

[2] L. Zhang, H. Wang, and M. Li, "Strategic Planning of Electric Vehicle Charging Infrastructure: A Comprehensive Review of Location Optimization Methods," *Renewable and Sustainable Energy Reviews*, vol. 168, pp. 112–128, 2024.

[3] A. Kumar, R. Singh, and N. Patel, "Machine Learning Approaches for Smart Transportation Systems: Challenges and Opportunities," *IEEE Transactions on Intelli- gent Transportation Systems*, vol. 25, no. 3, pp. 1245–1260, 2024.

[4] M. Chen, X. Liu, and K. Anderson, "Unsupervised Learning in Urban Planning: Applications and Methodological Challenges," *Smart Cities*, vol. 7, no. 2, pp. 89– 105, 2024.

[5] P. Rodriguez, S. Martinez, and J. Thompson, "Integration of Renewable Energy Sources in Electric Vehicle Charging Networks: A Systematic Approach," *Applied Energy*, vol. 342, pp. 121–135, 2024.

[6] W. Chen, Y. Zhou, and L. Garcia, "Multi-objective Optimization for Electric Vehicle Charging Station Placement Using Genetic Algorithms," *Transportation Research Part D: Transport and Environment*, vol. 118, pp. 103–119, 2024.

[7] A. Rodriguez, S. Kim, and M. Brown, "Machine Learning-Based Framework for Predicting Electric Vehicle Charging Demand in Urban Environments," *Energy Policy*, vol. 186, pp. 114–128, 2024.

[8] V. Kumar, P. Sharma, and C. Lee, "Clustering Algorithms for Optimal Charging Station Location Identification in Smart Cities," *IEEE Transactions on Smart Grid*, vol. 14, no. 4, pp. 2876–2888, 2023.

[9] J. Wang, Q. Liu, and R. Davis, "Deep Reinforcement Learning Approach for Dynamic Electric Vehicle Charging Station Deployment Optimization," *Neural Computing and Applications*, vol. 35, no. 12, pp. 8745–8762, 2023.

[10] D. Thompson, K. Miller, and E. Johnson, "Renewable Energy Integration in Electric Vehicle Charging Networks: Optimization Strategies and Grid Stability Analysis," *Renewable Energy*, vol. 198, pp. 1123–1137, 2022.

[11] R. Patel, A. Singh, and T. Williams, "Graph Neural Networks for Modeling Electric Vehicle Charging Network Topology and Infrastructure Optimization," *IEEE Trans- actions on Network Science and Engineering*, vol. 9, no. 4, pp. 2234–2247, 2022.

[12] H. Zhang, W. Li, and B. Taylor, "User Behavior Analysis for Electric Vehicle Charging Station Placement Using Unsupervised Learning Techniques," *Transportation Research Part C: Emerging Technologies*, vol. 132, pp. 103–118, 2021.

[13] S. Liu, F. Yang, and C. Martinez, "Multi-criteria Decision Analysis Framework for Sustainable Electric Vehicle Charging Station Deployment," *Journal of Cleaner Production*, vol. 315, pp. 128–142, 2021.

[14] F. Ahmad, A. Iqbal, I. Ashraf, and M. Marzband, "Optimal location of electric vehicle charging station and its impact on distribution network: A review," *Energy Reports*, vol. 8, pp. 2314–2333, 2022.S. Hussain, M. A. Ahmed, K. B. Lee, and Y. C. Kim, "Fuzzy logic weight based charging scheme for optimal distribution of charging power among electric vehicles in a parking lot," *Energies*, vol. 13, no. 12, pp. 3119, 2020.

[15] S. Deb, K. Tammi, K. Kalita, and P. Mahanta, "Impact of electric vehicle charging station load on distribution network," *Energies*, vol. 11, no. 1, pp. 178, 2018.

[16] S. Guo and H. Zhao, "Optimal site selection of electric vehicle charging station by using fuzzy TOPSIS based on sustainability perspective," *Applied Energy*, vol. 158, pp. 390–402, 2015.

[17] P. Sadeghi-Barzani, A. Rajabi Ghahnavieh, and H. Kazemi-Karegar, "Optimal fast charging station placing and sizing," *Applied Energy*, vol. 125, pp. 289–299, 2014.

[18] H. Xu, S. Miao, C. Zhang, and D. Shi, "Optimal placement of charging infrastructures for large-scale adoption of pure electric vehicles: A case study of Beijing," *Transportation Research Part D: Transport and Environment*, vol. 65, pp. 738–751, 2018.

[19] A. Awasthi, K. Venkitusamy, S. Padmanaban, R. Selvamuthukumaran, F. Blaabjerg, and A. K. Singh, "Optimal planning of electric vehicle charging station at the distribution system using hybrid optimization algorithm," *Energy*, vol. 133, pp. 70–78, 2017.

[20] Y. Xiong, J. Gan, B. An, C. Miao, and A. L. Bazzan, "Optimal electric vehicle charging station placement," in *Proceedings of the 24th International Conference on Artificial Intelligence*, AAAI Press, pp. 2662–2668, 2015.

[21] A. Y. Lam, Y. W. Leung, and X. Chu, "Electric vehicle charging station placement: Formulation, complexity, and solutions," *IEEE Transactions on Smart Grid*, vol. 5, no. 6, pp. 2846–2856, 2014.

[22] J. Dong, C. Liu, and Z. Lin, "Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data," *Transportation Research Part C: Emerging Technologies*, vol. 38, pp. 44–55, 2014.

[23] I. Frade, A. Ribeiro, G. Gonçalves, and A. P. Antunes, "Optimal location of charging stations for electric vehicles in a neighborhood in Lisbon, Portugal," *Transportation Research Record*, vol. 2252, no. 1, pp. 91–98, 2011.

[24] F. Baouche, R. Billot, R. Trigui, and N. E. El Faouzi, "Efficient allocation of electric vehicles charging stations: Optimization model and application to a dense urban network," *IEEE Intelligent Transportation Systems Magazine*, vol. 6, no. 3, pp. 33– 43, 2014.