World Electric Vehicle Journal

Review

A Comprehensive Review of Optimizing Multi-Energy Multi-Objective Distribution Systems with Electric Vehicle Charging Stations

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Abstract: Electric vehicles worldwide provide numerous key advantages in the energy sector. They are advantageous over fossil fuel vehicles in many aspects: for example, they consume no fuel, are economical, and only require charging the internal batteries, which power the motor for propulsion. Thus, due to their numerous advantages, research is necessary to improve the technological aspects that can enhance electric vehicles' overall performance and efficiency. However, electric vehicle charging stations are the key hindrance to their adoption. Charging stations will affect grid stability and may lead to altering different parameters, e.g., power losses and voltage deviation when integrated randomly into the distribution system. The distributed generation, along with charging stations with the best location and size, can be a solution that mitigates the above concerns. Metaheuristic techniques can be used to find the optimal siting and sizing of distributed generations and electric vehicle charging stations. This review provides an exhaustive review of various methods and scientific research previously undertaken to optimize the placement and dimensions of electric vehicle charging stations and distributed generation. We summarize the previous work undertaken over the last five years on the multi-objective placement of distributed generations and electric vehicle charging stations. Key areas have focused on optimization techniques, technical parameters, IEEE networks, simulation tools, distributed generation types, and objective functions. Future development trends and current research have been extensively explored, along with potential future advancement and gaps in knowledge. Therefore, at the conclusion of this review, the optimization of electric vehicle charging stations and distributed generation presents both the practical and theoretical importance of implementing metaheuristic algorithms in real-world scenarios. In the same way, their practical integration will provide the transportation system with a robust and sustainable solution.

Keywords: review; multi-objective; DG sources; metaheuristic techniques; EV charging stations; IEEE networks

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Citation: Kumar, M.; Kumar, A.; Soomro, A.M.; Baloch, M.; Chaudhary, S.T.; Shaikh, M.A. A Comprehensive Review of Optimizing Multi-Energy Multi-Objective Distribution Systems with Electric Vehicle Charging Stations. *World Electr. Veh. J.* **2024**, *15*, 523. https://doi.org/10.3390/wevj15110523

Academic Editor: Vladimir Katic

Received: 20 October 2024
Revised: 9 November 2024
Accepted: 12 November 2024
Published: 14 November 2024

1. Introduction

1.1. Electric Vehicles Scenario

The environmental issues that conventional internal combustion engine vehicles present have been addressed by electric vehicles (EVs), which have become a potentially viable option. Since they run on rechargeable batteries and emit no direct pollutants, electric vehicles are a more environmentally friendly mode of transportation. Government incentives, greater consumer awareness, and breakthroughs in battery technology have all contributed to the steady increase in the use of electric vehicles as the worldwide movement toward decarbonization and renewable energy gains momentum. Distributed generation is a notion that has acquired a lot of traction alongside the emergence of electric vehicles. The term "distributed generation" describes the localized, small-scale production of electricity—often from renewable sources that replace centralized power plants. Numerous advantages can result from this method of producing power, such as enhanced integration of renewable energy sources, less transmission losses, and improved grid resilience. The convergence of distributed generation and electric vehicles presents a compelling prospect to augment the sustainability and efficiency of our energy system. Utilizing solar or wind power as a renewable energy resource to power electric vehicles can greatly lessen the environmental impact of transportation. By scheduling EV charging to occur at times of significant renewable energy generation, this integration can also assist in balancing the grid by reducing the load on the electrical system. The principal fossil fuel reserves on the planet are nearly depleted because of the massive energy resource consumption over the past 20 years. Governments are increasingly concerned about harmful environmental repercussions, energy security, and changing climate circumstances. The International Energy Agency (IEA) presents the 3Es as economic prosperity, energy security, and environment regarding the above repercussions [1]. The European Union has stated that the reduction of greenhouse gas emissions should be at least 20% below 1990 [2]. Governments have pushed electric transportation heavily in recent years to lessen reliance on internal combustion of fossil fuels and air pollution (ICE)-powered vehicles, drawing a lot of attention because they provide benefits over internal combustion engine (ICE) vehicles, such as lower noise levels and much lower greenhouse gas emissions. Moreover, a significant EV adoption rate in the power distribution networks has the following negative effects: voltage decreases, unwanted load surges, increase in loss of energy, stress on every component of the grid, decrease in load factor, decline in reliability indices, and problems with quality of power [3,4]. The specialized literature has a substantial amount of study on EVs and power distribution systems. Many objective functions have been considered in previous studies regarding the problem of optimizing Electrical vehicle charging Station (EVCS) and Distributed generation (DGs) in the distribution system to provide an effective solution for a sustainable grid. Therefore, this article comprehensively reviews the objective functions, metaheuristics techniques, IEEE distribution networks, and different types of renewable energy resources used along with EV infrastructure, converters, BES, and charging scenarios from Sections 1–7.

1.2. Current Literature Survey

The initial relevant search was conducted using different search engines like IEEE Explore, Google Scholar, and Web of Knowledge. Different aspects were considered, such as techniques used for optimal siting and sizing of ECVS and DGs and objective functions. Relevant articles were considered and included in the survey. The articles surveyed are arranged in Table 1, and the literature survey is presented for multi-objective optimization of EV charging stations and distributed generation. This can provide the gist of efficient techniques used to solve the problems related to the cumulative placement of DGs and EVCS. However, the main considerations are active power loss, reactive power loss, voltage stability index, voltage deviation, GHG emissions, and costs related to EVCS and DGs. The most relevant papers from different journals, conferences, and sources based on optimizing DGs and EV charging stations were selected. The selected articles were reviewed in depth. In contrast to prior evaluations, the technique used in this article is different. Unlike previous review articles, this review focuses on a detailed evaluation of the procedures and outcomes of a varied variety of articles, presenting a holistic perspective on the optimization approaches, methodology, types of DGs used, and research objectives previously solved. The titles, abstracts, and the whole text of research articles were screened to determine their relevance to the review's aims. Furthermore, a list of references for significant papers and pertinent reviews was manually searched to find other works that fit the inclusion requirements. By following this technique, the selection process attempted to include high-quality and relevant research that would provide a solid foundation for the review's analysis and discussion. The study aims to provide various advantages over previous review articles from its comprehensive and systematic technique for paper selection; the article enabled a fair and full inclusion of the most relevant material.

1.3. Prior Review of the Literature

Numerous studies have been previously published [5]: Arias et al. categorized the types of interaction between power grid and electric vehicles; Umar Hanif Ramadhani et al. [6] explained various approaches used for probabilistic load flow to solve uncertainties between generation and load; Luigi Rubino [7] discussed the innovative infrastructure to face challenges in charging infrastructure and plug-in hybrid vehicles. Enrico Mancini et al. [8] explain how electric cars affect the distribution network when their adoption is high in the coming time. They also present the prevention for the grid to maintain stability with an increase in such energy consumption. Tirupati U. Solanke et al. [9] presented the effective controllers for electric vehicles and renewable sources integrated into the microgrid and feasible techniques for energy management in the microgrid. Bindeshwar Singh et al. [10] considered diverse load models for optimal siting and sizing of DG and EV charging stations. Asaad Mohammad et al. [11] described the potential benefits of electric vehicles as energy storage in vehicle-to-grid technology and evaluated the uncertain modeling methods in V2G technology. Vivek Nikam [12] explained the model of predictive cooperative, centralized, decentralized, and multi-agent control strategies for distributed generation and electric vehicles in the microgrid. Md Rabiul Islam [13] explained that distribution network reconfiguration can mitigate the network imbalance after DGs and EVCS placement. Fareed Ahmad et al. [14] explained that the electrification of transportation systems brings many challenges due to underdeveloped infrastructure, charge schedule, and EVCS location, and they explained different strategies and techniques to overcome these effects. Several considerations in this area have been presented in the present review, including the lack of suitable reviews for multi-objective EVCS and DG placement in the distribution system.

2. Survey Trend Analysis

Given the collected literature in Table 1, the percentage of optimization used is provided in Figure 1. Many articles have different objective functions, constraints, and algorithms. The multi-objective optimal placement of DGs and EVCS is the main consideration of this review. In this review, the literature from the last half-decade, from 2019 to 2024, was reviewed; however, some older references were also considered, to define the conventional and metaheuristic techniques. In the literature, the percentage of objectives to improve power loss was 46%, Voltage deviation was 36%, voltage stability index was 9%, greenhouse gas emissions were 3%, and operation and maintenance cost was 6%, as depicted in Figure 2, To achieve these objectives different optimization techniques were employed as shown in Figure 3. All these algorithms were used to optimize the different objectives considering different networks.

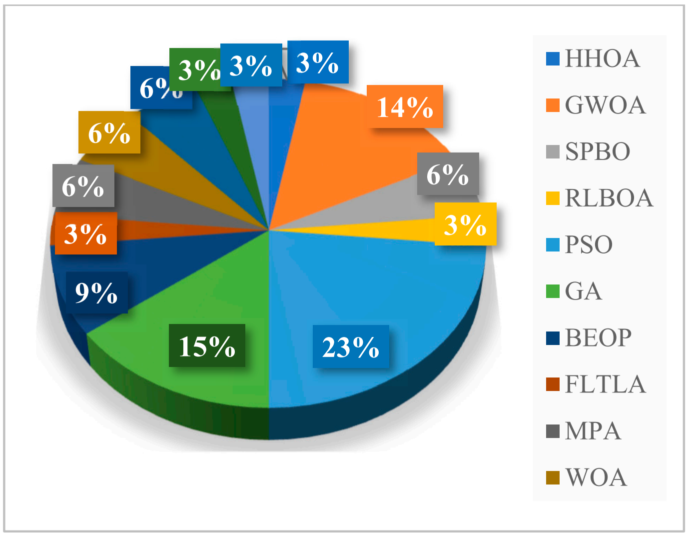

Figure 1. Optimization techniques.

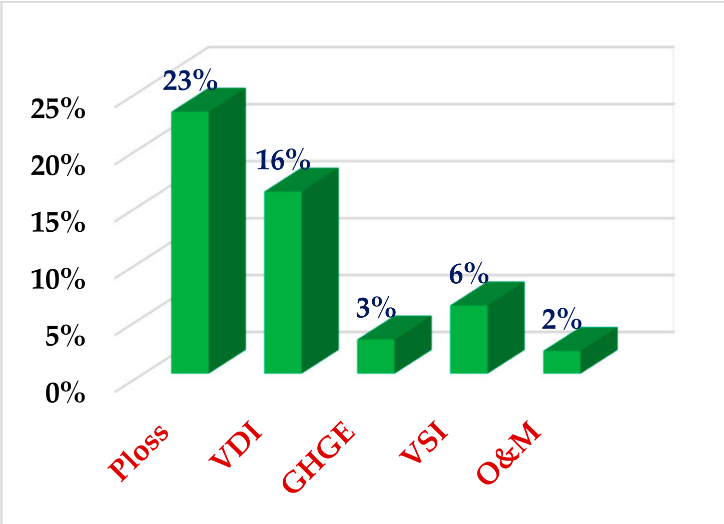

Figure 2. Objective functions.

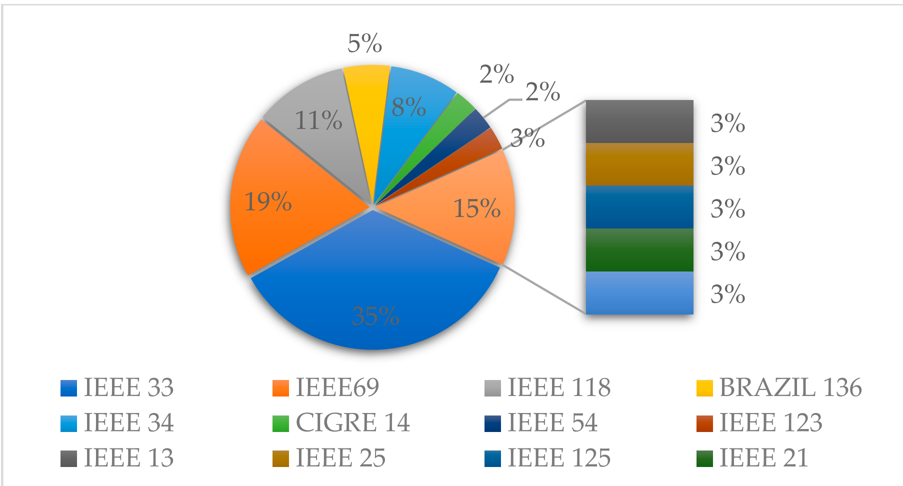

Figure 3. Networks used previously.

Table 1. An exhaustive review of the previous literature on DG and EVCG placement.

Ref	Sources (DGs)	Objective Functions					Year	Network	Technique/ Algorithm	Journal/Conference
		Ploss	VD	VSI	O and M Cost	Other Objectives				
[15]	BESS, SDG	✓	✓	✓	✓	-	2021	33	HHO, GWO	Journal of Energy Storage
[16]	SPV-BESS, WT-BESS Biomass	✓	✓	✓	✓	-	2023	33, 136 Brazil	(SPBO) and (CSPBO)	Journal of Energy Storage
[17]	PV-DG, BESS, WT	✓	✓	✓	✓	Emission cost	2022	33, 118	A reinforcement learning-based approach.	Applied Energy
[18]	PV/WT/BESS	✓	✓	-	-	-	2024	-	(MOPSO)	Energy
[19]	PV is used as DGs.	✓	✓	-	-	-	2023	33, 69	Hybrid GA-PSO	Green Energy and Intelligent Transportation
[20]	DG	-	✓	-	✓	-	2022	13, 34	(NSGA-II)	Conference on IX Brazilian Symposium on Electrical Systems
[21]	PV, WT, and Gas turbine.	-	-	-	✓	CO_2 Emissions	2022	54	An augmented e-constrained method is used.	International Conference on Power systems with probabilistic approaches.
[22]	DG, EVCS, and STATCOM.	✓	-	✓	-	Enhance substation PF	2022	69	RAO-3 algorithm.	MDPI energies
[23]	FC, WT, SPV	✓	-	✓	-		2023	33, 123	(TLBO)	MDPI energies
[24]	DG	✓	-	✓	-	Optimize AVDI	2024	33, 69	HHO and TLBO	Engineering, Technology & Applied Science Research
[25]	Solar PV and BESS	✓	✓	-	-	To increase the capture of EV flow	2021	25, 125	(MOGWO)	Energy research Willey
[26]	DGs	✓	✓	-	-	DG cost and energy consumption of EV users	2019	118	Hybrid shuffled frog leap-teaching and learning-based optimization algorithm.	IET Electrical Systems in Transportation
[27]	PV, WTGS	✓	✓	-	-	EV owner's dissatisfaction	2022	69	Multi-objective metaheuristic based on MODA is used.	IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY
[28]	Solar and wind	✓	-	✓	-	LPQ and PVSI	2023	69	Marine predators' algorithm (MPA).	International Engineering Conference on Renewable Energy & Sustainability
[29]	DGs	✓	✓	-	-	FCS Cost	2019	118	The MINLP is solved using algorithm II (NSGA-II).	J. Mod. Power Syst. Clean Energy
[30]	SPV, WT, and Diesel Generator	✓	✓	-	-	-	2021	33	(PSO), (GWO), (HPSOGWO)	IEEE Region 10 Symposium
[31]	Battery-backed SPV	✓	-	✓	-	-	2021	33	(GA) and (WOA)	ICOCPCTnternational Conference on Computing, Power and Communication Technologies
[32]	DGs	✓	✓	-	-	-	2023	34	(NSGA-II)	Springer
[33]	DGs, Capacitor	✓	-	✓	-	-	2023	33, 69	(WOT)	Springer
[34]	SDGs, WGs, and capacitor banks.	-	-	✓	-	GHG emission and total cost	2020	21	Unconventional PEM is used to deal with uncertainties, and MCS is used to obtain the results.	Journal of Control, Automation, and Electrical Systems
[35]	SPV, WT, DSTATCOM and Biomass	✓	✓	-	-	To reduce the negative effects of EVCS	2024	33,136 Brazils	(MOSPBO)	Electrical power and energy systems
[36]	Type 2 DG is utilized in this work.	✓	✓	✓	-	-	2022	33, 69	(AI) approach, the hybrid of grey wolf optimization and particle swarm optimization.	Applied Energy
[37]	Distributed generator.	✓	✓	-	-	-	2022	33	(AOA)	IEEE Access
[38]	Type 2 DG is utilized in this work.	✓	✓	-	-	-	2022	CIGRE-14	(BRO)	International Journal of Renewable Energy Research
[39]	SPV	✓	✓	-	-	Voltage unbalance factor	2022	37	Hybrid fuzzy Pareto dominance concept with differential evolution algorithm.	IEEE Access
[40]	DG and DSTATCOM.	✓	-	-	-		2023	34–118	Bald eagle search algorithm (BESA).	Energy Reports
[41]	SDG and DSVC.	✓	✓	✓	✓	MitigatingCO_2 emissions	2024	33	Improved bald eagle search algorithm (IBESA).	Energy Reports

Table 1. *Cont.*

Ref	Sources (DGs)	Objective Functions					Year	Network	Technique/ Algorithm	Journal/Conference
		Ploss	VD	VSI	O and M Cost	Other Objectives				
[42]	PV, WT, and BESS	✓	✓	-	-	-	2022	108	(GTO)	Journal of Energy Storage
[43]	PV, WT	-	-	-	✓	EVCSs charging	2019	54, 25	(MONAA)	Electrical Power and Energy Systems
[44]	DG and BESS	✓	-	-	-	-	2022	33	(AOA)	Electric Power Systems Research
[45]	Solar	-	-	-	-	Location of (EVCS)	2021	Wroclaw Uni:	(EHO)	International Journal of Electrical Power and Energy Systems
[45]	Solar	-	-	-	-	Location of (EVCS)	2021	Wroclaw University	(EHO)	International Journal of Electrical Power and Energy Systems
[46]	DG, ESS	-	-	-	-	Battery degradation cost	2023	33	Latin hypercube sampling method.	Applied Energy
[47]	Solar, wind	✓	-	✓	-	Harmonic distortion, error accuracy	2023	19, 25	Dove-based recursive deep network (DbRDN).	Energy
[48]	(REDG)	✓	✓	-	-	Penetration enhancement	2022	33	Dynamic fault tree analysis and Bayesian optimization techniques.	Electric Power Systems Research
[49]	Solar, wind, ESSs	✓	✓	-	-	Capacity of DGs, EVCSs, ESSs	2020	33, 85	Hybrid soccer league competition-pattern search algorithm.	Engineering Science and Technology, an International Journal
[50]	DGs and capacitor banks	-	-	-	-	To minimize O&E cost	2023	18, 23	MILP	Sustainable Energy, Grids, and Networks
[51]	DG units and BESS	-	-	-	✓	Cost of substation, DG units, EVCS, and circuits	2022	24	Mixed-integer linear programming model.	IEEE Access
[52]	DG	✓	✓	-	-	-	2022	33	Symbiotic organism search algorithm.	International Conference on Condition Assessment Techniques in Electrical Systems
[53]	DERs and capacitor	✓	✓	-	✓	-	2023	33	(MOCSA)	Seminar on Power Electronics and Control
[54]	DGs and DSTATCOM	✓	✓	-	-	-	2023	85	(SCA) based on (iMOF).	International Conference on Smart Technologies for Power, Energy, and Control
[55]	DGs	✓	✓	-	-	-	2024	33	PSO	ICOPE and IoT Applications in Renewable Energy and its Control
[56]	PV	✓	✓	✓	✓	-	2021	69	(BFOA-PSO)	IEEE Access
[57]	DG	✓	✓	-	-	-	2022	33	(PSO) and (ABC)	International Middle East Power Systems Conference
[58]	PV and batteries	✓	✓	-	-	System frequency index	2023	33	Honey badger optimization algorithm.	IEEE 3rd International Conference on Smart Technologies for Power, Energy, and Control
[59]	DGs	✓	✓	✓	✓	-	2023	33, 69	(MPA)	International Conference on Contemporary Computing and Informatics
[60]	RDGs	✓	✓	-	-	Phase angle distortion	2023	85	Backward and forward sweep method.	International Conference on Power Electronics, Smart Grid, and Renewable Energy
[61]	DGs	✓	✓	✓	-	-	2023	69	Gorilla troops optimization algorithm (GTOA).	International Conference on Contemporary Computing and Informatics
[62]	DGs, capacitor	✓	✓	✓	-	-	2024	33	(HGWO_PSO) and (HPSO_CS)	Journal of Modern Power Systems and Clean Energy

The IEEE 33 network was the most commonly used network for study, comprising 42%, because this network is not too complex and not too easy; the IEEE-69 test system contributed about 17%; likewise, IEEE-118 contributed to about 9%; Brazil 136–3%; IEEE-34 stands out at 7%; CIGRE 14–2%; IEEE-54 contributed about 3%; IEEE 123–2%; IEEE 13–2%;

IEEE 25–7%; IEEE 125–2%; IEEE 21–2%; and IEEE 37–2%. Different types of test networks were tested in the literature. It is obvious from Figure 3, that the IEEE-33 test network is the most widely used test system in previous studies. However, other test systems reflect the diversity in analyzing networks. In this review, it is shown that the most common renewable energy source used is solar, comprising 29%; BESS stands out at 14%; WT, comprising 16%; BM at 2%; capacitor as a DG is also implemented about 6%; STATCOM about 6%; and DGs contributed about 26%. Hence, there is more preference given to solar, as it has more pros than other renewable sources, and biomass contributed very little among these energy resources, as shown in Figure 4. In previous studies, biomass and capacitors as DGs are less commonly used distributed energy resources. Moreover, analyzing the energy resources integrated shows that solar power predominantly contributes the most to the renewable energy resources explored. Other resources cumulatively contribute to the energy mix in the studies.

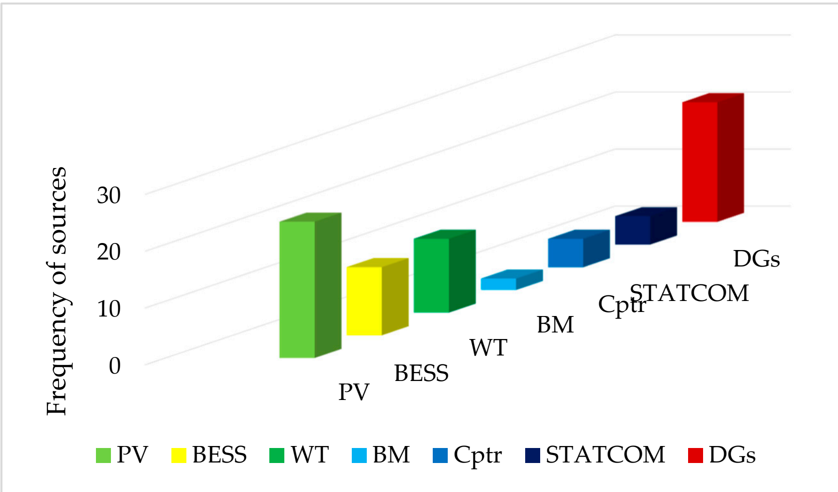

Figure 4. Energy sources used in the literature.

3. Electric Vehicle Infrastructure

Electric vehicles are equipped with an energy storage system called a battery pack, and this power is used to propel the vehicle with the help of an electric motor. The methods of battery swapping, grid supply, and regenerative braking are used to store energy in battery packs. Figure 5 represents how an electric vehicle gets charged from the grid supply [63–66].

Electric vehicle charging stations use three levels of chargers—level 1, level 2, and level 3, 4 modes—for charging, and three methods, as shown in Figure 6. In levels 1 and 2, an alternating current supply is used, which is changed into DC with the help of onboard chargers. However, in level 3, DC supply is used. Electric vehicle charging infrastructure uses four modes for charging in mode 1, a single and three-phase AC supply with the current rating of 16 Ampere is used with no control and a communication device present between the EV charging station and the electric vehicle. In modes 2–3, a single and three-phase AC supply with current ratings of 32 Ampere and 32–250 Ampere is used with a control and protection device present between the EV charging station and the electric vehicle. These control and protection devices help to monitor and control the state of charge of the battery (SoC) and avoid overcharging to reduce the risk of damage. However, in mode 3, a DC power supply with current ratings of 250–400 Ampere is used, reducing the cost and weight of an EV with no use of an AC-DC converter [64,67].

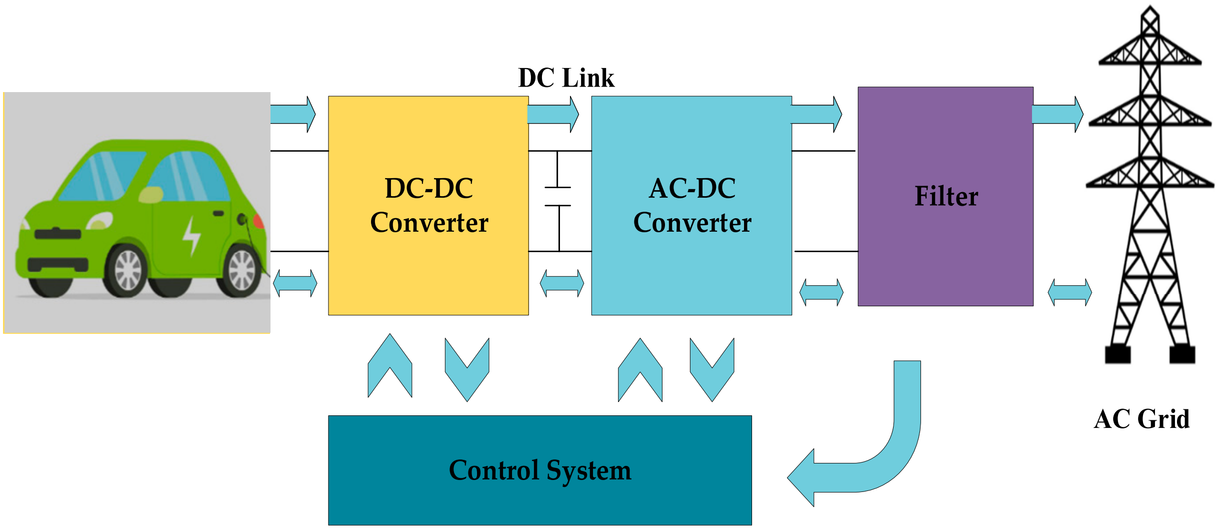

Figure 5. Electric vehicle charging infrastructure [68].

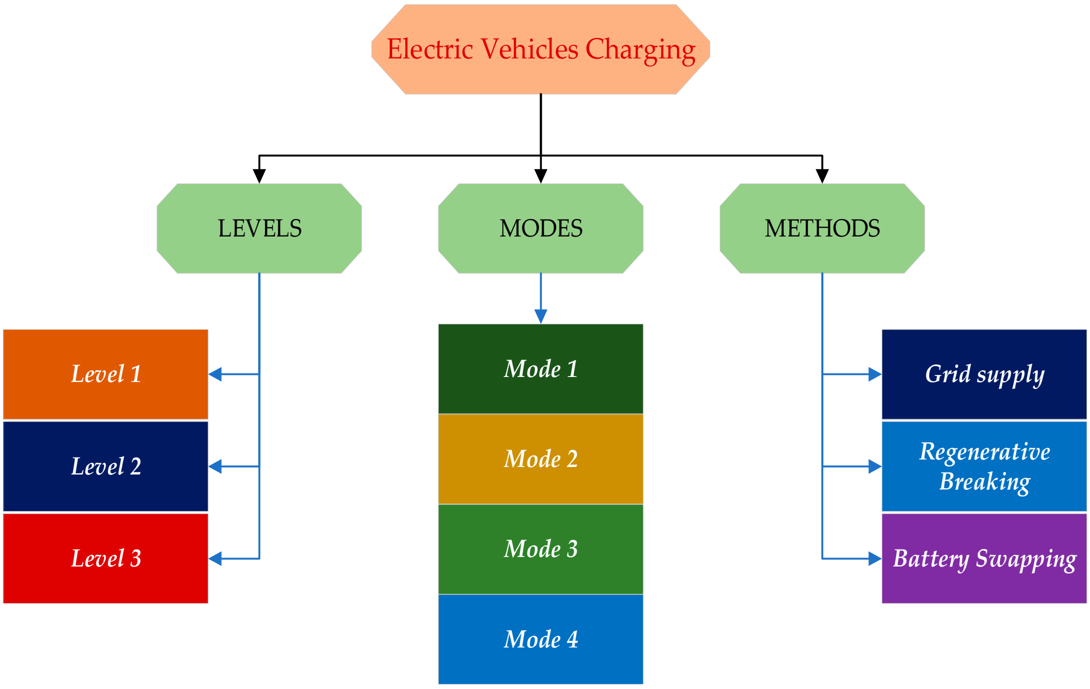

Figure 6. Electric vehicle levels, methods, and modes [67].

The author in [69] has presented the future and current scenarios of energy storage systems for EVs. The most commonly used storage systems in electric vehicles comprising batteries are lead acid batteries, lithium-ion batteries, and nickel–cadmium batteries, as depicted in Figure 7. The study has given insights into the performance of supercapacitors and fuel cells. Supercapacitors can be used for fast charging/discharging and, in the same way, fuel cells for clean energy generation. Many storage elements with higher efficiency and higher charge density are discussed.

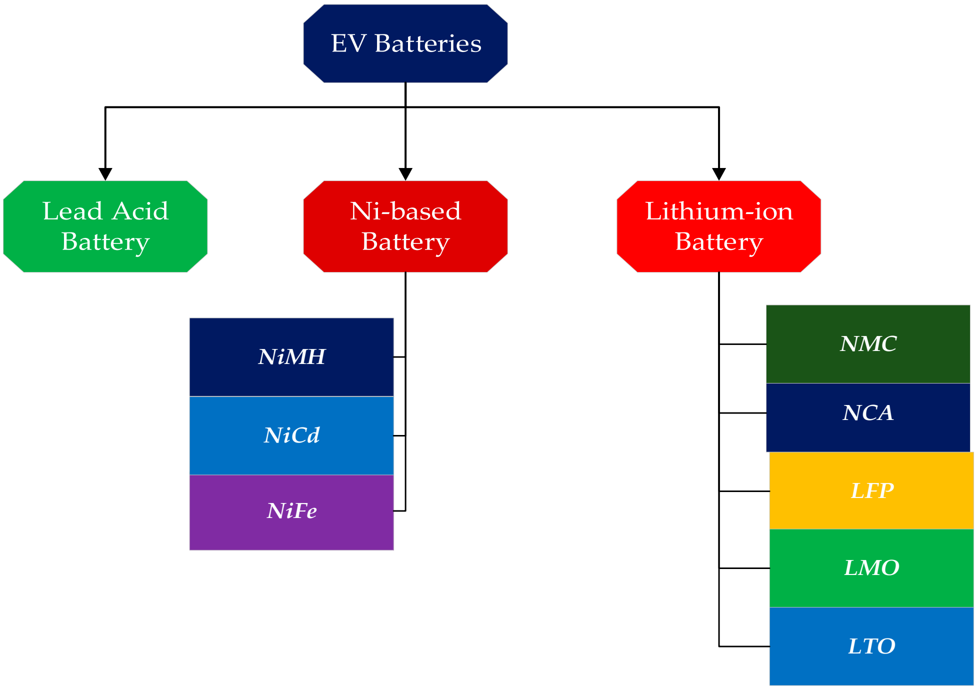

Figure 7. Electric vehicle batteries [67].

Electronic converters play a crucial role in the reliability and efficiency of electric vehicle operation. A high-power converter can increase the rate of power transfer from the grid to the vehicle and reduce the charging time. Till today, different types of electric vehicles use different converters based on cost, efficiency, weight, and charging time, as shown in Figure 8.

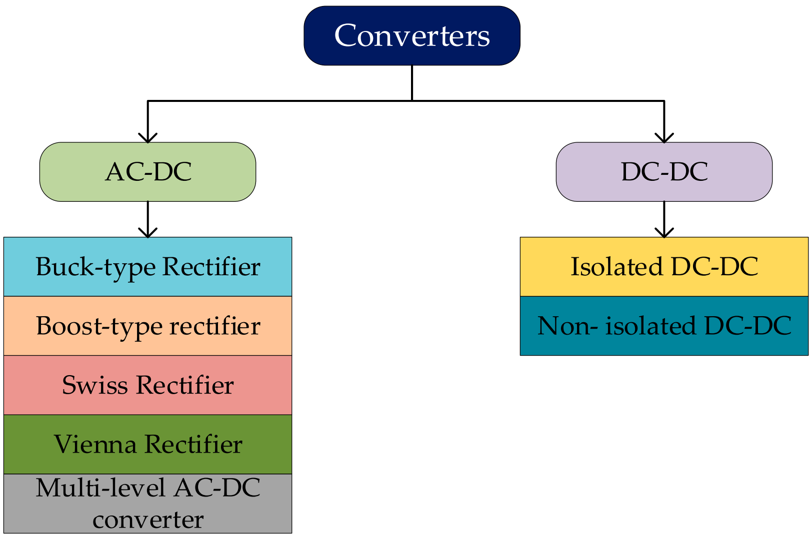

Figure 8. Converters in electric vehicles.

3.1. AC-DC Converters

AC-DC converters supply power from the grid to onboard electric vehicles, maintaining high power quality. The H-type or three-phase three-leg configuration is commonly used for conversion. AC-DC converters can be unidirectional for the G2V scheme and bidirectional for the V2G and G2V schemes.

3.2. DC-DC Converters

DC-DC converters convert high DC voltage from battery to low voltage DC voltage for auxiliary supply in electric vehicles. These converters are used to maintain grid stability while charging electric vehicles in a level 3 charging system. DC-DC converters can also be unidirectional and bidirectional, but due to complex switching, difficult design, and increased bandwidth control, they possess low efficiency.

In the end, from the grid side, filters are used to maintain power quality issues between grid and electric vehicles. The inductive–capacitor–inductor (LCL) and capacitor–inductor (LC) filters are mostly used for their high efficiency in ultra-fast charging systems [67].

4. Objective Functions

4.1. Power Loss

Distribution system losses are an essential factor in design consideration. The distribution System is mostly fed with slack bus power present at a far distance; due to resistance, inductive reactance, and capacitive reactance, there is a constant power loss. An idea arises that if that slack bus power is replaced with renewable energy resources at suitable buses, power loss can be minimized, and with their integration, greenhouse gas emissions can be reduced significantly. This is an optimization problem and can be solved using iterative techniques. However, these techniques are very complex and can not lead to the best approximate results when solved manually. Thus, choosing the best location and size for these resources is crucial. The best position for these resources is determined using a variety of optimization algorithms, each of which yields a different set of outcomes based on convergences. The equation given below is used to find the power loss [15,16,41,70–72].

$$P_{lossT} = \sum_{i=0}^{n-1} R_{i,i+1} \frac{P_i^2 + Q_i^2}{V_i^2} \quad (1)$$

where P_{lossT} is the loss of power in the various branches, $R_{i,i+1}$ is the resistance between brach i and i + 1, and Q, P are load apparent power demands at bus i and Vi.

4.2. Voltage Deviation Index

In the distribution system, there are many load tapings at each bus, and the end user may feel some voltage deviation due to this and variation in the load curve. This is another issue with the distribution system. However, the voltage permissible limit in the distribution system is 5% for proper and efficient operation. Optimal siting and sizing of these DG's also play an important role in maintaining voltage variations. The equation given below is used to calculate the deviation in voltage [15,16,41,71–73].

$$\mathrm{VD} = \sum_{i=1}^{N_T} \frac{(V_i - V_{Ni})^2}{V_{Ni}^2} \quad (2)$$

where N_T is the number of network nodes, V_{Ni} is the nominal voltage at node i, Vi is the voltage at node i, and VDI is the voltage deviation index.

4.3. Index of Voltage Stability

The index of voltage stability represents the margins in which the voltages remain stable. If the system voltages increase or decrease beyond this, the system becomes unstable. Integration of DG's and EVCS may also affect this stability. However, with proper sizing and siting, the system voltages may remain in this range. The equation given below is used to measure the magnitude of the voltage stability index [15,16,41,71,72,74].

$$\mathrm{VSI} = \frac{4(P_i R_i + Q_i X_i)}{V_{i-1}^2 cos^2(\delta_{i-1} - \delta_i)} \quad (3)$$

Using the bus voltage information from the load flow solution, the VSI for each branch, which ranges from 0 to 1, is found. The value of VSI must be selected smaller than 1 for stable operation. An unstable bus is indicated by a suggested VSI value that is getting closer to 1, which eventually results in instability.

4.4. Cost Function

The operation and maintenance cost of DG consists of its power output. Investment cost depends upon system construction, equipment cost, and installation. These costs can be calculated using Equations (4)–(7) [29,51,53,56,59,75].

$$C_I = \sum_{g=1}^{N_{DG}} \left(P_{DG,g} C_{INV,g}\right) \tag{4}$$

$$C_{OP} = \sum_{y=1}^{N_Y} \sum_{g=1}^{N_{DG}} \left(P_{DG,g} T_h C'_{OP} \left(\frac{1+R_{INF}}{1+R_{INT}}\right)^{N_Y}\right) \tag{5}$$

$$C_M = \sum_{y=1}^{N_Y} \sum_{g=1}^{N_{DG}} \left(P_{DG,g} T_h C'_M \left(\frac{1+R_{INF}}{1+R_{INT}}\right)^{N_Y}\right) \tag{6}$$

$$C_{DG} = C_I + C_{OP} + C_M \tag{7}$$

where P_{DG} is the rate real power and R_{INF} and R_{INT} are each DG's interest rate and inflation.

4.5. Optimization Techniques

By selecting the optimum answer from a range of feasible options, optimization techniques are essential tools for resolving complicated issues. Subject to different constraints, these strategies seek to maximize or decrease a specific objective function. A broad variety of mathematical programming techniques, such as integer, dynamic, non-linear, and linear programming, are used in optimization approaches. The features of the issue, such as the kind of objective function, The existence of constraint, and the problem's size and complexity, all influence the choice of a suitable optimization strategy. In decision-making and problem-solving, effective optimization tactics can result in major gains in productivity, cost savings, and overall performance across a range of fields. Many metaheuristic optimization techniques have been employed to solve the optimization problem of sitting and sizing DGs and EVCS [70].

5. Conventional Techniques

Traditional optimization approaches are predicated on the research problem's mathematical models, which are often resolved by an iterative numerical method. When allocating DG-EVCS simultaneously, traditional optimization methods described in the literature mostly rely on the optimum power flow (OPF) and analytical techniques based on sensitivity. The foundation of sensitivity analysis is the idea that changes in any one parameter will result in changes in the targeted parameter. This paper presents the review for five years; hence, the authors have seldom used conventional computational methods. Figure 9 represents different conventional techniques used previously. These analytical techniques are explained in complete detail as under.

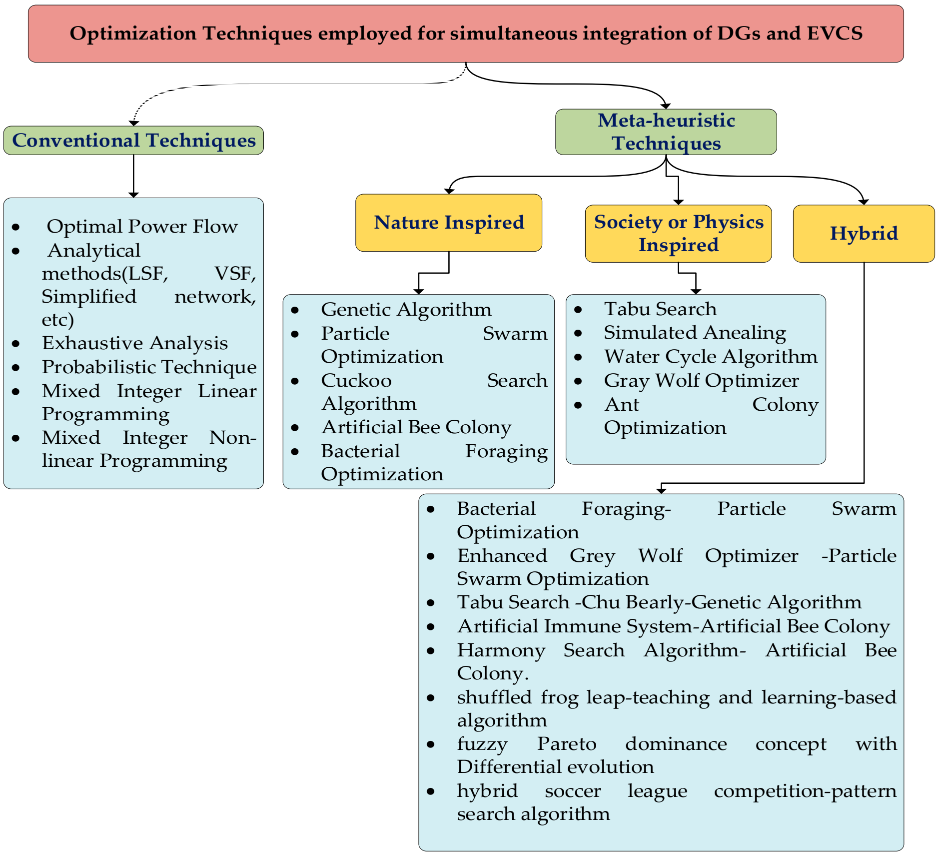

Figure 9. Categorization of the optimization methods used for concurrent DG-EVCS-SCB allocation.

5.1. Analytical Techniques

These techniques are conventionally used to perform the analysis of the distribution network mathematically, employing various equations from which an objective function was then formed [76]. They are very simple to employ and help in the convergence of DG integrating solutions [77]. They can solve various optimization problems, including minimization of power loss [78,79] and improvement of voltage profile [80,81]. The author [82] has proposed finding the best location and size to improve power losses in the distribution network. Further, the author of [80] presented a multi-objective index-based technique to find the feasible capacity of SDG to improve voltage deviation and to minimize reactive and active power losses [76].

5.2. Exhaustive Analysis

These analytical techniques can optimize one objective function only [76], e.g., minimization of power loss by intensely peering through the overall solution in the distribution network corresponding to the candidate solution, location, and capacities of DG. A multi-objective index was implemented to find the best sizes and locations for minimizing voltage drops and power losses in the distribution system [83,84]. This technique is more efficient in single objective function and single DG for a specific load generation.

5.3. Optimal Power Flow

The optimal power flow optimization technique finds a power system's optimal settings for control variables, like transformer taps and generator outputs. The goal is to minimize an objective function, like generator cost or power losses, while meeting operational constraints, like power balance and voltage limits. It often minimizes power loss [85] and maximizes DG capacity [86]. It is more accurate and highly efficient, however, after perturbation of technical parameters [87].

5.4. Probabilistic Technique

The uncertain elements of the process of DG planning, such as the usage of electricity, erratic production, and the accessibility of renewable energy sources, are addressed using probabilistic approaches [87]. The author in [88] optimized DG planning and reduced system costs while enhancing dependability, and a probabilistic load model was employed. In order to achieve optimal distributed generation planning, a probabilistic multi-objective strategy must balance the reduction of economic costs and pollution emissions [89]. This method took into account the uncertainties associated with load consumption and electricity prices. However, in order to effectively use these probabilistic methodologies, a large volume of operational data and a high level of data processing power are frequently needed [87].

5.5. Mixed Integer Linear Programming

An optimization method called mixed integer linear programming (MILP) involves resolving linear programming issues involving discrete (integer) and continuous decision variables. Because MILP models may reflect logical limitations, on/off options, and other discrete choices, they are able to capture real-world complexities more accurately than pure linear programming. The capacity to model binary or integer decisions is essential for identifying the best solutions in a wide range of applications, including industrial planning, scheduling, logistics, and energy systems optimization. This method relies on the power flow's linearization method and employs discrete and continuous variables [87].

The author in [90] optimizes annual investment and operation cost using mixed integer linear programming. Dispatchable and non-dispatchable DGs were used for optimal planning in the distribution techniques [91].

5.6. Mixed-Integer, Non-Linear Programming

This technique is based on finding non-linear optimization problems that implement discrete and continuous variables. Power loss and stability of voltage were improved using the MINLP technique [92]. In [93], the author improved the efficiency of DGs by their optimal location and size. MINLP with greater computational complexity can present more efficient results. However, in the case of huge distribution, these strategies impair the MINLP solution's capacity to scale because they necessitate concurrent assessment of the collection of choice variables [94].

6. Metaheuristic Techniques

Metaheuristic approaches are predominant in the research on optimal DG-EVCS allocation. These techniques hold great promise for resolving challenging optimization issues across a variety of domains. The most intriguing feature of a metaheuristic is its ability to be applied without a thorough comprehension of the optimization problem at hand. Since metaheuristic algorithms do not always produce the best possible global answer, they are approximation techniques. In addition, the metaheuristic approaches can be divided into three categories: hybrid algorithms, physics or society-inspired, and inspired by nature. In this review, it is shown that the genetic algorithm was most commonly used in the literature, comprising 15%, and particle swarm optimization holds 23%. All these algorithms were used to optimize the different objectives considering different networks. In particular, premature convergence may prevent these algorithms from achieving global optimality in the case of large-scale DG placement [94].

6.1. Particle Swarm Optimization

The metaheuristic optimization technique known as particle swarm optimization (PSO) was inspired by the group dynamics of fish schools and bird flocks. PSO operates by iteratively refining a population of potential solutions, referred to as particles, which "fly" through the search space by trailing the currently optimal particles. Compared to other evolutionary algorithms, this one is easier to construct, needs fewer parameter adjustments, and performs well when it comes to resolving various optimization issues, such as those involving power systems, scheduling, and engineering design. PSO is a well-liked option for resolving a variety of optimization problems due to its effectiveness in exploring intricate search space and locating close to ideal solutions. Many objective functions were optimized using PSO with the integration of DG units and static compensators by optimally locating them in the distribution system [95]. Compared to GA, PSO can produce better-quality solutions with fewer iterations; nevertheless, the solution may converge too soon and become stuck in a local optimal state [96].

6.2. Genetic Algorithm

The search technique known as a genetic algorithm (GA) is based on the ideas of natural selection and genetics, crossover, inheritance, and mutation. An enhanced non-dominated sorting genetic algorithm version II was put out in [97] for the best possible scheduling of several DG units in order to increase voltage stability and decrease line losses and voltage variance. In addition to taking demand and generation uncertainties into account, and in order to reduce power losses and voltage deviation in radial distribution, the author in [98] employed an adaptive GA-based distributed generation planning system. In order to minimize economic expenses, the authors of [99] employed GA to identify the best location for renewable distributed energy sources while considering generation uncertainties. GA works well for resolving complex planning issues with several goals.

6.3. Ant Colony Optimization

To find the optimum solution, ant colony optimization techniques follow how insects behave. Photovoltaic systems, batteries, hydrogen technologies, and wind turbine systems are used to improve the reliability of the system and its cost [100]. Although ACO ensures that the solution will converge, the amount of time needed to do so may vary [94].

6.4. Tabu Search Algorithm

This algorithm is based on responsive exploration and adaptive memory. A hybrid model is used to integrate capacitor banks and DG units considering stochastic renewable generation to optimize power losses in the distribution systems [101]. To optimize the operational cost of electric vehicle charging stations in the distribution network, the author in [102] implemented the Tabu search algorithm. Its efficiency is degraded by several optimizing parameters and iterations for solving the planning issue with large-scale integration of DG [100].

6.5. Simulated Annealing

The primary source of inspiration for simulated annealing is the crystallization process in a real system. This iterative method works well for discrete search space optimization problems. The author in [103,104] used a simulated annealing technique where he optimized the optimal size and site of mixed DG systems to minimize the expansion cost of the system and improve system reliability. For combinatorial problems, simulated annealing frequently yields better solutions, which is similar to PSO. However, SA solutions could get trapped in local optima if they converge too soon [77].

6.6. Cuckoo Search Algorithm

Deb and Yang introduced a most influential approach to amend complex optimization problems called the Cuckoo search algorithm in 2006, relying on the nursing of cuckoo species. The cuckoo search algorithm helps in solving path problems. This algorithm requires only a few parameters, making it unique and reliable in solving optimization problems [105].

6.7. Bacterial Foraging Optimization Algorithm

In 2002, Professor Passino introduced a novel optimization algorithm that relies on the foraging behavior of *E. coli* bacteria. The bacterial foraging optimization technique consumes maximum energy when it starts finding an optimum solution in search space, making it the most reliable and least time-consuming technique for solving optimization problems [106].

6.8. Artificial Bee Colony Optimization Algorithm

The artificial bee colony algorithm is inspired by the biting behavior of honey bees, which was introduced back in 2005 by Dr. Dervis Karaboga. Three types of bees are used to find the optimum solution; scouts are related to random search, onlooker bees with global search, and employed bees are related to local search [107].

6.9. Water Cycle Algorithm

The water cycle optimization algorithm was introduced in 2012. The whole search space above, on, and below is intensively searched by this technique to find the best solution for optimization problems like water flows in its natural cycle. Both equality and inequality, as well as constrained and unconstrained optimization problems, can be solved solely by the water cycle algorithm [108].

6.10. Enhanced Gray Wolf Optimizer

This technique is inspired by the hunting and leadership scenario of Gray and Wolf. The rate of exploration/exploitation depends upon the leading wolf, which affects the performance of an algorithm because, due to its fast speed, it is seldom stuck in local minima [109].

7. Hybrid Optimization Algorithms

Different hybrid optimization algorithms have been used in the literature. The hybrid nature of algorithms increases convergence's robustness, efficiency, and speed. However, the complexity and latency of the algorithm is increased. The GA-PSO is implemented to solve the problem of optimal allocation of DGs and EVCS to optimize voltage deviation and power losses [19]. The objective functions of DG cost and energy consumption of EV users have been optimized using a hybrid algorithm of shuffled frog leap-teaching and learning-based algorithm [26]. To improve the efficiency of the GWO algorithm, it has been hybridized with PSO to solve the objective functions of power loss, voltage deviation, and index of voltage stability [36]. However, the hybridization process can increase computing costs and algorithm latency. In [39], the hybrid fuzzy Pareto dominance concept with a differential evolution algorithm is implemented to improve power losses in the distribution network with optimal placement of solar DG considering the voltage unbalance factor. The hybrid nature of artificial bee colony (ABC) with the harmony search algorithm and artificial immune system algorithm results in improved quality of solutions due to their search techniques. However, it also poses tuning and computational complexities [107]. The author in [49] implemented a hybrid soccer league competition-pattern search algorithm to find the optimal placement of BES, Wind, and solar to optimize the objective functions of voltage deviation and power loss. The ability to search and fast convergence of BFO can be achieved when combined with the PSO algorithm. The hybrid BFOPSO results in improving the fast convergence to optimal solutions. The complex optimization problems can be solved with BFOPSO as its area of exploration is improved due to its hybrid nature [56].

8. Discussion

The use of multi-energy multi-objective optimization in distribution systems with EV charging stations yields numerous practical results by simultaneously optimizing many objective functions like cost, efficiency, and environmental effects of DGs and EVCS. This methodology is critical for handling the complexities of modern energy systems while efficiently balancing competing objectives. While its use is rapidly rising in research and pilot projects, broad adoption is still limited. Recognized benefits include comprehensive optimization, increased efficiency, resilience, and environmental benefits, but problems such as complexity, data requirements, and scalability remain. Despite these challenges, the approach's potential to transform energy system operations through complete optimization and sustainability advances highlights its significance for future study and practical use.

9. Conclusions and Future Recommendations

To sum up, research on the optimization of multi-energy, multi-objective distribution systems with electric car charging stations is essential. It has a lot of promise for attaining effective and sustainable energy management. This thorough review has emphasized this sector's most important difficulties and prospects. In this review, it seems that only optimal planning and allocation of electric vehicles and distributed generation were under study, and no specific technology and type of electric vehicles were seamless. Nonetheless, research was being made on conventional Li-ion battery technology electric vehicles such as plug-in hybrids and battery electric vehicles. Cutting-edge optimization algorithms and renewable energy sources may all work together to improve distribution system performance and encourage the use of electric vehicles. It is obvious from this review that problems the grid is facing and in order to mitigate those problems, what were the key areas of research in previous studies to provide an effective solution for a most efficient and sustainable grid. Moreover, it was reviewed that the flexibility and resilience of the distribution system can be further increased by integrating demand response strategies with energy storage devices. However, more investigation is required to resolve system scalability, interoperability, and cost-effectiveness concerns to reap this optimization's benefits fully. Overall, the results point to a potential strategy for a more sustainable and environmentally friendly future: optimizing multi-energy distribution systems with electric vehicle charging stations.

From the above literature, it is obvious that to optimize multi-energy multi-objective distribution systems with electric vehicle charging stations, more study is needed in a few areas. Among them are:

- to research the best ways to incorporate different renewable energy sources, like wind and solar power, into the distribution system to balance supply and demand and guarantee effective use;
- to create sophisticated optimization algorithms that can manage the distribution system's complicated multi-objective structure while taking energy costs, system dependability, and greenhouse gas emissions into account;
- to decrease the peak-load-demand and optimize the charging schedules, smart charging techniques involve investigating novel approaches that take grid limits, electric vehicle owners' charging habits, and preferences into account. Moreover, research is needed to handle the intermittent nature of renewable energy resources;
- to examine how demand response strategies, such as load shifting and vehicle-to-grid integration, might improve how electric cars and the grid interact, allowing for bidirectional energy flow and demand flexibility.

Author Contributions: M.K. and M.B.: conceptualization, formal analysis, data curation. A.M.S., M.A.S. and S.T.C.: writing original draft. A.K. made and reviewed the work to completion, and supervision was by M.K. and M.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Acknowledgments: The authors acknowledged the A' Sharqiyah University, Ibra Oman for the support and facilities to complete this research with the collaboration of Dhofar University, Oman and Mehran University, Pakistan.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

SDG	solar distributed generation
ICOCCI	International Conference on Contemporary Computing and Informatics
WT	wind turbine
BESS	battery energy storage system
EVCS	electric vehicle charging stations
IEA	International Energy agency
V2G	vehicle 2 grid
VD	voltage deviation
VSI	voltage stability index
ICE	internal Combustion engine
HPSOGWO	hybrid particle swarm optimization and Gray wolf optimizer
OPF	optimal power flow
MILP	mixed integer linear programming
GA-PSO	genetic algorithm particle swarm optimization.
AVDI	average voltage deviation index
TLBO	teaching learning-based algorithm
BESA	the bald eagle search algorithm
IBESA	improved bald eagle search algorithm
Ploss	active power loss
CHGE	greenhouse gas emissions
AVDI	average voltage deviation index
HHOA	horse herd optimization algorithm
SPBO	student psychology base optimization
RLBOA	reinforcement learning-based optimization algorithm
(iMOF)	innovative multi-objective function
MPA	marine predator algorithm
BM	biomass
BEOP	bandwidth exchanging and power optimization
NMC	nickel manganese cobalt
NCA	lithium nickel–cobalt–aluminum oxide
LFP	lithium iron phosphate batteries
LMO	lithium-ion manganese oxide battery
LTO	lithium–titanium–oxide
BFOPSO	hybrid bacterial foraging and particle swarm optimization algorithm

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