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SURVEY

Optimization Approaches for Fast Charging Stations Allocation and Sizing: A Review

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ABSTRACT The widespread use of fossil fuels in transportation has resulted in significant carbon dioxide emissions and increased reliance on non-renewable energy sources. To address these environmental challenges, the electrification of transportation systems through Electric Vehicles (EVs) has emerged as a promising solution. However, the successful deployment of EVs hinges on the availability of a robust charging infrastructure capable of meeting the charging demands and extending the driving range of EVs. Nonetheless, the large-scale deployment of EV charging infrastructure presents several challenges, including the ability of the electric grid to supply the required energy to accommodate the charging demand. Moreover, determining the optimal locations for fast-charging stations (FCS) in the traffic network to ensure accessibility, convenience, and efficient resource utilization poses a significant challenge. As a result, numerous studies have investigated the optimal allocation and sizing of EV charging infrastructure. The primary objective of this research is to conduct a comprehensive literature review to examine how this optimization problem has been addressed in the literature over the past decade. The review aims to identify the key factors considered in the problem formulation and the optimization techniques for allocating and sizing the charging stations. To achieve this goal, a systematic literature review was conducted following the PRISMA methodology for a comprehensive and unbiased approach. This review contributes to the existing literature by highlighting critical gaps and proposing a framework that can possibly bridge these gaps. The review identifies several critical gaps in current research, including: 1) Transportation-focused studies largely ignore electrical grid constraints; 2) Electrical-focused research often relies on statistically modeled EV charging demand, which may include some geographical assumptions; 3) Multidisciplinary approaches integrating both transportation and electrical networks are still in early stage; 4) Dynamic traffic flow of EVs is rarely considered; 5) Exact optimization methods largely rely on linearized or approximated models; 6) Dominance of approximate methods in transportation and electrical network modeling, primarily relying on evolutionary algorithms; and 7) Hybrid approaches are mainly utilized to solve a specific part of the problem rather than enhancing the quality of the solution. In response to these gaps, the research proposes a novel framework to integrate the transportation network and the electrical grid planning process, offering a holistic and practical solution in FCS infrastructure development.

INDEX TERMS Allocation, fast charging station, optimization, power flow, transportation electrification.

I. INTRODUCTION

Electric vehicles (EVs) have the potential to revolutionize the transportation sector by reducing greenhouse gas emissions

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and improving energy efficiency. However, challenges such as high purchase costs, limited driving range, relatively long charging time, and lack of charging infrastructure obstruct the wide adoption of EVs [1]. To address these challenges, a plausible solution is the deployment of Fast Charging Stations (FCS), which can help overcome EVs' limited range, also known as range anxiety, and reduce charging time [2]. Nevertheless, the high voltage requirement and the anticipated peak demand for EV charging associated with FCS can stress the electrical power grid. If not managed properly, this stress can result in high charging costs, infrastructure degradation, major system upgrades, and potential compromises to power quality and grid safety. Moreover, inadequate placement of FCS in inaccessible or highly congested areas within the transportation network may lead to market displacement due to misalignment with the needs and preferences of EV drivers.

Hence, the main goal of this research is to investigate the optimization approaches applied to the allocation of FCS in terms of placement and sizing, considering the electrical and transportation networks. The main objective of the optimization is to provide the needed services for EVs while considering the limitations and requirements of both networks and the preferences of users. For this purpose, a systematic literature review is conducted to highlight research trends, develop formulations, and solution tools, and identify the gaps that should be considered in future research.

Previous review papers in the literature have addressed the same topic. For example, a comparative analysis was conducted to highlight the academic research-practice gap, concluding that node-serving approaches are more common in practice [3], while flow-capturing models are prevalent in academic research [4]. Another review article [5] surveyed the literature for the mathematical models for optimizing the locations of FCS and modeling the EV demand. However, these articles focused on the concerns of the traffic networks and overlooked the electrical grid's requirements for supplying EV charging power. On the other hand, some other studies considered the FCS, from the electrical grid's perspective. For example, the advancement of FCS technologies and their impact on the grid with an emphasis on renewable energy integration have been considered in a previous review [6]. Similarly, another paper [7] reviewed the planning strategies for ultra-fast charging stations and their impact on the allocation problem compared to conventional charging stations. Moreover, the EV charging demand and its incorporation into the FCS allocation planning problem, highlighting the reliance on simplified assumptions have been investigated [8]. However, these reviews mainly focused on the electrical network. In contrast, a detailed review of the demand modeling of EV charging, including the distribution and transportation networks was conducted previously [9]. In addition, a comprehensive literature review highlighting the interdependence between transportation and electrical networks has been proposed [10]. This recently conducted review focused mainly on the overall framework for integrating transportation and electrical systems without emphasizing the mathematical formulation and the optimization techniques applied. Furthermore, the other review articles focused on different aspects of the allocation problem and EV demand modeling, a standard systematic review methodology was not followed, which could introduce bias and affect the comprehensiveness, quality, and relevance of the included studies. To ensure a comprehensive and unbiased study, this research follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology [11] to conduct a systematic literature review of the mathematical formulation and optimization techniques and methodologies applied to address the allocation and sizing problem of FCS. In addition, this paper focuses more on the formulation utilized in the optimization process, the factors impacting the process, and the applied solution procedures.

The remainder of the paper is structured as follows: Section II outlines the systematic review methodology, Section III focuses on the review of allocation problems in the transportation network, Section IV covers the allocation problem within the electrical distribution network, and Section V presents a multidisciplinary modeling approach for both networks. The final sections include discussions and conclusions.

II. THE PRISMA METHODOLOGY

The use of a rigorous methodology is crucial for conducting a comprehensive and systematic literature review. One such methodology is PRISMA, which provides a standardized approach to the search, screening, and selection of relevant studies [12]. This methodology has gained popularity in various fields due to its ability to reduce bias and increase the transparency and reproducibility of the review process, thus, it is the chosen methodology to conduct this literature review. This research aims to investigate the literature for the FCS's optimum allocation and sizing problem in both transportation and electrical networks by adhering to the PRISMA guidelines [11]. The objectives of this study include:

1. Review the optimization of FCS's allocation in the transportation networks along with the main factors and considerations affecting it.
2. Review the FCS's allocation problem tackled in the electrical network along with the factors impacting the optimization process.
3. Investigate how both networks are incorporated into the optimization problem.
4. Identifying the main gaps in the literature and providing directions for future research.

The aim and objectives of the study have guided the inclusion and exclusion criteria for the adopted methodology. Hence, the selection criteria for this study were restricted to English language for broad accessibility and understanding, peer-reviewed articles for academic quality assurance published within the last decade to capture the most recent development in the field. Specifically, the focus was on articles addressing

FIGURE 1. Trends in research.

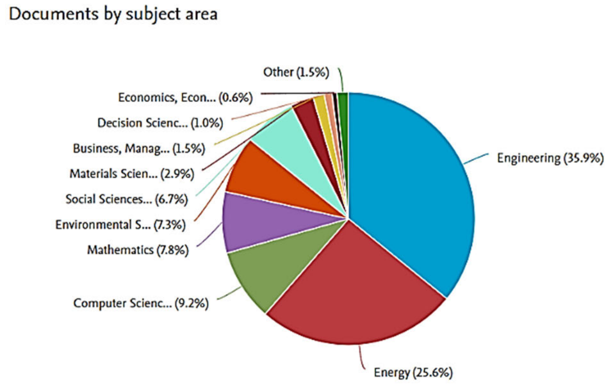

FIGURE 2. Distribution of the topic by the research field.

the optimization problem of locating and/or sizing charging stations for electric vehicles (EVs) while considering fast-charging technology. This technology is crucial as it enables EVs to quickly recharge and continue their journey, and its effectiveness is significantly influenced by the strategic placement of charging stations along busy roads and highways to maximize the range of EVs

Additionally, the location of the charging stations must be accessible from the electricity utility's perspective to avoid compromising power quality, incurring high losses, or necessitating extensive infrastructure upgrades, which can increase costs and cause delays in the widespread adoption of EVs. Therefore, this study included articles that address the optimal location of FCS to align with the objectives of the research. Specifically, it considered articles that utilized optimization methods, where the optimal locations of FCS are among the decision variables. It excluded other charging technologies to focus solely on the location and sizing problem. This excludes scheduling, or coordinated charging problems that involve energy management or routing for EVs, which are considered operational approaches rather than planning approaches. Moreover, this study excluded articles that employed qualitative approaches to address the problem and studies that relied solely on surveys or simulations instead of mathematical optimization modeling.

For this purpose, high-impact databases such as Scopus, IEEE, and Science Direct were used to conduct the literature review. The main keyword search used across the databases included terms like "fast charging stations," "allocation," "optimization," and "electric vehicles." For example, in Scopus, the following query was used:

(TITLE-ABS-KEY ("fast charging station" OR FCS) AND ("electric vehicle" OR "EV") AND (optima* OR planning OR allocation OR location* OR distribution OR infrastructure OR sizing OR siting)) for the time frame from 2013 to 2024.

Over the past decade, there has been a significant interest in the research community to study the optimal allocation and sizing of FCS from various perspectives. As shown in Figure 1, which displays the number of published articles per year in the Scopus database for the allocation problem of FCS, there has been a significantly increasing trend in this area. Additionally, Figure 2 demonstrates the distribution of the topic across research fields, indicating widespread interest across different disciplines, with the engineering discipline having the largest share.

To demonstrate the interest in the research topic, Figure 3, generated by Vosviewer [13], illustrates the publications and co-authorship collaborations per country. It is evident that China has the largest number of publications, followed by the United States and Canada. The links between countries indicate collaborations between institutions in this research field, with the thickness of the link reflecting the frequency of collaboration. The largest collaboration occurs between China and the USA, indicating their dominance in this field. It is noteworthy that a threshold of 2 publications was set. It is also clear from Figure 3 that there is a lack of research on this topic within the UAE.

The flow chart in Figure 4 provides a detailed description of the PRISMA process and illustrates how articles were screened and selected based on the inclusion criteria, including the number of articles screened, included, and excluded.

Based on the search keywords, Scopus yielded 363 articles, Science Direct had 93, and IEEE had 64. After merging and removing duplicates, a total of 422 articles were selected for initial screening. Based on titles and abstracts, 272 articles were excluded for various reasons, such as having similar keywords but addressing a different topic (e.g., Finite control set abbreviated as FCS for motor controls), being social or psychological disciplinary articles to focus on the technical optimization aspects of the problem, or being review papers as they were discussed earlier in the introduction section. Out of the remaining 234 articles, 84 were not retrieved because they were either qualitative studies, survey approaches, or not related to mathematical optimization modeling. Through a more in-depth review of the full papers, an additional 73 articles were excluded due to being simulation-based, focusing on different charging technologies, or addressing operational optimization problems not the location of the stations. Thus, a total of 77 articles were thoroughly reviewed and

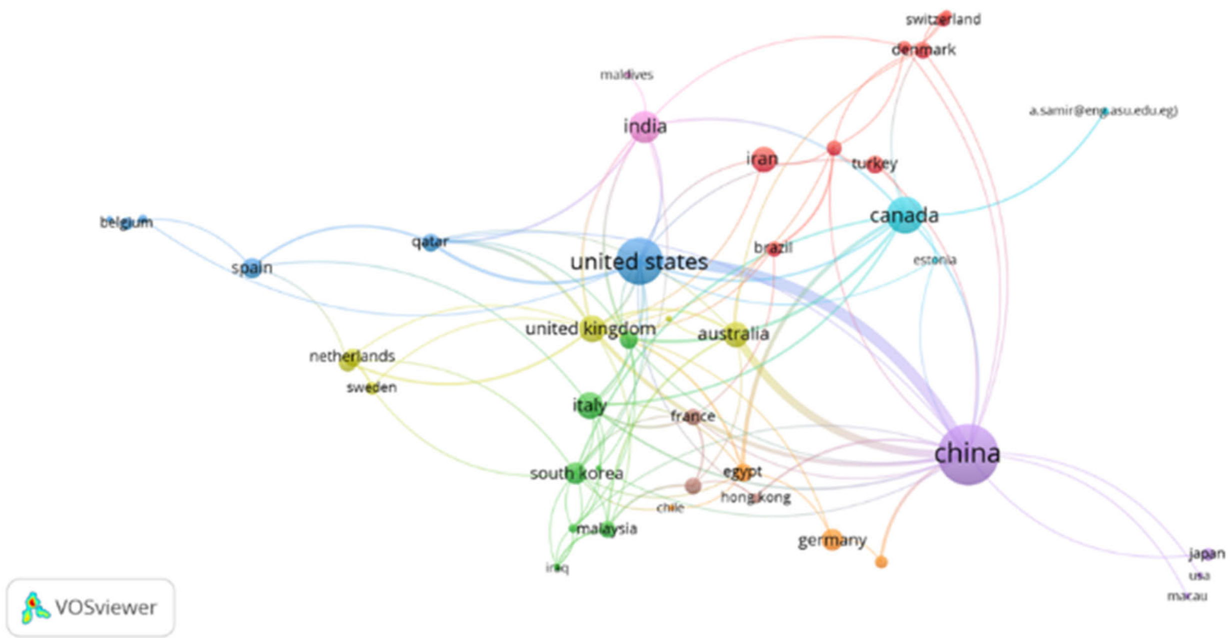

FIGURE 3. Vosviewer countries and co-authorship.

categorized in this research. In addition, another 27 papers were considered through the backtracking of the research development.

These backtracked articles are included to refer to models, data or methodologies being used in the reviewed articles. The inclusion of these backtracked articles help in reproducibility of the presented research as well as provide clear understanding of the adopted models and methodologies.

The following sections provide detailed discussions of the selected articles for review. Each article is categorized based on the system being optimized (i.e., transportation, electrical, or multidisciplinary), and further categorized based on the problem formulation and solution approach. This categorization highlights the factors and measures considered in each study along with the optimization formulation and solution techniques. Following this methodology will help shed light on the gaps in the literature.

III. FCS ALLOCATION IN TRANSPORTATION NETWORK

In this section, the articles that focused only on the transportation network in the allocation and sizing of FCS are reviewed. These articles are categorized into three categories according to the optimization problem formulation and the solution approach. The first category includes the exact approaches in solutions for linear and nonlinear formulations. Approximate approaches that encounter heuristic and metaheuristic approaches are considered in the second category. Finally, the hybrid approach of combining more than one solution approach represents the third category. In each of these categories, the main factors taken into consideration are highlighted.

A. EXACT APPROACHES

This sub-section has grouped the research that utilized exact solutions for the allocation and sizing of the FCS from the transportation network perspective. In these studies, a single objective is typically considered. For example, some aim to minimize the driving distance directly [14], CO2 emissions [15], or the installation cost [16]. The objective was to maximize the flow through the servicing unit (i.e. the charging station) or the EV share, in some other studies. The allocation problem is also formulated as a set covering problem [17] to minimize the number of stations required to cover a certain geographical area, as presented by Zhang [18]. Similarly, a node-based approach to the problem is presented in other research [19].

A widely adopted methodology in service allocation within transportation networks is the "flow capturing model". This model seeks to maximize the flow passing through the servicing unit, in this case, the charging station. It can be expressed as

$$Max \sum_{q \in Q} f_q x_q \tag{1}$$

where f_q represents the EV traffic flow on the shortest paths for the qth origin-destination (O-D) pair in the network. This flow is measured by the number of vehicles that are expected to pass by a certain O-D pair in the network and x_q is the binary decision variable that represents the inclusion or capture of that flow. While Q representing the set of all O-D pairs in the modeled traffic network. This is achieved by summing up the product of the EV traffic flow and the binary decision variable across all O-D pairs in the set Q.

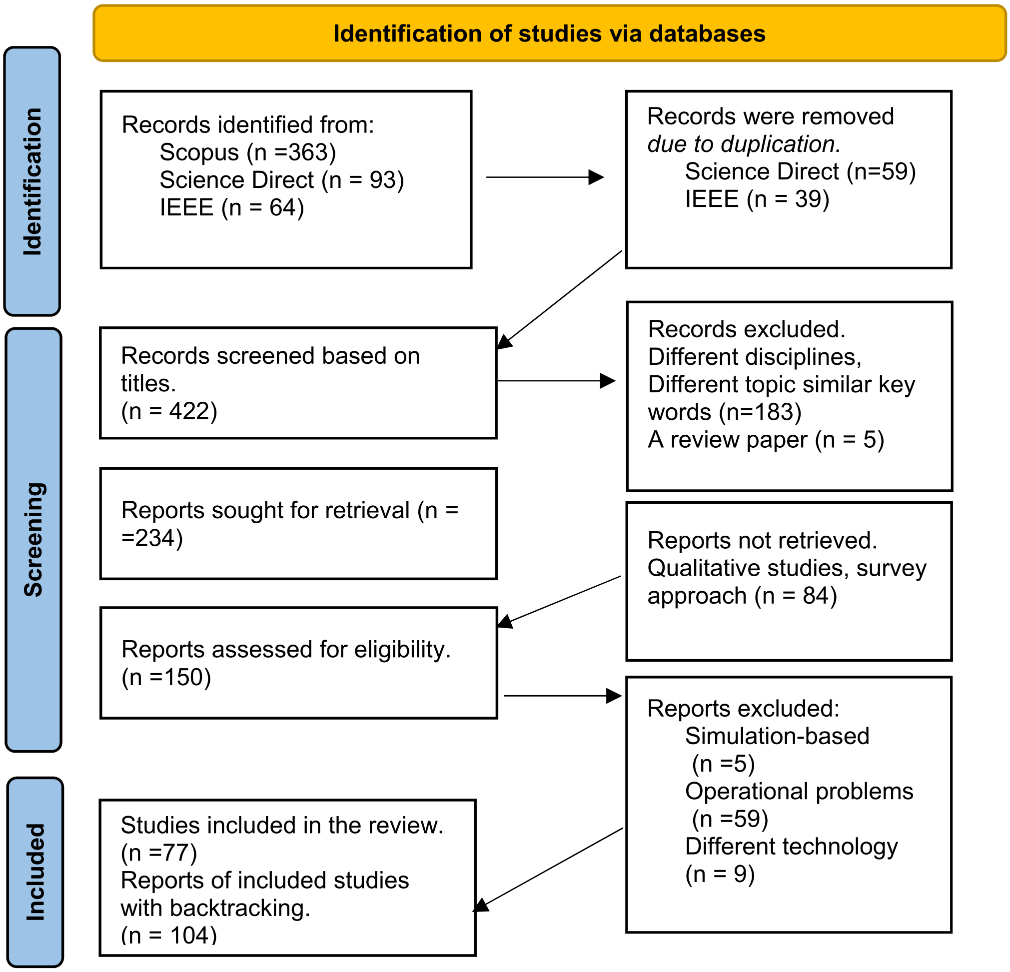

FIGURE 4. Flow chart of PRISMA methodology.

Two notable approaches under this framework are the Flow-Capturing Location Model (FCLM) [20] and the Flow Refueling Location Model (FRLM) [21]. The FRLM is a variant of the FCLM that considers the demand for refueling or recharging vehicles in this problem, where a set of O-D pairs represents the EV flows and is utilized to maximize the flow volume of charged vehicles. This approach has been adopted in several research studies [22], [23], [24].

From the review of the exact approaches for allocating FCS within a transportation network, it is evident that flow-capturing models are dominant, where nodes in the network are considered candidate locations. While existing methodologies offer valuable insights into FCS allocation, one significant gap is the lack of representation of the dynamic network flows. Most studies adopt static models that assume constant traffic patterns, disregarding temporal variations in EV demand and traffic conditions. This simplification overlooks the potential for FCS locations to influence route choices and create new traffic patterns, impacting the utility and profitability of the charging stations. The lack of consideration for the traffic flow dynamics may not only result in suboptimal station placements but could also lead to unexpected issues such as traffic congestion or market displacement. Moreover, in this category, the reliance on exact optimization techniques faces scalability challenges, when adopted to large-scale planning problems such as the allocation of FCS.

Additionally, the choice of optimization methodology is heavily influenced by the problem's complexity, the need for scalability, and the level of accuracy required. For instance, Mixed Integer Linear Program (MILP) methods, while robust and versatile, may not be practical for large-scale and dynamic systems due to computational constraints. Dynamic Programming offers a structured approach to multi-stage decision problems but can become computationally infeasible for high-dimensional problems. Table 1 provides a summary of the exact solution approach, including the formulations, algorithms/solvers used, modeling procedure, and the main limitations of each study.

B. APPROXIMATE APPROACHES

Several studies propose approximate approaches to address the complexity of the allocation problem in the transportation network. In approximate approaches, there is an inherent

TABLE 1. Exact approaches in transportation networks.

	Obj.	Formulation	Solver/ Algorithm	Ref.	Modeling procedure	Limitations
Exact	Multi-stage	Dynamic programming.	Floyd's algorithm.	[14]	Minimizing the driving distance. Locating FCS in the first stage, and sizing in the next stage. Monte Carlo simulation to model travel behavior Queuing theory for FCS sizing	Relies on Monte Carlo and queuing theory, which may not capture real-world complexity. Floyd's algorithm may face scalability issues.
	Single	Convex programming	MATLAB [25]	[15]	Minimizing CO2 considering Budget, peak hour demand, Co2 emissions,	Parameters are arbitrarily chosen, affecting the robustness of the convex programming model.
		Stochastic programming	Bender's decomposition	[22]	FCLM formulation [20] considering the uncertainty of EV demand.	Computational intensity in large-scale scenarios. High data requirement for modeling probability distributions.
		Binary LP	CPLEX [26]	[18]	Set covering problem formulation [17]	Fails to consider the network's capacity and user preferences in the set covering approach. Identified FCS candidate locations.
		MILP	CPLEX	[16]	Minimizing costs considering Electric bus fleets, and the uncertainty of the buses' consumption due to different congestion levels.	Focuses only on electric bus fleets, limiting applicability to a broader range of EVs.
			SCIP solver in Python [27]	[19]	A node-based approach considering EV penetration, driving range, available services, traffic loads, and distance between areas.	Limited to network nodes, leading to uneven FCS distribution. Scalability concerns with network growth, especially for exact methods.
		Non-Linear Integer Program (NLIP)	CPLEX	[23]	FRLM formulation [21] considers the demand for recharging vehicles.	Each pair of the (O-D) matrix is set to have at least 1 charging station, which may not be practical or cost-efficient.
				[24]	FRLM with dedicated corridors.	Limited to dedicated EV corridors, constraining the model's broader applicability.

trade-off between solution optimality and computational efficiency. While these methods may not guarantee an optimal solution, they are particularly useful for tackling the complexity and scalability issues often associated with FCS allocation in transportation networks. Several studies propose approximate approaches utilizing specific well-known models such as the set covering approach [28], the arc-based approach [29] as presented by Csiszár and Csonka [30], FRLM [31], [32], or the Multipath Refuelling Location Model (MPRLM) [33], which is a more flexible model than FRLM and allows EVs to deviate from the predefined path to reach the FCS. The MPRLM has been utilized for the FCS allocation problem, as presented by Li and Huang [34]. These models consider a set of candidate locations as inputs, either by dividing the region into zones and developing assumptions to generate initial candidate locations and constraints, or by developing selection criteria for the locations. However, these assumptions and inputs may not accurately reflect drivers' behaviors or preferences in real-world applications, potentially impacting traffic flow. Other researchers have adopted different approaches for the allocation problem, such as minimizing driving distance and waiting time [35] or maximizing EV share [36].

Furthermore, to accommodate drivers' decisions, some researchers introduced a driver preference function and adopted a multi-objective approach to balance between minimum installation costs and maximum driver satisfaction. This function includes factors such as electricity prices and driving distance to the station, as presented in [37], and may further include considerations like crowdedness, brand of charging station, and level of attraction [38]. Additionally, to incorporate traffic flow, researchers have adopted the concept of system optimum [39] or user equilibrium [31] or even developed a novel mathematical program to minimize social costs with equilibrium constraints [40].

In the approximate approaches category, incorporating traffic flow into the allocation problem is a challenging task that requires careful modeling and efficient solutions. Furthermore, the inclusion of factors such as EV penetration level, charging demand uncertainty, charging time, waiting time, and driving distance further complicates the problem formulation. Table 2 summarizes the findings of this category,

TABLE 2. Approximate approaches in transportation network.

	Obj.	Formulation	Solver/ Algorithm	Ref.	Modeling procedure	Limitations
Approximate	Single	Chance-constrained MILP	Partial Sampling Approximation Approach [41],	[32]	FRLM considers uncertainties in vehicle driving range, energy availability, and power consumption.	Uncertainty modeling limitations, relaxation of assumptions high data requirements - Limited scalability only tested on medium-sized instances.
		MINLP	GA	[28]	Set covering	-Most of the introduced or applied algorithms are applied to preselected candidate locations to reduce the search space. -Dynamic traffic flow is not considered -GA depends on the parameter's selection.
				[35]	Minimize driving distance and waiting time	
				[40]	Mathematical program with equilibrium constraints (MPEC) to minimize total social cost (public parking lots)	
		MINLP	PSO	[39]	Minimize cost and driving time	PSO may get trapped in a local optimum.
		MINLP	Heuristic algorithms	[30]	Arc-based [29],	Specific heuristics may perform differently under large-scale instances.
				[34]	MPRLM [33],	
				[36]	Maximize EV share.	
	Bi-level			[31]	FRLM for the upper level and user equilibrium [42] on the lower level	
	Multi-Objective	MINLP	Strengthening Pareto Evolutionary Algorithm-II,	[37]	Minimize cost and maximize satisfaction.	The performance of SPEA-II can be affected by the selection of algorithm parameters. In the game theory approach, accurately modeling user preferences and crowdedness could be challenging, impacting the robustness of charging station placement strategies.
			Game Theory	[38]		

including the objectives, algorithms used, modeling procedures, and limitations.

There are two main well-known optimization techniques utilized in this category, either Genetic Algorithms (GA) or Particle Swarm Optimization (PSO), each with its strengths and weaknesses. For instance, both approaches can achieve good results within a reasonable computational time. However, GA relies heavily on parameter selection, while PSO may get trapped in a local optimum. Other research that utilizes problem-specific heuristics may perform differently under large-scale problems or different instances. Therefore, care should be taken as the allocation and sizing problem is a large-scale planning problem.

C. HYBRID APPROACHES

To enhance the solution quality, account for more factors, and eliminate some of the limitations of a single optimization technique, hybrid approaches are introduced [43], [44], [45], [46], [47]. These approaches combine metaheuristic methods with other techniques to solve the allocation and sizing problem.

Some researchers have utilized metaheuristic approaches for the allocation of FCS, combining them graphically with Voronoi diagrams to determine the service area [43], [44]. The Enhanced Heuristic Descent Gradient (EHDG) algorithm is applied in a study [43]. The method employs a two-step strategy beginning with GA to generate sets of feasible solutions and then applying a series of gradient descent for optimization enhancement. The method's main strength lies in its ability to utilize GA's global search capabilities and gradient descent's fine-tuning, particularly useful for problems with complex solution landscapes. However, its scope is limited to electric buses with predefined routes and schedules, constraining its broader applicability. Another study employed PSO for FCS allocation and the Voronoi diagram for sizing [44]. The Voronoi diagrams offer spatial granularity, allowing the model to consider the service areas more realistically. However, like GA, PSO still has its limitations, including the risk of converging to local optima.

A more complex approach uses a hybrid problem-specific heuristic combined with GA to solve the location and sizing problem [45]. This method focuses on maximizing the captured EV flow in the network. However, it becomes

TABLE 3. Hybrid approaches in transportation network.

	Obj.	Formulation	Solver/ Algorithm	Ref.	Modeling procedure	Limitations
Hybrid	Single	MINLP	(EHDG) and Voronoi diagram	[43]	Minimize travel distance to the station. GA is first used to generate feasible solutions and the DG is for selection among them and the Voronoi diagram is for the service area	The problem is formulated for electric buses with predefined routes and schedules. . It has similar limitations to GA.
			PSO and Voronoi diagram	[44]	Minimize total cost. Spatial and temporal charging demands are generated using travel survey data	PSO limitations for allocation still hold.
			Hybrid problem-specific heuristic and GA	[45]	Maximize charger EV (capacitated flow model) Utility theory for drivers' charging strategies.	Some chromosomes may represent the same solution. Gets complex on a large scale.
	Bi-level	MINLP	Cross entropy and Successive Average	[46]	Minimize system cost and environmental impacts. Cross entropy to decide the FCS locations of the upper level and the Successive average for stochastic user equilibrium in the lower level.	Low performance on large-scale problems
	Multi-objective	MINLP	PSO and Simulated Annealing	[47]	Minimize cost and charging time considering functional zoning and traffic factors.	The area is divided based on the points of interest and some areas are excluded. A promising hybrid algorithm that needs to be tested against other algorithms

computationally complex on a large scale and some chromosomes in the GA may represent the same solution, reducing the algorithm's efficiency.

On the other hand, a bi-level approach was presented, where each level is solved using a specific algorithm [46]. The upper level aims to minimize installation cost and environmental impacts using cross-entropy, while the lower level optimizes routing and ensures traffic network equilibrium using successive averages. For traffic assignment, the authors adopted a stochastic user equilibrium model with Poisson (O-D) demand and stochastic charging demand. This approach is a mathematical model tailored for EV users. However, it may require several assumptions that could potentially limit its applicability in real-world scenarios.

A multi-objective optimization problem is formulated to minimize costs and EV charging time [47]. The study divides the area into zones based on congestion and signal waiting time. A combination of PSO and Simulated Annealing is used to allocate and size the FCS. While promising, this algorithm needs to be tested against other algorithms for validation. Moreover, the authors did not consider the range anxiety of EVs and assumed that drivers are aware of traffic congestion levels and will therefore seek alternative charging locations based on this knowledge.

Additionally, the use of hybrid models to enhance solutions should be tested against other algorithms and in different instances, including large-scale planning that reflects the complexity of the problem. The promising aspect of hybrid models is their ability to enhance the search space to overcome the limitations of a single approach and obtain higher-quality solutions. However, this has only been addressed in a limited number of studies [47]. Thus, testing these hybrid approaches, especially in multi-objective problems, presents a major challenge in assessing solution quality. Table 3 summarizes the findings of this category, along with the limitations of each method.

Despite these advancements, all mentioned articles have considered transportation aspects from different perspectives to capture the EV demand and hence allocate the charging stations. However, these approaches have assumed a static assignment of EVs, which may not reflect realistic situations as traffic conditions can substantially affect FCS locations. The focus has been narrowly on capturing the flow of EVs, with no research measuring the broader impact of FCS locations on overall traffic performance, especially when considering the future scenario of high EV penetration levels. Moreover, by solely focusing on the transportation aspect, the electrical demand of FCS is completely overlooked, despite its significant impact on electric service and charging costs.

The next section discusses the research studies that consider the electrical system performance and the needed upgrades to accommodate the EV-FCS load.

IV. FCS ALLOCATION IN ELECTRICAL NETWORK

This section discusses the research that focused solely on the FCS allocation problem considering the electrical network. According to the optimization problem solution approach, they have been categorized into the three levels that were used before (i.e., exact approaches, approximate, solutions, and hybrid approach). The section also addresses key challenges such as modeling EV charging demand, grid reinforcement, and incorporating power flow equations.

Modeling the charging demand for EVs is one of the biggest challenges facing the FCS allocation and sizing problem for the electrical system operators. Due to the lack of data, several approaches have been introduced in the literature and will be presented in this section along with the problem formulation and solution approaches. Moreover, the grid reinforcement or upgrade to accommodate the introduced load of FCS is another challenge, some researchers considered transformers and voltage regulators upgrade for the grid according to the maximum expected power consumption of the added EV charging load. Some other researchers considered the integration of renewable distributed generation (RDG) and battery energy storage systems (BESS) for grid reinforcement and Co2 emissions reduction which elevate the complexity of the planning problem due to their stochastic nature. Additionally, the inclusion of power flow equations in the problem to guarantee operational constraints poses another challenge due to their highly non-linear nature. The power flow equations (PFE) [48] are crucial in electrical grid optimization. These equations generally describe how power flows through the network. Since FCS represent significant power load, which is often fluctuating due to the fluctuation in EV charging demand, their placement in the electrical grid affects the distribution of active and reactive power. Therefore, to analyze how this load impacts the overall power flow in the grid, equations (2) and (3) describe the active and reactive power at each bus in the electrical network, respectively.

$$P_i = P_{Gi} - P_{Li} = \sum_{k=1}^{N} |V_i V_k Y_{ik}| (Cos(\delta_i - \delta_k - \theta_{ik})) \quad (2)$$

$$Q_i = Q_{Gi} - Q_{Li} = \sum_{k=1}^{N} |V_i V_k Y_{ik}| (Sin(\delta_i - \delta_k - \theta_{ik})) \quad (3)$$

where P_{Gi} *and* Q_{Gi} are the generated active and reactive power at bus i, respectively, whileP_{Li} *and* Q_{Li} are the active and reactive load at bus i, respectively. This represents the FCS load and the conventional loads that already exist in the network. Additionally, V_i is the voltage magnitude at bus i, δ_i is its angle, Y_{ik} is the admittance of the transmission line connecting buses i *and* k and θ_{ik} is its angle. While N is the total number of busses in the distribution network. This analysis is critical for maintaining power quality and stability in the network, especially considering the fluctuating demand associated with EV charging.

The voltage V_i and current I_i at each bus should remain within the minimum and maximum values as technical limits during planning, as presented in (4) and (5):

$$I_{min} < I_i < I_{max} \quad (4)$$

$$V_{min} < V_i < V_{max} \quad (5)$$

These limits ensure that voltages and currents remain within safe operational bounds, thus preventing network overload and ensuring the reliability and safety of the electrical grid. By maintaining these limits, overloading parts of the distribution network due to the addition of FCS can be avoided.

A. EXACT APPROACHES

In this category, researchers have utilized exact methods to optimize the FCS allocation in the electrical grid to accommodate such incoming load either by adding it optimally to the existing grid, considering upgrades of the infrastructure such as transformers, voltage regulators, and feeders, or renewables reinforcement to account for the added FCS load. For instance, some studies considered the grid's upgrade by increasing the capacity of transformers or voltage regulators using different EV demand models [49], [50].

On the other hand, recognizing the significance of RDG in reinforcing the grid, some researchers proposed an optimization model for the allocation problem that integrates RDGs. For example, both RDGs and BESS sizes and locations are integrated in the same process [51], while other studies suggested using FCS equipped with BESS [52], and FCS equipped with RDS [53].

In this category of research, all the articles focused on a single objective problem, which was either minimizing the power losses (Eq. 6 and 7) and/or the total investment costs (Eq. 8).

$$Min \sum P_{loss} \quad (6)$$

$$P_{loss} = \sum_{i=1}^{N} \sum_{k=1}^{N} [B_{ik}(V_i^2 + V_k^2 - 2V_i V_k Cos\,(\delta_i - \delta_k)] \quad (7)$$

where P_{loss} is the power lost in the transmission lines of the distribution system, while B_{ik} is the conductance in the line connecting buses i and k. The voltage magnitudes at these buses (V_i and V_k) and their respective phase angles (δ_i and δ_k) contribute to the power loss and they are directly impacted by the placement of FCS in the distribution system.

$$Min \sum C_{total} \quad (8)$$

where C_{total} is the total investment costs, which may include FCS installation costs, grid upgrade equipment costs, RDGs, and BESS costs.

In the existing literature on FCS planning using exact methods in the electrical network, there is a methodological divergence in constraint formulation. Researchers either incorporate the electrical network's technical limitations only or facilitate the exact solution of the problem through linearization, or relaxation of the power flow equations adopted [54], [55], [56]. While such simplifications enable the use of robust and exact optimization methods, they introduce critical concerns for the steady-state power flow representation. These linearized models may lead to suboptimal FCS locations, especially when the conventional loads already present in the grid are considered, a factor that is absent in the studies within this category. Thus, a research question that arises from the review of this section is whether these linearized models or relaxations have a significant

TABLE 4. Exact approaches in electrical power network.

	Obj.	Formulation	Solution / Algorithm	Ref.	Modeling procedure	Limitation
Exact	Single	(MINLP)	Branch and cut.	[49]	Refueling behavior based on travel surveys for EV demand modeling. PFE not included.	Linearization or approximated procedures for power flow equations Static representation of transportation network and relying on assumptions. It may not be suitable for large-scale representation
		Chance-Constrained (MILP)	GAMS	[51]	Electric bus routes for demand modeling Linear PFE model presented.	
		MILP	CPLEX	[50]	Zonal demand model and queuing theory for EV demand modeling Linearized PFE [54].	
				[52]	Queuing theory for EV demand modeling, Linearized PFE [55].	
				[53]	Monte Carlo Simulation for EV arrival rate and State of charge Relaxed convex PFE model [56].	

impact on the final optimal locations of the FCS or not. To investigate this, future research should aim to assess the impact of using linearized models on the planning problem's solutions. A suggested investigative strategy could involve a comparative analysis between the outcomes derived from linearized models and those obtained using the actual power flow equations. Such an approach would offer an understanding of the trade-offs involved, establishing the reliability and effectiveness of employing linearized or approximated models in the allocation problem considering the dynamic operational constraints of the grid. Table 4 provides a summary of the findings in this category, including the modeling procedure that investigates the EV demand modeling for the FCS, the solution approach, and formulation along with the limitations.

B. APPROXIMATE APPROACHES

The approximate approach is one of the most widely used approaches in this area of research, due to the high nonlinearity of the power flow equations and the complexity of the problem when considering different factors such as the time-varying existing loads in the distribution network, the power quality issues that arise due to the added load of the FCS and the temporally dynamic nature of EV charging demand. Some researchers have formulated the FCS allocation problem without considering any grid reinforcement or upgrade [57], [58], [59], [60], [61], [62], [63]. While this approach simplifies the problem, it poses significant stress on the existing electrical infrastructure, particularly considering the time-dependent nature of FCS demand, which may coincide with peak grid demand. Consequently, such a scenario would strain the infrastructure to its limits, resulting in degradation potential of power quality issues and electrical service interruption. Therefore, this approach may not be sustainable in the long-term planning, especially as the adoption of EVs continues to grow. On the other hand, other researchers have considered alternative grid reinforcement approaches such as increasing the capacity of distribution transformers [64], [65]. While this approach addresses the limitations of the existing infrastructure, it shifts the primary objective of reducing carbon emissions from transportation networks by EVs to the electrical network to meet the charging demands of FCS. This could potentially compromise the environmental benefits of transitioning to EVs, as the electrical grid may still rely on non-renewable energy sources to meet the increased demand. Conversely, recognizing the importance of integrating RDGs into the electric grid as a tool for reinforcing the system to meet FCS demand and reduce carbon emissions, some researchers have formulated the problem of allocating FCS equipped with RDGs [66], [67]. However, this approach may not be practical in real-world applications due to the environmental dependency of RDGs and space constraints especially in urban settings. A more realistic yet complex formulation, freely allocating the RDGs and FCS to meet the demand has been proposed in different studies [68], [69], [70], [71]. This approach offers the flexibility to adapt to different scenarios and constraints. While this approach is more aligned with real-world conditions, it also increases the complexity of the problem, requiring more sophisticated optimization algorithms and computational resources.

An additional challenge facing this category of research is the representation of the EV electrical demand present in the

TABLE 5. Approximate approaches in electrical network.

	Obj.	Formulation	Solution / Algorithm	Ref.	Modeling procedure	Limitations
Approximate	Single	MINLP	PSO	[60]	charging demand model for electric buses. No PFE no RDG.	As PSO performs both global and local searches simultaneously, it might get trapped in a local optimum. Did not include the power flow equations for optimal operation.
				[62]	EV demand prediction model No PFE no RDG.	
	Multi-Objective	MINLP	Adaptive PSO	[71]	Random EV demand modeling and Random RDG placement	
			LaGrange Multiplier to solve sub-problems	[57]	Assuming predetermined candidate locations and sizes of FCS Included PFE, no RDG or upgrade	The proposed algorithms are compared with existing algorithms, and they provide better solutions. Not tested in multi-objective problems or large-scale problems. Rely heavily on assumptions of EV demand modeling.
			local search algorithm	[61]	Assuming predetermined candidate locations and size of FCS No PFE, not including upgrade	
			Binary Atom	[63]	Gas stations are the candidate locations and travel time to estimate the demand Included PFE, no RDG	
			Improved Krill Swarm Optimization Algorithm	[64]	Statistical model for EV demand No PFE, upgrade	
			Heuristic algorithm	[65]	EV statistical diffusion model [72] Included PFE, upgrade	
			Improved Bal Eagle Search (IBES)	[68]	Calculated candidate number and size of FCS[73] No PFE, RDG included.	
			GA	[58]	Geographic information is used to determine EV energy loss. Included PFE, no RDGs or upgrade	The solution efficiency of the GA and its variants depend heavily on the parameters of the model such as fitness function, selection, mutation, and crossover
				[59]	EV user behavior is considered to determine the expected charging demand and the expected EV user cost. included PFE, no RDGs or upgrades.	
				[66]	Monte Carlo included PFE, RDGs	
				[67]	A worthiness metric is proposed to rank FCS candidate locations based on their attractiveness to EV drivers, and the EV-project dataset to build a stochastic demand model. included PFE, RDGs	
	Multi-Objective	MINLP	Non-dominated Sorting Genetic Algorithm (NSGA-II)	[69]	Zonal analysis PFE not included, RDGs included.	
				[70]	A worthiness metric is proposed to rank FCS candidate locations based on their attractiveness to EV drivers, and EV-project dataset to build a stochastic demand model. Included PFE, RDGs	

planning problem, since this area of research focuses on the electrical network and due to the lack of real data to represent the EV demand, different approaches have been presented in this category. Some studies have followed basic assumptions for the initial candidate locations of the FCS [57], [61], [63], while others have utilized mathematical formulas for the initial number and sizes of FCS [68].

These approaches may lack adaptability to dynamically changing demand patterns. A step forward to more realistic initial candidate locations is the use of zonal analysis [69],

TABLE 6. Hybrid approaches in electrical network.

	Obj.	Formulation	Solution/ Algorithm	Ref.	Modeling procedure	Limitations
Hybrid	Two Stage	NLP	GA-minimax Game theory	[75]	kernel density estimation and a nearest-neighbor search algorithm for EV demand modeling. -A mini-max game theory combined with GA is introduced to min. the peak demand.	No RDGs or PFE; GA parameters control performance.
	Single	MINLP	Gray Wolf and PSO	[77]	Calculated candidate number and size of FCS [73] Considered RDG- Exploration skill of GWO combined with solution efficiency of PSO. -Enhance search ability and overcome the local optimum trap	-Random placement of RDG -Search space is reduced based on the owner criteria (a developed index) -Compared with PSO only -Did not consider PFE
			Recalling-enhanced recurrent neural network (RERNN) and Marine Predators Algorithm (MPA) algorithm	[78]	Shortest deviation path and a physics-based model to calculate the energy consumption of EVs RDGs -MPA allocates the FCS and RDGs, and RERNN is for sizing.	- No search-enhancing approach -Each method is responsible for a task FCS equipped with RDGs. -No PFE
			GA, Information entropy [82], and Game theory	[79]	Historical travel data for EV demand modeling, considering RDGs. -Uncertainties of conventional loads with EV demand and RDG output	Although the hybrid algorithm is very promising, it might not handle multi-objectives. NO PFE
			GA and generalized reduced gradient descend.	[80]	Assuming the maximum number and candidate locations for FCS -A stochastic approach for RDG and FCS for allocation and sizing.	GA is used to generate the locations while the gradient descent is for Power flow optimization. Thus, the algorithm did not contribute to the solution selection or initial population.
	Multi-Objective	MINLP	SFL and TLBO	[74]	Zonal analysis and Monte-Carlo simulation for EV demand modeling - Enhance search ability which could be promising.	Not tested on large-scale problems, Excludes PFE
				[76]	Ev demand is estimated by a statistical model. -Load model of EV as constant impedance constant current instead of constant power -Considering RDGs -Enhance search ability which could be promising	

and geographic information-based models [58], which refine the assumed locations to make them more realistic but may still not capture the dynamic nature of EV demand and require solid knowledge about the geographical locations, attractions, and population. Other studies have adopted statistical models to represent EV demand [60], [62], [64], [65]. While these models can be data-driven, they may not account for real-time variations and could be sensitive to the quality of past data and assumptions employed which impacts the universal adoptability. Finally, the most sophisticated approaches, such as Monte Carlo methods and worthiness metrics used in studies [66], [67], [70] add computational complexity and require extensive data, making them less practical for real-world applications.

From the solution algorithm perspective, GA and PSO are the most widely used approaches in this category. Table 5 represents a summary of the research in this category including the problem formulation, solution algorithm, modeling procedure for EV demand and electrical network considerations, and finally, the associated limitations.

TABLE 7. Exact approaches in multidisciplinary.

	Obj.	Formulation	Solution/ Algorithm	Ref.	Modeling procedure	Limitations
Exact	Single	MILP	BARON with GAMS	[83]	Deterministic O-D matrix Power flow equations (PFE) Linear approximation [95]	Linearization or approximated procedures for power flow equations Static mathematical representation of transportation network
		MILP	Commercial solvers	[93]	Bi-level, linearized and reformulated as single level. A modified user equilibrium model for traffic. Only technical limits.	
			GAMS solver	[99]	Modified Staircase Facility Location Model (MSCFLM) [100] Power flow equations (PFE) Linear approximation [95]	
			Branch and cut	[85]	CFRLM Linear approximation [54]	
			CPLEX	[89]	CFRLM PFE Linear approximation [96]. RDGs.	
				[90]	FCLM Linearized model and RDGs [96]	
		Mixed Integer Second-order cone programming (MI-SOCP)	Branch and cut / CPLEX.	[87]	CFRLM PFE Linear approximation [97]	
				[88]	CFRLM Only technical limits	
		NLIP	Not specified	[91]	Traffic flow model Only technical limits	
		MINLP	An enumeration technique	[94]	User Equilibrium Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks and Queuing Theory PFE are included with normal distribution for active and reactive power.	
	Multi-objective	ILP	GUROBI solver	[86]	CFRLM PFE Linear approximation [98]	
		MINLP	Bilayer Expanded Benders Decomposition proposed in the article	[92]	Traffic flow model Power loss is approximated for convexity	

C. HYBRID APPROACHES

In this sub-section, researchers who focused on utilizing more than one optimization method to allocate and/or size the FCS in the electrical network are being discussed. As categorized in the previous sub-section, certain studies have formulated the problem without considering grid

TABLE 8. Approximate approaches in multidisciplinary.

	Obj.	Formulation	Solution/ Algorithm	Ref.	Modeling Procedure	Limitations
Approximate	Single	Mixed-Integer Quadratically Constrained Programming (MIQCP)	Lagrange multiplier and Karush-Kuhn-Tucker (KKT) conditions are verified	[103]	Minimizing the cost, Linearized travel assignment model, Linearized PFE [110]	Power flow equations are linearized, and the problem is relaxed to find the optimal solution.
		MINLP	Natural Aggregating Algorithm [111]	[105]	Minimizing the cost, Data-driven agent-based traffic assignment model Only technical limits. No PFE	Not considering RDGs for grid reinforcement No Comparison with other algorithms
			Cooperative Coevolutionary Genetic Algorithm (CCGA)	[102]	Traffic O-D matrix and travel survey data to generate EV demand scenarios.	
	Two-Stage	ILP	Harris Hawks Optimization (HHO)	[107]	Traffic assignment mathematical model [112] No PFE RDGs and BESS	It may not account for real-time variability in EV demand or charging behavior.
	Multi-objective	MINLP	A graph-based Cross-Entropy method [113]	[101]	Assuming candidate locations and FCLM generates EV demand modeling not included PFE, upgrade included	Excluded all time-dependent variables for power flow
			Multi-objective decomposition evolutionary-based algorithm [114]	[104]	Minimizing the cost and maximizing the flow captured. User equilibrium for traffic assignment PFE included	Solving each sub-problem separately No Comparison with other algorithms
	Bi-level	Reformulated as a linearized single level by KKT conditions	Optimization-based bound tightening and sequential bound tightening	[108]	maximize profit on the outer layer and minimize charging costs in the inner layer. A proposed linearized energy demand assignment model	Problem formulation was linearized by the Big-M method and McCormick relaxation method
		MINLP	A descent algorithm	[106]	location and sizing on the upper level, Modified user equilibrium for traffic assignment on the lower level. relaxed branch flow model, no RDGs.	Relaxed branch flow model, no RDGs, a linear approximation to convert the bi-level to a single-level problem.
			Approximate Iterative Optimization Algorithm	[109]	Minimize the cost on the upper level and operational costs on the lower level. Dynamic traffic flow simulation platform Only voltage limit. No PFE	Congested areas and intersections are excluded from the candidate locations

reinforcement or upgrades [74], [75]. This simplification, while computationally less intensive, often overlooks the long-term sustainability of the electrical infrastructure. On the other hand, given the significance of integrating RDGs into the electrical grid to meet the expected FCS load and reduce the peak-valley ratio resulting from high demand at specific times of the day, several studies have investigated the joint allocation and sizing of both FCS and RDGs [76], [77], [78], [79]. Others have further extended the scope with additional considerations for mobile energy storage [80].

There is a divergence in the primary motivation for employing a hybrid approach in this category. One primary driver is the need to address complex, multi-faceted problems through specialized optimization methods where the utilization of more than one optimization technique can be to perform a specific task within a large problem. For instance, the Marine Predators Algorithm (MPA) is tailored for FCS and RDG allocation and combined with the Recalling-Enhanced Recurrent Neural Network (RERNN) for station sizing [78]. Another hybrid approach is the combination of GA and the Generalized Reduced Gradient descent (GRG) algorithm. The algorithm starts with generating a population of GA chromosomes, where each chromosome represents the planning decision variables. Then, for each chromosome in the current generation, the GRG method is used to solve the monthly operating costs, followed by evaluating the solutions based on the fitness function and checking the stopping criteria [80]. This modular approach allows for specialized techniques to be applied to different aspects of the problem, potentially

TABLE 9. Hybrid approaches in multidisciplinary.

	Obj.	Formulation	Solution / Algorithm	Ref.	Modeling Procedure	Limitations
Hybrid	Two-stage stochastic	MIP	NSGA-II + Fuzzy	[117]	Integration of queuing theory and gravity model to maximize served EV flow. Minimizing the power loss, PFE, and technical limits	No conventional loads, RDGs and BESS are on site of FCS. No dynamic traffic flow analysis. Fuzzy Logic for Decision-makers
	Multi-objective	MINLP	GWO + Fuzzy GWO generates a set of non-dominating solutions, Fuzzy to choose among them by trade-offs in each objective function	[115]	Integration of gravity model and O-D matrix to maximize served EV flow. Minimizing the power loss, PFE, and technical limits	No conventional loads or RDGs and gas stations are the candidate locations. No dynamic traffic flow analysis. Fuzzy Logic for Decision-makers.
		Multilayer	Metaheuristic and ILP	[119]	Different congestion levels with EV demand uncertainty using the 2m point estimation method for historical data Renewable, upgrades, PFE included	It might not capture the dynamics of the traffic network by relying on mathematical modeling for EV scheduling and doesn't test the impact on the traffic network
	Bi-level	MINLP	NSGA-II + ILP	[118]	(upper layer optimal locations of FCS and PV, lower level economic dispatch of electric generation Dynamic Traffic Assignment [120]. PFE and technical limits conventional loads	Only locations of FCS without sizing.
			Improved genetic algorithm (IGA) and GA	[116]	A sequential capacitated flow-capturing location model (SCFCLM) PFE and technical limits, conventional loads, upgrade	Chance constrained no RDGs No dynamic traffic flow analysis.

yielding more accurate or efficient solutions. Conversely, other studies have leveraged hybrid methods to refine the selection process among a generated set of solutions. For example, a hybrid approach combining GA and minimax game theory has been developed to optimize both the peak load demand and service level at FCS locations [75]. The most promising utilization of the hybrid methods can be viewed as enhancing the searchability of a single approach for better search exploration and avoiding the limitations of a single approach thus enhancing the quality of the obtained solution. Examples include the integration of Teaching and Learning-Based Optimization (TLBO) with Shuffled Frog Leap (SFL) for its superior search space exploration [74], [76] and the combination of Grey Wolf Optimization (GWO) with Particle Swarm Optimization (PSO) for enhanced solution efficiency [77]. Furthermore, a combination of GA, information entropy, and game theory was presented by Wei and Chan [79] where 3 populations are generated in parallel, Information entropy decides the most diverse solution, and game theory selects individuals in populations. Nonetheless, it is important to compare the employed method against alternative approaches and conduct extensive validation on large-scale, real-life problems to ensure its suitability for FCS planning and multi-objective optimization.

A critical gap in this section of research lies in the modeling of EV demand and the associated strategic placement of FCS. Existing models predominantly rely on pre-selection criteria for demand estimation and FCS location [74], statistical models [75], [76], [79], mathematical calculations [77], [78], or assumptions [80]. None of the previously mentioned models have taken into account how the location and size of FCS may affect the transportation network flow. These models usually select candidate locations based on dense areas, but this approach could attract more vehicles to these areas and negatively impact the network flow and transportation network performance. In addition, failure to incorporate traffic network conditions may result in underutilization of charging stations, congestion at some stations, or bottlenecks within the traffic network. Since the charging time of EVs is much longer than refueling, it is essential to test the planning output on traffic flow during different scenarios, including low, medium, high, and extreme traffic congestion and rush hours. It is crucial to incorporate the dynamic characteristics of charging operations and traffic movements while extending the fast-charging network [81]. Placing large-sized FCSs in highly congested areas may increase traffic congestion and divert EV drivers to less congested stations for time and energy saving. Based on the above discussion, multidisciplinary optimization approaches are essential for the success of the deployment of FCS and higher penetration of EVs.

Table 6 presents an overview of the utilized methods, modeling procedures, and associated limitations.

V. MULTIDISCIPLINARY OPTIMIZATION OF TRANSPORTATION AND ELECTRICAL NETWORKS

In this section, the articles that focused on optimizing both networks simultaneously are being reviewed. According to the optimization problem solution approach, they have been categorized into the same three levels discussed earlier (exact, approximate, and hybrid approaches).

As a general starting task in this multidisciplinary approach, coupling between the transportation and electrical network should happen to reflect common locations for the decision variables of FCS.

A. EXACT APPROACHES

In this sub-section, the coupling between the transportation and electrical network happens to accommodate both networks' limits and constraints. These methodologies are predominantly directed towards minimizing the installation costs of the FCS station or travel time to the station. One proposed approach is to couple the two networks and consider the electrical network requirement while constraining the locations to the special coupling points only [83]. Although this approach succeeds in incorporating both networks in a comprehensive model, it relies on a deterministic O-D traffic flow matrix and deterministic electrical load profile. Such determinism, however, fails to capture the dynamics inherent in transportation, EV charging demand, and existing electrical loads, thus representing a considerable limitation.

A more prevalent model adopted in this sub-section is the Capacitated Flow-Refuelling Location Model (CFRLM) [84]. This model offers increased flexibility compared to the FRLM and incorporates queuing theory for estimating EV demand, [85], [86], [87], [88], with additional accommodation of RDGs [89], [90]. Furthermore, Modified Staircase Facility Location Model (MSCFLM) [100], which is a modified CFRLM that accounts for traffic deviation and adopts a multi-period perspective in conjunction with user equilibrium [99]. Additionally, some researchers have employed mathematical models for traffic flow assignment [91], [92], [93]. Although these models incorporate the transportation network aspect in the problem, relying on mathematical modeling to represent traffic flow may fail to capture the dynamics of the transportation network. In addition, the upgrade or reinforcement of the grid was not taken into account, and the demand for EVs was modeled using user equilibrium traffic assignment along with queuing theory to ensure a satisfactory level of service for the FCS [94]. Furthermore, the representation of the electrical network in this area either focused on the technical limitations of the network, such as voltage and current limits, or utilized linearized or relaxed formulation for power flow equations [95], [96], [97], [98]. Hence, the major drawback in this area is the unrealistic representation made for both networks, which is a significant gap.

Table 7 provides a comprehensive overview of the optimization techniques used, including the formulation, solver, and utilization of linearized models. To be able to provide an exact solution to the optimization problem in this subsection, researchers relied exclusively on linearization procedures for power flow equations during the planning process. This may oversimplify the problem fail to capture the operational constraints of the electrical network and overlook its critical aspects. Furthermore, when considering the transportation network perspective, the utilization of capture flow models or static flow assignments could have adverse impacts on real-world transportation network performance. Thus, it becomes crucial to conduct further analysis and compare the outcomes of these models with the original power flow formulation. Additionally, incorporating RDGs is essential to address the environmental requirements of EV charging. However, due to the uncertainties associated with RDGs, the existing formulations may not be sufficient for optimal integration.

B. APPROXIMATE APPROACHES

In this category, the presented research aims to optimize both the electrical and transportation networks utilizing approximate optimization techniques. The studies employ varying models for the transportation network, ranging from static Flow-Capturing Location Models (FCLM) for generating EV demand [101], to more dynamic models incorporating Origin-Destination (O-D) matrices and travel surveys [102]. A significant portion of these studies utilize some form of traffic flow modeling to better reflect the real-world transportation network [103], [104], [105], [106], [107], [108]. Notably, a subset of these works explicitly incorporates dynamic flow elements within the transportation network by utilizing a traffic simulation tool [109].

In the context of the electrical network, some studies do not take into account grid reinforcements or upgrades [104], [106], [109], while other cases consider RDG [105], [108]. Few studies also consider the need for electrical network upgrades [101], [102]. Furthermore, some research addresses the broader aspect of expansion planning for both the transportation and electrical networks [103].

Table 8 presents the details of the references in this category, including the optimization algorithms utilized and the limitations of the models presented. The wide array of solution algorithms employed across these studies could indicate that research in this multidisciplinary area is still in its formative stages. This diversity can be seen as both an asset and a challenge. On the one hand, it represents a rich landscape of approaches to tackle complex problems. On the other hand, it highlights the need for more consistent methodologies and benchmarking to assess the relative merits and drawbacks of these various approaches.

C. HYBRID APPROACHES

In this category, there is a general lack of research due to complexity and multidisciplinary dependency. Studies in this category predominantly utilize MINLP formulations. Additionally, the electrical network operational constraints are being recognized in the form of the power flow equations and the technical limits. However, the research diverges in whether it includes any system upgrades or reinforcement to account for the increased load of EVs. Moreover, the inclusion of conventional grid loads varies among the studies. While some studies neglect the need for grid upgrades or reinforcements [115], others incorporate aspects like substation and feeder upgrades [116]. RDGs are also considered in a few cases [117], [118] While a more comprehensive approach considering RDGs and upgrades is presented by Pal and Bhattacharya [119].

The main differences were the transportation network adoption and the optimization algorithm used. For transportation network representation in the problem, either by maximizing the served flow by integrating of gravity model with spatial-temporal O-D analysis [115], or integrating the gravity model with queuing theory [117] or a sequential capacitated flow-capturing location model (SCFCLM) which is a variant of the well-known FCLM [116], or EV demand uncertainty modeling considering different congestion levels [119].

These methodologies heavily rely on assumptions to predict EV demand and may not adequately account for the influence of FCS locations on traffic flow. Conversely, a more realistic way of representing the transportation network using a Dynamic Traffic Assignment simulation tool to control the level of service [118].

Regarding the use of hybrid models, their primary function is not to augment the algorithmic searchability of a single method but to enhance the selection among the generated solutions [115], [117], or perform a specified task within the problem [116], [117], [118], [119].

The proposed algorithms generally provide good coverage and fast convergence compared with others as represented in each research. However, there was no utilization of hybrid algorithms to enhance the searchability of a single method as presented in previous hybrid sections. The efficiency of the GWO or GA chosen in this category mainly depends on the parameter's choice. As a future recommendation, a combination of Mata-heuristic algorithms may yield better quality in terms of solutions and will also need to be compared with other methods to evaluate the computational time and quality. Details of the methods and models are presented in Table 9.

VI. DISCUSSION AND FUTURE RESEARCH

The literature review presented in this research highlights the significance of addressing the allocation and sizing problem of FCS to meet the growing demand for EVs. However, several areas require further research to promote EV adoption and facilitate a sustainable future for the transportation and electrical sectors. These areas can be viewed from two perspectives: A. the factors considered within each network as part of the multidisciplinary approach, and B. the optimization techniques employed. The following subsections discuss these aspects in detail.

A. FACTORS

One of the key findings of this review is the limited consideration given to the impact of FCS placement on the transportation network flow. While many studies have focused on optimizing FCS location based on factors such as demand, driving distance, and EV penetration rates, few have considered the interaction of the FSCs with the traffic network to assess the impact of FCS on traffic flow and system equilibrium. To mitigate these negative impacts, it is crucial to integrate traffic flow analysis when planning the location and sizing of FCS. Additionally, the static consideration of traffic flow needs to be expanded to include dynamic traffic conditions to represent the spatial-temporal EV charging demand and the traffic performance under various scenarios. Therefore, a major research question to guide future research direction in this area is what is the impact of FCS locations on traffic flow, especially with a high penetration level of EVs?

In response to that, Figure 5 presents a conceptual planning framework for integrating both networks, considering their unique factors to achieve optimal FCS locations. The main structure of the proposed framework is the dynamic EV driving and charging demands through traffic simulation tools rather than relying on static mathematical representation of driving behaviors or historical data combined with electrical grid optimization. The framework begins with integrating dynamic EV movement in the transportation network, enabling precise identification of spatial-temporal demand locations. For that purpose, suggestion of traffic simulation tools to represent EV driving and thus charging demands may account for the realistic representation and allow for reassessment of the network performance. Subsequently, these demands and associated locations are introduced into the electrical network as candidate sites for the charging stations. The electrical network optimization with the fed-in locations and demands along with the conventional loads of the distribution network, decides upon the upgrade or reinforcement of the grid along with the optimum locations from the perspective of electrical network requirements. In some cases, the electrical network optimization may suggest new proposed locations for the FCS. This methodology differs significantly from existing approaches in the literature, which often rely on static or oversimplified representations of traffic networks. In addition, the proposed approach accounts for existing loads in the electrical network as well as testing the impacts of the locations on the traffic performance, which has not previously addressed in the literature.

In the subsequent stages, the proposed locations within the electrical network are reintegrated into the dynamic transportation simulation to evaluate their impact on traffic flow. This iterative process continues until both networks exhibit minimal requirements for further changes, marking the convergence to optimal solutions that satisfy both networks' requirements.

For effective integration of the transportation and electrical networks, a comprehensive set of parameters is necessary. These include the parameters of the electrical distribution network to be used where IEEE standard test systems play an important role [121] as well as existing conventional loads in the electrical distribution network, and factors related to RDGs such as the and necessary upgrades. Whereas, transportation network parameters including the nodes, links, capacity of the network as well as the EV consumption related parameters.

The proposed framework offers a roadmap for policymakers to address the multidimensional planning problem, emphasizing a comprehensive tool that integrates multiple stakeholder needs. This includes accommodating EV users' needs by elevating service levels and ease of access to charging stations, which is a critical social aspect. Environmental considerations involve complementing the EV transition with renewable generation to prevent shifting loads from the transportation to the electrical network. Additionally, the framework presents economic solutions, enabling sustainable electrification of the transportation system.

Moreover, the review highlights the importance of a multidisciplinary approach in addressing the complexities of FCS allocation and sizing. Collaboration among various fields such as electrical engineering, transportation engineering, urban planning, and environmental science is essential. Such collaboration will reveal different aspects of the problem, ensuring that all facets of FCS deployment – technical, environmental, social, and economic – are adequately addressed. This holistic approach will lead to sustainable, efficient, and user-friendly EV charging infrastructures that align with broader environmental and societal goals.

Moreover, the lack of a mix of charging technologies is another area requiring attention. Future research should explore the potential of combining multiple technologies, such as wireless charging, mobile battery storage, or battery swapping stations, to effectively accommodate the increasing EV load. It is important to investigate the impact of these technologies on both transportation and electrical networks, considering their advantages and disadvantages. This direction can be guided by the research question of What is the optimal mix of EV charging technologies to effectively serve different penetration levels of EVs?. Furthermore, the focus on RDGs as a cost-driven factor should be complemented by considering the reduction in CO2 emissions, which is a key driver for the transition to EVs.

Moreover, there is a lack of studies focusing on the Middle East and North Africa (MENA) region, which has unique driving behavior and road layouts. Besides, the impact of hot weather conditions and driving habits on EV energy consumption and allocation should be examined to account for the specific challenges faced in this region as the use of air conditioners in extreme weather regions (i.e., cold, or hot aired climate regions) causes an about 33% drop in the driving range [122]. Therefore, it is crucial to investigate how these regional factors influence the optimal placement of FCS. Additionally, investigating the impact of FCS locations on power quality and the extreme load consumption of FCS in conjunction with conventional loads connected to the grid would provide valuable insights.

Furthermore, the technological advancement in EV and its charging infrastructure highlights the need of investigating new technologies and their impact on the locations of FCS. Such technologies include autonomous and connected EVs as well as automatic and coordinated charging systems. These research directions also emphasis the multidisciplinary approach incorporating optimized routing of EVs and the smart grid demand response strategies. This can be motivated by testing the hypothesis that high penetration of fully autonomous and connected EVs may significantly impact FCS optimal locations, particularly since it is believed that automated and connected EVs consumption rate might be different from conventional EVs [123].

Finally, government incentive programs play a crucial role in promoting EV adoption and supporting the required infrastructure. Future studies should evaluate how different government incentive programs affect EV market share growth and the development of EV infrastructure.

B. OPTIMIZATION TECHNIQUES

This paper has demonstrated the use of various optimization techniques in FCS allocation and sizing. However, further research is needed in the following areas:

Exact Approaches: While exact approaches utilizing mathematical programming models have been widely employed, they provide a significant strength over the other methods in finding a global optimum solution using commercial solvers. However, their reliance on linearization formulations may oversimplify the problem. Future research should carefully evaluate the accuracy of these linear approximations and compare them with the original power flow formulations to ensure an accurate representation of system behavior and examine the impact of linearized models on the allocation and sizing problem. A potential research question could be: How do the results of optimal FCS locations, from linearized mathematical models, differ when compared to results derived from original power flow formulations?

Approximate Approaches: The performance of approximate approaches, including heuristic and metaheuristic algorithms, should be assessed, and compared. These approaches have the strength of finding good solutions within a shorter computation time and are particularly effective in handling NP-hard and highly non-linear problems. However, their weakness lies in their reliance on initial parameters and the risk of getting trapped in local optima. Comparative analyses will aid in selecting appropriate methods

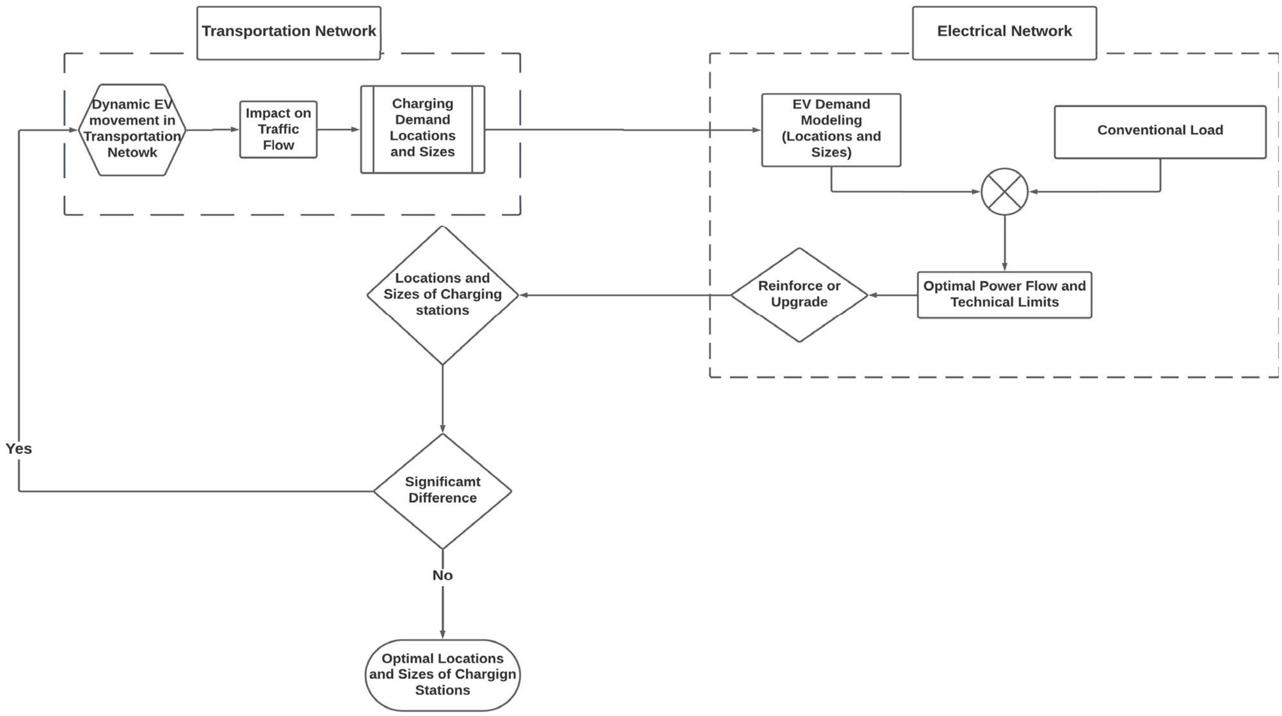

FIGURE 5. Conceptual planning framework.

for specific problem instances. Besides the need for algorithms that handle multi-objectives and large-scale planning problems.

Hybrid Approaches: The utilization of hybrid approaches combining multiple optimization techniques shows promise. These methods offer a major advantage by allowing the combination of different methodologies to benefit from the strengths of each. Future research should focus on enhancing the search capability of these hybrid models and compare their performance with alternative approaches. Multi-objective optimization within hybrid approaches should also be explored to simultaneously consider conflicting objectives, such as cost, power loss, environmental impact, grid reliability, traffic flow, and user preference.

Moreover, the coupling between transportation and electrical networks should be based on realistic assumptions and real-world data to ensure the relevance and accuracy of the optimization models.

VII. CONCLUSION

In recent years, the deployment of fast charging stations on highways has become a significant concern due to the increasing number of electric vehicles. Many researchers have proposed various approaches for allocating and sizing fast charging stations on highways. The literature review presented in this paper has broadly categorized the literature into three main categories: a traffic network-centric approach an electrical network-centric approach and a multidisciplinary approach focused on integrating both networks seeking a more efficient and realistic representation.

In each of these categories, the researchers have adopted an exact approach, an approximate approach, and a hybrid approach. While each approach has its advantages, they often fall short of addressing the complexity of the problem comprehensively. Particularly in the use of linear or nonlinear formulations with exact solutions, the problem is frequently oversimplified, making it challenging to scale to larger contexts like cities or countries. This limitation is evident across all three main categories of research. Due to the complexity and the variety of factors involved, the most widely adopted approach among the three subcategories is the approximate approach. Hybrid approaches are emerging as a promising area of research where more than one solution approach is utilized. These are either employed for specific tasks within the problem, such as location or sizing, or used to enhance population selection in metaheuristic approaches. They also offer the potential to merge two or more solution approaches, thereby enhancing the searchability of a single method.

However, the main research gap in this area is the lack of a comprehensive approach that integrates both the electrical and traffic networks into a single optimization problem while accounting for the main needs and factors of both networks. The vast majority of the existing research has primarily focused on either incorporating traffic information to generate realistic candidate locations for the electrical optimization problem or selecting candidate locations on the electrical system and optimizing the network flow. Relatively little research has focused on the incorporation of both networks. Thus, there is a need for a multidisciplinary approach, where collaboration among experts from various fields can address all aspects of FCS planning. Such an approach would not only provide more accurate and comprehensive solutions that consider technical, environmental, social, and economic factors, but also offer a framework robust enough to scale to larger problems at the city or country level. It should also account for a possible mix of charging technologies thereby aiding policymakers and stakeholders to make informed decisions regarding the deployment of fast charging stations on highways.

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