Applications of Machine Learning in the Planning of Electric Vehicle Charging Stations and Charging Infrastructure: A Review

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Abstract

While electric vehicles (EV) and plug-in hybrid electric vehicles (PHEV) have the potential solution from an environmental perspective, they face an obstacle in accessing charging systems. Moreover, the charging system offers its own challenges compared to petrol stations due to the participation of different charging options. Researchers have been studying the optimization of PHEV/EV charging

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M. Fathi et al. (eds.), *Handbook of Smart Energy Systems*,
https://doi.org/10.1007/978-3-030-72322-4_202-1

infrastructure for the past few years. Introducing electric vehicle charging infrastructure services creates new challenges and opportunities for the development of smart grid technologies. In this study, an extensive literature review has been carried out regarding the use of several optimizations and machine learning models for determining the optimal location of EV charging stations (EVCS) and infrastructure. Previous literature has also proposed different model-solving algorithms or techniques to solve the complex and dynamic nature of EVCS location problems, suggesting that the research on EVCSs has recently gained popularity. Although research seems to have advanced, findings indicate to incorporate of real-time EV user behavior for optimal geographical placement of new charging stations, satisfying the transportation demand, randomness, and variability in space as well as time. Coupled EV networks will be cost-effective from the power grid perspective. Identification of factors resulting in spatial inequities for EVCS location across different cities based on socioeconomic characteristics needs to be addressed for robust EV charging infrastructure.

Keywords

Electric vehicle · Charging stations · Charging infrastructure · Machine learning

1 Introduction

Fossil fuel-dependent transportation systems have aggravated environmental and energy challenges (Aghakhani et al. 2022; Beigi et al. 2022c; Rajabi et al. 2022a). Therefore, a growing number of countries around the world are promoting emerging vehicle technologies, such as battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and fuel-cell electric vehicles (FCEVs) (Beigi et al. 2022a, b). The environmental implications of electric vehicles (EVs) depend largely on the fuel mix of electricity generation but can replace vehicular tailpipe emissions using liquid fossil-based fuels for power plants which are concentrated and easier to control (Moeinifard et al. 2022; Mudiyanselage et al. 2021). On the other hand, the rapid growth of electric vehicles can cause several problems, such as an insufficient number of charging stations, uneven distribution, excessive cost, etc. (Rajabi et al. 2022b). The unplanned installation of EVCS can adversely affect the voltage stability, reliability, and other operating parameters of the power distribution network. Further, charging opportunities should be abundant, fast, and inexpensive to expand EV adoption. Moreover, understanding complex interactions of social-economic and demographic factors leading to the inequitable placement of EVs charging stations (EVCS) is crucial to mitigating accessibility issues and improving EV usage among all people (Lotfi et al. 2022; Shakerian et al. 2022). Public charging infrastructure must be able to simultaneously support diverse types of demand from local users, taxis, city logistics, and long-distance drivers visiting the city, which are expected to increase in the future. This demands for well-designed EVCS network and infrastructure (Amir Davatgari 2021; Kavianipour et al. 2022; Niroumand et al. 2018).

Currently, three types of Electric Vehicle Supply Equipment (EVSE) are used for charging BEVs. Level-1 EVSE with 110 V/15 A connection typically takes 10–20 h to charge, restricting to a vehicle's home base. Level-2 (220–240 V/15–30 A) chargers require about 4–8 h and are used in both commercial and home charging settings. Level-3 constitutes a "supercharging station" that uses high-voltage (often 400–500 V) DC fast charging and takes as little as 20 min to charge to 170 miles, making in-route/mid-trip charging feasible for most travelers. But the cost of setting up Level-2 charging stations is almost doubled and goes up to 20 times for Level-3 charging stations than Level-1. Though energy requirements of EVs can be met through single nighttime in-home charging or route to public EVSE, to use these static facilities, EV drivers must stop and wait for charging. Thus, dynamic wireless charging technologies have been developed, evaluated, and commercialized to enable charging while driving.

The EV charging station location is basically a facility location problem focusing mostly on associated costs of charging stations, station-user factors, station power supplier factors, and environmental factors. Previous literature has paid attention to the optimal layout of charging stations and proposed different model-solving algorithms, which points out that the research on EVCSs has recently drawn extensive interest. Studies on the planning of electric vehicle charging infrastructure (EVCI) involved charging station placement, charging demand prediction, charging scheduling and pricing, charger utilization computation, etc.

2 Review of Different Machine Learning Used for EV Charging Station Location Problem

Investigating and dealing with the EVCI planning and modeling problem can be grouped into three broad categories such as optimal placement of charging stations based only on the transportation network or based only on the distribution network, or based on the superposition of transport and distribution networks (Fig. 1).

According to the above figure, the modeling approach considering only transport networks can be sub-divided into a node-, tour-, and path-based approaches. Therefore, modeling approaches for transport and distribution networks individually can be combined and will be compatible for modeling coupled networks. However, combining three approaches at the same time may not be practical and has not been acknowledged in any existing research (Deb et al. 2018).

Popular optimization methods include conventional optimization approaches (such as linear, non-linear, integer, and mixed-integer programming), nature-inspired optimization (NIO) methods (such as genetic algorithm, particle swarm optimization, or evolutionary algorithm), or hybrid approaches. Optimal EVCI is based on various key performance indicators, including proximity to chargers (slow charging EVCI), waiting for time minimization (fast charging EVCI), placement and sizing of charging stations, charging demand, etc. Models are classified as

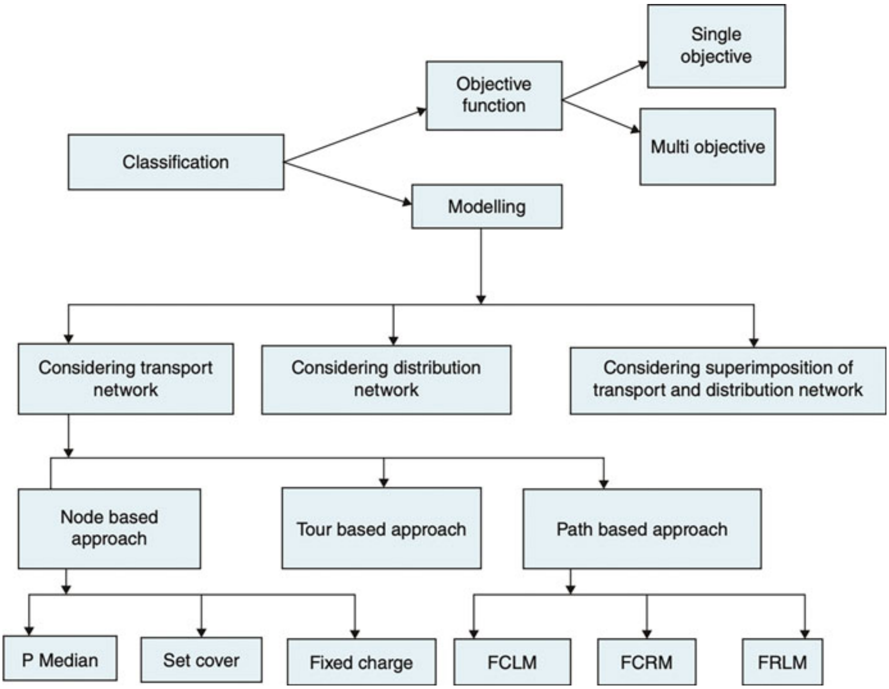

Fig. 1 Schematic overview of the classification of charging infrastructure planning problem (Deb et al. 2018)

either node-based such as set covering location models, node-based capacitated vehicle routing problem, maximum covering location model, uncertainty modeling and random sampling, zone-based demand formulation, etc., or flow-based, such as flow-capturing location model, user equilibrium traffic assignment model, flow-refueling location model, etc. or agent-based as multi-agent simulation models, parametric Markov queues (M/M/s), non-parametric queuing models following Kendall's notation, etc. (Unterluggauer et al. 2022).

Geospatial and statistical approaches focus on density calculation and clustering methods by calculating the charging demand at individual points, thereby aggregating to certain demand areas using conversion tools, the sum of block statistics, k-means fuzzy clustering method, etc. Explicit spatial location methods use statistical data such as census data, EV travel data, EVCS data, fossil-fueled vehicles travel data, questionnaire surveys, and simulation or test data (Fig. 2). Agent-based models can define exact geographical allocations for EVCS using GPS-tracked user behavior of EVs or conventional vehicles (Pagany et al. 2019).

Data partitioning can be employed by techniques such as hash partitioning, list partitioning, and composite partitioning. Semi-supervised machine learning can combine a small amount of labeled data and a large amount of unlabeled data during training. Gaussian mixture model (GMM) is a probabilistic learning model that con-

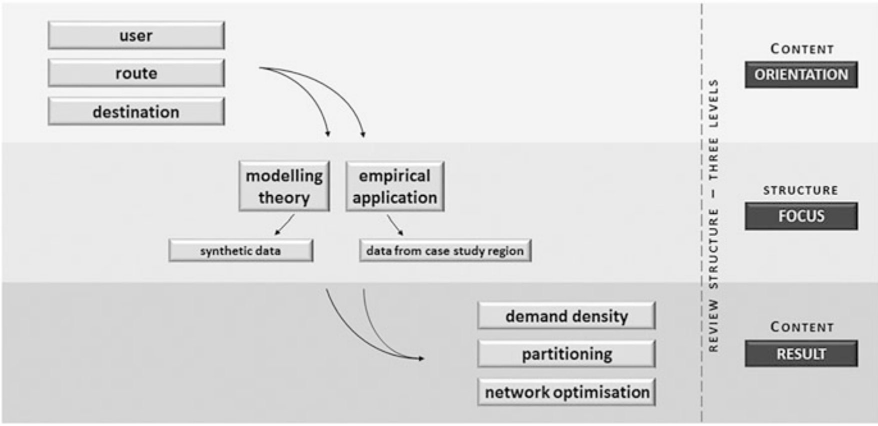

Fig. 2 Three levels of categorization on a structural and a content level (Pagany et al. 2019)

siders multiple normal distributions of the dataset to represent normally distributed subpopulations. Hierarchal clustering, cellular automaton agent-based model, and kernel density estimator (KDE) were used in the nonparametric probability density function. Integration of genetic algorithm (GA) with reinforcement learning (RL) improved model performance by not being stuck in local optima (Deb 2021).

The EVCS location problem was divided into the P-median problem (Lagrangian relaxation algorithm, etc.), P-center problem (Drezner-Wesolowsky method), and Maximum Coverage problem (Branch and Bound Method, Genetic Algorithm, etc.). The traditional EVCS location problem is divided into Point Demand (charging demand generated at a fixed point, such as residence, workplace, etc.), Flow Demand/Traffic Demand (also known as the Flow Capturing Location Model, assuming that charging demand is generated during driving) and Mixed Model (also known as Flow Refueling Location Model that maximized capture flow and minimized the sum of weighted distance). Multilevel charging station location model and algorithm is based on TABU search algorithm and finding solution using 2-opt domain strategy. A combination of decision-making models with traditional EVCS location models, such as game theory, queuing theory, grey hierarchical analysis (GAHP), etc., is used for optimal EVCS location. Real-time site selection requirements can be integrated into the Voronoi diagram in computational geometry for a dynamic assignment using advanced hybrid algorithms such as chaos theory, particle swarm optimization algorithm, NIO algorithms, etc. (Wang et al. 2019).

3 Present Research on Charging Station Network Design

Researchers have utilized a variety of approaches, objective functions, and optimization algorithms to solve the complex and dynamic nature of the EVCS location problem. In the following sections, the latest findings, developments, and literature related to different machine learning approach for the location of charging stations and charging infrastructure planning for electric vehicles are reviewed and presented.

3.1 Traditional Mathematical and Probabilistic Models

A location model for EVCS was proposed considering the EVs charging requirement, economy, and power grid safety along with the satisfaction of EV traffic. The objective was to minimize the cost, with the waiting time of the EV users and the ability of the distribution network to run safely as the constraint condition. Lastly, the EVCS service area was divided by the Voronoi diagram, modeling a 25-node traffic network with a 24-node underground distribution network, and the proposed method was demonstrated using the MATLAB environment (Zhu et al. 2017).

A multidisciplinary approach in the form of a two-stage stochastic programming model was proposed for the location and size of coupled EVCS and distributed photovoltaic (PV) power plants. The comprehensive model considered explicit EV driving range constraints in transportation networks, probability-based quality of service constraints of EVCS, PV power generation with reactive power control, and alternating current distribution power flow. First, a mixed-integer second-order cone program was generated, and then a generalized Benders Decomposition Algorithm was developed for the solution. Results showed positive effects of the combined design of PV power plants with EVCS, such as reducing social costs, promoting renewable energy integration, and relieving power congestion (Zhang et al. 2018a).

Considering heterogeneous PHEVs driving ranges and charging needs, a closed-form model quantifying the service capabilities of fast-charging stations was developed by modifying capacitated flow refueling location model based on sub-paths (CFRLM SP). A stochastic mixed-integer second-order cone programming (SOCP) model was proposed for planning PEV fast-charging stations. In the model, CFRLM SP was used to consider the transportation network constraints as well as the power network constraints to enhance the model's computational efficiency and accuracy and was demonstrated numerically through simulations (Zhang et al. 2018b).

A GIS-based multi-objective particle swarm optimization model was developed for optimal placement of EVCS and rapid EV production in Changping district, Beijing. Based on the dual benefit of public service and investment in EVCI, two objectives were identified as minimizing the total costs and maximizing the coverage. Results suggested that EVCS scale and expansion cost limited the type of station that could be built in some nodes. The Pareto curve between costs and coverage indicated a change in scale economies (diseconomies of scale) in the process of designing and constructing EVCS (Zhang et al. 2019).

A novel and simple approach were formed to determine the best site for charging stations, where the integrated cost of installation of charging stations was considered along with the penalty for violating grid constraints. Teaching-Learning Based

Optimization (TLBO) and Chicken Swarm Optimization (CSO) were both efficient evolutionary algorithms that were combined to achieve an optimal solution to this problem. Several benchmark and charging station placement problems were used to assess the effectiveness of the proposed algorithm by comparing the results of the hybrid algorithm with other algorithms (Deb et al. 2021a).

Previous studies emphasized the mileage anxiety of EV users but ignored their competitive and strategic charging behavior. Therefore, depending on the choice of other EV users, an EV user's charging cost was calculated consisting of the travel cost to access the charging station and the queueing cost at the charging stations. Firstly, a Charging Station Placement Problem (CSPP) was formulated as a bi-level optimization problem, which was then converted into a single level by using the equilibrium of the EV charging game. To compute the optimal allocation of electric charging stations, the properties of CSPP were analyzed, and an optimization algorithm, OCEAN (Optimizing electric vehicle charging stations) was introduced. To address the scalability issue of OCEAN, an algorithm using continuous variables was developed to manage large-scale real-world problems. Results from the analysis of extensive experimental data showed that the above approach outperformed the baseline method significantly (Xiong et al. 2018).

A game theory-based method for determining the optimal location of electric vehicle charging stations was developed by analyzing the traditional site-selection method. Detailed steps were given for the game experiment and its algorithm. According to the results, this optimization method was able to make charging station locations more rational and scientific using game theory (Meng and Kai 2011).

The impact of EV charging station loads on voltage stability, reliability, and harmonics of the IEEE 69-bus distribution network was analyzed and was used for optimal placement of EVCS in the distribution network using a Genetic Algorithm without disturbing the operating parameters of the network. Results showed the degradation of operating parameters following the addition of EV charging load (Deb et al. 2019).

Point spatial patterns identified by G-estimation can be compared with complete spatial randomness (CSR). A generalized log-linear model (GLM) or a Poisson lognormal spatial model using Besag York Mollié Model (BYM2) method addresses any residual clustering issues using the Bayesian method. Integrated Nested Laplace Approximations (INLA) combines Laplace approximations and numerical integration and enables Generalized Linear Mixed Models (GLMMs) to address temporal and spatial error terms. The intrinsic Conditional Auto-Regressive (ICAR) model focuses on spatial autocorrelation with K-means clustering analysis identifying similar regions in terms of socioeconomic and housing patterns. A geographically weighted regression (GWR) model identifies sensitivities of concerned predictors in EV charger installations to census tracks. Empirical analyses of residential EV chargers in Seattle, WA, included equitable spatial distribution analysis of EV charger-installed buildings with respect to housing and socioeconomic characteristics by advanced data mining techniques. Results revealed social equity and economic status issues based on the uneven or clustered distribution of residential

EV charger installations, i.e., certain communities don't deserve clean energy technologies (Min and Lee 2020).

Traditional adaptive algorithms for EV charging station location problems mainly include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Tabu Search (TS), Simulated Annealing (SA), etc. To improve efficiency, various combination of algorithms was used, such as quantum particle swarm optimization algorithm, Fuzzy multi-objective-based grasshopper optimization algorithm, multi-group hybrid genetic algorithm (MPHGA) combining standard genetic algorithm (SGA) with the Alternate Location Allocation Algorithm (ALA), two-step optimization model combining immune algorithm and fuzzy analytic hierarchy process, etc. (Wang et al. 2019).

3.2 Heuristic and Data-Driven Algorithms

A methodology was proposed for decision-makers in the field of developing EVCI, which combined with multiple heterogeneous real-world data sources, which includes business data describing charging infrastructure, historical data about charging transactions, information about competitors, geological information, data about places of interest located near chargers (e.g., hospitals, restaurants, and shops), and driving distances between charges. The study suggested the optimal location of a new EVCS by incorporating the proposed methodology into decision support tools and using historical data on EVCS utilization. The methodology was illustrated by using Dutch EVCI data from 2013 to 2016, based on various objectives, such as increasing the number of chargers in sparsely populated areas or maximizing the overall charging network utilization (Pevec et al. 2018).

A hybrid approach incorporating geographical information system (GIS) and Bayesian network (BN) was developed to solve the location selection problem of EVCS in Singapore. GIS integrated spatial and geographical data, whereas the BN model demonstrated the cause-effect relationships of nine criteria when selecting suitable alternative sites. Conditions such as the number of rapid mass transit (MRT) stations, the number of household units, transportation efficiency, and the charging efficiency were identified to be the most crucial factors in influencing location selection over social and economic factors. Compared to the traditional decision-making method (TOPSIS, etc.), the hybrid GIS-based BN approach was more accurate and stable in the presence of noise interruption (Zhang et al. 2022).

Four solution strategies were explored for the location of charging stations, and a heuristic solution for fleet routing was established. In addressing the routing problem, the location strategy was applied at the client site without considering displacements for the recharges. While the other three proposals performed poorly when it came to locating the charging stations at the center of the cluster, the K-means approach performed the best (Gatica et al. 2018).

A heuristic methodology was presented for an extensive urban transportation network that considered the deployment of EVCS for coverage and the fulfillment of user preferences and constraints as two separate processes. This methodology proposed a reallocation algorithm to prioritize the selection of Locations of Interest and to reduce the number of stations with overlying coverage areas. The results were compared to those derived from a Greedy Algorithm based on a multipath consideration, and the proposed methodology was able to significantly reduce the computational time required for the solution of the location problem (Torres Franco et al. 2021).

An agent-based traffic simulation-based approach was presented for EVCS placement using heuristic objectives to achieve sufficient network coverage to keep charging-related inconvenience within an acceptable range while minimizing the overall number of EVCS in Singapore. The algorithm identified locations where the charging procedure was seamlessly integrated into driving routes, thus reducing detours and waiting times. Results showed that the proposed methodology was able to cover the charging needs of 20,000 EVs with approximately 2500 EVCS by accepting average detours of 410 m and waiting times of less than 10 min. Based on the results, the algorithm was able to converge toward an EVCS distribution that was effective at satiating charging demand within the constraints of inconvenience (Bi et al. 2017).

A data-driven approach was developed for optimizing the layout of existing electric taxis (ET) charging stations in a more realistic manner by using four different types of data: ET trajectory, points of interest, station data, and road network information. Citywide charging behavior was modeled using a 3D tensor, filling in the missing entries of times and stations with sparse data using contextual-aware tensor collaborative decomposition techniques to estimate the popularity of charging stations and develop queueing systems to estimate the frequency of visits among stations. A spatial-temporal demand coverage method, Bass model or Bass diffusion model, and Dynamic traffic simulation-based optimization were proposed to predict the permeability and optimize the layout of charging stations for electric taxis. The search and navigation behavior and charging patterns of EV users were analyzed, and a Bayesian reasoning-based method was developed for evaluating charging demand. A charging spot model known as a single output multiple cables (SOMC) charging spot was proposed to increase the utilization of charging stations and decrease investment costs associated with coordinated charging. Propose (Yang et al. 2020).

Gray Analytic Hierarchy Process (GAHP), comprising of AHP and gray statistics decision-making along with the Delphi technique, were combined to form a new comprehensive evaluation method to solve the personal one-sidedness problem of expert judgments and to deal with ambiguous gray factors. The new method was applied to produce the comprehensive evaluation index system of EVCS and to determine the weights of its indicators. Based on this, the rationality comprehensive evaluation value for each optional hail was defined and used to formulate an optimal decision regarding the location of charging stations (Liu et al. 2012).

Maximum Covering Location Problem (MCLP) was formulated for optimally allocating PHEV Charging Stations (CSS) in a highway network. The model considered the Trip Success Ratio (TSR) to estimate Charging Station Service Range (CSSR) and enhance CS accessibility for PHEV drivers, allowing for different driving habits and trip types. Essentially, the allocation model had two stages. In the first stage, the CSSR was estimated utilizing TSR, considering the uncertainty of the trip distances (city, highway) and the uncertainty associated with the remaining electric range (RER) of PHEVs. As part of the CS allocation process, the estimated CSSR was used to select the optimal EVCS locations covering the network with a certain guaranteed TSR level (Alhazmi et al. 2017).

The location model was formulated to minimize total social cost (direct and indirect costs covering construction, operation, charging, and the wastage cost), and a genetic algorithm using a moderate value function was used to solve for quantity and location of charging in the urban area of Nanjing. The evaluation index was based on five location influencing factors: land cost, construction costs, road traffic flow, power grid conditions, and the surrounding environment. Numerical results showed that both grey correlated scheme decision-making and grey target theory could conveniently conduct quantification treatment to the qualitative problem while selecting the optimal location. This model was advantageous as it has less data collection requirement and treatment, a simple calculation process, presents quantified results, and is more credible than a qualitative description. Multi-expert scoring and selection or repeated testing was conducted during the evaluation (Ren et al. 2019).

A multi-period multipath refueling location model capturing the dynamic intercity origin-destination (O-D) trips on both spatial and temporal dimensions was developed to expand the public electric vehicle (PEV) charging network in Sioux Falls Road in South Carolina. The objective of the model was the minimization of the installation cost of new stations and relocation of existing stations to satisfy every O–D trip or at least one path between an O–D pairs called the deviation path. The multi-period or dynamic facility location problem was formulated as a mixed-integer linear program and solved by a heuristic-based genetic algorithm using a CPLEX solver. Results indicated that the geographic distributions of cities, vehicle range, deviation choice, and the types of charging station sites are the major factors impacting charging station location. Heuristics and anticipation of future demands can yield high-quality solutions, especially when the problem is getting complex with deviations, and help reduce the overall cost of EVCI (Li et al. 2016).

The machine learning frame, work along with quantitative spatial analysis, examined spatial disparities and barriers in EVCS placements by combining social, economic, and demographic factors with field data for predicting future ECVS density and identifying the optimal spatial resolution for Orange County, California. Finally, the optimal EVCS placement density was compared with a spatial Electric Vehicle Charging Inequity index, developed using a multicriteria decision analysis approach to quantify how equitable these placements would be. The existing EVCS location was evaluated using kernel density estimation (KDE), and supervised machine learning models with repeated "k" fold cross-validation predicted the EVCS grids for further spatial analysis using constructed raster layers. Random Forests achieved the highest predictive accuracy of EVCS placement density at a spatial resolution of 3 km using. Results indicate that a total of 74.18% of predicted EVCS placements will lie within a low spatial equity zone, indicating less accessible populations require the highest investments in EVCS placements (Roy and Law 2022).

Neural network and multivariate optimization conditions using historical or experimental data were used to create the Ethe VCI network model (Wang et al. 2019).

3.3 Optimization Models

Access to the mobile charging station (MCS) for electric vehicles was examined, where charging station owners were the EV parking lots, proposing a new self-scheduling model for EV smart parking lots (SPLs) that optimized SPL energy generation and storage schedule while scheduling MCSs as temporary charging infrastructures. By modeling prioritized demand of the prioritized events based on several indices, the MCSs accessibility measures, the equity impacts of MCSs locations, the optimal set of SPL components (such as coupled heat and power, photovoltaic system, and electric and heat energy storage) to manage electrical peak demand and the economic benefits of SPLs were accessed. Results showed that the proposed demand prioritization function model was able to meet the required EV charging demands for prioritized events, while the self-scheduling model for SPLs was able to meet the changing demands of EVs located at SPL locations (Nazari-Heris et al. 2022).

Two optimization models were investigated to determine the locations of public EVCS using fast and charging modes in Greater Toronto and Hamilton Area (GTHA) as well as Downtown Toronto. The objective was to minimize the overall cost while satisfying coverage needs. Geometric objects were used to represent charging demands instead of discrete points, using the polygon overlay method, which was extended to split the demand on the road network to resolve the partial coverage problem (PCP). The methods offered better accuracy than complementary partial coverage (CP) models and were able to eliminate PCP (Huang et al. 2016).

Bi-level programming model addressed the planning of fast-charging stations located in electrified transportation networks with uncertainty in charging demand. An upper-level model for locating refueling stations was used to minimize the cost of planning fast-charging stations, whereas a lower-level traffic assignment model was used to estimate the location and timing of plug-in electric vehicle flow on whole transportation networks. Two-level models reveal a correlation between charging demands, electrical demands, and the spatial and temporal distribution of plug-in electric vehicle traffic. Under distribution-free uncertain charging demands, robust chance constraints were formulated to describe the service capability of fast-charging stations, where the ambiguity set was constructed to estimate the potential values of the uncertainties based on their moment-based information, thus reducing the robust chance constraints exactly to mixed-integer linear constraints. Adding new variables converted the bi-level model to a single-level mixed-integer second-order cone programming model that can be solved with off-the-shelf solvers, which guarantee the optimality of the solution. The effectiveness of the proposed planning model was illustrated by a case study that revealed the significant impact of the three critical factors on the planning outcomes (Zhou et al. 2020).

A review of the literature was performed to examine the impact of electric vehicle charging stations on the power distribution network. As a result of the findings, 34%, 34%, 15%, and 19% of the literature have examined voltage stability, power quality, peak load, and transformer performance associated with EV charging stations, respectively. Although there were fewer publications analyzing the effect of EV charging stations on peak loads, it was observed several researchers were becoming intrigued by this paradigm. It has been documented in all research studies that the addition of EV charging load degrades the power grid's operating parameters. While EVs may suffer negative impacts from the charging load, the vehicle-to-grid (V2G) scheme has several positive impacts which should not be ignored (Deb et al. 2017).

A comprehensive review of the Nature Inspired Optimization (NIO) algorithms for solving the charging station placement problem was presented. The goal of this work was to provide the research community with a deep understanding of the key features, advantages, and disadvantages of the various NIO algorithms for solving the charging station placement problem. In other words, this review would help researchers not only in selecting suitable algorithms but would also serve as a model for developing efficient algorithms to solve the charging station placement problem. Also, a general classification of NIO Algorithms was proposed, as depicted in the Fig. 3 below.

Furthermore, the performance of seven NIOs in solving four variants of the charging station placement problem was compared. The hybrid algorithms involving Genetic Algorithm, Particle Swarm Optimization, Chicken Swarm Optimization, and Teaching Learning Based Optimization were found to be more efficient in solving the charger placement problem than the standalone algorithms. However, hybrid algorithms run slower than stand-alone algorithms (Deb et al. 2021b).

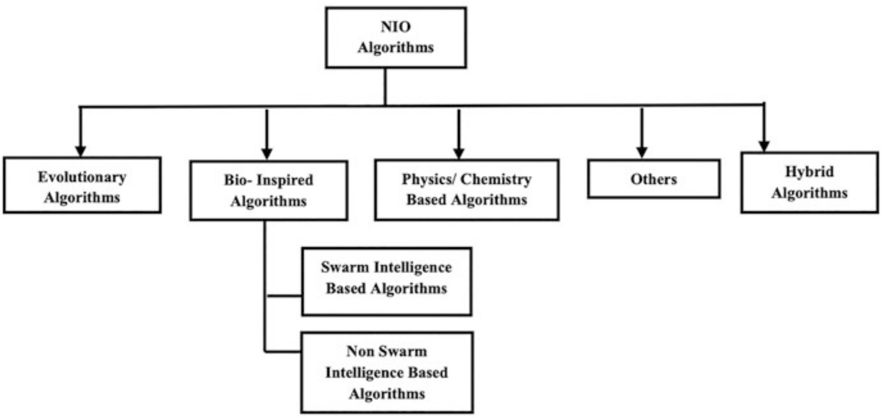

Fig. 3 Classification of NIO Algorithms (Dhal et al. 2019)

Long-distance travel data was used to place charging stations with the objective of maximizing long-distance trip completions. To reduce the dimensionality of the problem, K-means clustering was used to reduce the area centroids down to 200 cluster centers with the highest total density (sum of households and jobs per square mile), and only heavily used OD paths were tracked between them. A mixed-integer problem scenario assuming 50–250 charging stations and an all-electric range (AER) of 60–250 miles, based on a modified flow-refueling location model (FRLM) was formulated and solved via a branch-and-bound optimization algorithm. The final proposed model was a facility location and network expansion problem to maximally serve long-distance demands between clusters' origins and destinations. Balance constraints are used to expand the scope to all potential paths and guarantee that EVs can pass a path smoothly when there is a charging station. Restrictions on the total number of stations installed were introduced, along with power and budget constraints. Results reveal that at least 100-mile-range EVs were needed to avoid long-distance-trip issues for U.S. households, whereas 200-mile-range EVs can serve nearly all long-distance trips with just 100 charging locations in eastern and central U.S. (He et al. 2019).

A simulation-optimization model was used to locate Level-1 and Level-2 EV charging infrastructure for maximizing EV service levels in the central-Ohio region, utilizing Mid-Ohio Regional Planning Commission (MORPC) data. The volume of EV flows was determined by assigning an EV adoption probability, which depends on demographic and macroeconomic data. Simulation of expected service levels with different numbers of chargers was conducted by bootstrapping EV trips from the tour record data by randomly generating Bernoulli trials. Finally, the linear integer programming (IP) model was used to determine the location and size of charging stations, with the objective of maximizing fleet-wide EV charging and the amount of battery energy recharged. Constraints include higher distribution-level transformer capacity of chargers and general budget limits. Sensitivity analysis was conducted through simulation to account for interdependencies such as the possibility of an EV being charged earlier at another charging station and EV driving patterns. Results showed that with two chargers, 87% of EVs at a university parking location and around 45% at workplace and shopping locations could charge up to 90%. Moreover, the station locations were "robust" when the budget constraint was relaxed, proving that the optimal location is sensitive to the specific optimization criterion, irrespective of overall service levels (Xi et al. 2013).

Mixed Integer Linear Programming (MILP) optimization model to maximize the electrified fleet vehicle-miles-traveled (VMT), minimize the total travel distances without electrification, and select the locations of public charging stations based on real-world vehicle travel patterns and public charging demand from large-scale individual vehicle trajectory data. Vehicle trajectory data of 11,880 taxis over a period of 3 weeks in Beijing, China, was used in the model to capture the variation in vehicle travel behavior. The mathematical problem was formulated in the GAMS modeling environment, and the CPLEX optimizer was adjusted to find the optimal solutions using a branch and cut algorithm. Along with 40 existing public charging stations, the 40 optimal ones selected by the model were able to increase the electrified fleet VMT by 59% and 88% for slow and fast charging, respectively. With the increase in the number of charging stations, the optimal station locations expand outward from the inner city. Results indicate that the optimal slow charging stations have a higher retention rate than the fast-charging ones and can be used for long-term planning. Additionally, more charging stations can cover the variation of travel patterns among different weeks (Shahraki et al. 2015).

A mixed-integer bi-level program was formulated for an optimal deployment plan of static and dynamic charging infrastructure allowing for interdependency between transportation and power networks, with an objective to minimize the total social cost of the coupled networks. First, a variational inequality (VI) network equilibrium model was devised and solved by converting it to a nonlinear program to describe the correlation among BEVs route choices, charging plans, and electricity cost. Active-set algorithm was used for the solution to the model. Sensitivity analysis was conducted to study the impact of the variations in power rate, charging efficiency, and battery size on the numerical equilibrium results. Results on three networks suggest that for individual BEV drivers, the choice between using charging lanes and charging stations is more sensitive to the value of travel time, service fee markup, and battery size than to the charging rates and travel demand. Charging lanes are more beneficial for transportation networks with sparser topology, while charging stations is desirable in denser networks (Sun et al. 2020).

A social total cost model based on economic cost (construction costs and fees) and environmental cost (electricity consumption and carbon dioxide emissions) calculates the total operating cost of charging stations under various distribution conditions. Secondly, a genetic algorithm-based EVCS location optimization model provides the solution to an operating cost minimization problem and distribution of charging stations. Data from five major cities in Ireland was used to establish EVCS and distribution optimization model based on reality, simulate the optimal results, and conduct sensitivity analysis. Sensitivity analysis showed that the total cost is extremely sensitive to the number of charging stations and the probability of EV charging per day. Instead of traditional Euclidean distance, this model calculates the distance and demand between the electric vehicle and the charging station by introducing a parameter known as the road bending coefficient for realistic model results (Zhou et al. 2022).

A multi-objective optimization based on data envelopment analysis for the optimal placement of slow EVCI in a combined transportation and distribution network, solved by a cross-entropy algorithm. Game-theoretical optimization, Harris hawk's optimization, and the Differential evolution approach were useful for the placement of public EVCI in the urban area for plug-in hybrid EVs, solved by an active-set algorithm. Decomposition-based multi-objective evolutionary algorithm, Nature-inspires optimization (NIO) algorithm (binary lightning search algorithm, hybrid chicken swarm optimization, GIS-based particle swarm optimization, Ant colony optimization, etc.), mixed-integer non-linear programming problem solved by a genetic algorithm and commercial solvers, bi-level planning model based on dynamic real-time data solved by a surrogate-based optimization algorithm were used for deployment of fast EVCI in urban areas. Chance-constrained programming approach, teaching learning-based optimization approach, multi-objective grey wolf optimization with the fuzzy satisfaction-based decision, reliability-oriented multi-objective planning model solved by simplified reliability correlation analysis were used in the deployment of fast EVCI in residential areas. Mixed-integer linear program solved by a branch-and-bound method, stochastic mixed-integer second-order cone programming model solved by the branch-and-cut method, iterative column generation algorithm, branch-and-reduce optimization navigator in GAMS, fuzzy multi-objective optimization approach, solved by a cooperative co-evolutionary genetic algorithm, decomposition-based multi-objective evolutionary algorithm, multi-stage charging placement strategy based on a Bayesian game were used for allocation of fast EVCI for long-distance travel along highway and for non-private EVs (electric taxis, electric buses, and freight EVs). Mixed-integer convex programming approach was used for optimal siting and sizing of EVCI, power generation, new transportation lanes, and distribution feeders (Unterluggauer et al. 2022).

A five-stage multicriteria- and GIS-based EVCS location methodology (5MAGI-SEV) was formulated for designing the EVCS network for personal and commercial vehicles, considering the existing locations in urban areas of Poznan, Poland, and the interaction between every EVCS in the network. A DBSCAN clustering algorithm was used to the reduction in the number of possible EVCS locations. The design stages include defining potential EVCS locations, constructing evaluation criteria, generating alternatives, selecting appropriate multiple criteria decision aid, wherein light beam searching or LBS solution method was selected, and conducting the multicriteria evaluation of alternatives. LBS method was able to manage a set of numerous alternatives and criteria and make comparisons among alternatives using the natural scale of each criterion (Schmidt et al. 2021).

An optimization-based Flow Refueling Location Model (FRLM) was formulated for EVs fast-charging stations along designated EV corridors to improve EVs adoption. The objective was to maximize Corridor-Miles Traveled (CMT) in EV corridors with high density based on corridor-utilizing and corridor-weighted traffic flow concepts. EV corridors selected from numerical experiments in the Maryland highway network and major population centers were inputs to the model. Results showed that corridor-focused objective function and corridor prioritization is essential for deciding on a solution with more stations on corridors (Erdoğan et al. 2022).

4 Conclusion and Future Directions

Following are the observations and future scope of work for improving EVCS location problem and setting up an efficient EVCI according to the researcher's opinions and findings from various literature.

1. Faster computers or smarter algorithms such as greedy algorithms, heuristics and/or simulated annealing, etc. can allow enormous OD pairs, more network

details, charging station capacity, trip scheduling information, charging time and speed, and demand of all EVs to reflect the city level public charging infrastructure for mixed uses. Deep learning-based location algorithms can attain multi-factor coverage ability, independent feature selection ability of the model, evolvability over time, and simulation of large-scale vehicle movement scenarios.
2. Route choice for EV travelers, congestion feedbacks mostly arising from local-trip sources at peak times of day, driver's willingness to wait, shorter local travel, queuing delays (queuing models), travel behavior before and after EV adoption and limitations on EV range could have a strong influence in charging station location modeling. Monitoring user behavior in a real-world environment is resource-intensive and costly. Optimal location decisions can be automatically updated based on observations from GIS. Further, a bi-level optimization framework can be utilized to incorporate traffic flow between O–D pairs at the lower level and locational decisions at the upper level. A variety of data-based driving behavior and travel behavior analysis methods can be used to improve the positioning strategy.
3. Not only charger station location but the number or type of chargers to install at each location must be determined for developing static slow or fast charging infrastructure for EV. Large-scale deployment of public charging infrastructure will lead to more regular and profound interactions between the transportation, charging infrastructure, and power networks increasing the risk of supply bottlenecks in the power system, hence requiring integrated planning and operation of coupled networks. Moreover, photovoltaic power generation coupled with reactive power control can enhance the quality of power supply to EVCI. Most studies considered energy consumption to be directly proportional to the distance traveled; rather, more energy is used going uphill or higher speed compared to going downhill or lower speed. Future charging infrastructure planning would include finding an optimal geographical placement and new charging station sizing to satisfy the transportation demand, considering a mix of several types of charging options to account for randomness and variability in space and time, as well as being cost-effective from the power grid perspective. Elastic demand for EVs should be considered in establishing optimal charging infrastructure deployment plans and changes in electricity locational marginal price (LMP).
4. Future models can expand to optimize the environmental benefits of EVs fleet, which depends on the grid fuel mix, charging time, and individual driving conditions.
5. The dynamic programming method is suitable for the multi-period charging location problems (two-phase approach), wherein the first phase can utilize integer programming to identify the locations to be placed over time, and the second phase solves a linear program to identify optimal routes between O–D pairs. Multistage stochastic program using nested decomposition solution can address the stochasticity of multiple trajectories embedded in future demand, though challenging in both modeling and solution. Combined geospatial analyses of the EV transport and charging station location planning were found in a few studies.

6. Studies reveal that EV charger infrastructures are clustered in neighbors with higher income levels, single housing ownership rates, and urban areas; however, further research is required to identify factors contributing to spatial inequities across different cities based on socioeconomic characteristics. The rapid transition to clean energy technologies can impact community response and create inequalities resulting in uneven distribution of the charging infrastructure. The inequity index levels can identify regions with limited access to charging infrastructure and propose prospective charging station locations.

5 Cross-References

- ▶ A Novel Mathematical Model for Infrastructure Planning of Dynamic Wireless Power Transfer Systems for Electric Vehicles
- ▶ Analysis of the Renewable Energy Generation Capability for Attending a National Renovation Fleet Through Ethanol-Cell Electric Vehicles in a South American Market
- ▶ Applications of Machine Learning for Renewable Energy: Issues, Challenges, and Future Directions

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