A Literature Review on Optimal Placement of Electric Vehicle Charging Stations

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Abstract. Indonesia's greenhouse gas emissions were almost 697.75 million tons in 2022. The largest source of emissions is from the supply side, which accounts for around 50% of total emissions. On the demand side, the transport sector is the largest source of emissions, with 90% of total emissions coming from road transportation. Switching to electric vehicles (EVs) is one of the easy strategies to implement to reduce emissions. Electric vehicle charging station (EVCS) planning has a strategic impact on promoting the use of EVs. This paper presents a comprehensive literature review on optimal EVCS placement, covering models and methodologies, including GIS-based approaches, machine learning techniques, multi-criteria decision analysis (MCDA), and advanced optimization algorithms. The aim is to analyze trends, identify gaps, and synthesize findings to comprehensively understand effective EVCS placement strategies, contributing to Indonesia's goal of achieving a low-carbon future. The findings in this paper highlight the importance of integrating robust optimization models into national infrastructure plans to support sustainable growth in EV adoption.

Keywords: *Literature Review, EVCS Location, Optimization, Electric Vehicle*

1 Introduction

In 2022, the energy sector in Indonesia emitted approximately 697.75 million tons of CO_2, an increase of about 14.8% compared to 2021, which recorded 600 million tons of CO_2 emissions. The largest contributor to carbon emissions is electricity generation activities, accounting for 297 million tons of CO_2. The manufacturing and transportation sectors are the next largest contributors, with carbon emissions reaching 206.4 million tons of CO_2 and 155.6 million tons of CO_2, respectively. Meanwhile, the household and commercial sectors contributed emissions of 27.1 million tons of CO_2 and 3.9 million tons of CO_2, respectively [1]. In its Long-term Strategy on Low Carbon and Climate Resilience 2050 (LTS-LCCR 2050) document, the Indonesian government stated that under the current policy scenario (CPOS), carbon emissions from the transportation sector will decrease to 145 million tons of CO_2 by 2050. However, suppose the Low Carbon Scenario Compatible with the Paris Agreement (LCCP) is implemented. In that case, carbon emissions from the transportation sector are expected to reach 100 million tons of CO_2 by 2050, which is 31% lower than the CPOS scenario [2].

The shift from internal combustion engine vehicles (ICEV) to electric vehicles (EV) is a key strategy in decarbonizing road transport, as EVs produce significantly lower carbon emissions than ICEVs. One source of carbon emissions from EVs is the electricity generation required to power EVs. In the CPOS scenario, with the current electricity mix, EVs generate 47%-49% less carbon emissions than ICEVs. In the LCCP scenario, EVs sold in 2030 are projected to have 54%-56% lower emissions than ICEVs. Emissions from battery production contribute the smallest portion of total lifetime emissions. When accounting for battery replacement during the vehicle's lifespan, EVs are expected to produce 44%-52% lower emissions under the CPOS scenario and 50%-53% lower emissions under the LCCP scenario [3].

With the rapid development of EVs and their advantages over ICEVs, there is potential to achieve a more energy-efficient and environmentally friendly transportation system [4]. EV adoption has been increasing in recent years. In 2022, the number of EVs on the road increased by almost 4-5 times compared to 2021 [5]. This condition indicates that EVs are an appealing technology for widespread adoption. The government is working to build reliable infrastructure and create a conducive ecosystem to support the development of electric vehicles in Indonesia. The strategic placement of EVCS is crucial for facilitating the integration of EVs into daily life, enhancing energy efficiency, and supporting economic growth. Understanding the background of optimal EVCS location is essential to driving a modern economy and fostering a sustainable future [6]. This paper aims to thoroughly review relevant research on the topic of optimal EVCS location.

This paper aims to develop a comprehensive review of several studies related to the determination of EVCS locations. Based on their findings, research conducted in 2023 and 2024 is classified into two different categories. The findings are then compared, and suggestions for future research are provided.

2 Methodology

The methodology for conducting this literature review followed a systematic approach to ensure comprehensive coverage and critical research analysis on optimal EVCS location. The first step is to define the scope and objectives of the review, focusing on key themes related to EVCS placement strategies, optimization techniques, and influencing factors. A set of specific research questions was established to guide this step and to identify gaps and trends in existing research on EVCS location methodologies. The next step involved developing a structured search strategy to gather relevant literature. Databases such as Scopus and Google Scholar were chosen for their extensive engineering, technology, and environmental research collections. A combination of keywords —including "EVCS," "optimization," and "location"— was used to create precise search strings. The search was refined using inclusion and exclusion criteria, prioritizing recent, peer-reviewed articles from the last two years and excluding research that did not directly address EVCS location methods or was unrelated to the main research questions. After collecting an initial set of research, a screening process was conducted to ensure relevance and quality. Titles and abstracts were reviewed first, followed by a full-text review of the research that passed the initial screening. Relevant data from each selected study, such as methodology, findings, and limitations, were systematically extracted and organized into thematic categories. A critical analysis was then performed to compare findings, highlight prevailing trends, and identify research gaps. These findings are synthesized in the following sections, structured by themes to offer a clear narrative and discussion of significant insights on optimal EVCS location methodologies [7].

3 Discussion

3.1 Location Strategy

Narayanan et al. introduced a city-agnostic optimization framework based on mixed-integer linear programming (MILP) to identify the optimal location and sizing of EVCS by retrieving data on EV demand. The framework allowed for a systematic evaluation of potential locations and capacities for new EVCS based on the data retrieved and the projected EV charging demand in the target city [8].

Charly et al. introduced a Geographic Information System (GIS)- based approach to identifying suitable locations for deploying community EV charging points. The investigation in Dublin identified 770 ideal locations to prioritize for the initial EVCS installation and 3080 potential sites to be implemented by 2030, considering accessibility by five minutes of walking or cycling [9].

Alanazi et al. employed machine learning techniques by utilizing two specific machine learning models: linear regression and support vector machines (SVM). These models were chosen for their ability to analyze complex relationships between various factors influencing EVCS placement. This study analyzed the impact of various factors, including EV percentage, population density, and energy costs, across nine selected US states [10].

Sarmas et al. introduced a robust Multi-Criteria Decision-Analysis (MCDA) framework to identify the optimal locations of EVCS in diverse municipalities to maximize profits. The model is validated through an experimental application conducted in ten Greek municipalities, showcasing its effectiveness in strategic planning for potential investors in the EV market [11].

3.2 Algorithmic Solutions

Zare et al. proposed a stochastic MILP model to address the collaborative expansion planning of multi-energy distribution networks, integrating EVCS uncertainties. The model, designed to minimize total investment and operational cost, was validated through extensive testing on real-world data, including an 18-bus and a 123-bus distribution system. This rigorous evaluation demonstrated the model's resilience and scalability, confirming its applicability in complex planning scenarios [12].

Woo et al. introduced an optimization method that considered installation costs, drivers' preferences, and existing EVCS. The model was formulated using kernel density estimation and Genetic Algorithm (GA) to minimize the peak charging demand. The minimax GA, a metaheuristic method, is used to solve the non-convex optimization problem [13].

Altaf et al. used a Backward and Forward Sweep (BFS) method and the PSO algorithm to identify optimal locations and sizes of EVCS and DG allocations. The results indicated that the PSO algorithm outperformed other methods, achieving a significant reduction in power loss, validated by using the IEEE-33 bus system [14].

Ulfa et al. employed the Flower Pollination Algorithm (FPA) to determine the optimal location and capacity of DG and EVCS, considering the most efficient plan for minimizing power losses and enhancing voltage profiles. The results showed that optimizing DG and EVCS in a fast charging method is better than other scenarios in the East Sumba Area of Indonesia [15].

Yuvaraj et al. explored various optimization techniques considering EV charging load on the Distribution System (DS), environmental implications, and economic impact in India. Different strategies were evaluated based on their ability to maximize economic benefits, load balancing, and energy source utilization. In summary, the research utilized a combination of heuristic and advanced optimization algorithms and mathematical programming techniques to effectively address the challenges associated with the optimal allocation of EVCSs in distribution networks [16].

Mondal et al. proposed a modified forward-backward sweep (MFBS) method to determine the Maximum Additional Load (MAL) within a radial distribution system (RDS) considering the non-unity power factor. By calculating the MAL for different nodes, the nodes with the highest MAL values are identified as the optimal locations for installing EVCS [17].

Shahbazi et al. explored the optimal location and sizing of EVCS to reduce their negative impact on the power network, incorporating uncertain loads through probabilistic modeling using Monte Carlo simulations. Simulations conducted in MATLAB show a 10% increase in power losses during peak hours but a reduction in losses during low-load periods while successfully limiting voltage deviations to within 8% of the nominal value. This study highlights the critical role of strategic planning in mitigating the impact of EVCS on the power network [18].

4 Discussion

From the explanations presented in the previous section, a comparison is then made to provide a general overview of the progress in research on EVCS location planning. While existing research explores a variety of methodologies and applications, there remains a notable gap in addressing the socio-economic and environmental dimensions of EVCS location planning.

Table 1 Category 1. Location Strategy

Methodological Approaches	Relevant Aspects
- MILP framework - GIS-based approach - Machine learning modeling - MCDA framework	- EVCS location and size - Accessibility - Emissions - Operational cost

Table 2 Category 2. Algorithmic Solutions

Methodological Approaches	Relevant Aspects
- Stochastic MILP model - Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) - Backward and Forward Sweep (BFS) method - Flower Pollination Algorithm (FPA) - Monte Carlo simulation	- Total Investment & Operational Cost - Power load - Power loss and voltage - Load balancing, energy source utilization - Network design

In category 1, location strategy, several methodologies, and approaches can be utilized, such as the MILP framework, GIS-based framework, machine learning modeling, and MCDA framework. Using these methods, the recommended aspects to consider when determining EVCS location are the location and size of the EVCS, accessibility, reduced emissions, and operational cost. Linear programming and GIS-Based methods are expected to provide effective solutions for decision-making when establishing EVCS in a specific area.

Several algorithmic methods can be applied, such as MILP, GA & PSO, BFS, and FPA (Table 2). These algorithmic methods allow researchers to consider aspects of EVCS location planning, including total investment and operational cost, power load, and power loss at EVCS locations. BFS and FPA methods are considered the best for evaluating power loss and voltage profiles at EVCS locations to ensure that the presence of EVCS does not disrupt the electrical conditions in the surrounding area. The heuristic approach is most suitable for power distribution systems that impact the community's social and economic conditions. Various simulation schemes conducted can yield the best results for real-world applications.

Although some researchers have already considered the involvement of government and policy takers, a more in-depth analysis is still needed regarding the social and economic impacts of EVCS development on local communities, businesses, and urban development. Furthermore, greater focus is required on the environmental aspects of EVCS location decisions. Evaluating factors such as air quality improvements, reduction in greenhouse gas emissions, and the ecological impact of infrastructure development could offer a more holistic understanding of the environmental implications associated with the deployment and expansion of EVCS.

5 Conclusion and Prospects

This literature review conducted in this paper underscores the diverse methodologies developed to optimize EVCS locations, highlighting the rapid evolution of approaches tailored to meet growing EV demands. The reviewed research demonstrates a range of optimization models, from GIS-based and machine-learning approaches to multi-criteria decision analysis (MCDA) and heuristic optimization techniques. Each methodology offers unique strengths—GIS models enhance spatial visualization and site selection based on geographic and demographic factors, while machine learning and stochastic programming provide predictive insights and adaptability to real-world uncertainties in EV demand and load management. These approaches also reveal emerging trends in EVCS placement, such as balancing accessibility with grid reliability and cost-effectiveness, which are critical for large-scale deployment.

However, the review also identifies gaps, including the need for more context-specific research in developing regions, such as Indonesia, where unique infrastructure, economic, and environmental considerations impact EVCS planning. By synthesizing the existing body of work, this paper highlights the importance of integrating robust optimization models into national infrastructure plans to support sustainable growth in EV adoption. Future research should focus on hybrid models and adaptive frameworks that can respond dynamically to Indonesia's specific energy landscape, supporting its transition to a low-carbon economy. Moreover, investigating real-time data analytics and predictive modeling could improve the flexibility and responsiveness of EVCS placement strategies in rapidly changing urban areas, ultimately enhancing their efficiency and long-term sustainability.

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