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Optimization techniques for siting solar-powered EV charging stations: A systematic review and methodological classification

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ABSTRACT

Solar-powered electric vehicle (EV) charging stations are essential in advancing low-carbon transportation. However, determining optimal locations remains challenging due to spatial, technical, and environmental constraints. This systematic review, conducted under the PRISMA 2020 framework, synthesizes optimization techniques for siting solar-powered EV charging stations from 15 peer-reviewed studies published between 2016 and 2024. The reviewed methods are classified into five major categories: geographic information systems (GIS)-based spatial models, multi-criteria decision-making (MCDM) frameworks, hybrid approaches integrating fuzzy logic and GIS, heuristic/metaheuristic algorithms such as genetic algorithm (GA) and particle swarm optimization (PSO), and artificial-intelligence-based models for predictive site selection. GIS-MCDM hybrid approaches were the most prevalent, offering improved robustness in spatial decision-making. Nevertheless, the literature reveals persistent gaps, including limited empirical validation, insufficient use of real-time data, and weak integration with smart-grid planning. This review provides a structured methodological classification, highlights sustainability considerations, and outlines a research roadmap toward intelligent, data-driven, and sustainable EV infrastructure planning aligned with global energy-transition goals.

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1. INTRODUCTION

Low carbon transportation has become a central element in global climate mitigation strategies. As countries move toward decarbonization goals under international agreements such as the Paris Accord, the transport sector is rapidly electrifying [1]-[3]. The adoption of electric vehicles (EVs) is accelerating as they emerge as an effective replacement for gasoline-powered transportation, driven by their capacity to mitigate air pollution, reduce fossil fuel consumption, and contribute to emission reduction goals [4]-[7]. To fully take advantage of these benefits, we need a charging infrastructure that's reliable, scalable, and sustainable to support the broad adoption of EVs. Among the different energy options for powering EV charging systems, solar photovoltaic (PV) is especially promising because it allows for localized energy production and reduces reliance on the main power grid [1]. Using solar PV to charge electric vehicles fits well with urban sustainability goals and helps advance national renewable energy targets [8], [9]. Multiple simulation studies, such as those by Hasan *et al.* [10] and Ahmed *et al.*, [11] emphasize the benefits of optimizing PV-wind hybrid systems to boost yearly energy output and strengthen the resilience of energy infrastructure. While prior reviews focus on individual techniques (e.g., geographic information systems (GIS) or multi-criteria decision-making (MCDM)), this study provides a comprehensive synthesis of EVCS optimization methods from 2016–2024, incorporating underexplored machine learning and AI-driven approaches. It identifies key gaps in the limited use of real-time data, empirical validation, and smart grid integration and underscores the multi-criteria nature of siting decisions involving solar potential, grid proximity, land use, accessibility, cost, and environmental impacts [9]. Choosing poor locations for EV charging stations can result in them being underused, causing grid overload, or leading to overall inefficiency. To address these issues, researchers have developed a range of spatial and algorithmic approaches that tap into the power of geographic information systems (GIS). Although GIS is a common tool for making spatial decisions. MCDM frameworks provide a structured way to rank different options using a variety of evaluation criteria, and they're widely used in planning both energy and transportation infrastructure. Hisoglu *et al.* [12] used a combined GIS and the analytic hierarchy process (AHP) to determine the most suitable urban locations for deploying solar-powered EV charging infrastructure. Zhao *et al.* [13] also created a siting model in Qingdao by combining GIS–AHP with entropy weighting, which helped better prioritize the characteristics of potential sites. Similarly, Razeghi *et al.* [14] employed GIS MCDM techniques to optimize the spatial deployment of solar-powered EVCS, showcasing how spatial tools and decision models can jointly enhance data-driven siting

At the same time, heuristic and AI-driven methods have become increasingly popular for tackling complex location planning problems. Heuristic techniques like genetic algorithms (GA) and particle swarm optimization (PSO) have been used to assess important factors such as cost-efficiency, economic feasibility, system dependability, and network reach when designing EV infrastructure. Lazari and Chassiakos [15] showed how these methods can help strike a balance between environmental and financial goals. Some researchers have even introduced hybrid GA–PSO models to boost the effectiveness of the solutions. On the AI front, techniques like K-Nearest Neighbors (KNN) have been used to predict ideal EV charging station sites by analyzing user behavior patterns [15], [16]. Despite this growing body of research, several issues remain unaddressed. First, a unified framework to compare and classify the growing number of optimization techniques for solar-based EVCS is lacking. Second, while many studies reference sustainability, few explicitly incorporate solar irradiance data or smart grid variables into their decision frameworks. Third, geographical coverage remains uneven, with most studies focusing on Asia and the Middle East, leaving Sub-Saharan Africa, Latin America, and island nations underrepresented. Furthermore, validation procedures and sensitivity analyses are often overlooked, limiting practical implementation [17]. Arsel *et al.* underscored the importance of solar radiation estimation in siting precision, demonstrating that cubic spline regression outperforms traditional Ångström models in improving PV siting accuracy [18].

To fill these identified gaps in the literature, this research undertakes a structured review of relevant academic studies and optimization methods used for siting solar-powered EVCS. Following the PRISMA 2020 guideline, we screened over 60 articles from the Scopus database and selected 15 that fulfilled the inclusion criteria: i) focus on EVCS siting optimization, ii) integration of solar energy or renewable sources, and iii) methodological clarity. These studies were grouped into five major categories: GIS-based models, MCDM frameworks, fuzzy-GIS hybrid methods, heuristic/metaheuristic algorithms, and AI-driven models. For example, Choudhary and Akella demonstrated that integrating PV and biomass in hybrid systems could reduce carbon emissions to as low as 82 kg/year with a levelized cost of $0.077/kWh [19], [20] underscoring the significance of siting in renewable energy outcomes. By classifying techniques, assessing sustainability and smart grid integration, and identifying gaps, this study advances data-driven, sustainable EV infrastructure planning and underscores the need for interdisciplinary collaboration in solar-enabled EVCS siting [21]. Having a thorough grasp of existing methods and their shortcomings is crucial for steering future research and helping shape policies grounded in evidence for clean mobility efforts. This review integrates the PRISMA 2020 and PICOC frameworks to transparently classify fifteen studies from 2016 to 2024 into five sustainability and smart grid-oriented methodological categories, combining systematic and bibliometric analysis to capture research evolution and support evidence-based clean mobility planning.

2. METHOD

2.1. Research question formulation

To maintain coherence between the review objectives and article selection criteria, this study adopted the PICOC framework, a widely recognized structure for defining research problems in systematic reviews [22], [23]. To ensure that the review questions are systematically structured and aligned with the study objectives, this research adopts the PICOC framework, which helps define the population, intervention, comparison, outcome, and context of the review. Table 1 summarizes the PICOC criteria applied in this study and illustrates how each component guided the formulation of the research questions and inclusion parameters for article selection. Based on this formulation, the review addresses three core research questions concerning the most commonly used optimization approaches for solar-powered EVCS siting, the spatial, technical, and sustainability criteria prioritized in the decision process, and the remaining methodological gaps in the existing literature [22].

Table 1. PICOC criteria for this study

Component	Description
P	Solar-powered electric vehicle charging stations (EVCS)
I	Location optimization techniques (GIS, MCDM, heuristic, and hybrid)
C	Comparison across methods and spatial planning contexts
O	Identification of dominant methods, criteria, and knowledge gaps
C	Scholarly publications reviewed from the period 2014 to 2024

2.2. Literature search strategy

A structured and reproducible literature search was carried out using the Scopus database, which is widely recognized for its extensive indexing of peer-reviewed publications across engineering, energy, and environmental sciences [24]. The main goal was to identify scholarly works that explore the optimization of electric vehicle charging station (EVCS) placement, particularly those that integrate solar photovoltaic (PV) systems or other forms of renewable energy. To ensure alignment with the study objectives, a Boolean query was designed and applied to the TITLE-ABS-KEY fields of Scopus. The initial search string combined keywords such as: "EV charging station" OR "electric vehicle charging") AND ("location optimization" OR "site selection" OR "siting analysis".

Using logical operators (AND/OR). This strategy was intended to capture relevant literature that intersects both EV infrastructure planning and renewable energy-based siting methods. The initial query yielded 61 potentially relevant articles. A secondary filtering process was applied to refine the dataset, limiting results to English-language articles, published between 2014 and 2024, and document types including journal articles only. Additionally, keyword filters such as “solar energy”, “photovoltaic system”, and “sustainable location optimization” were used to further ensure the retrieved documents emphasized renewable-powered EVCS. This search strategy laid the foundation for subsequent screening and inclusion procedures as outlined in the following sections.

2.3. Screening and eligibility criteria

The initial database search was conducted in January 2025 and yielded 61 records. These records were exported in CSV format from Scopus and served as the basis for subsequent screening and bibliometric visualization. The review followed the PRISMA 2020 protocol [22], [25]. During the screening stage, the titles, abstracts, and keywords of all retrieved articles were reviewed systematically. Studies were excluded if they met any of the following criteria: i) Lacked methodological clarity or failed to describe the optimization framework; ii) Did not integrate solar, photovoltaic, or any form of renewable energy; and iii) Focused exclusively on financial, hardware, or techno-economic analyses without spatial or siting components.

After applying the exclusion criteria, 46 articles were removed, yielding 15 eligible studies that focus on EVCS site selection or location optimization, incorporate renewable energy aspects (particularly solar or hybrid sources), apply spatial, multi-criteria, or heuristic-based methods (e.g., GIS, MCDM, or hybrid models), are published in peer-reviewed journals between 2014 and 2024, and are written in English. Conversely, the review excluded general literature reviews lacking original methodology, papers focused solely on power electronics or policy issues without spatial planning, and studies unrelated to infrastructure siting or renewable energy integration. The entire process of screening and selecting studies is illustrated as illustrated in the PRISMA flowchart (Figure 1), which presents the number of studies collected, reviewed, removed, and ultimately selected for inclusion in the final analysis. Figure 1 illustrates the process used to select studies. Out of 61 articles initially retrieved from Scopus, 15 were included in the final analysis after applying the screening and eligibility criteria.

2.4. Research quality assessment

To maintain methodological rigor and consistency in the final dataset, each of the 15 selected studies underwent a structured quality assessment. This evaluation relied on five criteria derived from well-established systematic literature review (SLR) frameworks [1]-[3] and applied to each article based on the available abstract, methods, and conclusions. Each article was evaluated using a binary scoring system (✔ = criterion met; ✖ = not met). Studies scoring at least four of five criteria were included, ensuring methodological clarity and relevance.

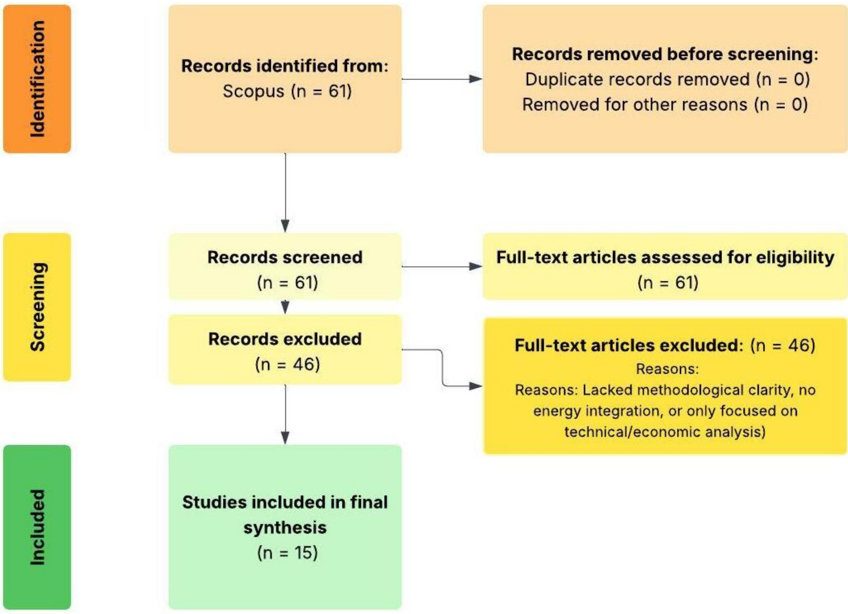

Figure 1. PRISMA framework illustrating the article screening and inclusion stages

Table 2. Quality assessment criteria

Code	Quality criteria
Q1	Clarity of research objective
Q2	Relevance to the optimization of solar-powered EV charging station locations
Q3	Methodological transparency and replicability
Q4	Suitability and application of optimization techniques (e.g., GIS, and MCDM)
Q5	Well-defined conclusions and implications

2.5. Data extraction and coding

Following the study selection and quality assessment, relevant data were extracted from each of the 15 included articles. The extraction focused on both bibliographic metadata and substantive content, focused on the spatial planning of EV charging infrastructure powered by solar technology. The fields extracted are listed [25]: Extracted data include publication details, keywords, optimization methods, energy types, decision criteria, and study context, obtained from Scopus metadata and abstract screening. Articles were grouped by dominant method and energy focus, with the coded information summarized in Table 2 and used for thematic and bibliometric analysis. Was tabulated (see Table 2) and further used for thematic classification and bibliometric analysis.

2.6. Bibliometric analysis

Biblioshiny, an interactive module of the Bibliometrix R environment, was employed for bibliometric mapping and visualization to identify research trends, collaborations, and thematic structures through keyword and citation analyses. By integrating bibliometric mapping with methodological classification, this approach reveals the conceptual and methodological evolution of EVCS optimization, highlighting core and emerging themes such as GIS–MCDM integration, heuristic algorithms, and AI-based models. The Scopus-derived metadata of 15 studies were analyzed using default co-occurrence thresholds, association-strength normalization, and thematic clustering in Biblioshiny.

3. RESULTS AND DISCUSSION

3.1. Descriptive characteristics of the selected studies

The general features of the 15 reviewed articles were extracted using the main information panel in Biblioshiny (Bibliometrix R package) [26]. This dashboard summarizes key bibliometric attributes such as temporal coverage, authorship, international collaboration, and citation performance. The analysis highlights trends in publication growth, co-authorship, and citation impact, as shown in Figure 2, which presents the visual summary of the main bibliometric indicators.

Figure 2. Visual summary of main bibliometric indicators from the dataset

Figure 2 presents the bibliometric profile of the dataset spanning 2016–2024, comprising 15 articles published in 12 journals by 56 authors, with an average of 3.8 co-authors per paper—reflecting moderate collaboration. The corpus shows a 25.1% annual publication growth and an average of 34.5 citations per article, underscoring increasing scholarly attention to solar-powered EVCS research. About one-third (33.3%) of the studies involve international co-authorship, confirming the field's emergence as a globally collaborative and cross-disciplinary research domain.

3.2. Trends in scientific publications

To examine the evolution of research interest in solar-powered EVCS location optimization, the annual publication trends of selected studies from 2016 to 2024 were analyzed using Biblioshiny. This time series analysis reveals the field's growth and increasing research momentum, with the annual distribution of publications presented in Figure 3. Figure 3 show from 2016 to 2019, research output was minimal, with no more than one publication per year. However, a shift began in 2020**,** and the field reached its highest output in 2024 with 6 articles**,** comprising 40% of the dataset. This reflects a growing recognition of the relevance of renewable energy and electric mobility infrastructure as an integral component of long-term sustainable city development**.**

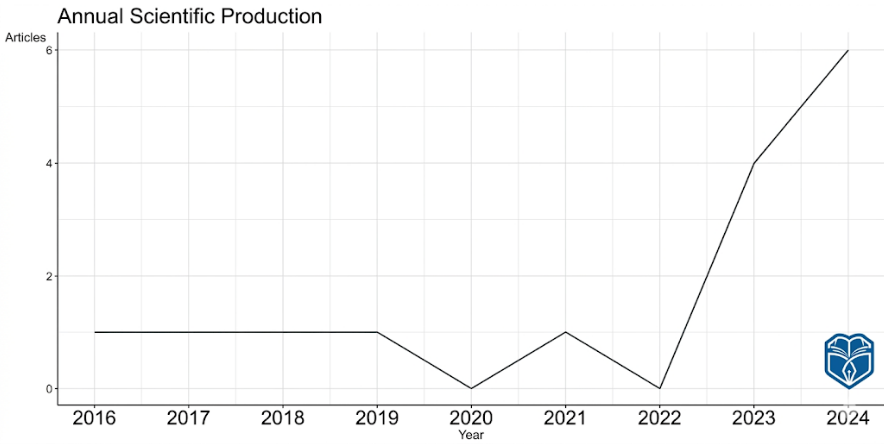

Figure 3. Annual distribution of publications in the dataset (2016–2024)

3.3. Distribution by journal sources

The 15 selected articles were published across 12 distinct journals, reflecting the broad disciplinary reach of investigations into the optimal placement of solar-powered EV charging systems. As illustrated in Figure 3**,** Sustainable Cities and Society emerged as the most dominant source, with 3 articles**,** followed by Energies (2 articles). The remaining journals each published one article. The reviewed articles were published across multiple journals, reflecting the interdisciplinary scope of the topic. To identify the most influential sources contributing to this domain, Figure 4 shows the distribution of the 15 articles among 12 journals.

Figure 4 shows this distribution highlights the **i**nterdisciplinary nature of the topic, which spans domains such as urban planning, energy systems, transportation infrastructure, and spatial decision-making. Journals such as IEEE Transactions on Fuzzy Systems and Computers and Industrial Engineering reflect the application of algorithmic modeling and structured decision-making methodologies in this area of study [27].

The absence of article clusters in a single journal also suggests that research on this topic is still emerging and not yet consolidated within a dominant publication outlet Putra *et al.* [25]. This fragmentation is typical for complex, interdisciplinary topics that require integration across traditional academic boundaries [25].

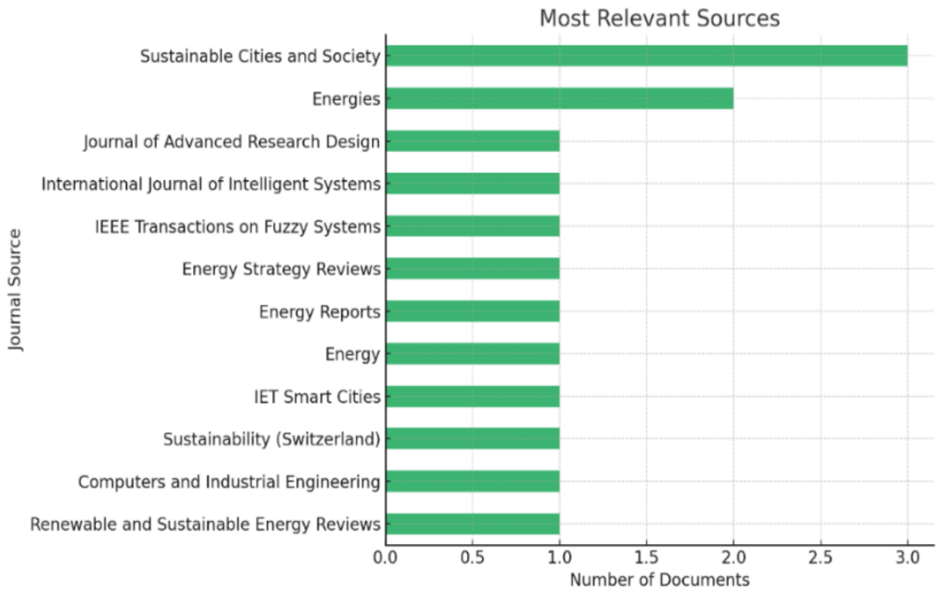

Figure 4. Most relevant journal sources in the reviewed dataset

3.4. Conceptual structure mapping based on author keywords

The co-occurrence network reveals that electric vehicle charging, site selection, and charging station form the central core of the research field, indicating their fundamental role in the development of EV charging infrastructure. These core themes are supported by peripheral terms such as decision making, GIS, and renewable energy, which highlight the interdisciplinary nature of the topic and its integration across spatial, technical, and environmental domains [28]. Furthermore, the frequent integration of MCDM with GIS tools underscores the critical role of spatial analysis in enabling informed siting decisions and enhancing the effectiveness of structured decision-support frameworks. This combination allows researchers and planners to evaluate multiple criteria simultaneously while incorporating geographic variability, ultimately improving the robustness and practicality of EVCS deployment strategies.

Figure 5 shows the thematic map, where site selection, electric vehicle charging, and battery charging occupy the upper-right quadrant, indicating their maturity and significance in solar-powered EVCS research. These align with dominant trends emphasizing MCDM and GIS approaches. However, the use of AI and machine learning remains limited despite their growing potential, while fuzzy and hybrid models show promising depth but lack broad application. This review advances prior studies by providing a broader comparison of GIS–MCDM hybrids and emerging optimization techniques, supported by a meta-analysis of algorithmic performance. It highlights key research gaps, particularly the need for real-time data integration and smart-grid compatibility to enhance scalability and efficiency in future EVCS siting models. Figure 6 illustrates that the field’s thematic core focuses on infrastructure siting and electric vehicle deployment, increasingly reinforced by environmental indicators and algorithmic decision-making tools. The continued use of GIS and MCDM, along with the emergence of K-means clustering, reflects the field’s growing methodological sophistication and shift toward data-driven, spatially aware optimization strategies [27], [29].

3.5. Classification of optimization techniques for solar-powered EVCS siting

Optimization models for solar-powered EVCS siting are evolving toward more integrated and computationally adaptive frameworks. From the review of 15 studies (2016–2024), five main methodological categories were identified: MCDM frameworks, hybrid models, heuristic optimization, spatial analysis, and machine learning. Among these, hybrid approaches dominate, often combining MCDM with GIS or fuzzy logic with AHP/VIKOR to improve decision robustness and contextual adaptability. As illustrative examples, the studies conducted by Gönül *et al.* [30] proposed location planning models for EV charging infrastructure by combining GIS with structured decision-making tools such as AHP, thereby enhancing spatial prioritization under multiple stakeholder constraints. Fuzzy-enhanced hybrids, such as the FAHP-GIS method (2019), also reflect growing attention to linguistic uncertainty in expert input. The second major group consists of MCDM-based models**,** which are widely applied to handle multiple conflicting objectives in EVCS siting. Approaches such as AHP (2016), fuzzy-TOPSIS (2021), and the entropy-VIKOR-TOPSIS combination (2024) are frequently used due to their interpretability and ease of integration with qualitative and quantitative indicators. Identifying optimal employed customized MCDM frameworks, for instance, the 2023 model titled a novel framework for decision-making in EV charging station siting, which contributes to enriching the methodological variations in this domain [13], [14].

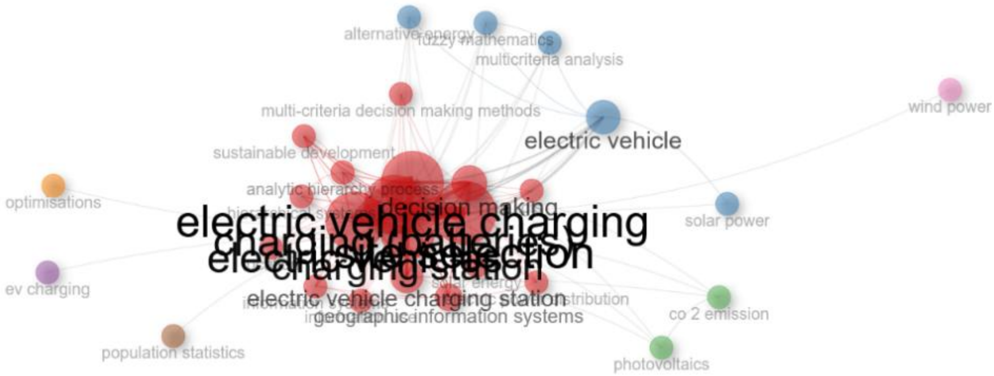

Figure 5. Keyword co-occurrence network from reviewed studies

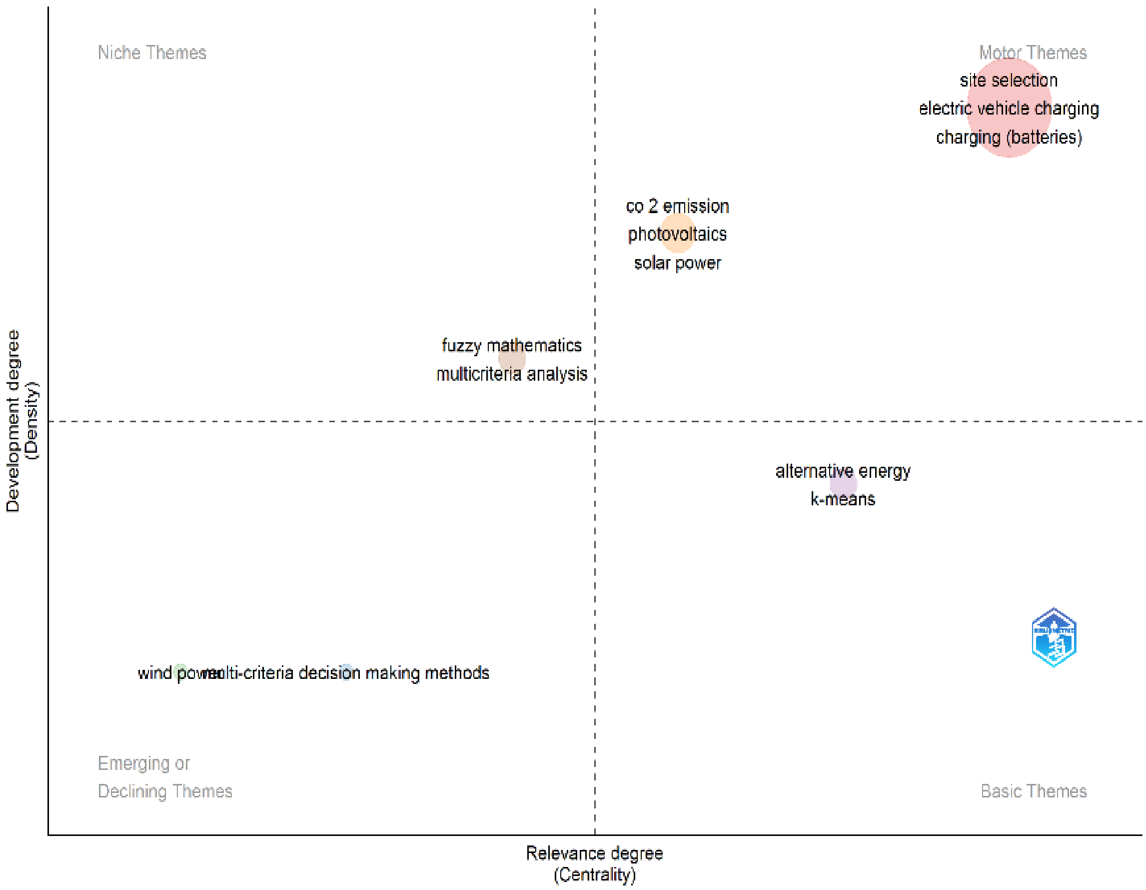

Figure 6. Thematic map of author keywords based on centrality and density

Heuristic optimization methods are used in technically oriented studies to address high dimensional and multi objective EVCS siting problems, with GA and PSO demonstrating potential for handling nonlinear spatial constraints. Meanwhile, GIS based spatial analysis remains the primary foundation for location modeling, particularly in studies utilizing real world data such as urban density, solar potential, and grid access. Javanmardi *et al.* [31] showcased the use of solar mapping via GIS for identifying rooftop and roadside deployment zones of EVCS in Bilbao. Lastly, machine learning is emerging as a promising frontier. A study by Xie and He [32] applied machine learning clustering and ranking techniques to recommend optimal EVCS locations within smart city contexts. and ranking to recommend charging station zones, indicating the shift toward autonomous, data-driven planning models that are suitable for smart city integration. A recent study by Gökler [33] demonstrated how combining FUCOM and GIS provides a robust model for evaluating multiple site-selection criteria in EVCS planning. Feng *et al.* [34] proposed a method aimed at identifying sustainable sites for electric vehicle charging infrastructure, incorporating environmental indicators into the decision framework. After reviewing and classifying the 15 selected studies, five dominant methodological categories were identified. To provide a concise comparison across these categories and their representative approaches,

Table 3 classifies optimization techniques for solar-powered EVCS siting, highlighting differences in adaptability, computational demand, and transparency. MCDM methods offer simplicity and interpretability but rely on subjective weighting and lack real-time adaptability, while hybrid approaches combine spatial accuracy and uncertainty handling at the cost of higher data and expertise requirements. Heuristic and AI-based models provide strong optimization capability and scalability but face higher computational demands and limited real-world validation.

Table 3. Verified classification

Year	Article title	Technique category	Representative method
2024	A holistic site selection approach for EV charging infrastructure utilizing multi-criteria evaluation and spatial analytical techniques [30]	Hybrid model	MCDM + GIS
2024	An ideal location identifying the most suitable sites for EV charging infrastructure through a combined fuzzy AHP–VIKOR approach [35]	Hybrid model	Fuzzy AHP–VIKOR
2019	An analysis of EV charging station siting using a fuzzy AHP–GIS integrated approach [31]	Hybrid model	FAHP-GIS
2017	Identification of ideal locations for an integrated wind–solar energy system charging station using improved PSO [36]	Heuristic optimization	Improved PSO
2023	A methodological framework for EVCS siting based on fuzzy AHP integrated with GIS [12]	Hybrid model	Fuzzy AHP+GIS
2018	Allocation optimization for optimizing EV charging station locations through genetic algorithm techniques [10]	Heuristic optimization	Genetic algorithm
2024	Location optimization of EV charging stations: A comparative analysis of entropy-VIKOR and TOPSIS [21]	MCDM	Entropy-VIKOR/TOPSIS
2024	Structured siting methodology for solar-driven EV charging stations through MCDM and geospatial techniques [37]	Hybrid model	MCDM+Spatial tools
2023	A study proposing a decision-support framework based on MCDM for EVCS siting [13], [14]	MCDM	Framework-based
2024	Research presenting a geospatial methodology for deploying urban solar-powered EVCS [31]	Spatial analysis	Geospatial solar mapping
2016	AHP-based spatial prioritization for siting electric vehicle charging stations [33]	MCDM	AHP
2021	An innovative fuzzy-TOPSIS approach for multi-criteria planning of electric vehicle charging stations [28], [34]	MCDM	Fuzzy TOPSIS
2023	Machine learning-based site recommendation model for electric vehicle charging in smart urban environments [32]	Machine learning	ML-based recommendation
2024	The significance of localized need analysis and sustainability criteria in identifying strategic PEVCS locations across Malaysian urban regions [38]	Need analysis-based criteria	Survey-based weighting & descriptive
2024	An integrated GIS-MCDM model used for public EV charging location evaluation [39]	Hybrid model	GIS-MCDM

This transition is further supported by a meta-analysis assessing algorithmic performance in terms of solution quality, efficiency, and scalability, as summarized in Table 4. Hybrid and machine learning–based approaches generally outperform traditional MCDM models in adaptability and scalability, though classical MCDM methods remain useful for early-stage planning due to their clarity and low computational demand. The growing integration of heuristic and data-driven techniques reflects a shift toward balancing computational rigor with practical decision-making efficiency.

Table 4. Comparative meta-analysis of algorithmic performance in EVCS siting

Optimization method	Average solution quality*	Computational efficiency	Scalability to large datasets	Remarks/representative studies
Genetic algorithm (GA)	★★★★☆ (High)	★★★☆☆ (Moderate)	★★★★☆ (Good)	Strong multi-objective handling; convergence sensitive to parameters [15], [18]
Particle swarm optimization (PSO)	★★★★☆ (High)	★★★★☆ (Fast)	★★★☆☆ (Moderate)	Efficient for continuous search spaces; limited by local minima [36]
Fuzzy–MCDM (AHP, VIKOR, TOPSIS)	★★★☆☆ (Moderate)	★★★★★ (Very Fast)	★★★☆☆ (Moderate)	Highly interpretable; lacks adaptability for dynamic conditions [12], [13]
Hybrid (GA–PSO, Fuzzy–GIS)	★★★★★ (Very High)	★★★☆☆ (Moderate)	★★★★☆ (Good)	Combines interpretability with adaptability; increased computational demand [30], [37]
Machine learning (KNN, ANN, Clustering)	★★★★☆ (High)	★★★☆☆ (Moderate)	★★★★★ (Excellent)	Excels in predictive analysis and data scalability; requires large datasets [32]

3.6. Integration with sustainability and smart grid planning

As EVCS networks expand, siting strategies increasingly prioritize sustainability and smart grid integration. Among the 15 reviewed studies, eight incorporate sustainability criteria such as solar potential, land use compatibility, carbon footprint, and proximity to distributed energy resources, underscoring the growing emphasis on solar-based EVCS siting [31]. Employ GIS-based solar mapping to identify optimal rooftops and open areas for PV-integrated charging, enhancing spatial efficiency and reducing grid dependence. This dual optimization maximizes renewable energy use while minimizing reliance on centralized, fossil-based grids. Several studies also emphasize smart grid alignment, evaluating proximity to distribution lines, load balancing potential, and vehicle-to-grid (V2G) compatibility. Although few perform detailed grid simulations, the integration of spatial grid data layers, as demonstrated in Suitable Site Selection of Public Charging Stations Using Integrated GIS-MCDM Framework (2024) [31], reflects a growing commitment to linking location modeling with grid resilience.

Importantly, these sustainability and grid-integration efforts are not treated as secondary objectives. Rather, they are embedded within the core siting methodology**,** often through weighted MCDM frameworks or hybrid fuzzy logic systems. In doing so, the reviewed studies reflect a shift in paradigm from finding available land to finding sustainable, energy-synergetic land. Moreover, Naseri *et al.* [37] proposed a GIS–MCDM framework for systematically identifying EVCS locations that align with sustainable transport goals. Hisoglu *et al.* [12]. The fuzzy AHP and GIS approach demonstrates that incorporating environmental constraints enhances the robustness of EVCS siting decisions without reducing accuracy. Overall, the literature shows a clear shift toward integrating EVCS optimization with urban sustainability and smart grid strategies, with future research emphasizing the coupling of spatial optimization, load forecasting, and grid impact analysis to improve system reliability and planning effectiveness.

Table 5 further complements this discussion by illustrating the characteristics of different EV drive systems and their implications for charging demand and infrastructure planning. Variations in motor type, efficiency, and regenerative capability directly influence charging patterns, load profiles, and infrastructure requirements. For instance, high-efficiency motors such as PMSM support fast charging with stable current profiles, whereas induction motors may require longer charging durations due to higher energy consumption. These differences highlight the importance of incorporating vehicle technology characteristics into EVCS siting models to improve demand estimation and grid compatibility.

Incorporating drive system load variability into siting models enhances demand forecasting accuracy and grid alignment. Urban fast-charging contexts require higher grid capacity, while rural or mixed-use areas benefit from lower-power distributed charging, highlighting the need to consider vehicle types, drive cycles, and charging behavior. Optimization algorithms further support both siting and power-electronic control, enabling co-optimized EV infrastructure and power system design. The review reveals significant regional disparities in research coverage and methodological use. Most studies focus on Asia and the Middle East, with limited attention to Sub-Saharan Africa, Latin America, and island nations, regions with rising solar potential and EV adoption. This imbalance underscores the need for broader geographic representation to ensure context-sensitive and adaptable optimization frameworks.

Table 6 presents the cross-domain application of optimization techniques in EVCS siting and power electronics. It shows that methods such as GA, PSO, fuzzy MCDM, VIKOR/TOPSIS, machine learning, and hybrid models are not only useful for spatial decision-making and site selection, but also play important roles in converter control, MPPT, diagnostics, and energy management. This demonstrates the strong methodological linkage between infrastructure planning and electrical system operation in solar-powered EVCS.

Table 5. summarizes typical drive system characteristics and their corresponding charging implications

Motor type	Typical power rating (kW)	Efficiency range (%)	Regenerative capability	Charging impact on EVCS
Switched reluctance motor (SRM)	50–150	85–90	Moderate	Moderate charging demand, higher current ripple requires converter filtering
Permanent magnet synchronous motor (PMSM)	60–200	90–95	High	Higher charging efficiency, supports fast charging with a stable current profile
Brushless DC motor (BLDC)	40–120	88–92	Moderate–high	Common in mid-range EVs; adaptable for Level-2 and DC fast charging
Induction motor	70–250	85–90	Low–moderate	High torque demand; longer charging cycles due to higher power consumption

Table 6. Cross-domain application of optimization techniques

Optimization method	Application in EVCS siting	Application in power electronics
Genetic algorithm (GA)	Optimal site selection under multi-objective constraints (cost, grid distance, irradiance)	Converter parameter tuning, maximum power point tracking (MPPT), and inverter efficiency optimization
Particle swarm optimization (PSO)	Multi-objective spatial optimization for EVCS network design	Control of DC–DC converters, hybrid converter optimization, MPPT for PV systems
Fuzzy AHP/fuzzy MCDM	Handling subjective and uncertain criteria in site ranking	Adaptive inverter control, fuzzy logic-based voltage and current regulation
VIKOR/TOPSIS	Multi-criteria ranking and trade-off analysis among candidate sites	Weight-based control mode selection, converter fault detection, and prioritization
Machine learning (KNN, K-Means, ANN)	Predictive siting based on spatial demand and behavioral patterns	Load forecasting, anomaly detection in drive systems, predictive converter diagnostics
Hybrid heuristic models (GA–PSO, fuzzy–VIKOR)	Enhancing siting robustness and accuracy across datasets	Multi-objective control of bidirectional converters and energy management systems

3.6.1. Power electronic converter considerations in solar-powered EVCS siting

Power-electronic interfaces are central to the efficiency and flexibility of solar-powered EVCS, with converter topology selected based on irradiance, grid access, and feeder distance. DC–DC converters support MPPT and voltage regulation, while bidirectional DC–AC inverters enable grid interaction and V2G. Siting conditions influence converter sizing, thermal design, and configuration, with grid-connected systems prioritizing bidirectional control and voltage support, and off-grid systems relying on multi-stage converters with storage for stability. Integrating converter parameters with spatial variables in siting models enhances technical feasibility, control stability, and system reliability.

As shown in Figure 7, PV-integrated EV charging systems may operate under several topological and power-flow arrangements. Figure 7(a) illustrates direct PV-to-EV charging through a DC–DC converter, which is appropriate for high-irradiance locations with strong daytime demand. Figure 7(b) presents a PV–battery–EV topology, where storage buffers solar intermittency and improves charging continuity. Figure 7(c) shows a grid-connected configuration in which PV generation is coordinated with utility support to enhance flexibility. Figure 7(d) highlights interaction control with the main grid, including bidirectional energy exchange and V2G functionality. Meanwhile, Figures 7(e) and 7(f) describe representative operational power-flow profiles for direct and buffered/grid-assisted charging modes, respectively. Overall, Figure 7 indicates that the technical feasibility of solar-powered EVCS siting depends not only on spatial suitability, but also on the compatibility between site conditions, converter topology, storage requirements, and grid interaction strategy.

Understanding power flow topology in solar-powered EVCS is vital for linking siting decisions with converter design and energy management. Depending on configuration, energy may flow through distinct pathways, affecting converter sizing, control complexity, and grid interaction. Figure 7 illustrates the main power flow scenarios in solar EVCS systems.

- PV → Converter → EV (Direct Charging): PV energy is converted through a DC–DC stage for voltage regulation before directly charging EVs—ideal for high-irradiance sites with minimal grid reliance.
- PV → Battery → EV (Buffered Charging): Surplus solar energy is stored in batteries and later used for charging, ensuring supply during low irradiance; suitable for semi-urban or off-grid systems.
- EV → Converter → Grid (V2G): In grid-tied setups, EV batteries export energy to the grid via bidirectional inverters, requiring advanced synchronization with IEEE 1547 and IEC 61850 standards.

Figure 8 presents a unified framework that links spatial siting factors with power-electronics design parameters for solar-powered EVCS planning. This framework integrates location-based criteria with converter configuration and optimization algorithms to balance cost, efficiency, and system resilience. Through an iterative feedback mechanism, the model enables co-optimization between siting decisions, power-electronic design, and control strategies within a smart grid-oriented decision-support system.

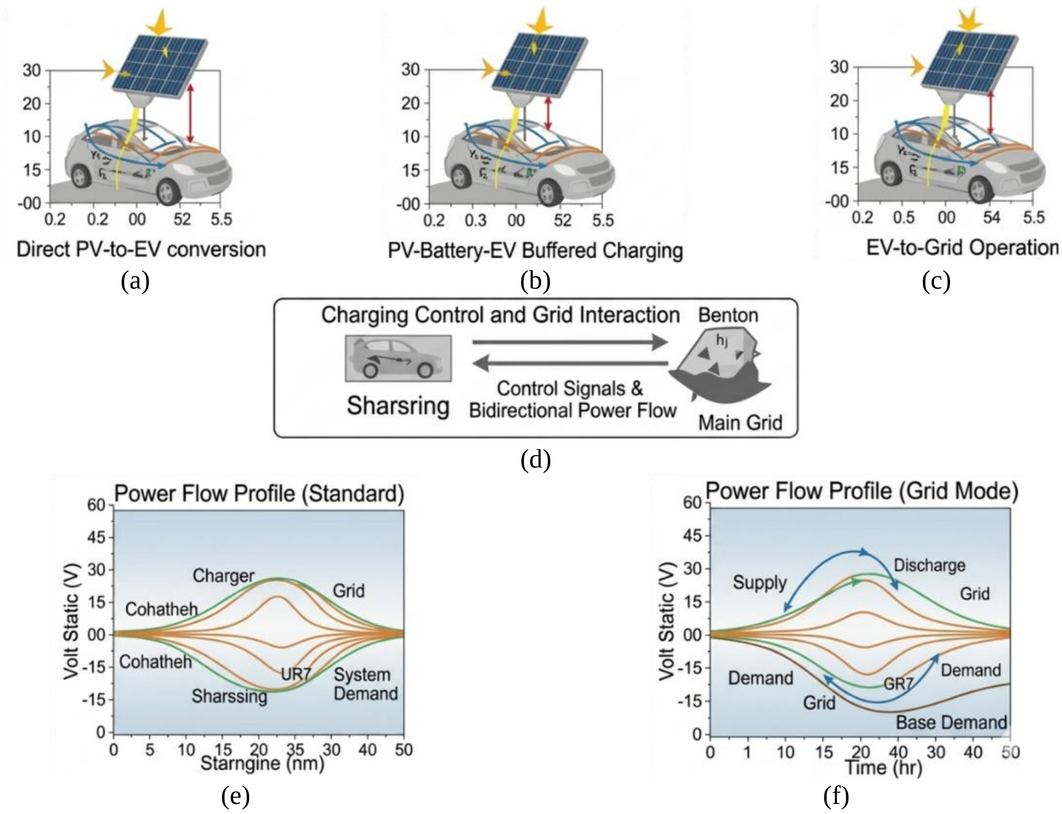

Figure 7. Configuration of the PV-integrated EV charging system: (a–c) charging topologies, including (a) direct PV-to-EV conversion, (b) PV–battery–EV buffered charging, and (c) EV-to-grid operation; (d) charging control and interaction with the main grid; and (e, f) operational power flow profiles, including (e) power flow profile (standard) and (f) power flow profile (grid mode)

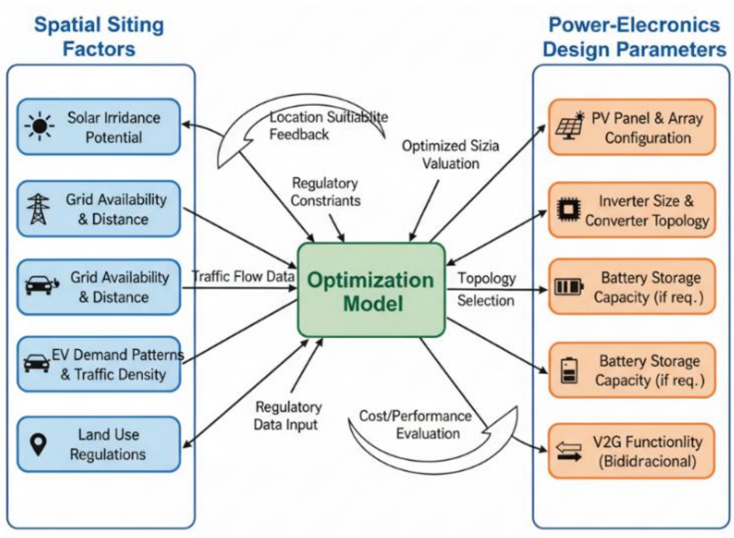

Figure 8. Unified framework linking spatial siting factors with power-electronics design parameters for solar-powered EVCS planning

4. CONCLUSION

This systematic review analyzed optimization techniques for solar-powered EVCS siting and identified five major methodological categories: GIS-based modeling, MCDM frameworks, hybrid models, heuristic/metaheuristic algorithms, and AI-based approaches. Among these, hybrid GIS MCDM methods dominate, offering robust decision-making under spatial and environmental uncertainty. Despite this progress, key gaps remain limited empirical validation, weak smart-grid integration, and underuse of AI-driven prediction. The review presents an organized framework mapping the evolution from deterministic to data-driven models and emphasizing sustainability indicators. These insights provide academic and practical value for developing scalable, context-aware decision-support systems. Future research should advance hybrid and ensemble frameworks combining metaheuristics (GA, PSO, ACO), MCDM, and data-driven learning to enhance adaptability and robustness across diverse spatial and grid contexts. Persistent challenges land-use constraints, investment costs, and fragmented stakeholder coordination demand participatory planning, transparent policies, and stronger collaboration among academia, government, and industry. Incorporating sensitivity and robustness analyses will further ensure model reliability under variable environmental conditions. The study is especially relevant for Indonesia and ASEAN, where rapid urbanization and solar potential require evidence-based EVCS deployment aligned with energy transition goals. A GIS-based, open-access decision-support roadmap is proposed to integrate solar data, EV demand, and grid capacity, accelerating the shift toward intelligent, sustainable EV infrastructure.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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