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Towards Wind Energy-based Charging Stations: A Review of Optimization Methods

Ali M. W. Alhasan[1], Dallatu A. Umar[1,2], Gamal Alkawsi[1,3], Ammar A. Alkahtani[4], Mohammad A. Alomari[5,6], and Hazleen Aris[5,]*

[1]Institute of Sustainable Energy (ISE), Universiti Tenaga Nasional (UNITEN), Kajang 43000, Malaysia
[2]Department of Physics, Kaduna State University, Tafawa Balewa Way, PMB 2339, Kaduna 800283, Nigeria
[3]Faculty of Computer Science and Information Systems, Thamar University, Thamar, Yemen
[4]Renewable Energy Engineering Department, Fahad Bin Sultan University, Tabuk 71454, Saudi Arabia
[5]Institute of Informatics and Computing in Energy, Universiti Tenaga Nasional (UNITEN), Kajang 43000, Malaysia
[6]Faculty for Engineering and Information Technology, Taiz University, Taiz, Yemen

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Abstract: Due to the growing importance of renewable sources in sustainable energy systems, the strategic deployment of robust optimization techniques plays a crucial role in the design of Electric Vehicle Charging Stations (EVCSs). These stations need to smoothly incorporate renewable sources, ensuring optimal energy utilization. This study provides a comprehensive overview of the methodologies and approaches employed in the enhancement of wind energy based EVCSs. The aim is to discern the most efficacious techniques for optimizing charging stations. Researchers engage diverse strategies and methodologies in the realm of sizing and optimization, encompassing a spectrum of algorithmic implementations and software solutions. Evidently, each algorithm or software application bears distinctive merits and demerits. Singular reliance on a solitary algorithm or software for charging utility optimization is discerned to be potentially limiting. The investigation reveals that achieving better results in Electric Vehicle Charging Station (EVCS) optimization is facilitated by the collaborative use of multiple algorithms like GA, PSO, and ACO, among others, or software tools like Homer or RETScreen.

Keywords: electric vehicle, charging station, sizing, optimization, wind energy.

1. Introduction

Greenhouse gas (GHG) emissions have caused considerable changes in the planet's climate [1] and are primarily driven by the daily use of fossil fuels [2]. Notably, the transportation sector, especially vehicles powered by diesel or gasoline, contributes significantly with a carbon dioxide (CO2) emission of 5.7 gigatons, a crucial GHG component [3]. Therefore, planning and executing favorable changes in the transportation sector will significantly benefit the environment and the energy economy [4]. One long-term and sustainable solution is replacing vehicles that use fossil fuels with electric vehicles (EVs) [5]. However, for this transition to be successful, the challenges related to EV charging and the sources supplying these stations must be effectively analyzed and addressed, ensuring the public's acceptance of EV adoption [6].

Most EVCS are supplied directly from grids [7], [8]. With the rapid growth of EVs, constructions of CSs are expected to expand, resulting in increased electricity demand. Power quality issues related to grid connections and integration with these non-linear loads and high frequency switching converters were expected due to this increase, as mentioned in [9]. Several countries have decided to utilize renewable energy for EVCSs to solve the grid connection issue and create clean and sustainable CSs [10].

Besides the grid, renewable energy sources (RES), such as wind, have also powered EVCSs [11], [12]. Wind energy has been used for EVCSs connected to grids and off-grid CSs [13], [14], while other studies have focused on the hybrid system using solar wind [15], [16]. Nonetheless, wind and solar generators are unreliable in supplying consistent power, particularly for fast charging facilities [13], [17]. Hence, several studies have focused on design issues and proposed optimization methods for sizing EVCS [13], [18]. Most EVCS optimization studies have focused on the economic factor or power grid concepts.

*Corresponding author e-mail: hazleen@uniten.edu.my

Therefore, this study thoroughly examines various methods and techniques for optimizing EVCSs. Various algorithms were employed for the design of optimal CSs. However, this review focuses on the algorithms and other optimization methods used for sizing small-scale wind turbines. In addition, software deployed for effective sizing of CSs will also be considered. The remaining sections of the paper are organized as follows: Section two discusses the installation site and wind speed assessment in several countries with wind speeds ranging from 7 m/s to 15 m/s. System architecture for wind energy-based charging stations are covered in section three. Finally, section four thoroughly examined the techniques and tools used to optimize EVCSs.

2. Site Selection and Wind Data Assessment

Over the last decade, there has been a surge of interest in the design and placement of EVCSs [19]. Centralized strategic planning and optimization in CS placement selection have significantly reduced the initial cost required to meet EV charging demand and alleviate range anxiety [20]. The strategic location of a CS by power engineers, one that minimizes adverse effects on the power grid and adheres to permissible CS size within grid limitations would be highly beneficial [21]. According to [22], [23], the site's installation should consider traffic facilities, grid load, user preference, service radius, and construction cost.

Many stations have been built worldwide based on the factors mentioned above. For instance, in [14], a research team investigated the feasibility of using wind energy to power an EV charging station with fast charging. This study gathered information from the National Renewable Energy Laboratory's National Wind Technology Center (NWTC), located at an 80 m elevation in Colorado, USA. They found that the area has an average wind speed of 12 m/s, sufficient for a fast-charging port. Another study [24] designed a wind-powered EV charging station connected to the grid in Athens, Greece. The station is where the onshore wind blows with an average wind speed of 11.4 m/s.

3. Optimal System Configuration for Wind Energy-Based Charging Stations

The electrical grid will undoubtedly be taxed as EVs increase rapidly. One solution is incorporating renewable energy (RE) sources into the grid [25]. Alternative energy sources that could be explored include wind, solar, and biomass. Several types of research have been conducted to evaluate the long-term impact of wind energy in meeting the additional energy demand created by EV charging [26], [27]. With 17.2 MW of wind turbines, [28] used a grid-connected wind turbine to power a charging station for DC fast charging.

Another study [29] discussed an alternative to place a modest PV array and Wind Energy Generation System (WEGS) over the buildings and parking lots and use the produced energy directly to charge the EVs. However, it should be noted that wind energy-based systems necessitate adequate sites and large premises to house turbines. The difficulty is exceptionally significant in metropolitan areas where massive structures are the primary impediment to wind routes. Furthermore, the variable nature of wind speed makes it less desirable for EV charging than other resources. Hasan Mehrjerdi in [30] developed a wind energy-based charging station and incorporates battery storage to address the wind speed intermittency challenge. A block diagram of a wind energy-based charging station integrated with battery storage is presented in figure 1.

Biomass energy (i.e., bioelectricity from biomass) differs from wind energy in that it can be easily stored and used when needed [25]. While liquid biofuels are a viable alternative vehicle fuel, bioelectricity offers several advantages for EV charging stations. It can be produced from a variety of biomass feedstocks, including, but not limited to, forestry and agricultural waste, wood energy crops, and whole tree harvesting. Bioelectricity provides a higher energy return than biofuel processes from a financial standpoint. Several recent studies have been published to assess the potential application of biomass energy in electric mobility [31] – [33]. Despite these advantages, bioelectricity production generates a high-polluting environment, making it unsuitable for densely populated areas.

The literature on solar energy for EV charging is much more advanced. A study conducted by Bhatti et al. in [34] presented a case study on charging using a standard grid system, a PV-grid system, and a PV- standalone in an energy storage unit (battery banks). According to the study, the PV grid is more profitable than PV-standalone and standard grid charging systems. Moreover, Tulpule et al. [35] have listed numerous advantages of PV-powered charging stations. Since this charging is done during the day, the cost savings are significant when load demand and electricity tariffs are highest.

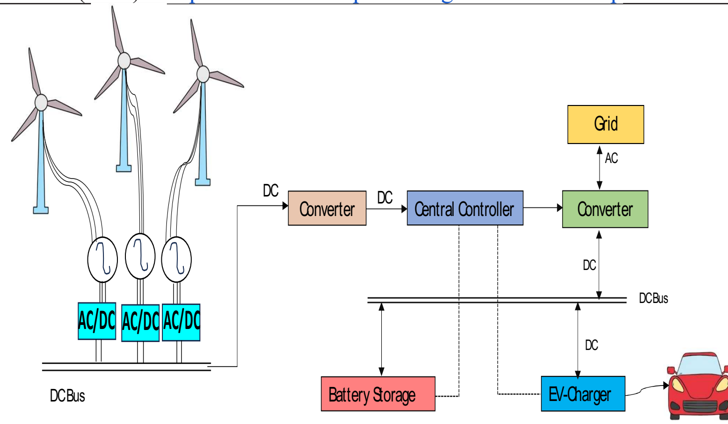

Fig. 1: Wind energy-based charging station [36],[37]

4. Optimal Sizing

4.1 Optimization Algorithms and Software

Optimization algorithms and software are methods or techniques that must be executed iteratively by comparing several solutions until the optimal or adequate option is discovered. There are several optimization algorithms employed to obtain an optimal EVCS. These algorithms and software could provide economic benefits by minimizing the cost functions, including the land, construction, transportation and operating costs for the sitting and sizing of the EVCS. The algorithms and software used to optimize the EVCS are discussed below.

4.2 Genetic Algorithm (GA)

GA is a technique that uses natural evolution to provide solutions for various optimization problems [38]. The primary objective of GA is to find optimal global solutions through optimization [39]. GA was used to optimize EVCS sizing and siting. Recently, GA was employed to address the Mixed Integer Non-linear Programming (MINLP) problem using a priori-technique [40]. Multiple single-objective issues were combined to form the required multi-objectives problem. Meanwhile,

[41] implemented GA to determine the optimal charging and discharging schedule for Battery Storage Systems (BSSs).

For instance, the authors in [42], recommend proper planning for EVCS networks in cities with dense traffic. The proposed method is developed based on a grid partition that aims to optimize or reduce the cost of transportation by using GA to reach the charging station. In GA, station capacity and traffic density are considered constraints. Also, in other studies, GA has been presented as a suitable method for determining locations for EVCS, such as in [43], where they proposed a GA-based tool for regulating taxi, station, and eclectic taxi demand. The GA is utilized to determine the spatial and temporal demand coverage location model (STDCLM). Parameters such as the charging period, the taxis' action radius, and the EVCS's capacity were considered as the inputs in the study.

In another study conducted by [44], the GA was employed to determine the required optimal location and type of CS. They used an algorithm to reduce the number of lost trips while maintaining an optimal budget. The city is represented as a grid, with each cell containing information about the number of journeys. When deciding on station placement, the most popular destinations are considered. Other studies, including [45] and [46], have implemented a hybrid GA and HGA to determine the optimal number and size of EVCS. The hybrid algorithm determines location by reducing investment and travelling expenses. However, optimization of the system does not consider some other costs.

A similar technique was employed in [47], where investment and travelling costs were reduced or minimized. The research recommended a multi-objective programming optimization model with a hard-time window constraint to optimize the scale and layout of the EVCS. The technique was implemented using a two-stage heuristic algorithm. According to the study's findings, the EVCS layout was determined based on the charging requirements of various locations and the charging time constraints. In contrast, the size of CS is proportional to the number of EVs, the arrangement of CS, and the peak charging time. Moreover, it was discovered that GA required considerable time to identify the optimal placement and size for EVCS, on top of premature convergence.

Overall, Genetic Algorithm (GA) has proven to be a versatile tool in optimizing various aspects of EVCS design and operation. It has been instrumental in tackling challenges related to sizing, siting, scheduling, and layout, with potential applications for efficient planning of electric vehicle charging networks. However, challenges persist in terms of the time required for GA to identify optimal placements and sizes for EVCS, along with concerns related to premature convergence.

4.3 Particle Swarm Optimization (PSO)

PSO is an optimization algorithm introduced in 1995 to solve non-linear functions [48]. PSO is a simple technique compared to other evolutionary methods as it requires a simple problem specification and few parameters to solve the problem [49]. In contrast to different algorithms, PSO is highly efficient and able to provide optimal global solutions. PSO has an advantage over GA because it can be implemented rapidly to achieve faster convergence. This is due to the evolution operator of PSO, which includes mutation and crossover [50], [51].

PSO is being used to optimize the EVCS as in [40]. It is also used to determine the best site for the EVCS based on the construction cost, including the land price and the material used and the operating cost, taking the traffic flow and the geographic information into account as constraint conditions. After that, a PSO technique was improved by modifying the inertia factor and applied to existing EVCS, and the outcomes were compared to the best result.

In [52], multi-objective PSO was employed to determine the optimal capacity and location of the CS. The algorithm computes the optimal charging and discharging rates and times for EVs. Consequently, PSO was developed to determine the optimal or best value for CS planning [18]. A variety of CS planning optimizations program selection processes was simulated utilizing a continuous optimization process of particles that characterize the capacity and location of the CS. The PSO was employed based on the partitions of the defined area by utilizing weighted Voronoi diagrams.

In another study [53], PSO was utilized to optimize the effect of EVCSs on unbalanced radial distribution systems (URDS) with optimal re-configuration. The PSO's objective functions are to optimize the site of EVCSs and the re-configuration of URDS to reduce system losses. However, the PSO algorithm with a time-varying coefficient was implemented for the vehicle to grid (V2G) sizing and placement in the distribution grid during peak hours [54]. The results demonstrated that V2G stations could increase power loss reduction and energy savings, making the system more reliable.

Generally, while PSO offers efficient optimization solutions in terms sizing and placement of EVCSs, however, ensuring PSO's effectiveness across various scenarios, considering the diversity of EVCS contexts and distribution systems, could pose another challenge. Additionally, real-world implementation might require accounting for uncertainties and unexpected variables that could influence the outcomes of PSO-based optimizations.

4.4 Integer Programming (IP)

IP is a thriving area of optimization in various fields [55]. IP presents the optimization of linear functions based on a set of linear constraints over integer variables. IP has been used in EVCS in several studies, including [56], in which mixed-integer linear programming (MILP) was employed in EVCS to solve the issue of an unbalanced electrical distribution system (EDS). According to the current injections, the linearization approaches, including a linear approximation of a non-linear function piecewise, are implemented over a mixed-integer non-linear programming model to meet the required MILP formulations. The results showed that the formulations could optimize the charging schedule for the EVCS batteries, resulting in a highly efficient and cost-effective operation of the EDS. Similarly, [57] used MILP formulation based on detailed information on battery charging profiles, where the main objective of the used model was to optimize the changing cost.

However, a different study used IP to determine the optimal routes and CS sites [58]. The IP model was developed specifically to obtain the least expensive or optimal routes and reduce transportation distance by locating the optimal CS sites. EV from a single depot or station must meet all demand and not travel further than the EV's range without stopping or at a CS. In another study [59], mixed integer programming (MIP) was used to find the EVCS locations. The MIP aims to minimize the cost of station access for EV consumers and maintain a suitable distance between CS. This technique helped identify the optimal locations for placing a limited number of CS around the selected city. According to [60] research, the optimal location of the EVCS was determined using game theory. The game theory was transformed into a linear programming model. Then, the model was determined by employing a primal-dual route to simplify and validate the procedure. The study's outcome showed that the game theory-based optimization strategy could make CS sites more scientific and reasonable.

4.5 Ant Colony Optimization (ACO)

ACO is a proposed probabilistic algorithm for minimizing complex computational problems to find the optimal path [57]. Multiple studies are utilizing ACO to optimize EVCS. [61] employed hybrid optimization algorithms, including a meta-heuristic based on the ACO to optimize EVCS location. The location was determined by an energy-saving analysis based on the number of days in a year. It could be obtained by installing and clustering EVCSs at various nodes of a microgrid composed of distributed energy sources (DES).

Similarly, [62] has identified the optimal location for the CS on the distribution grid by minimizing power losses and total cost. The study results suggested that the ACO algorithm could achieve the optimum location of EVCSs on residential power distribution. This could be obtained at minimal expense. Additionally, this technique could be carried out while adhering to several technological and geographical constraints.

4.6 Complex Commercial Software

Many scholars have conducted analyses using commercial software tools such as HOMER (HOMER stands for Hybrid Optimization of Multiple Electric Renewables) and RETScreen (Renewable Energy Technology Screen). These software applications are frequently employed by researchers to carry out comprehensive analyses to identify the optimal size and configurations for various energy sources [63]. For example, Ratil's [64] conducted simulations studies using the HOMER programme and data from the Nasa Database. Another research conducted by [65], examined off-grid and grid-connected energy systems for standalone and distributed generation (DG) applications for charging EVs with HOMER. Another study carried out by [66], detailed the use of the HOMER software to optimize a hybrid energy system. The NRG symphonies data collection system collected monthly wind and solar radiation data at an elevation of 18 meters in Singapore for nearly a year. Meanwhile, other researchers incorporated RETScreen into their studies. RETScreen Expert is the software's professional edition, covering energy efficiency optimization, feasibility studies for new projects, energy evaluations for existing facilities, and financial analysis for all accessible alternatives [67]. In the feasibility research done by Gerard Ledwich and Zhipeng Liu, RETScreen assesses the possibility of establishing EV charging stations by analyzing the systems deployed at six different locations in Germany. Locations, energy models, wind and humidity data are essential parameters considered for the feasibility analysis [68]. A fundamental rationale for choosing this application is its capacity to generate the optimal configuration for a given set of conditions and evaluate its financial viability. Different scenarios could be examined to demonstrate the incremental benefits of modifying specific parameters. A further advantage of this application is the high resolution at which input data can be processed. For example, monthly power consumption can be examined with RETScreen and can suggest a preliminary feasibility study.

4.7 Other Algorithms and Methods

Other algorithms, besides the aforementioned, have also been used for the EVCS optimization, but only limited objective only. For instance, [62] and [69] used Voronoi Diagram and branch and bound, respectively, to find the exact point of a solution. These techniques require the input data to be processed to determine the optimal paths. A summary of the methods and algorithms used for the optimization process is presented in Table 1.

Furtherly, comparison of the optimization methods based on their strength and weakness are summarized in Table 2

Table 1: Other algorithms and methods used to optimize the EVCS

Method or algorithm used	Remarks	Ref.
Greedy algorithm	This algorithm is used to reduce the cost of construction. Dependent on the station coverage and user's preference for the CS placement	[70]
A cost model was created with reference to the total operating and investment costs. MATLAB was used to calculate the cost and find the optimal CS.	This method considers the traffic and geographic condition to determine the optimal location	[71]
Weighted Voronoi Diagram on Geographical Map	The traffic flow is considered in this study to determine. the new CS location with similar CS capacity.	[62]
Frank-Wolfe Algorithm on the Linearized model of Bi-Level optimization model	Linearization techniques are thoroughly discussed in order to address multi-objective optimization problems utilizing single-level algorithms. Shows the trend of the number of long-distance journeys that are conceivable with a variation in range.	[46]
Optimization objective functions	EVCS site optimization discussed by overlapping road network grid.	[60]
Mixed Integer Second Order Cone Programming (MISOCP) on coupled Geographical-Electrical System	Discusses EV-Grid integration as well as site planning.	[40]

Sharing charging station	Sharing CSs are an excellent option for charging electric vehicles on a regular basis; however, we must arrange charging stations to appropriate areas in order to balance demand and supply.	[72]
NSGA-II	Discuss the optimization method including CS location, the capacity option and service types	[66]

Table 2: Comparison of various optimization techniques in EVCS siting and sizing schemes

Algorithm	Strength	Weakness
GA	GA requires an extended time frame to resolve sizing and placement problems [73].	GA requires an extended time frame to resolve sizing and placement problems [74].
PSO	In high-dimensional spaces, PSO might become trapped in local optima [75].	In high-dimensional spaces, PSO might become trapped in local optima [74].
IP	IP can only operate with linear variables [76].	IP can only operate with linear variables [76].
ACO	The time it takes for ACO to converge is uncertain [69].	The time it takes for ACO to converge is uncertain [69].

5. Discussion

The optimization of EVCS is a multifaceted process with paramount significance for reducing power losses and financial expenditures. Achieving precise results that determine optimal station locations, suitable system components, and precise power requirements is essential for the seamless integration of electric vehicles into our energy systems. The quest for optimal solutions has driven the application of various algorithms, each with their unique strengths and limitations. The optimization of EVCS is a multifaceted process with paramount significance for reducing power losses and financial expenditures. Achieving precise results that determine optimal station locations, suitable system components, and precise power requirements is essential for the seamless integration of electric vehicles into our energy systems. The quest for optimal solutions has driven the application of various algorithms, each with their unique strengths and limitations.

Amongst the optimization algorithms employed, GA and PSO have emerged as prominent contenders in this domain, acknowledged by many researchers for their efficacy [77], [78]. Yet, a nuanced approach is necessary due to the inherent strengths and weaknesses of individual algorithms. The analysis of these algorithms' attributes, as demonstrated in the accompanying table (Table 1), underlines the need for a comprehensive strategy. A strategic combination of techniques, leveraging the strengths of one against the weaknesses of another, has demonstrated the potential to enhance optimization outcomes [46], [75]. Hybrid optimization algorithms, which synthesize the best attributes of multiple methods, have been recommended for their capacity to yield improved results across diverse optimization scenarios.

In this landscape, the choice between HOMER and RETScreen takes center stage. HOMER's automation, simplicity, and widespread adoption have positioned it as a favored choice for many researchers. Its ability to perform calculations automatically and its user-friendly interface contribute to its popularity in the optimization process [75]. RETScreen, while offering valuable capabilities, tends to lag behind HOMER due to its less streamlined workflow. When discussing EVCS size optimization, these software considerations underscore the importance of not only algorithm selection but also the software tools that facilitate the optimization journey.

The evolution of EVCS optimization methodologies reflects the intricate balance between algorithmic potency, software efficiency, and the underlying complexity of energy systems. As the transition towards electric mobility accelerates, the synergy between advanced algorithms, software applications, and holistic optimization strategies remains pivotal to shaping the future of sustainable transportation and energy management.

6. Conclusion

This study has presented an updated review of various types of optimization methods and techniques that might be used in optimizing wind based EVCSs. The optimization of Electric Vehicle Charging Stations (EVCS) stands as a critical endeavor that holds the potential to revolutionize both our transportation systems and energy landscapes. The diverse challenges associated with selecting optimal station locations, sizing system components, and determining power requirements underscore the need for sophisticated solutions. Researchers have leveraged a range of algorithms, with GA and PSO emerging as prominent contenders due to their efficiency and efficacy. However, a one-size-fits-all approach is inadequate, as each algorithm presents its own set of strengths and limitations. However, a one-size-fits-all approach is inadequate, as each algorithm presents its own set of strengths and limitations. The power of optimization lies not only in individual algorithmic prowess but also in their strategic combination. Hybrid optimization algorithms offer a promising path forward by harnessing the strengths of different methods and offsetting their weaknesses. This approach, coupled with the utilization of advanced software tools like HOMER, facilitates the realization of precision-driven results. HOMER's automation, intuitive interface, and wide acceptance among researchers highlight its significance in shaping optimal EVCS strategies.

As the world transitions towards sustainable transportation and energy systems, the convergence of innovative algorithms, software applications, and holistic optimization frameworks remains crucial. The journey towards EVCS optimization represents an intricate dance between technological advancement and the intricate dynamics of modern energy ecosystems. By continually refining the existing techniques and embracing hybrid strategies, the potential of EVCS can be unlocked, paving the way for a greener and more efficient future.

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Conflict of interest

The authors declare that there is no conflict regarding the publication of this paper.

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