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TOPICAL REVIEW

A Comprehensive Review and Analysis of the Allocation of Electric Vehicle Charging Stations in Distribution Networks

T. YUVARAJ[1], K. R. DEVABALAJI[2], J. ANISH KUMAR[3], SUDHAKAR BABU THANIKANTI[4,5], (Senior Member, IEEE), AND NNAMDI I. NWULU[5], (Senior Member, IEEE)

[1]Centre for Computational Modeling, Chennai Institute of Technology, Chennai 600069, India
[2]Department of Electrical and Electronics Engineering, Aarupadai Veedu Institute of Technology, Vinayaka Mission's Research Foundation, Chennai 603104, India
[3]Department of Electrical and Electronics Engineering, Saveetha Engineering College, Chennai 602105, India
[4]Department of Electrical and Electronics Engineering, Chaitanya Bharathi Institute of Technology, Hyderabad 500075, India
[5]Centre for Cyber Physical Food, Energy and Water Systems, University of Johannesburg, Johannesburg 2006, South Africa

Corresponding author: Sudhakar Babu Thanikanti (sudhakarbabu66@gmail.com)

ABSTRACT In recent times, the limited availability of fossil fuels and growing concerns regarding the emission of greenhouse gases (GHGs) have directly impacted the shift from conventional automobiles to electric vehicles (EVs). Additionally, there have been notable advancements in new energy research, which have significantly improved the viability of EVs. Consequently, EVs have gained widespread recognition and have been rapidly adopted in many countries worldwide. However, the rapid growth of EVs has given rise to several challenges, such as insufficient charging infrastructure, unequal distribution, high costs, and a lack of charging stations, which have become increasingly significant. The limited availability of charging facilities is hindering the widespread adoption of EVs. However, as more people embrace EVs, there has been a growth in the installation of electric vehicle charging stations (EVCSs) in public locations. Recent research has focused on identifying the ideal locations for EVCSs in order to assist the electrification of transport systems and meet the growing demand for EVs. A well-developed EVCS infrastructure can help address some key issues facing EVs, such as pricing and range limitations. Researchers have used various methodologies, objective functions, and constraints to formulate the problem of identifying the best sites for EVCSs. Current research is focused on determining the best locations for EVCSs. This endeavor intends to ease the transition to electrified transport networks while also addressing the growing demand for EVs. This review article explores various optimization techniques to achieve optimal solutions while considering the impact of EV charging load on the distribution system (DS), environmental implications, and economic impact. The research used a standard IEEE 33-bus radial distribution system (RDS) with a full variety of potential energy sources to improve understanding of the subject. The use of the bald eagle search algorithm (BESA) and cuckoo search algorithm (CSA) aided in the best identification of energy source locations and their relative capacities. In addition, the examination of EV charging techniques, including both the traditional charging technique (TCT) and the innovative charging technique (ICT), is being undertaken to assess the effectiveness of these approaches. The study included ten separate scenarios, each of which was thoroughly evaluated to demonstrate the individual and synergistic usefulness of various energy sources in mitigating the effects of EV charging on the DS. The collected data from the empirical inquiry was aggregated and thoroughly analyzed.

INDEX TERMS Electrical vehicles, electric vehicle charging stations, bald eagle search algorithm, cuckoo search algorithm, renewable distributed generations, distribution static compensator, battery energy storage system, capacitor, innovative charging technique, radial distribution system.

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I. INTRODUCTION

In modern times, the emergence and widespread adoption of alternative energy sources have garnered significant attention worldwide. This has led to the rise in the popularity of electric vehicles (EVs) as a symbol of the progress and implementation of these new energy technologies [1]. In the past decade, there has been a notable surge in the demand for EVs attributed to their remarkable capacity for reducing carbon dioxide (CO_2) emissions [2], along with their cost-effectiveness in operations compared to conventional internal combustion engine (ICE) vehicles [3]. Studies have indicated that by 2030, EVs could potentially contribute to a noteworthy 28% reduction in CO_2 emissions [4]. The rising prevalence of new energy vehicles has consequently generated an increased need for accessible electric vehicle charging stations (EVCSs). Nevertheless, during the transition to EVs, the general public encounters two major challenges: the relatively high upfront costs of EVs and the insufficient availability of EVCSs [5]. The integration of EVs and EVCSs into DS carries significant systemic implications, encompassing heightened electrical losses, alterations in voltage profiles, and potential congestion in power lines. Moreover, the current absence of efficient fast EVCS further exacerbates the underlying strain on power demand, exerting an impact on the overall electrical grid dynamics [6]. As a result, the precise determination of optimal EVCS placements has emerged as a pivotal focal point in scholarly research.

According to one study, the EV market will be worth USD 974 billion by 2027. This expansion is fueled by a strong compound annual growth rate from 2020 to 2027, which is affected by global industries and governments [7]. The rising global use of EVs offers new problems for DS infrastructure and operators. Elevated electrical power needs, bus voltages, power loss, stability, harmonic distortion, voltage mismatches, and power efficiency are all potential difficulties. These elements, taken together, have the potential to have a significant impact on the DS. Notably, experts highlight the scarcity of EV charging infrastructure as a major worry. The increased popularity of EVs has created a demand for more dependable EVCS capable of quickly refilling EV battery charges. This necessity has given rise to the concept of fast charging, which allows for the quick charging of EVs in as little as 20-30 minutes [8]. However, the deployment of fast charging has some constraints, particularly in terms of its impact on the DS. To address this issue, EVCSs must be meticulously planned [6]. Significant research has recently been spent to understanding the appropriate placement of EVCSs and the ramifications for the DS [9].

This study's researchers investigated several strategies for locating EVCS. These strategies include those used by distribution network operators (DNOs), EV customers, and EVCS owners. While several studies have focused on the tactics used by investors in EVCS, there has been no extensive research into the perspectives of EV users regarding the best placement of EVCS. Prior research has looked into the DNO technique for EVCS deployment, which focuses on minimizing bus voltage fluctuations, reducing overall power loss, and improving DS reliability.

The global sales of electric vehicles (EVs and PHEVs) are illustrated in Figure 1. The Electric Vehicle World Sales Database predicts that the EV industry will generate \$457.60 billion in sales by 2023, with revenue expected to grow at a 17.02% annual rate (CAGR 2023-2027). This growth is expected to result in a market volume of US\$858.00 billion by 2027, with projected unit sales of 16.21 million cars. The volume weighted average price of EVs is estimated to be US\$53.19k in 2023. China is anticipated to earn the most considerable income in 2023, with a forecasted revenue of US\$190,400.00 million [10]. These statistics highlight the significant impact of EVs and EVCSs in modern society, with the International Energy Agency predicting global EV sales to reach 16.21 million.

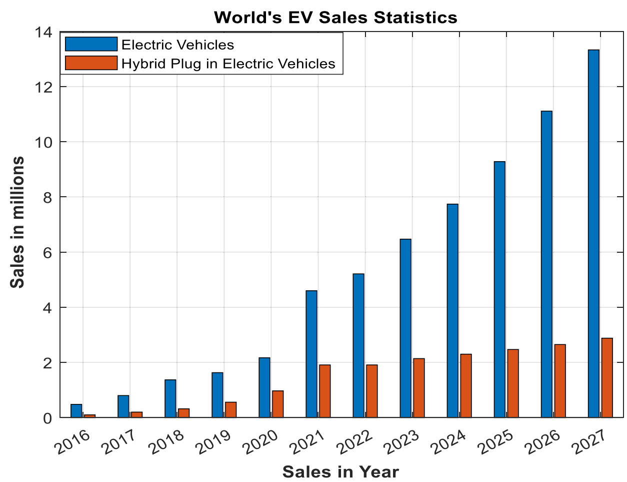

FIGURE 1. Yearly world's EV sales statistics.

In recent times, the rise in EVs and the corresponding expansion of charging infrastructure have presented a range of challenges for the existing electricity DS. Researchers have extensively delved into addressing these challenges, focusing on the effects of EVs on electricity generation capacity, aging of transformers, and power quality within the DS. It is anticipated that the act of charging EVs during periods of peak demand could potentially result in an escalation of peak load requirements, consequently necessitating the augmentation of power generation capabilities. Furthermore, the increased demand for EV charging has the potential to strain substation and service transformers, thereby shortening their operational lifespans. The integration of EVCS may also introduce power quality complications like voltage fluctuations, imbalances in power distribution, and disturbances in voltage/current waveforms [11]. Nonetheless, the quantity and strategic placement of EVCSs are influenced by a variety of factors, encompassing economic considerations for operators, the satisfaction levels of EV drivers with the available charging amenities, vehicle energy efficiency, traffic flow in the transportation network, and the overall stability of the power grid. While EVs offer substantial environmental and economic benefits, the strategic deployment of charging infrastructure must be a meticulously calculated endeavor to effectively meet the requirements of EV users [12].

The primary goal of this review article is to examine various issue formulations offered by researchers to establish the appropriate allocation of EVCSs and discover the optimum solution using multiple solutions. The significant contributions are summarized here.

i. This article provides an overview and comparative study of several issue formulation methodologies for EVCSs placement used by researchers. Each strategy comprises of various goal functions for placing the EVCSs. As a result, all techniques of placing the EVCSs have been evaluated in this work.
ii. This paper provides a comprehensive review of the objective functions and constraints in formulating the problem of identifying optimal sites for EVCS. The study also explores various solution strategies for achieving the optimal solution to this problem.
iii. This study also examines the impact of EV load integration on current distribution networks.
iv. This article provides a thorough examination of the benefits and drawbacks EVCS on DS.
v. This article presents a comprehensive evaluation of various EV types and EVCSs from different perspectives.
vi. This article discusses the optimization methods utilized for determining the appropriate sizing and placement of EVCS while considering multiple objectives and constraints.
vii. Addressing the vital problematic challenges and research gaps in the EVCS allocation dilemma in the suggestions and future directions section.
viii. To analyze the performance of various energy sources, a case study was undertaken on a conventional IEEE 33-bus system with varied situations.

i. An innovative charging approach is suggested for EV owners, enabling them to generate income through the Vehicle-to-Grid (V2G) mode.
ii. Two optimization algorithms (BESA & CSA) have been implemented in IEEE 33-RDS to show the effectiveness of the proposed methodology.

II. ELECTRIC VEHICLES TECHNOLOGY

EVs include various modes of transportation, such as trams, metros, electric automobiles, electric trains, and trolley-buses, which operate either fully or partially using electricity. Although private EVs have received a lot of attention in recent years, the technology that powers them is not new. It dates back to the nineteenth century when lead-acid batteries were used to power them. However, due to the higher energy density of fuel, ICE vehicles outperformed EVs and were more commonly used. Despite this, EVs have become more mature and widely used in recent times.

A. ELECTRIC VEHICLES MARKET

While several manufacturers provide a variety of EVs with varying specifications, the global market for EVs in the category of light-duty passenger vehicles has yet to expand significantly. Despite the rapid growth of the EV sector, there is still a long way to go to effectively reduce greenhouse gas emissions and significantly reduce reliance on oil. Therefore, much work must be done to increase the adoption and market share of EVs to make a meaningful difference in reducing carbon emissions and dependence on fossil fuels. It is crucial to consider the possible economic impacts of widespread EV adoption from both the perspective of EV owners and the power grid [13]. One consideration is that the addition of a high-power load represented by EVs to the power system may result in increased fuel and generating capacity costs [14]. Additionally, there may be an increase in power losses on the grid, although this can be alleviated by implementing regulated charging procedures [15]. On the other hand, EV owners may experience various benefits, such as lower operating costs due to cheaper electricity prices in comparison to gasoline and greater efficiency of electric motors (EMs) used in EVs versus ICEs used in traditional gasoline-powered vehicles (ICEVs) [16], [17].

B. TYPES OF ELECTRIC VEHICLES

Different types of EVs can be classified based on their energy converter, power source, and charging method. The energy converter can either be an ICE or an EM that moves the vehicle. The power source can be a battery, fuel cell, or gasoline. Additionally, EVs can charge from an external source such as a charging station or home charger. Figure 2 illustrates the fundamental structure of different EV types. The subsequent sections provide a brief overview of these various types [18].

1) HYBRID ELECTRIC VEHICLE (HEV)

HEVs are similar to ICEVs, except they have a larger electric motor and battery. At low loads, the battery can be charged using regenerative braking and the ICE. At lower speeds, the vehicle is typically powered by the battery and EM, while the ICE takes over at higher speeds. Moreover, the electric motor can assist the ICE during high-load situations, improving the car's efficiency and performance. HEVs are environmentally friendly, emitting fewer greenhouse gases and consuming less fuel compared to ICEVs. The current model does not make use of EV chargers to obtain power from the DS. As a result, its impact on battery charging and inability to provide electrical services is negligible. HEVs are available in a variety of configurations, including series, parallel, series/parallel, mild, and complicated HEVs. In the following section, we will look at a series/parallel plug-in hybrid electric vehicle (PHEV). Figure 2(i) depicts the fundamental similar HEV layout.

2) PLUG-IN HYBRID ELECTRIC VEHICLE (PHEV)

This vehicle is classified as a HEV, capable of charging its battery through regenerative braking, the ICE, and an external

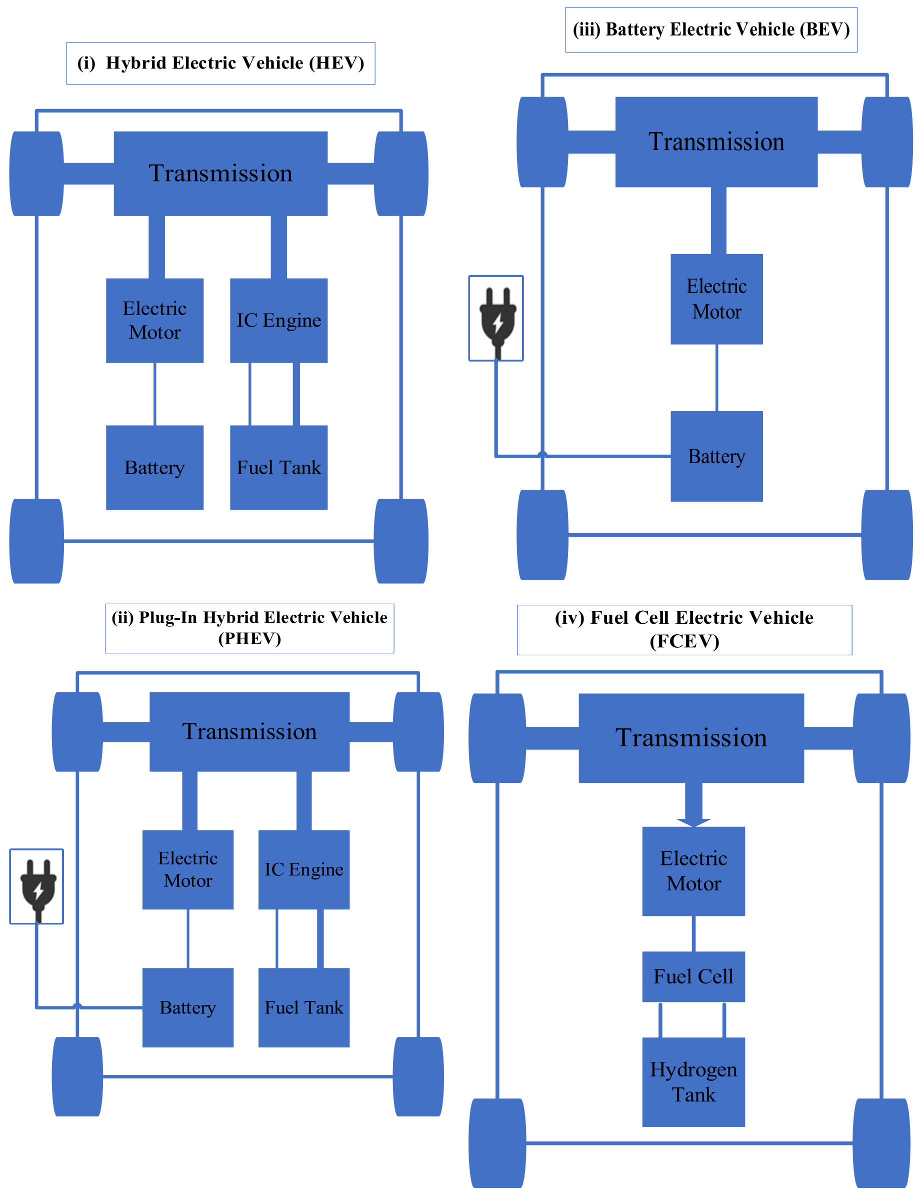

FIGURE 2. Various types of EVs.

EV charger. To improve its electric range, it features a higher electric motor (EM) power, a smaller ICE, and a larger battery capacity than a typical HEV. It can operate solely on electricity powered by the EM, resulting in zero GHG emissions. However, due to its relatively low battery capacity, its impact on the electric power system is predicted to be minor, with limited ability to provide electricity services. The parallel PHEV configuration can be applied to any hybrid system. See, Figure 2(ii) for an essential representation of the similar PHEV setup [19].

3) BATTERY ELECTRIC VEHICLE (BEV)

As battery technology advances and prices drop, BEVs are poised to become the dominant form of EV. BEVs rely solely on electric motors powered by batteries, with no ICE. Its battery capacity determines the range of a BEV, and one of its main advantages is its ability to produce no local emissions, making it a desirable option in densely populated urban areas. Different EV chargers can be used to charge the battery from the DS. While different companies may have variations on this basic design, the core configuration and primary components are illustrated in Figure 2(iii).

4) FUEL CELL ELECTRIC VEHICLE (FCEV)

FCEVs are fuel cell electric vehicles that, unlike BEVs, use a fuel cell to create electricity from hydrogen rather of relying on a battery to store energy. The procedure entails refueling the vehicle with hydrogen, which is then transformed from chemical energy to electrical energy by the fuel cell and used to power the vehicle's motor. Hydrogen can be obtained through processes such as natural gas extraction or water electrolysis. FCEVs, like standard ICE vehicles, have the advantage of quick refueling. Figure 2(iv) depicts the essential configuration of an FCEV, with the option of incorporating a battery and super capacitors. It's worth noting that when a battery isn't used, FCEVs put no load on the power system because they don't require charging from the power grid [20].

C. CHARGING AND DISCHARGING METHODS

Charging strategies are classified into two types: unidirectional charging and bidirectional charging. The method of transmitting energy solely from the electrical grid to an EV is referred to as unidirectional charging. This includes strategies such as uncontrolled charging, delayed charging, and regulated charging. Bidirectional charging, on the other hand, lets electricity to flow both ways, allowing the EV to not only collect power from the grid but also feed power back into the system or other energy users such as buildings and residences. V2X (vehicle-to-everything) system help to realize this capability. Figure 3 depicts the various charging and discharging methods that are used in EVCS [21].

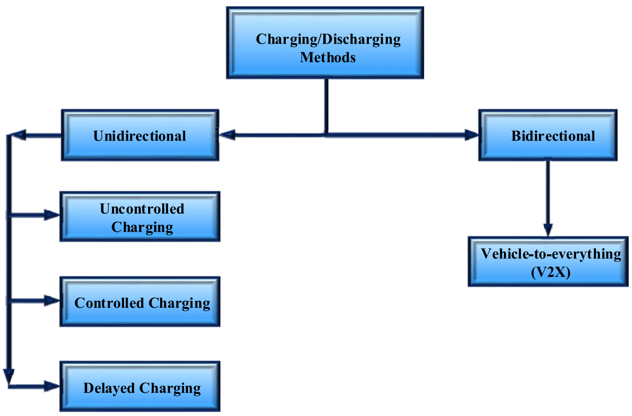

FIGURE 3. Various types of charging and discharging methods.

1) UNCONTROLLED CHARGING

The most common method for charging EVs is similar to the way used to charge other rechargeable devices such as laptops and smartphones. This requires connecting the EV to a charger, which administers power at full capacity until the vehicle's battery reaches full charge, which is normally 100% charge. This charging method is also known as uncoordinated, or uncontrolled charging. Nonetheless, numerous research papers have shown the negative effects of unregulated EV charging on DS. These implications include increased peak load demands, overloaded transformers and cables that result in shorter lifespans, voltage dips, and system imbalances caused by single-phase chargers, magnified power losses, and increased harmonic distortion [22], [23].

2) DELAYED CHARGING

Delayed charging can be an effective way to prevent the negative consequences of uncontrolled charging of EVs. This involves taking advantage of variable electricity pricing offered by utility companies, where electricity costs are lower during off-peak hours and higher during peak hours. Instead of regulating charging power, delayed charging encourages EV owners to charge their vehicles during off-peak hours, which can maximize both their utility and the utility of the power grid. This approach is also called on-peak or indirectly regulated charging with time-of-use pricing. By implementing an ideal pricing structure that incentivizes charging during low-cost hours, delayed charging can help control the timing of EV charging cost-effectively and sustainably [24].

3) CONTROLLED CHARGING

When compared to uncontrolled charging, delayed charging is a more advantageous technique for reducing the demand on DS. It does, however, have certain restrictions. Regulated charging offers a feasible solution to these disadvantages. Using data from the DS, this strategy entails careful monitoring of both the charging schedule and the power levels of EVs. Such information includes overall power consumption, transformer capacity utilization, voltage stability, power efficiency, and other pertinent characteristics. Furthermore, by considering the EV as a managed load, regulated charging provides the extra benefit of potential cost savings. This method is known as synchronized or smart charging, and it can be efficiently implemented using one of three control frameworks: centralized, decentralized, or autonomous [25].

D. V2X TECHNOLOGY

V2X, or vehicle-to-everything, represents a comprehensive energy technology paradigm. In this concept, EVs are regarded as mobile batteries, where the stored energy within the vehicle can be discharged for various purposes, depending on the specific application.

V2X technologies offer a range of advantages for both vehicle owners and grid operators, including:

Grid Flexibility: V2X services provide grid operators with an accessible power source that can be utilized during peak energy demand periods. This can involve either directly feeding energy back into the grid or temporarily fulfilling the power needs of buildings, homes, or other loads.

Compensation Opportunities: Vehicle owners, such as school districts and other operators, have the potential to receive financial compensation for the V2X services they offer to the electric grid. This compensation may be provided in the form of an electricity bill credit, offsetting other electricity consumption at the site.

Emergency Preparedness: During emergencies, when there may be power outages or disconnects from the electric utility, V2X services can step in as a reliable backup power source for shelters, homes, command centers, and other critical locations.

Renewable Energy Support: V2X technology facilitates the more efficient utilization of energy derived from renewable sources. It achieves this by storing excess renewable energy during periods of abundance and releasing it when demand exceeds supply. This helps to optimize the use of clean energy resources.

Various types of V2X technologies are integral to the EV ecosystem, enabling interactions and exchanges of energy and information between vehicles and their surroundings. Some of the key V2X technologies in EVs include:

1) VEHICLE TO GRID (V2G)

EVs are being extensively researched for their ability to contribute electricity to the power grid and serve as decentralized energy storage units. Engineers are working on bidirectional EV chargers, which allow electricity to flow in both directions: from the grid to the EV for charging and back to the grid for discharging. This novel technique offers two operational options. To begin, extra power can be used to charge EVs during periods of excess electrical supply (known as Grid to Vehicle or G2V mode). Second, when there is heavy demand and insufficient energy generation, EVs can feed power back into the grid, improving the DS's efficiency and dependability [26]. The increasing popularity of EVs has altered utilities' perceptions of EVs. They are no longer viewed only as power users, but as potential electricity suppliers. As a result, the relationship between EVs and power system management bodies like the DSO has grown in importance. The DSO is responsible for ensuring that the power system operates reliably. Notably, V2G technology may perform a wide range of grid activities, including frequency management, provision of spinning reserves, integration of renewable energy sources (RES), peak load mitigation, and load balancing facilitation [27].

2) VEHICLE TO BUILDING (V2B)

V2B is a mode similar to V2G, but it functions differently in that it only interacts with buildings and not with the grid. It allows EVs to power buildings to utilize the energy stored in their batteries. This mode is beneficial during peak load times and power outages. EV batteries can operate in two modes, G2V and V2B. During low power demand and excess electric power generation, the battery charges in G2V mode at a low cost. However, during peak hours when power prices are high, the battery switches to V2B mode and supplies the building loads. These processes help balance power demand and supply and optimize energy usage [28].

3) VEHICLE TO HOME (V2H)

The concept presented here is similar to V2B, focusing on a single residence and EV. The EV is engineered to intake electricity from the household while also being capable of supplying power back to the home when necessary. This arrangement involves a simpler design in contrast to V2G and V2B setups, and offers a more limited range of electrical services to the overall power grid. Its primary objective revolves around diminishing the energy consumption of the household during peak usage hours, thereby contributing to a more evenly distributed daily energy consumption pattern. Moreover, surplus energy produced by local sources like PV panels or wind turbines can be stored within the EV's battery for subsequent utilization. [29].

4) VEHICLE-TO-VEHICLE (V2V)

Vehicle-to-vehicle (V2V) communication stands as a pivotal technology in the realm of connected transportation. It enables direct communication between vehicles in close proximity, allowing them to share crucial information such as speed, position, and direction. This real-time exchange of data empowers vehicles to anticipate and react to each other's movements, significantly enhancing road safety and mitigating the risk of accidents. V2V technology holds immense promise in revolutionizing traffic management, enabling features like adaptive cruise control, emergency braking, and cooperative merging, ultimately contributing to a safer and more efficient transportation ecosystem [30].

5) VEHICLE-TO-LOAD (V2L)

Vehicle-to-Load (V2L) technology represents a pivotal advancement in the realm of EVs, enabling them to serve as mobile power sources. With V2L capabilities, EVs can discharge stored energy back into the grid or directly power electrical devices. This versatile functionality holds immense potential in various scenarios, from providing emergency backup power during outages to supporting off-grid activities. V2L not only enhances the overall grid resilience but also empowers consumers to leverage their EVs as dynamic energy assets, ushering in a new era of decentralized and sustainable energy solutions [30].

6) VEHICLE-TO-DEVICE (V2D)

Vehicle-to-Device (V2D) technology is a pivotal sub-domain within the broader landscape of Vehicle-to-Everything (V2X). V2D facilitates seamless communication and data exchange between EVs and various electronic devices, including smartphones, tablets, laptops, and wearables. This technology enables EV owners to remotely monitor and control their vehicles, offering features like pre-conditioning the car's interior, checking charging status, and locating the vehicle. V2D holds significant potential for enhancing user convenience and optimizing EV performance by allowing efficient data transfer and interaction between the vehicle and personal devices. Additionally, it contributes to the development of smart and interconnected mobility ecosystems, supporting the growth of EV adoption and fostering user engagement in sustainable transportation [30].

7) VEHICLE-4-GRID (V4G)

Vehicle-for-Grid (V4G) technology represents a pioneering advancement in the realm of electric mobility. Unlike conventional approaches where vehicles primarily draw energy from the grid, V4G enables EVs to serve as active contributors to grid stability and energy management. In this paradigm, EVs are equipped with bidirectional charging capabilities, allowing them not only to charge from the grid but also to discharge excess energy back when needed. This innovative two-way flow of electricity transforms EVs into dynamic grid assets, capable of alleviating peak demand periods and supporting the integration of renewable energy sources. V4G not only optimizes the utilization of the existing grid infrastructure but also paves the way for a more sustainable and resilient energy ecosystem [30].

8) STANDARDIZING V2X TECHNOLOGY FOR SEAMLESS INTEGRATION

The international energy agency (IEA) has emphasized the need for comprehensive market, social, and technological steps to be taken by actors and stakeholders for the successful application of V2X technology. While numerous studies have explored strategies, operations, and technologies related to V2X application, they often fall short in addressing the essential operational framework and standards necessary for V2X implementation. A dedicated survey delved into the development of new design processes and standards specifically tailored for V2X implementation. Several prominent organizations are actively engaged in formulating standards and grid codes for utility interface. Key standard-setting bodies include the international electro technical commission (IEC), Society of automotive engineers (SAE), Institute for electrical and electronics engineering (IEEE), Infrastructure working council (IWC), and international organization for standardization (ISO). Notably, SAE and IEC have introduced distinct standard groups. SAE's classification of chargers encompasses three DC levels and three AC levels, with on-board chargers utilizing AC 1 and 2 levels, and off-board chargers utilizing all DC levels due to the high power demand of DC charging. AC Level 3 is also employed for off-board charger applications. For the effective deployment of V2X, the establishment of fast charging requirements is imperative. Presently, the fast chargers available in the market are designed based on IEC standards, with four primary types: the combined charging system (CCS), Tesla supercharger, Charge de move (CHAdeMO), and 43KW AC. Among these, CCS and CHAdeMO emerge as the most prevalent fast chargers and play a critical role in facilitating V2X application implementation. These fast chargers adhere to the standards stipulated by the European automobile industry and beyond, ensuring a standardized approach to V2X integration [30], [31], [32].

9) GLOBAL V2X PROJECTS ADVANCING EV INTEGRATION AND SUSTAINABLE ENERGY

The widespread adoption of V2X technologies is garnering significant attention from both researchers and industry experts due to its wide-ranging benefits for EV owners and society at large. By enabling more efficient and flexible utilization of energy resources, V2X empowers EVs to serve as distributed energy resources (DERs), contributing to grid stability and facilitating the integration of renewable energy sources. Reports have indicated enhanced vehicle efficiency and reduced greenhouse gas emissions and air pollution with the proliferation of millions of EVs globally. Governments worldwide have recognized the pivotal role of EVs in their emissions reduction strategies, with 2020 witnessing a remarkable 43% surge in global EV sales, resulting in an unprecedented 4.6% market share for the EV sector. Research suggests that V2X services hold the potential to unlock nearly 600 GW of flexible capacity across major regions like China, the United States, the European Union, and India. This adaptable capacity stands poised to mitigate fluctuations in renewable energy generation during peak periods. Projections indicate that by 2030, V2X could obviate the need for generating 380 TWh of power during peak demand in these regions. Opting for V2X from EVs over fossil fuel-based generation during high-demand periods could translate to a substantial reduction of 330 million tons of CO_2 emissions on a global scale. This section provides an overview of significant completed and ongoing large-scale V2X technology projects worldwide, encompassing V2G, V2B, V2L, V2H, and V4G technologies [31].

10) CHALLENGES AND BARRIERS IN VEHICLE-TO-EVERYTHING (V2X) INTEGRATION

As EVs continue to gain momentum worldwide in response to environmental concerns, with substantial growth in sales due to government incentives, this shift extends beyond cars to encompass a range of transport modes, from trucks and buses to trains. Simultaneously, infrastructure enhancements are underway to support this transition. While the EV industry witnesses ongoing research addressing concerns such as battery degradation, V2X technology emerges as a crucial component for integrating EVs with the grid and other systems. V2X offers numerous benefits and services, yet it is not without its share of challenges and limitations that require careful consideration [33], [34].

11) BARRIERS TO WIDESPREAD ADOPTION OF EVS AND V2X TECHNOLOGY

Numerous barriers hinder the broad adoption of EVs and V2X technology. Technical challenges arise from consumer unfamiliarity with these new technologies, concerns about EV performance and durability, and ensuring a reliable supply chain of EV components. Infrastructural limitations, including insufficient charging stations, a lack of maintenance facilities, a limited variety of EV models, and the need for a consistent power supply during charging, present hurdles. Financial obstacles stem from the high initial cost of EVs, uncertainties about their resale value, and operational expenses. Behavioral barriers encompass a lack of consumer awareness about the benefits of EVs and skepticism regarding their reliability and safety. Addressing these challenges is crucial for the widespread adoption of EVs and V2X technology [30], [34].

12) FUTURE PERSPECTIVES AND CHALLENGES IN V2X TECHNOLOGY IMPLEMENTATION

The implementation of EVs and V2X systems holds great promise in terms of load management, energy storage, and grid stability. However, several hurdles must be surmounted to fully realize their potential. Key obstacles include the deployment of necessary infrastructure, associated costs, and their impact on the power grid. The V2X system, facilitating two-way communication between EVs and the grid, presents a promising avenue to address frequency deviations and reduce carbon emissions. Yet, it brings its own set of challenges including handling generation uncertainty, implementing robust controllers, mitigating communication delays, and fortifying against cybersecurity threats. To navigate these complexities and unlock the full potential of V2X technology, future research and development efforts will be crucial. This includes advancements in grid management strategies, controller technology, and cybersecurity measures. Additionally, policy frameworks and industry collaborations will play pivotal roles in shaping the trajectory of V2X technology in the years ahead.

III. THE EFFECT OF EVS ON THE DISTRIBUTION SYSTEM

As the deployment of EVCSs continues to grow, it is becoming increasingly clear that the existing DS will encounter various challenges. Researchers have conducted extensive studies on this topic. They have defined EV impact analysis as evaluating EVs' effects on multiple aspects of the power grid, including the sufficiency of electricity generation, the aging of transformers, and the efficiency of the DS. One notable impact is that EV charging during peak load hours may increase demand for peak load power, which may necessitate an expansion of generating capacity. The rise in demand for EVs poses a potential risk of overloading substations and service transformers, which can lead to a decrease in their overall lifespan. Additionally, EV charging can cause power quality issues such as voltage dips, power imbalances, and voltage/current harmonics. A diagram in Figure 4 illustrates the potential effects of EV load on the DS, both positive and negative. The impact of EV load on DS is further categorized and explained in detail below. It is essential to consider and address these issues when implementing and managing EV charging infrastructure to ensure the stability and reliability of the DS.

A. NEGATIVE IMPACTS

There is growing agreement that EVs have the potential to considerably reduce GHG emissions, making them an appealing alternative to traditional gas-powered vehicles [35]. The broad use of EVs, on the other hand, poses considerable challenges to the electric power infrastructure. One of the most significant challenges is the unexpected increase in electricity demand that would result from the spread of EVCSs. Peak demand spikes, power loss, voltage instability, lower transformer longevity, and power quality issues linked to harmonics, voltage sag, and imbalance could all result from this rise in demand. As EVs grow more common, managing and planning the electrical grid will become more difficult.

1) VOLTAGE STABILITY

Voltage stability is a critical aspect of power DS that refers to their ability to maintain stable voltages across all buses after disturbances are eliminated. Modern power DS often face voltage instability due to the sudden rise in load resulting from fast charging stations (FCSs). Such FCS loads are intrinsically non-linear, requiring significant power to recharge EV batteries quickly. As a consequence, FCS load characteristics considerably impact voltage stability, making it one of the leading causes of power system blackouts [36].

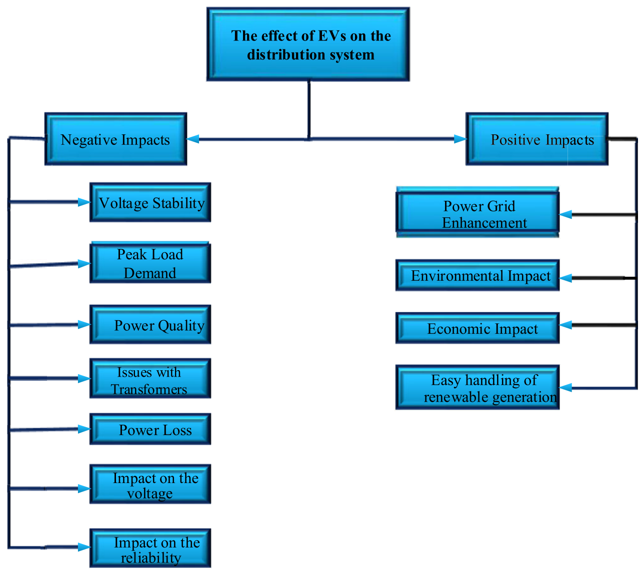

FIGURE 4. Potential impacts of EV load on distribution system.

2) PEAK LOAD DEMAND

As the demand for FCSs continues to rise, there is a corresponding increase in peak load demand in UPN, further aggravated by a reduction in reserve margin. Unplanned charging patterns can particularly strain existing generation capacity. To prevent this, it is recommended that 93% of EV charging occurs during off-peak hours. Failure to do so may result in a 53% surge in peak demand, assuming a 30% penetration rate for EVs. The good news is that adopting smart/coordinated charging and ToU pricing plans can significantly reduce peak demand without requiring additional generation capacity, as per sources [35], [36].

3) POWER QUALITY

The dynamic nature of EVCS load requirements makes maintaining power quality (PQ) a significant concern. Harmonics, voltage imbalances, and voltage sags characterize load demand. The conversion of AC power to DC electricity during the process of charging EV batteries introduces total harmonic distortion (THD) into the power system, usually via high-frequency switching converters. This THD injection has a number of unfavorable outcomes. These include the possibility of distribution transformer electrical and thermal overloading, waveform component distortion, and increased stress on DS equipment such as cables, fuses, and neutral wires. The cumulative effect of these factors has the potential to degrade the grid's overall power quality [37], [38].

4) ISSUES WITH TRANSFORMERS

The increasing adoption of EVCSs can cause extra stress on power distribution transformers, leading to a shorter lifespan. This can result in higher loads and hotter hotspot temperatures for the transformer. Inadequate coordination of EV charging can further deteriorate transformer performance and speed up its aging process. However, a study [22] has shown that having up to 10% of EV penetration does not adversely affect transformer lifespan.

5) POWER LOSS

Power system losses become a severe problem when contemplating the future demand caused by incremental EV grid inclusion. The source [22] suggests that during off-peak hours, power loss can increase by approximately 40% when 60% of EVs are charging. This increase is primarily due to uncoordinated charging, which can result in significant power losses. However, consistent charging practices can effectively minimize power losses, as highlighted by sources [35], [36]. To further mitigate the increase in power loss, optimize the placement of the EVCSs.

6) IMPACT ON VOLTAGE

In this section, the focus is on the effect of integrating EVs on the voltage profile of the electricity DS. This voltage profile is critical in ensuring efficient electricity delivery to customers. Adding EV loads to the current DS can cause voltage loss at buses, affecting the system's overall efficiency. Various studies have reported voltage losses of less than 96% of the standard voltage in some regions due to charging EVs. Therefore, system upgrades may be required to address this issue.

7) IMPACT ON THE RELIABILITY ANALYSIS

The analysis of power systems' dependability has emerged as a significant area of research, focusing on the evaluation of the probability of a system operating correctly within specific operational conditions over a defined timeframe. In this context, reliability pertains to a system's capacity to function efficiently for a given duration under particular operational scenarios [35]. Assessing the reliability of a power system encompasses the assurance of dependable power generation, transmission, and distribution. Moreover, the contentment of consumers is intrinsically tied to the reliability of the DS. Accurate statistical data pertaining to diverse factors like failure rate, repair rate, average outage duration, and the number of users linked to network buses or load points is indispensable for evaluating DS reliability [35], [36]. Figure 5 illustrates a comprehensive categorization of reliability indices for DS, encompassing both consumer-centric and energy-centric perspectives. Consumer-oriented indices consist of SAIFI, SAIDI, and CAIDI, while energy-oriented indices encompass ENS and AENS. It is imperative to ensure precise collection and analysis of statistical data to effectively appraise DS reliability.

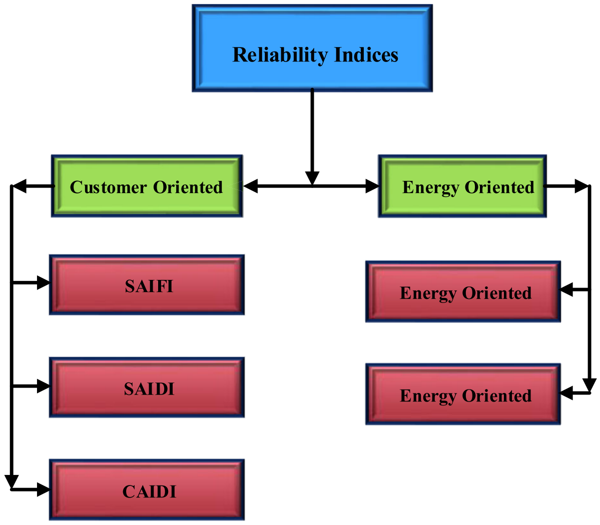

FIGURE 5. Reliability indices in distribution system.

The phrases SAIFI and SAIDI pertain to the frequency and duration of power outages, respectively, while CAIDI assesses the level of customer dissatisfaction resulting from disruptions. AENS, on the other hand, measures the average amount of load reduction caused by service interruptions. Examples of common causes of power disruptions include outages, equipment malfunction that disrupts power system operations, sudden spikes in demand necessitating load shedding, scheduled maintenance requiring service interruption, and severe weather events that damage infrastructure.

In recent times, there has been notable research focused on the assessment of the dependability of DS. A variety of metrics are employed to gauge the robustness of these networks, encompassing factors like failure rate, repair rate, average duration of outages, and the count of affected consumers. An important metric, known as the bus reliability index, serves as a crucial measure to evaluate the susceptibility of individual buses within a DS. Additionally, system reliability indices, which are subcategories of both consumer-oriented and energy-oriented reliability indices, play a pivotal role in evaluating the overall resilience of the DS.

Within the realm of consumer-oriented reliability indices, there are commonly used abbreviations: SAIFI, SAIDI, and CAIDI. SAIFI stands for System Average Interruption

Frequency Index, and it quantifies the frequency of system interruptions experienced by customers within a specific timeframe. On the other hand, SAIDI, or System Average Interruption Duration Index, represents the average duration of outages per customer. It's important to note that SAIDI is influenced by both the duration of the outages and the number of customers impacted [39].

B. POSITIVE IMPACTS

1) POWER GRID ENHANCEMENT

V2G technology can be used to pump power back into the power grid during power outages, offering numerous advantages when paired with RES. These benefits include peak load reduction, increased spinning reserve, improved load management, reduced power line loss, and enhanced frequency control [37]. Additionally, when EVs supply active power to the DS in V2G mode, there is a decrease in the percentage of bus voltage imbalance [23]. The use of V2G technology has the potential to transform EVCSs from being just load centers to becoming DGs [22], [40]. This transformation enables EVs, typically consumers, to become prosumers, taking on new roles such as participating in Demand Response programs, providing reactive power support, offering auxiliary services, tracking renewable energy production, and balancing the load. These new roles incentivize EV owners to help maintain power grid stability and generate income [20], [40].

2) ENVIRONMENTAL IMPACT

While most power plants worldwide use fossil fuels to generate electricity, EV batteries are charged using energy supplied through a power grid rather than directly burning fossil fuels. This means that some pollution is shifted from urban areas to power generation locations. However, integrating RES into EVCS can help to decrease pollutant emissions, especially in cities. Therefore, properly incorporating renewables in charging infrastructure can reduce GHG emissions and other pollutants in both power generation and transportation. Studies have shown that deploying EVCSs for EVs can lead to several environmental benefits, such as reduced emissions of CO_2, carbon monoxide, nitrogen oxide, and particulate matter. Furthermore, compared to ICEVs, EVs have lower well-to-wheel emissions [22].

3) ECONOMIC IMPACT

EVs offer cost benefits to both drivers and utility companies. In comparison to traditional ICEVs, EVs have lower fuel and operating costs. However, the price of purchasing and installing EVCSs remains high compared to the cost of ICEVs and conventional petrol stations. As a result, public EVCS are currently only marginally profitable due to the low rate of EV adoption [41]. However, the cost of EVs and EVCS installations is expected to decrease significantly with the widespread production of EVs and the subsequent deployment of EVCSs. Additionally, by implementing V2G technology, EV owners can earn money by selling their battery energy storage back to utility companies. Homeowners can also participate in DR programs, which help smooth the electricity grid's voltage and demand profile [42]. Establishing an EV charging station includes equipment, installation, and operation and maintenance expenses.

4) EASY HANDLING OF RENEWABLE GENERATION

The integration of renewable energy into power systems poses a challenge for providers due to the intermittency of the energy output. However, the use of EV chargers with rapid, responsive control electronic interfaces, along with battery storage, has been proposed as a viable solution for addressing source intermittency. According to a study conducted for one of the clients, when EVs were used for primary frequency control, the power system could withstand wind integration up to 59% of total grid generating capacity. Furthermore, certain types of solar energy can be used to charge EVs.

C. ENVIRONMENTAL CONSIDERATIONS IN EVCS ALLOCATION

The transition to EVs is hailed as a crucial step toward environmental improvement in the transport sector. However, for this transition to be truly sustainable, it must be accompanied by a shift towards clean energy sources. This necessitates powering EVCS with electricity generated from green resources. The integration of EVs into the distribution system calls for a mathematical model that considers environmental impact and uncertainties associated with both conventional and EV demand, as well as renewable generation. An innovative mixed-integer linear programming (MILP) model, implemented using AMPL and solved with CPLEX, addresses this challenge effectively [43]. Additionally, a joint planning algorithm is introduced to allocate DG units and EVCS in remote hybrid microgrids, striving to minimize both total costs and associated greenhouse gas emissions. This algorithm offers a range of optimal solutions, allowing for a balanced trade-off between economic and environmental objectives [44]. Another bi-level planning model is proposed, focusing on the integration of DG and EVCS, incorporating active management strategies for the distribution network. By employing advanced optimization techniques like improved harmonic particle swarm optimization (IHPSO), this model significantly enhances the overall profit of power supply companies while concurrently benefiting environmental and social welfare [45]. A comprehensive assessment of the environmental impact of green stand-alone energy systems and their implementation in the power supply of EVCS underscores the potential to reduce pollutant emissions and combat the greenhouse gas effect associated with conventional technologies [46], [47]. Finally, the introduction of smart electric grids is advocated, emphasizing the utilization of renewable energy sources to replace traditional thermal power plants. This transition not only conserves fossil fuels but also substantially mitigates greenhouse gas emissions, particularly CO_2, resulting from thermal generation [48]. This research article proposes an eco-friendly scheme for optimizing the charging and discharging schedules of Plug-in Electric Vehicle (PEV) aggregators in Smart Microgrids (SMG). The scheme aims to minimize system procurement costs and reduce CO_2 emissions, taking into account various types of PEVs (Battery Electric Vehicles and Plug-in Hybrid Electric Vehicles). The model considers V2G capabilities, actual driver behavior patterns, and practical constraints related to heterogeneous DERs and distribution networks. It employs stochastic programming to handle uncertainties in renewable generation, ultimately leading to a more environmentally sustainable and economically efficient power system. The approach involves utilizing a weighted sum methodology, which transforms the multi-objective problem into a single-objective Mixed Integer Non-Linear Programming (MINLP) model. This model is subsequently minimized using a collaborative grey wolf optimizer and Taguchi test method, resulting in a satisfactory solution [49].

The following sustainable solutions are presented based on the discussion of potential issues with eco-charging systems and recommendations for environmentally friendly EVCS allocation:

1) CLEAN ENERGY SOURCES
Embrace renewable energy sources like solar, wind, and hydroelectric power for generating electricity to power EVCS.

2) ADVANCED MATHEMATICAL MODELS
Implement sophisticated models like Mixed-Integer Linear Programming (MILP) to account for environmental factors and uncertainties related to conventional and EV demand, along with renewable generation in EVCS planning and allocation.

3) OPTIMIZED ALLOCATION ALGORITHMS
Develop algorithms that optimize the placement of DG units and EV charging stations, considering both cost efficiency and the reduction of greenhouse gas emissions.

4) BI-LEVEL PLANNING MODELS
Incorporate active management strategies into the distribution network to enhance profit, environmental welfare, and social benefits while integrating DG and EVCS, employing bi-level planning models.

5) ADVANCED OPTIMIZATION TECHNIQUES
Utilize advanced optimization techniques, such as Improved Harmonic Particle Swarm Optimization (IHPSO), to efficiently plan and manage EV charging infrastructure.

6) SMART GRID INTEGRATION
Promote the development of smart grids to optimize energy generation, transmission, and consumption, with an emphasis on renewable energy sources, reducing greenhouse gas emissions, particularly CO_2.

7) ECO-FRIENDLY SCHEDULING SCHEMES
Develop schemes and models to optimize the charging and discharging schedules of Plug-in Electric Vehicle (PEV) aggregators in Smart Microgrids (SMG) to minimize system procurement costs and reduce CO_2 emissions.

8) LEVERAGING V2G CAPABILITIES
Harness V2G capabilities to enable EVs to contribute to grid stability and renewable energy integration.

9) DIRECT RENEWABLE ENERGY INTEGRATION
Seamlessly integrate renewable energy sources such as solar panels and wind turbines into the EVCS infrastructure to provide clean and reliable power directly to charging stations.

10) COMMUNITY AWARENESS AND ENGAGEMENT
Educate and engage communities in the advantages of sustainable EVCS and green energy solutions to foster adoption and environmental responsibility.

11) GOVERNMENT POLICY ADVOCACY
Advocate for government policies, subsidies, and incentives aimed at promoting the use of renewable energy and EVs.

By adopting these sustainable solutions, future researchers can aim to drive the advancement of EVs and charging infrastructure integration while minimizing environmental impact and greenhouse gas emissions.

D. IMPACT OF HEAVY-DUTY EVS ON THE DISTRIBUTION GRID
The widespread adoption of Heavy-Duty Electric Vehicles (HDEVs) like buses, trucks, and fleet vehicles has significantly impacted the distribution grid. While promising for reducing emissions and enhancing cost efficiency, HDEVs pose challenges to grid infrastructure. The shift from fuel-based to electricity-based charging infrastructure is essential for mass electrification of such large vehicles, potentially affecting both grid operators and external market participants. Policy makers must take a data-driven, scientific approach to align the market adoption of HDEVs with the realities of existing grid infrastructure. Meeting increased electricity demand during peak charging necessitates grid upgrades and strategic placement of charging infrastructure. Maintaining load balance, implementing smart charging, and ensuring grid resilience are vital. The integration of HDEVs with renewable energy sources is pivotal for a sustainable and resilient grid. Unlike light-duty EVs, HDEV charging presents distinct challenges with higher power requirements and concentrated loads. While past research has addressed additional electrical loads on distribution systems, encompassing light-duty EVs, the impacts of HDEV charging remain predominantly unexplored.

This study emphasized optimizing charging stations for grid stability, favoring fewer stations with more ports. Simulations revealed a substantial number of HDEVs (about 30,000, or 11% of Texas' heavy-duty vehicles) needed to affect the transmission grid. Surprisingly, even a small number caused severe under-voltage problems. The paper proposed a metric for guiding grid reliability investments, highlighting the need for careful consideration before electrification. Prioritizing local grid upgrades was recommended [50]. Charging stations near generation sources minimally affected voltage, but peak loads from fast chargers posed downstream challenges. Longer charging times mitigated peak load issues, with only strong buses upstream suitable for charging station placement. Voltage fluctuations could disrupt EV charging stations and affect battery life [51]. This study covered depot charging for heavy-duty electric trucks, including causes, costs, and lead times. Most substations could handle HDVE charging without upgrades. Fleets with consistent schedules could strategically manage charging. Further research was needed for cost-effective HDEV charging and high-power charging trade-offs [52]. This paper introduced a systematic methodology for analyzing the grid impact of HDEV charging stations, applicable across different distribution systems. The results provide insights into potential voltage impacts and suggest an initial mitigation plan involving smart chargers. Future plans involve a more comprehensive mitigation strategy, integrating smart chargers with on-site DERs [51].

These studies [50], [51], [52] highlighted the significant impact of HDEVs on the distribution grid. The researchers stressed the importance of optimizing charging stations for stability and suggested prioritizing local grid upgrades. Considerations for station placement and challenges posed by fast chargers were emphasized, advocating for longer charging times and strategic bus placement. Additionally, the studies supported the feasibility of depot charging, particularly for fleets with consistent schedules. In essence, they underscored the critical need for careful planning and infrastructure optimization in integrating HDEVs into the distribution grid.

IV. REVIEW OF THE TECHNIQUES TO SOLVE THE OPTIMAL LOCATION PROBLEM OF EVCS

A. OPTIMIZATION TECHNIQUES

The optimization problem of determining the optimal placement of EVCSs is crucial for efficiently using available resources and achieving desired outcomes. It involves finding the best design that maximizes or minimizes the objective function while satisfying the given constraints. To address this problem, several heuristic optimization techniques and integer algorithms have been explored in the literature. For instance, the use of Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Simulated Annealing (SA) has been popular in EVCS research. Mixed-integer linear programming (MILP) and Mixed Integer Programming (MIP) have also been utilized for this purpose.

Optimization methods play a crucial role in achieving diverse objectives, encompassing tasks like outage management, harmonizing electricity production from DG units with load consumption, enabling efficient energy trade among aggregators and power loads, maximizing profits from electricity sales to PEVs, and determining optimal size and placement of fast-charging stations. Hence, the selection of suitable optimization strategies is vital for effectively addressing specific challenges. In this study, the authors deliver a comprehensive overview of optimization approaches aimed at determining the best placements for EVCSs. The primary focus is on two categories of optimization techniques: classical and advanced. Classical optimization methods are adept at pinpointing optimal solutions or extrema of continuous and differentiable functions. However, their practical utility can be restricted since certain techniques mandate objective functions that lack continuity and/or differentiability.

On the other hand, advanced optimization techniques prove adept at tackling optimization problems marked by features such as multi-modality, high dimensionality, and non-differentiability. Conventional optimization methods struggle with these issues, often necessitating gradient information and encountering difficulty in locating global optima within problems boasting multiple local optima. In contrast, advanced optimization techniques excel in surmounting these constraints, presenting solutions to intricate optimization problems.

1) PARTICLE SWARM OPTIMIZATION

PSO is a well-known optimization technique that employs real-number randomization and global particle communication to enhance performance [53]. In PSO, a swarm of particles searches the search space for the best solutions, continuously exchanging and comparing their personal and global bests. At the beginning of each iteration, each particle follows a route vector produced from its unique and global best, eventually converging to the global optimum. Recently, the original PSO has undergone significant changes to improve computational efficiency and yield more accurate results. The optimization problem's objective functions involve power loss and other objectives, which are solved by the PSO algorithm once EVCS and other energy sources have been deployed at an optimal position in the RDS. The prominent algorithms utilized for EVCS allocation and their respective advantages over PSO are elucidated here. The FPA excels in exploring complex solution spaces with diverse objectives, striking a balance between exploration and exploitation. TLBO leverages a knowledge-sharing process akin to a classroom, making it robust and effective for dynamic optimization scenarios. GWO emulates cooperative hunting strategies, demonstrating rapid convergence and proficiency in high-dimensional spaces. The AOA dynamically manipulates solutions through arithmetic operations, proving adaptable to various problem types and suitable for non-linear, non-convex objectives. Finally, the HHO draws from hawk hunting behavior, effectively balancing exploration and exploitation strategies and excelling in constrained optimization scenarios. These algorithms collectively offer powerful tools to enhance the efficiency and effectiveness of EVCS deployment, catering to a wide range of optimization complexities.

2) GENETIC ALGORITHM

GA is computer-based methods that simulate the natural selection process to optimize candidate populations for a particular problem [54]. However, implementing a GA requires careful consideration of its design elements, such as the gene-encoding system, cross-over process, and fitness functions, which can directly impact its ability to find the correct solution. A diverse set of data is necessary to prevent the algorithm from getting stuck in local minima, often achieved by randomly selecting genes for cross-over, which can slow down the convergence rate but ensures exploration. Although increasing population size can improve GA's solution, it also significantly increases computation time, even for minimal gains in performance. Researchers have explored various objective functions to formulate EVCS deployment problems using GA.

3) FLOWER POLLINATION ALGORITHM

The Flower Pollination Algorithm (FPA) is a highly efficient metaheuristic optimization technique inspired by the process of flower pollination [55]. One of the unique features of FPA is its simplicity in formulation and remarkable computational efficiency. Comparative studies have shown that FPA outperforms both GA and PSO in terms of performance. Thus, FPA is highly recommended for extracting optimal parameters as the fastest and most precise optimization approach.

4) TEACHING LEARNING BASED OPTIMIZATION ALGORITHM

The Teaching-Learning Based Optimization (TLBO) algorithm draws inspiration from the educational process and focuses on a teacher's influence on the learners' performance [56]. The algorithm distinguishes two fundamental learning modes: (i) through instructor interaction, known as the teacher phase, and (ii) through interaction with other learners, known as the learner phase. One of the significant applications of the TLBO method is the optimal placement of EVCS. It considers five different objective functions, namely EVCS cost, voltage variation cost, system reliability, power loss, and the accessibility index of EVCSs.

5) GRAY WOLF OPTIMIZATION

The Gray Wolf Optimization (GWO) technique was developed by Mirjalili et al. in 2014, based on the natural behavior and hunting strategies of gray wolves [57]. The author was particularly inspired by the leadership structure observed in wolf packs, where alpha wolves lead the group, followed by beta wolves who support the alpha, and delta wolves who have less importance and surrender to the alpha and beta wolves. The omega wolves are the least important and must obey the higher-ranked wolves. GWO has been applied in the literature to effectively address the allocation problem of EVCSs with other energy sources.

6) ARITHMETIC OPTIMIZATION ALGORITHM

Abualigah and his team introduced a new approach called the arithmetic optimization algorithm (AOA) that employs arithmetic operators (addition, subtraction, multiplication, and division) as a basis for solving arithmetic problems [58]. The AOA is a population-based metaheuristic technique utilized to identify the optimal position and number of EVCS in a DS, which helps to minimize power loss and increase bus voltage.

7) HARRIS HAWK OPTIMIZATION ALGORITHM

The Harris hawks optimization (HHO) is a metaheuristic algorithm that takes inspiration from the hunting tactics and cooperative behavior of Harris hawks [59]. The surprise pounce approach of Harris' hawks, where multiple birds attack prey from various angles to catch it off guard, is the primary source of inspiration for HHO. Harris hawks exhibit diverse pursuit behaviors based on the prey's movements and the dynamic nature of the event. HHO is utilized for finding the optimal placement and location of EVCS to optimize the single or multiple objectives of RDS.

8) GRASSHOPPER OPTIMIZATION ALGORITHM

The Grasshopper optimization algorithm (GOA), introduced in [60] by Saremi et al., is a novel swarm intelligence technique that mimics grasshoppers' foraging and swarming behaviors in nature to solve optimization problems. The algorithm draws inspiration from the natural behavior of grasshoppers, which are notorious agricultural pests. In [192], GOA was applied to the EVCS allocation problem in RDS, resulting in improved power factor, reduced power loss, and better voltage profiles.

9) AFRICAN VULTURE OPTIMIZATION ALGORITHM

The concept behind the African Vulture Optimization Algorithm (AVOA) stems from African vultures' feeding and orienting habits. It utilizes powerful operators to resolve optimization problems by striking a balance between exploration and efficiency [61]. In an attempt to enhance the allocation of DG and DSTATCOM and reduce the effect of EVCS on RDS, AVOA was employed.

10) COYOTE OPTIMIZATION ALGORITHM

The Coyote Optimization Algorithm (COA) is a novel optimization technique inspired by coyote intelligence [62]. This algorithm draws inspiration from coyotes' social organization and adaptive behavior and is designed to tackle continuous optimization challenges. The optimization approach of COA involves the allocation of RDGs and ESSs optimally within the RDS to reduce actual power loss and voltage variation index.

11) FIREFLY ALGORITHM

Yang created the Firefly Algorithm (FA) in 2008 by animating the unique behaviors of fireflies [63]. It is described as swarm intelligent, metaheuristic, and nature-inspired. In reality, the population of fireflies exhibits unique luminary flashing behaviors that serve as a means of attracting partners, communicating, and warning predators. Renewable DGs are installed in the RDS employing FA to mitigate power loss and maintain a consistent voltage at each bus.

12) WHALE OPTIMIZER ALGORITHM

The Whale Optimization Algorithm (WOA) is a modern technique for optimization in problem-solving [64]. It incorporates three operators that mimic the hunting behavior of humpback whales, including surrounding prey and bubble-net foraging. In the context of EVCS, WOA is combined with DG allocation to improve the voltage profile of the grid and reduce energy losses.

13) HYBRID OPTIMIZATION ALGORITHMS

During the compilation process, hybrid optimizations utilize a selection of optimization algorithms that serve the same purpose. A heuristic is applied to determine the optimal algorithm for each code segment that requires optimization. The EVCS allocation problem in RDS can be tackled using various objective functions and a combination of algorithms. For instance, researchers have proposed a hybrid GA and PSO-based algorithm, a hybrid of GWO and PSO algorithms, a hybrid of HHO and GWO algorithms, a hybrid soccer league competition and pattern search algorithm, a hybrid crow search algorithm along with the PSO, and a combination of GWO and PSO algorithms.

14) OTHER OPTIMIZATION ALGORITHMS

The literature also explores alternative methods for determining the optimal location and capacity of EVCSs. The main notable algorithms for the EVCS allocation problems are, Joint planning algorithm [44], Gorilla Troop Optimizer algorithm [187], Bear smell search algorithm [195], Marine Predator Algorithm [197], Salp swarm algorithm [188], improved bald eagle search algorithm [164], Binary Bat Algorithm [206], and Dragonfly algorithm [131].

Tables 1-6 display various applications of chosen optimization methodologies from 2011 to the present, including over 100 research publications on the EVCS allocation problem in the DS. Furthermore, most studies use single optimization methods, with just a few dealing with hybrid approaches and multi-objective optimization processes, as indicated in Tables 1-6. The pie chart in Figure 6 depicts several optimization strategies for EVCS allocation problems. In terms of problem-solving methodologies, the researchers employ a wide range of approaches. According to the survey, around 23% of the researchers used the PSO approach. Similarly, 6% of researchers employed GA and GWO optimization techniques, 3% used AOA, HHO, and GOA optimization techniques, and 20% used hybrid optimization strategies for EVCS placement. Other methods used by 36% of the researchers included the marine predator algorithm, salp swarm algorithm, the enhanced bald eagle search algorithm, and so on.

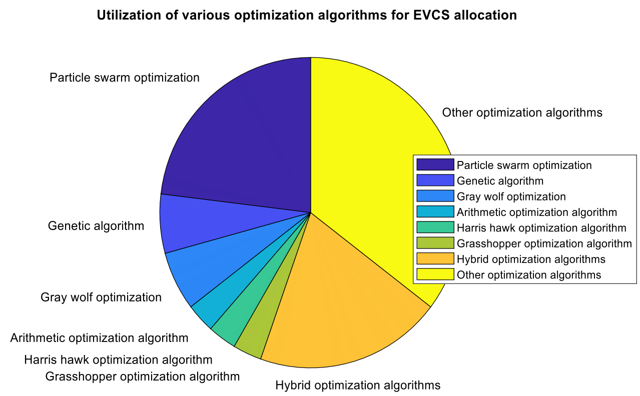

FIGURE 6. Utilization of various optimization algorithms for EVCS allocation.

B. OBJECTIVE FUNCTIONS

Numerous objective function equations may be used to allocate EVCS in energy distribution networks. The following are the most typically utilized goal functions for EVCS allocation issues on DS:

1) MINIMIZATION OF POWER LOSS

One common goal is to reduce power losses in the DS. The distribution system's power loss may be reduced by selecting the best locations for EV charging stations, RDG, capacitors, DSTATCOM, and BESS. It may be stated as follows:

$$Minimize = \sum P_{T,Loss} \tag{1}$$

where $P_{T,Loss}$ is the total power loss of the RDS.

2) MINIMIZE THE TOTAL VOLTAGE DEVIATION

This goal can be met by mitigating the sum of squared voltage variances from a target value across all system buses. The equation is written as follows:

$$Minimize = \sum (V_t - V_{ref})^2 \tag{2}$$

where V_t is the voltage at bus t, and V_{ref} is the target voltage.

3) MAXIMIZATION OF VOLTAGE STABILITY

This goal function tries to maximize DS voltage stability by optimizing the position and capacity of EV charging stations, DG, capacitors, and DSTATCOMs, as well as redesigning the network. The objective function can be expressed as follows:

$$\mathrm{Maximize} = \sum (\mathrm{V_t})^2 \tag{3}$$

4) MAXIMIZE THE UTILIZATION OF THE ENERGY SOURCES

This objective can be met by maximizing the ratio of active power generated by energy sources (ES) to rated capacity.

The equation is written as follows:

$$Maximize = \sum (P_{ES} - P_{ES,Max}) \tag{4}$$

where P_{ES} is the active power generated by the energy sources and $P_{ES,Max}$ is its rated capacity.

5) MINIMIZE THE TOTAL COST OF THE DISTRIBUTION SYSTEM

This aim may be met by reducing the total capital and operational expenses of all system components, including the EVCS, RDG unit, capacitor, DSTATCOM, and BESS. The equation is written as follows:

$$Minimize = \sum C_{ES} \tag{5}$$

where C_{ES} are the capital and operational costs of the energy sources.

6) MAXIMIZATION OF RENEWABLE ENERGY INTEGRATION

By calculating the ideal placements for The objective function equation aims to enhance the incorporation of RES, like solar and wind power, in the DS by maximizing their utilization.

$$Maximize = \sum P_{RDG} \tag{6}$$

where P_{RDG} is the sum of renewable energy generation in the DS.

7) MINIMIZATION OF CARBON EMISSIONS

This objective function equation seeks to reduce DS carbon emissions by evaluating the best sites for EV charging stations, DG, capacitors, DSTATCOM, and network reconfiguration. It may be stated as follows:

$$\text{Minimize} = \sum \mathrm{P}_{\mathrm{CO2,Emission}} \tag{7}$$

where $\sum \mathrm{P}_{\mathrm{CO2,Emission}}$ is the sum of carbon emissions in the DS.

8) MAXIMIZATION OF RELIABILIT

This objective function equation seeks to maximize DS dependability by selecting the best locations for EVCS and energy sources. It may be stated as follows:

$$\text{Maximize} = \sum \mathrm{P}_{Reliability} \tag{8}$$

where $\sum \mathbf{P}_{\boldsymbol{Reliability}}$ is the sum of reliability indices in the DS.

9) MAXIMIZATION OF ECONOMIC BENEFITS

This objective function equation seeks to maximize the DS's economic advantages by selecting the best locations for EV charging stations. It may be stated as follows:

$$\text{Maximize} = \sum \mathrm{P}_{Economic} \tag{9}$$

where $\sum \mathrm{P}_{Economic}$ is the sum of economic benefits in the DS.

10) MAXIMIZATION OF LOAD BALANCING

This objective function tries to maximize load balancing in the DS by optimizing the position and capacity of EV charging stations. The objective function can be expressed as follows:

$$Maximize = \sum \Delta P_{\mathrm{t}} \tag{10}$$

where $\sum \Delta P_{\mathrm{t}}$ is the deviation of the active power at bus t from its nominal value.

These goal functions might be blended and weighted based on the system's particular requirements. Furthermore, restrictions such as voltage limits, branch capacity limits, and budget constraints should be taken into account throughout the optimization process.

C. CONSTRAINTS

The consideration of critical parameters is imperative when addressing constraints within a system. It is crucial for the objective function to align with these constraints seamlessly. Failing to adhere to these limitations could lead to inadequate sizing and improper placement of components, potentially resulting in system malfunctions. The task of strategically planning the placement of EVCS involves navigating through a set of conditions, encompassing both equalities and inequalities. Once these EVCS units are integrated into the DS, a multitude of responsibilities arise, encompassing actual and reactive power compensation, voltage regulation at individual nodes, restrictions on current flow, and adherence to thermal thresholds.

Furthermore, it becomes essential to ascertain the optimal range of EVCS installations, setting the minimum and maximum thresholds. Additionally, the arrangement of EVCS units should account for appropriate spacing between them. The distance constraint takes into consideration the gaps between individual EVCS units. The pivotal restrictions inherent in the EVCS allocation quandary encompass the following factors.

1) POWER BALANCE

A formulation for power balance constraints, denoted by equalities, can be stated as follows.

$$\mathrm{P}_{\mathrm{T,Loss}} + \sum \mathrm{P}_{\mathrm{D(t)}} + \sum \mathrm{P}_{\mathrm{EVCS(t)}} = \sum (P_{\mathrm{ES(t)}}) \tag{11}$$

where, $\mathrm{P}_{\mathrm{D(t)}}$ is the power demand at two buses of t, $\mathrm{P}_{\mathrm{ES(t)}}$ is the power supplied by energy sources and $\mathrm{P}_{\mathrm{EVCS(t)}}$ is the load absorbed by EVCS.

2) VOLTAGE LIMIT

$$V_{t,\min} \leq |V_t| \leq V_{t,\max} \tag{12}$$

The boundaries for voltage at bus t are established through the employment of $V_{t,\min}$ and $V_{t,\max}$, which specify the lower and upper voltage limits, respectively.

3) REACTIVE POWER COMPENSATION

$$Q_{ES(t)}^{\min} \leq Q_{ES(t)} \leq Q_{ES(t)}^{\max} \quad t = 1, 2, \ldots\ldots\ldots nb \tag{13}$$

At bus t, there are minimum and maximum limits for the reactive power that can be compensated by energy sources, which are denoted as $\boldsymbol{Q_{ES(t)}^{min}}$ and $\boldsymbol{Q_{ES(t)}^{max}}$, respectively.

4) REAL POWER COMPENSATION

The power system must adhere to the constraint of real power, where the permissible limits of injected real power at each optimal bus must not be exceeded.

$$P_{ES(t)}^{\min} \leq P_{ES(t)} \leq P_{ES(t)}^{\max} \quad t = 1, 2, \ldots\ldots\ldots nb \tag{14}$$

where $\boldsymbol{P_{ES(t)}^{min}}$ is the minimum real power limits of compensated bus t and $\boldsymbol{P_{ES(t)}^{min}}$ is the maximum real power limits of compensated by energy sources at bus t.

5) BRANCH CURRENT

In order to ensure compliance with the maximum limit outlined in (15), it is crucial to observe the current $\boldsymbol{I_B}$ for every branch in the DS.

$$\boldsymbol{I_B} < \boldsymbol{I_{B,Max}} \tag{15}$$

where $\boldsymbol{I_B} < \boldsymbol{I_{B,Max}}$ is the maximum current flowing in the branch.

6) THERMAL CONSTRAINTS

It is essential to ensure that the thermal limit of a branch is set below its upper bound, as shown in the following representation.

$$S_B \leq S_{B,Max} \tag{16}$$

The apparent power of a branch is denoted as S_B, while the maximum allowable apparent power of the branch is represented as $S_{B,Max}$.

7) SOC OF BATTERY

To maintain the longevity of an EV's battery, it is essential to adhere to the permissible upper and lower limits of State of Charge (SOC) during both charging and discharging, as indicated in (17).

$$25\% \leq \text{SOC} \leq 90\% \tag{17}$$

D. ENERGY SOURCES

The most advanced EVCS have revolutionized the way we power our EVs by seamlessly integrating a wide array of energy resources and cutting-edge energy storage systems. This groundbreaking approach addresses the escalating power demands resulting from the surging population of EVs on our roadways, while also acting as a catalyst for the widespread adoption of renewable energy sources. The innovative EVCS harnesses an impressive spectrum of energy sources, effectively transforming the charging infrastructure landscape. By drawing from sources such as solar, wind, and hydroelectric power, it ensures a diversified and sustainable supply of electricity. This not only alleviates strain on conventional energy grids but also significantly reduces the carbon footprint associated with EV charging.

Furthermore, the integration of cutting-edge energy storage systems within the EVCS architecture contributes to a more resilient and reliable power network. These advanced storage solutions not only facilitate efficient energy distribution during peak charging periods but also allow for the accumulation of excess energy generated by renewables, which can then be utilized during periods of high demand or low renewable output. In embracing this multifaceted approach, the latest EVCS not only meets the immediate power requirements of the burgeoning EV market but also lays the foundation for a cleaner, greener, and more sustainable transportation ecosystem. This holistic strategy not only drives technological advancement but also incentivizes the ongoing development of renewable energy technologies, positioning us on a promising trajectory towards a more environmentally conscious future.

- ✓ Electrical Grid.
- ✓ Distributed Generation (DG).
- ✓ Capacitor
- ✓ DFACTS (DSTATCOM & SVC).
- ✓ Energy Storage System (ESS).
- ✓ Protective Devices.

1) ELECTRICAL GRID

The distribution of EVCSs for EVs depends on the electrical infrastructure. Most researchers minimize the impact of EVCS by utilizing the electrical grid as a source of energy for their study. Design engineers may assist guarantee that EVs are a viable and sustainable method of transportation by carefully developing and maintaining DS that can dependably transmit electricity to charging stations. The deployment and accessibility of EVCSs for EVs are intricately intertwined with the existing electrical infrastructure. To mitigate the potential impact of EVCSs on the overall energy landscape, numerous researchers have undertaken studies aimed at optimizing their integration with the electrical grid. By leveraging the power supply from the grid, these investigations seek to streamline the operation of EVCSs and ensure their harmonious coexistence within the broader energy ecosystem.

In this context, the expertise of design engineers becomes pivotal. Their role extends beyond conventional infrastructure design, as they are entrusted with the task of meticulously crafting and maintaining DS capable of reliably and efficiently transmitting electricity to charging stations. This undertaking carries profound implications for the viability and sustainability of EVs as a transformative mode of transportation. The intricate interplay between EVCSs and the electrical grid necessitates a holistic approach that addresses not only the technological aspects but also the societal and environmental considerations associated with widespread EV adoption. By orchestrating a seamless integration of EVCSs with the existing electrical infrastructure, researchers and design engineers alike contribute to shaping an electrified transportation future that is dependable, environmentally sound, and economically viable.

2) DISTRIBUTED GENERATION (DG)

DG refers to small-scale power production units that are interconnected with the distribution grid, encompassing technologies such as solar panels, wind turbines, and small-scale natural gas generators. In the context of sustainable energy solutions, the utilization of renewable DG systems gains prominence, presenting an innovative approach to alleviate the impact of EVCSs on the DS. By harnessing localized power sources, these DG systems play a pivotal role in bolstering system stability and enhancing overall grid resiliency. Numerous comprehensive studies have been conducted to explore the potential of both renewable and nonrenewable DGs as effective energy sources to mitigate the challenges posed by EVCS integration into distribution networks. A range of research endeavors have delved into this area, shedding light on the multifaceted benefits that renewable DGs can bring to the table. These studies underscore the significance of renewable DGs not only in reducing strain on the distribution infrastructure but also in paving the way towards a cleaner, more sustainable energy landscape. By strategically integrating renewable DG systems, such as solar and wind power, into the distribution grid, a dual objective is achieved. Firstly, the local generation of electricity near EVCSs minimizes the stress on the distribution network, effectively curbing potential overload and voltage fluctuations. Secondly, the deployment of renewable DGs aligns with broader environmental goals, enabling a reduction in greenhouse gas emissions and fostering the transition towards a low-carbon energy ecosystem.

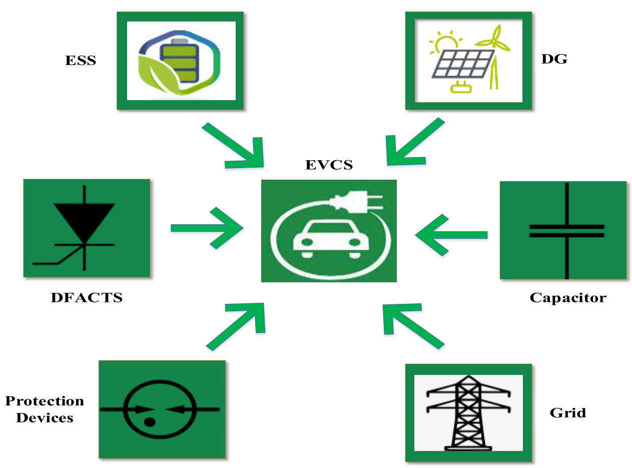

FIGURE 7. Energy sources for EVCS.

3) CAPACITOR

Reactive power management plays a pivotal role in optimizing the efficiency and performance of EVCSs and distribution substations. Through the strategic deployment of capacitors, both at EVCSs and within the distribution substation, a host of benefits can be harnessed to elevate the power infrastructure. One of the primary advantages lies in the capacitors' ability to inject reactive power into the system. This infusion of reactive power serves to augment the power factor, leading to a reduction in voltage losses and a consequent enhancement of the overall power quality. By mitigating voltage drops and minimizing wasteful losses, this approach not only fosters a more stable power supply but also extends the longevity of equipment and devices connected to the grid. A particularly noteworthy aspect of this endeavor is its synergy with EVs. By factoring in the reactive power demands of EVs, the incorporation of shunt capacitors can be leveraged to curtail distribution substation losses. This dual-effect mechanism not only promotes improved system efficiency but also translates into tangible energy savings. This energy conservation not only aligns with sustainability goals but also translates into cost-effective operational practices.

4) DFACTS (DSTATCOM & SVC)

Distributed Flexible AC Transmission System (DFACTS) technologies, specifically Distribution Static Compensator (DSTATCOM) and Distribution Static Var Compensator (DSVC), play a pivotal role in mitigating the challenges posed by EVCS on the DS. By intelligently manipulating voltage levels, improving power quality, and effectively distributing load, DSTATCOM and DSVC emerge as potent solutions to alleviate the potential disruptions caused by the integration of EVs into the power grid. This synergy of advanced technologies, as highlighted in references, offers a promising avenue to seamlessly integrate EVs into the power ecosystem while ensuring minimal impact on the distribution system. Through their dynamic voltage regulation and load-balancing capabilities, DSTATCOM and DSVC not only enhance the stability and reliability of the distribution network but also pave the way for a more sustainable and harmonious coexistence of EVs and traditional power infrastructure.

5) ENERGY STORAGE SYSTEM (ESS)

The surge in power demand due to widespread EV charging presents challenges such as voltage fluctuations and transformer overloads. Integrating Energy Storage Systems (ESS) with EVCS offers an innovative solution. This approach brings notable benefits, including peak shaving, voltage support, load balancing, and renewable integration. ESS, combined with EVCS, strategically manages energy. It stores excess energy during low demand and releases it during peak hours, reducing voltage fluctuations and transformer strain. ESS acts as a voltage regulator, maintaining stable voltage levels by injecting or absorbing power as needed. This proactive control enhances overall grid stability amid rapid EV charging.

ESS excels in load balancing, redistributing energy across phases and circuits to prevent overloads and optimize grid resources. It integrates renewable energy, capturing surplus power for high-demand periods, promoting renewables, and reducing carbon emissions from traditional sources. Incorporating ESS enhances EVCS adaptability, reducing distribution system impact and minimizing costly infrastructure changes. The combined effects of peak shaving, voltage support, load balancing, and renewable integration bolster grid resilience, facilitating harmonious EV-grid coexistence.

6) PROTECTIVE DEVICES

Safeguarding the stability and integrity of the DS in the face of EVCSs requires the strategic integration of protective devices. Fuses, circuit breakers, and surge protectors emerge as critical components in this defense against potential overloads stemming from EVCSs. These proactive measures serve as an intricate web of defense, promptly detecting and containing issues that may originate from EVCSs, thus preventing any detrimental ripple effects across the network. By deploying these protective devices, a two-fold objective is achieved. First, they act as vigilant sentinels, discerning anomalies attributed to EVCS operation, and promptly isolating them to prevent their escalation. Second, the introduction of these devices functions as a resilient barrier, mitigating the impact that EVCSs could exert on the DS. This delicate balance between safeguarding against disruptions and maintaining the reliability and safety of the entire system is a paramount consideration. The integration of protective devices introduces an added layer of sophistication to the management of EVCS-related challenges. These devices stand as a testament to engineering ingenuity, ensuring the smooth coexistence of EVCSs within the broader DS framework. In doing so, they bolster the resilience of the distribution infrastructure, assuring its ability to meet the demands of the present and the foreseeable EV-dominated future.

7) COMBINED ENERGY SOURCES

The integration of advanced technologies such as RDGs, energy storage systems, capacitors, and DFACTS presents a promising avenue for mitigating the potential adverse effects of EVCS on the DS. By synergistically harnessing these energy sources, the sustainable and efficient operation of EVCS can be realized, while simultaneously minimizing the overall impact on the distribution grid. RDGs offer a sophisticated framework for dynamically managing the reactive power flow within the distribution network. When intelligently integrated with EVCS, RDGs can proactively regulate voltage levels and enhance power quality, ensuring that the charging stations operate optimally without causing disruptions to the DS. Moreover, energy storage systems act as pivotal components, capable of storing surplus energy during periods of low demand and injecting it back into the grid during peak hours. This not only alleviates grid congestion but also facilitates a seamless charging experience for EVs, while concurrently bolstering the sustainability of the entire ecosystem.

Capacitors, renowned for their rapid response to fluctuations in power demand, further contribute to stabilizing the DS when harmoniously incorporated into EVCS infrastructure. Their swift discharge and recharge cycles provide an instantaneous counterbalance to load variations, thereby minimizing voltage drops and safeguarding the DS against potential instabilities. Meanwhile, the strategic deployment of DFACTS empowers grid operators to actively manage line impedance and regulate power flows. By intelligently optimizing the transmission parameters, DFACTS technology ensures that power is efficiently transported to charging stations, thereby enhancing operational efficiency and reducing losses. Through the judicious integration of these innovative technologies, the environmental footprint of EVCS can be substantially diminished. By effectively coordinating reactive power flows, harnessing surplus energy, swiftly responding to load changes, and optimizing power transmission, the operation of charging stations becomes not only sustainable but also harmoniously aligned with the overarching goals of grid stability and environmental preservation. In essence, this holistic approach guarantees the seamless delivery of power to EVCS while significantly minimizing their ecological impact, ultimately paving the way for a greener and more resilient energy landscape.

E. SERVICES AND TEST SYSTEMS

To enhance the dependability of the power grid and promote the adoption of EVs, various services are being offered to owners of EVs and parking lots. These services include (i) V2G, (ii) G2V (iii) P2G, and (iv) P2V. The above services are tested on standard and real-time practical distribution test systems for EVCS allocation problems with various energy sources. The majorly used test systems in the literature are: IEEE 9-bus test system, IEEE 15-bus test system, IEEE 24-bus test system, IEEE 30-bus test system, IEEE 33-bus test system, IEEE 34-bus test system, IEEE 37-bus test system, IEEE 38-bus test system, IEEE 51-bus test system, IEEE 54-bus test system, IEEE 69-bus test system, IEEE 84-bus test system, IEEE 85-bus test system, IEEE 118-bus test system, IEEE 123-bus test system, Modified IEEE 15-bus and 43-bus test systems [45], Unbalanced IEEE 19-bus test system, Unbalanced IEEE 25-bus test system, Practical Guwahati DS, Practical Changping, Beijing DS, Roy Billinton DS, Practical Allahabad DS, Alibeykoy and Hadimkoy DS in Istanbul, Turkey Practical DS in Singapore, Practical 31-bus DS in China, Industrial park in Shanghai, China, Practical distribution network of Nanjing, China, "Practical DS National University of Sciences and Technology in Pakistan, Washington D.C. transportation network, Practical 83-bus Taiwan DS, Indian 28-bus DS and Practical DS in Ireland, practical Brazil 136-bus RDS.

V. EMERGING TRENDS AND CONSIDERATIONS IN ELECTRIC VEHICLE CHARGING INFRASTRUCTURE

A. REAL-WORLD IMPLEMENTATIONS FOR INTEGRATING RENEWABLE ENERGY INTO EVCS

The integration of renewable energy sources into EVCS represents a pivotal step in the journey toward establishing a more ecologically sustainable and environmentally conscious transportation ecosystem. Through the utilization of renewable energy, particularly harnessed from sources such as solar and wind power, EV charging is poised to undergo a transformation that will significantly diminish its environmental impact and contribute to the reduction of the carbon footprint associated with EVs. In the realm of scholarly research, it is essential to delve into the tangible manifestations of this transition, examining the real-world implementations and innovative technologies that underpin this process. Consequently, this research article aims to provide insights into the practical cases and cutting-edge technologies employed to seamlessly integrate renewable energy sources into EVCS, elucidating the pivotal role they play in advancing sustainable transportation practices [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75].

1) TESLA SUPERCHARGER NETWORK

Tesla has implemented solar canopies with integrated solar panels at many of their Supercharger stations. These canopies not only provide shade for parked vehicles but also generate clean solar energy to offset the charging stations' power needs [65].

2) ENVISION SOLAR'S EV ARC

Envision Solar's EV ARC (Electric Vehicle Autonomous Renewable Charger) is a mobile charging station that is entirely powered by solar energy. It requires no grid connection and can be deployed in various locations, providing off-grid EV charging [66].

3) VIRTA'S DYNAMIC LOAD MANAGEMENT

Virta, a European EV charging platform, employs dynamic load management to optimize the use of renewable energy sources. By monitoring real-time grid conditions, the platform intelligently allocates renewable energy for charging EVs [67].

4) NISSAN'S VEHICLE-TO-GRID (V2G) TECHNOLOGY

Nissan has developed V2G technology that allows Nissan EVs to not only charge from the grid but also discharge back into the grid. This enables the vehicle's battery to serve as a mobile energy storage unit, contributing to grid stability and supporting renewable energy integration [68].

5) ALLEGO'S ULTRA-FAST CHARGING STATIONS

Allego, a European charging infrastructure provider, integrates renewable energy sources into their ultra-fast charging stations. By sourcing electricity from local renewable projects, they ensure that the energy used for charging is as sustainable as possible [69].

6) EVGO'S RENEWABLE ENERGY PARTNERSHIPS

EVgo, a leading U.S. public fast-charging network, partners with renewable energy providers to procure wind and solar energy for their charging stations. This ensures a significant portion of the energy supplied to their stations comes from renewable sources [70].

7) CHARGEPOINT'S EXPRESS PLUS

ChargePoint's Express Plus charging stations are designed to be highly scalable and grid-integrated. They can be configured to take advantage of renewable energy sources, helping to reduce the carbon footprint associated with EV charging [71].

8) ABB'S TERRA HP CHARGING STATIONS

ABB's Terra HP high-power charging stations are capable of integrating with renewable energy sources, such as solar or wind, to provide fast and sustainable charging options for EVs [72].

9) EFACEC'S QC45 ULTRA-FAST CHARGER

Efacec's QC45 charger allows for easy integration with renewable energy sources. It can be connected to solar panels or wind turbines, providing a green charging solution [73].

10) EMOTORWERKS' JUICENET GREEN

eMotorWerks, a subsidiary of Enel X, offers JuiceNet Green, a platform that allows EV owners to charge their vehicles when renewable energy generation is at its peak, minimizing reliance on non-renewable sources [74].

These real-world implementations and innovative technologies showcase the tangible progress being made toward making EV charging more sustainable and aligned with renewable energy sources, contributing to a cleaner and more eco-friendly future of transportation.

B. ADDRESSING FLUCTUATIONS IN EV LOAD MODELING: STRATEGIES AND INNOVATIONS

The surge in EV adoption heralds a promising shift towards sustainable transportation. However, this transition presents a unique challenge: the unpredictability of user behavior, which can lead to fluctuations in power demand. This poses a significant concern for grid stability and necessitates innovative solutions. Below are suggested insights and potential solutions to address this challenge, ranging from advanced demand forecasting methods to the integration of smart grid technologies:

1) ADVANCED DEMAND FORECASTING

Employ advanced demand forecasting methods that integrate historical data, user behavior analysis, and real-time inputs to predict EV charging patterns accurately. This helps grid operators anticipate and accommodate load variations effectively [75].

2) SMART CHARGING INFRASTRUCTURE

Invest in intelligent charging infrastructure that can communicate with both the grid and individual EVs. These systems enable dynamic adjustments in charging rates based on real-time grid conditions, reducing load fluctuations [76].

3) V2G INTEGRATION

Promote V2G technology, allowing EVs to discharge excess energy back into the grid during peak demand periods. V2G integration helps stabilize the grid and minimize load variability [76].

4) ENERGY STORAGE SYSTEMS

Incorporate Energy Storage Systems (ESS) at charging stations or within the grid. ESS can store surplus energy during low-demand periods and release it during high-demand times, acting as a buffer against load fluctuations [77].

5) COORDINATED CHARGING SCHEDULES

Implement coordinated charging schedules at the aggregator level, ensuring that EVs are charged and discharged strategically to reduce power fluctuation levels. This approach enhances load management [76].

6) DYNAMIC DEMAND RESPONSE

Develop a dynamic demand response program that incentivizes EV owners to adjust their charging times based on grid conditions and peak demand hours. This enables more controlled load distribution [77].

7) REAL-TIME DATA ANALYTICS

Leverage real-time data analytics to monitor and manage EV loads continuously. Grid operators can make data-driven decisions and apply load-shifting strategies to balance power consumption [78].

8) COMMUNICATION INFRASTRUCTURE

Strengthen communication infrastructure that facilitates seamless data exchange between EVs, charging stations, and the grid. Efficient communication enables real-time load adjustments and minimizes unexpected fluctuations [77].

9) SMART GRID TECHNOLOGIES

Embrace smart grid technologies, including advanced metering infrastructure (AMI) and grid sensors. These technologies enhance grid visibility, allowing for better control over energy consumption patterns and grid stability [79].

10) REGULATORY SUPPORT

Establish clear regulatory frameworks and policies that promote EV load management and V2G integration. Regulatory support is crucial for driving adoption and ensuring compliance with grid-friendly practices [78].

These suggestions and potential solutions empower grid operators and stakeholders to address the challenge of fluctuations in EV load modeling effectively. By implementing a combination of advanced technologies, demand forecasting, and demand response strategies, the power grid can accommodate the growing EV market while maintaining stability.

C. OPTIMIZING EV CHARGING PATTERNS SCHEDULING FOR GRID EFFICIENCY

The surge in vehicle electrification is poised to make a substantial impact on the power grid, primarily due to the increased demand for electricity. This shift will inevitably alter the overall load profile of the electric system, owing to the introduction of EV charging and discharging. The charging activities of a substantial population of EVs can exert a noteworthy influence on the power grid. It has been projected that in the U.S., the cumulative charging load from EVs could potentially reach up to 18% of the peak load during summer, provided the EV penetration reaches 30% [80]. Conversely, EVs can also function as energy sources for the power grid through a process known as V2G [81]. The implementation of an intelligent scheduling scheme holds the capacity to strategically plan EV charging patterns, consequently smoothing out the load profile of the electric system. This measure can lead to a reduction in capital costs and operational expenses. Intelligent scheduling for EV charging and discharging has emerged as a crucial stride towards the realization of smart grids [82]. The fundamental principle underpinning intelligent scheduling lies in reshaping the load profile by orchestrating the charging of EV batteries from the grid during periods of low demand, and discharging them back to the grid during peak demand periods. However, achieving optimal patterns of EV charging and discharging poses a challenge. Firstly, attaining a globally optimal scheduling solution that minimizes overall charging costs, especially in the context of a large EV population, is a complex task. Secondly, any scheduling scheme must possess the flexibility to effectively manage the sporadic arrivals of EVs [83].

The pivotal role that optimal scheduling plays in optimizing EVCS utilization and mitigating its impact on the grid is of paramount importance. Optimal scheduling in EVCS usage holds paramount importance in several key aspects.

1) LOAD BALANCING

Effective scheduling ensures an equitable distribution of charging sessions across the grid, averting the risk of overloading specific areas or substations. This, in turn, minimizes grid congestion and mitigates potential power quality issues.

2) PEAK DEMAND MANAGEMENT

Strategically timed charging sessions help divert demand away from peak periods, alleviating stress on the grid during times of heightened electricity consumption. This proactive approach reduces the necessity for costly infrastructure upgrades.

3) RENEWABLE ENERGY INTEGRATION

Scheduling can be synchronized with periods of heightened renewable energy generation, such as during sunny or windy conditions. This strategic alignment guarantees that EVs are charged using clean energy, curbing reliance on fossil fuels and curbing greenhouse gas emissions.

4) GRID RESILIENCE AND STABILITY

Controlled scheduling empowers grid operators to adeptly handle abrupt surges in demand, bolstering overall grid stability and fortitude against unforeseen events or disruptions.

5) DEMAND RESPONSE IMPLEMENTATION

Through scheduling, EV charging rates can be dynamically adjusted in response to real-time grid conditions. This facilitates demand response programs, allowing for modulation of charging rates to support grid stability during periods of stress or imbalance.

6) COST OPTIMIZATION

Scheduling allows for the implementation of time-of-use pricing strategies, incentivizing EV owners to charge during off-peak hours when electricity rates are lower. This culminates in cost savings for consumers.

7) USER CONVENIENCE AND FLEXIBILITY

Scheduling systems afford users the ability to establish preferred charging times, ensuring that their vehicles are ready for use without placing undue strain on the grid.

8) GRID-INTEGRATED PLANNING

When EV charging schedules are factored into grid planning and expansion, it enables more efficient sizing and placement of charging infrastructure, harmonizing with overall grid capacity.

9) REDUCTION OF GRID UPGRADES

Efficient scheduling has the potential to reduce the need for costly grid upgrades by managing demand in a way that aligns with existing infrastructure capabilities.

10) ENVIRONMENTAL IMPACT MITIGATION

By optimizing charging schedules, it's possible to align EV charging with periods of high renewable energy availability, thereby reducing the carbon footprint associated with charging.

D. INTEGRATION OF DSM AND V2G IN EVCS ALLOCATION

1) BENEFITS OF DSM IN EVCS ALLOCATION

The benefits of integrating DSM and V2G in EVCS allocation presented as bullet points:

Enhanced Grid Stability and Reliability: DSM and V2G integration allows for dynamic responses to grid conditions, ensuring stable voltage levels and grid frequency.

Reduced Grid Congestion and Overloads: By utilizing V2G capabilities, excess energy from EVs can be fed back into the grid during peak demand, reducing stress on the grid.

Optimized Energy Utilization: DSM and V2G balance supply and demand, leading to more efficient use of available resources.

Minimized Environmental Impact: Through intelligent charging and discharging, the integration reduces reliance on carbon-intensive power generation methods.

Cost Savings for Consumers and Utilities: Integration can lead to reduced energy costs for EV owners and potential revenue streams through grid services, benefiting both consumers and utilities.

Facilitation of Renewable Energy Integration: The integration synchronizes EV charging and discharging with renewable energy generation patterns, making it easier to integrate clean energy sources.

Grid Support During Emergencies: V2G capabilities can provide critical support in times of grid instability or emergencies, acting as a temporary power source or stabilizing the grid.

Promotion of Grid Modernization: The integration encourages the adoption of advanced technologies, promoting a more modern, efficient, and adaptive grid infrastructure.

Flexibility and Adaptability: DSM and V2G integration offers a flexible approach to energy management, allowing for adjustments based on real-time grid conditions, energy prices, and user preferences.

Improved Resilience to Supply Shortages: By actively managing energy flows, DSM and V2G integration helps ensure a steady power supply even in situations where the grid faces limitations or shortages.

2) ISSUES AND CHALLENGES IN IMPLEMENTING DSM IN EVCS ALLOCATION

The challenges associated with implementing DSM in EVCS allocation underscore the intricate considerations involved in optimizing energy consumption within the realm of EV charging. Each of these challenges addresses a specific facet of DSM integration, underscoring their critical role in achieving a successful and efficient implementation [84], [85], [86].

- Residential loads contribute significantly to peak demand, straining the grid system's capacity.
- Adapting pricing blocks to consumption levels can be complex.
- Selecting the most effective load scheduling approaches is crucial.
- Centralized controllers are needed for various control options, but balancing energy savings for clients and profits for utilities can be challenging.

- Consumer response to pricing signals varies, influenced by factors like adaptability, indifference to minor tariff changes, and awareness of pricing systems.
- Scalability measures are lacking for handling multiple vendors, upgrades, and expansions.
- Robust privacy measures are necessary to protect customer information.
- The neighbor effect can influence consumer behavior based on perceived price rates.
- A generalized operational framework for DSM participants is essential for providing energy consumption control.
- Balancing peak load reduction with user comfort and choice is a key consideration.
- Integration of volatile power sources like wind and solar can impact grid stability.

These challenges represent the complexities and considerations involved in implementing DSM in EVCS allocation and optimizing energy consumption within the grid system.

3) SUGGESTED SOLUTIONS METHODS

The suggested solutions methods for incorporating DSM and V2G in EVCS allocation are given below [86], [87]:

Load Management and Scheduling: Utilize DSM techniques to intelligently schedule and manage EV charging sessions based on grid conditions, user preferences, and cost-effective time slots.

Grid Support and Stability: Implement V2G capabilities to allow EVs to feed excess energy back into the grid during peak demand, helping stabilize the grid and alleviate stress on the system.

Price-Based Charging: Apply time-of-use pricing models to incentivize EV owners to charge during off-peak hours, reducing strain on the grid during high-demand periods.

Intelligent Charging Infrastructure: Install advanced charging infrastructure that can communicate with both the grid and individual EVs, enabling dynamic adjustments in charging rates based on real-time grid conditions.

DR Programs and Incentives: Offer incentives for EV owners to participate in demand response programs, allowing utilities to curtail or adjust charging during periods of grid congestion.

Energy Storage Integration: Integrate energy storage systems (ESS) with the charging infrastructure to store excess energy and provide it back to the grid when needed, enhancing grid reliability.

These methods collectively enhance the effectiveness and coordination of DSM and V2G implementation in EVCS allocation, contributing to a more efficient and sustainable EV charging infrastructure.

4) REAL TIME IMPLEMENTATION

In the article [88], a specific system architecture for Demand Side Management (DSM) of EVs operating in real-time urban areas was proposed and discussed. The study thoroughly examined the required data throughput for this system. The article delved into the communication requirements necessary for managing EVs within urban environments, with a particular focus on enabling mobile communication between EVs and smart grids. Additionally, it introduced a novel approach - a V2G Low-Power Wide-Area Network (LPWAN) infrastructure using LoRaWAN technology [88].

The step-by-step implementation for DSM of EVs in real-time urban areas covered the following key points:

Feasibility Testing: The study assessed the feasibility of the V2G LPWAN infrastructure by establishing mobile communication links between an EV and the LoRaWAN infrastructure of A2A Smart City in Brescia, Italy.

Interaction Between EVs and Power Grids: The article examined the intricate interactions between EVs and power grids. It emphasized the importance of DSM strategies for intelligent EV charging, particularly focusing on the V2G concept.

Operational and Management Objectives: Four main objectives were identified and discussed, namely medium-term operational planning, day-ahead optimal scheduling, intraday optimal scheduling, and real-time emergency grid control.

Communication Requirements for V2G DSM: The article analyzed the communication requirements for each operational scenario, including considerations such as data volume, refresh intervals, and the nature of communication (e.g., communication while the EV is in motion or connected to Electric Vehicle Supply Equipment).

System Architecture for Intraday DSM: The study proposed a specific architecture for implementing intraday DSM for EVs in urban areas. It introduced the concept of the Electric Vehicle Mobile Service Provider (EV-MSP), which was responsible for bidirectional communication with EVs and providing services to EV aggregators.

Data Exchange Procedure: The article detailed a structured procedure for data exchange, specifying the content, size of transmitted information, and required refresh intervals for functions like EV monitoring, EVSE (Electric Vehicle Supply Equipment) information provisioning, and V2G Demand Response (DR) requests.

Data Throughput Estimates: The study estimated the data throughput requirements for various functions, emphasizing the need for specific bandwidths for functions like EV monitoring and EVSE information provisioning.

LPWAN Technology for Mobile Communication: The article proposed the utilization of a Low-Power Wide-Area Network (LPWAN), specifically LoRaWAN, as an innovative approach to mobile communication between EVs and aggregators. This technology was presented as a complementary or alternative solution to traditional cellular-based approaches.

Communication Architecture With LoRaWAN: A specific communication architecture based on LoRaWAN technology was introduced, and its scalability was discussed in accordance with the defined communication requirements.

Scalability Assessment: The study's results demonstrated that each LoRa base station had the capability to serve a significant number of EVs and EVSEs, highlighting the scalability potential of the proposed solution.

Feasibility Demonstration: The article successfully showcased the feasibility of the proposed V2G LPWAN solution within an existing LoRaWAN infrastructure. It demonstrated the transmission of essential data related to EV battery state, vehicle and user identification, geographic coordinates, and acquisition timestamps.

The article offered a comprehensive analysis and a forward-thinking solution for the practical implementation of DSM in EVCS allocation, using the innovative V2G LPWAN infrastructure based on LoRaWAN technology, specifically designed for real-time urban scenarios [88].

E. LEGAL AND ECONOMIC CONSIDERATIONS IN THE PLACEMENT OF EVCS

The integration of EVCS into electric power systems necessitates a comprehensive examination of both legal and economic facets. Regulatory frameworks at local, state, and federal levels play a pivotal role in determining the permissibility and procedural requirements for EVCS deployment, encompassing zoning ordinances, building codes, and requisite permits [89]. Ensuring accessibility in compliance with the Americans with Disabilities Act (ADA) is imperative, entailing adherence to stipulations governing parking space dimensions, signage, and accessibility routes [90]. Moreover, considerations of land use and zoning are crucial, encompassing determinations of suitable deployment locations based on factors such as commercial or residential designations and proximity to essential facilities. Intellectual property considerations may arise, necessitating licensing agreements or addressing patent infringement issues depending on the technology employed [91]. Grid impact and capacity planning are paramount, requiring assessments and preparations by utility companies to accommodate heightened demand and prevent overloads. Interconnection agreements with utility providers delineate the terms of integrating EVCS with the grid, including technical specifications, responsibilities, and compensation arrangements. Liability concerns necessitate robust insurance coverage and contingency plans in the event of accidents or malfunctions [92]. Environmental compliance encompasses adherence to regulations governing hazardous materials and emissions standards, particularly with regards to battery disposal and emissions [93]. Safeguarding data privacy and security is imperative given the potential collection of user information and charging histories by EVCS, obliging adherence to relevant data protection laws and implementation of robust security measures. Contractual agreements between property owners, EVCS operators, and third-party entities should be clearly defined, covering maintenance protocols, revenue-sharing arrangements, and delineation of responsibilities [94]. Participants in the EVCS ecosystem may contemplate participation in energy markets such as demand response programs, necessitating a thorough understanding and compliance with relevant market regulations. Selling electricity from EVs involves navigating complex regulatory, billing, pricing, and grid management considerations. Agreements, data privacy measures, and liability plans are essential. Clear consumer protections and fair market practices are vital. Technological integration for grid interaction is crucial. Balancing these factors is key to a successful EV-based electricity sales model, advancing sustainable charging infrastructure [95].

F. THE ROLE OF EVs IN GRID FLEXIBILITY SERVICES

This section emphasizes the potential of EVs in providing flexibility for voltage control and congestion issues. Integrating EVs into flexibility services is a growing trend with substantial benefits, including demand response, peak shaving, and grid stabilization. Challenges such as V2G infrastructure, regulatory frameworks, and standardization need addressing. Generally, DSOs favored grid reinforcement over active demand management. However, with EVs proving efficient flexibility providers, they can reduce infrastructure needs, enhance congestion management, and aid in voltage control. Market design adaptations are essential [96]. The integration of EVs into power systems, especially distribution grids, presents challenges and opportunities. Identifying key technical and economic aspects is crucial. Recent advances and increased regulatory interest show promise [97]. Decentralized energy flexibility management is the most profitable strategy, benefiting both end users and aggregators. Smart strategies, treating end user flexibility as an interruptible load, and shiftable load constraints enhance profitability [98]. A method was developed to reduce load impact on charging service quality, with specific sites showing significant potential for flexibility. Office and residential sites prove most flexible for the power system, while shopping centers have a more substantial impact on service quality [99]. This study provides insights into the flexibility behavior of different vehicle fleets. The logistics site exhibits consistent charging profiles and high flexibility, distinguishing it from office and public agency sites. These findings hold implications for smart charging and ancillary services provision [100]. Seamless integration of EVs into distribution systems for grid operation and planning is crucial. Identifying technical, economic, and regulatory obstacles, along with recent advancements, is key to future applications [101].

Several technical hurdles impeded the development of flexibility services at the distribution level [101]. These included:

1) OBSERVABILITY IN DISTRIBUTION GRIDS

There was a demand for heightened observability by Distribution System Operators (DSOs) in near-real-time, enabling accurate forecasting and swift flexibility activation.

2) BATTERY AGING

A critical factor influencing economic viability and user acceptance of grid services, necessitating comprehensive examination in the context of distribution grid services, which could be more energy-intensive than frequency response services.

3) CHARGING TECHNOLOGY

Bidirectional chargers, while promising, were still in the nascent stage. Cost and round-trip efficiency remained concerns, though a decline in costs and potential additional functionalities, such as reactive power compensation, were anticipated.

4) ECONOMIC AND INSTITUTIONAL BARRIERS

The primary challenges in advancing EV flexibility pertained more to economic and institutional aspects:

Active Management of Distribution Grids: DSOs needed to transition from a passive approach to proactive grid management, necessitating the development of new roles and responsibilities. Regulators played a crucial role in incentivizing innovation and cost-efficiency.

EV Integration Status in the Grid: V2G-capable EVs faced notable regulatory and technical hurdles. Streamlined and standardized connection procedures, along with tailored metering options, were recommended.

DSO-TSO Cooperation: Enhanced cooperation and coordination between DSOs and Transmission System Operators (TSOs) were imperative for integrating flexibility across all grid levels, ensuring a secure and reliable power system.

Value Frameworks for Flexibility: Mechanisms for leveraging flexibility at the distribution level were still evolving, with ongoing projects like flexibility tenders and Network Access Rights (NWAs) serving as promising developments.

Value of Services: As the utilization of flexibility at the distribution level was a burgeoning field, the precise value derived from offering such services remained uncertain. Further research was needed to fully understand the additional value that V2G technology could bring compared to smart charging.

In recent years, significant strides were made in this domain, with regulators exhibiting a growing interest in tapping into local flexibility from diverse sources and promoting intelligent management of DERs. These advancements signaled a promising trajectory toward a more flexible and resilient grid infrastructure.

G. INTEGRATION OF V2G SERVICES IN SOC ANALYSIS FOR EVs

In the realm of EVs, SOC analysis plays a pivotal role in optimizing battery performance and ensuring efficient energy management. However, as the landscape of energy systems evolves, an increasingly important aspect is the integration of EVs into V2G services. V2G technology empowers EVs not only to draw power from the grid but also to feed excess energy back into the grid, transforming them into mobile energy storage units with the potential to provide invaluable grid support.

In the context of SOC analysis, it is essential to expand the discussion to incorporate the prospects and implications of V2G services. This entails considering the required state of charge of the EV battery after delivering V2G services. Defining the minimum SOC that must be maintained in the battery post-service is critical to ensure the vehicle's operational readiness or meet specific regulatory and operational requisites. Striking this balance is imperative to ensure that participating in V2G services does not compromise the primary function of the EV, which is transportation.

The integration of V2G services into SOC analysis requires a comprehensive understanding of the technical, economic, and regulatory aspects. This encompasses a thorough evaluation of the battery's charge and discharge characteristics, the impact on battery degradation, and the potential economic incentives and revenue streams for EV owners. Additionally, the integration necessitates addressing challenges such as V2G infrastructure, regulatory frameworks, and standardization to facilitate widespread adoption.

To support this expanded discussion, various studies and research articles offer valuable insights into SOC analysis, V2G technology, and the intricate relationship between EVs and grid services. Notable references include for a comprehensive overview of SOC analysis, for an exploration of V2G technology and its potential, and for insights into the economic and regulatory aspects of V2G services. By delving into these sources, this research article provides a holistic perspective on the evolving landscape of EVs in the context of grid integration, SOC analysis, and V2G services, contributing to the advancement of sustainable and responsive energy systems [102], [103], [104].

1) SOC EQUATIONS WITH V2G SERVICES

Incorporating V2G services into the SOC analysis adds a layer of complexity to the mathematical modeling of EV battery dynamics. The following set of equations provides a comprehensive framework that accounts for the bidirectional flow of energy between the battery and the grid. These equations not only capture the charging and discharging processes but also introduce V2G services, allowing the EV to actively contribute power back to the grid. This enhanced model ensures that the SOC remains within predefined limits, balancing the requirements for grid support with the need to maintain sufficient charge for continued vehicle operation.

2) BATTERY STATE OF CHARGE (SOC) DYNAMICS WITH V2G SERVICES

The SOC of a battery at any given time (t) considering V2G services can be represented as:

$$\begin{aligned} SOC(t) = SOC(t-1) &+ \left(\eta_{charge} * P_{charge}(t)\right) \\ &- \left(\frac{1}{\eta_{discharge}} * P_{discharge}(t)\right) \\ &- \left(\frac{1}{\eta_{discharge}} * P_{V2G}(t)\right) \end{aligned} \tag{18}$$

where, $SOC\ (t)$ is the state of charge at time t; η_{charge} is the charging efficiency; $P_{charge}\ (t)$ is the charging power at time t; $\eta_{discharge}$ is the discharging efficiency; $P_{discharge}(t)$ is the discharging power at time t; and $P_{V2G}\ (t)$ is the power sent back to the grid during V2G operation.

3) V2G SERVICES POWER CALCULATION

The power sent back to the grid during V2G operation can be determined by:

$$P_{V2G}\ (t) = min(P_{discharge}\ (t)\ , P_{V2G(max)}) \tag{19}$$

where, $P_{V2G(max)}$ is the maximum power that can be provided to the grid.

4) V2G EFFICIENCY

The efficiency of V2G services (η_{V2G}) can be considered, though it's typically less than 100% due to losses in the bidirectional power conversion process:

$$P_{V2G(actual)} = P_{V2G}\ (t) * \eta_{V2G} \tag{20}$$

where, $P_{V2G(actual)}$ is the actual power sent back to the grid; and η_{V2G} is the V2G efficiency.

These equations represent a more comprehensive model that takes into account the impact of V2G services on the battery's state of charge. It ensures that while providing grid services, the SOC of the battery is maintained within acceptable limits for continued vehicle operation. Keep in mind that specific parameters and efficiencies will vary based on the specific EV and V2G system being analyzed.

H. THE USE OF CARPORTS IN END-USER INSTALLATIONS

Carports serve as a versatile solution, especially in the context of EV adoption and the deployment of EVCS. They offer dual benefits by protecting vehicles from the elements and augmenting property value with solar panels. Integrated with EVCS, carports create a dedicated, convenient area for EV charging. For commercial sites, carports with EVCS provide a protected environment while generating clean energy on-site, offering potential advertising spaces and reducing parking lot maintenance costs. Carports, when combined with EVCS, optimize solar energy capture and offer opportunities for surplus energy storage or selling back to the grid, further supporting EV electrification efforts. This technology-oriented concept facilitates EVCS, utilizing onsite solar energy for EV charging and enabling G2V and V2G functionalities [105], [106].

Carports play a pivotal role in the integration of EVs into end-user installations, offering a range of benefits [107]:

Protection for EVs: Carports shield EVs from harsh weather, ensuring their longevity and reducing maintenance costs.

Integrated Charging Stations: They provide an optimal framework for incorporating EV charging stations, creating a dedicated and weather-resistant area for convenient charging.

Space for Charging Infrastructure: Carports can house various charging equipment, making them a crucial component of an EV owner's charging setup.

Solar Integration: Equipped with solar panels, carports serve as a sustainable energy source for EV charging, promoting clean energy adoption in transportation.

Enhanced Aesthetics and Property Value: Stylish carports, especially those with integrated EV charging, not only complement a home's exterior but also increase its value, appealing to the growing EV market.

Energy Efficiency: Compared to traditional garages, carports are more energy-efficient, requiring fewer resources for lighting and electronic systems, aligning with the sustainable ethos of electric mobility.

Multi-Vehicle Housing for EV Fleets: They provide an effective solution for housing multiple EVs, making them an excellent choice for homeowners with EV fleets.

Savings on Storage and Charging Costs: Carports can replace the need for off-site EV storage facilities, resulting in significant cost savings for EV owners.

Customized Design for EV Integration: Carports with integrated EV charging stations can be tailored to harmonize with the property's aesthetic, enhancing its overall appeal.

Efficient Organization for Charging Equipment: Carports enable the efficient organization of charging equipment, ensuring easy access while keeping it separate from indoor spaces.

By merging carports with EVCS and EVs, homeowners can establish a comprehensive and sustainable charging infrastructure that not only protects their vehicles but also contributes to the broader adoption of electric transportation.

I. RANDOMNESS IN EV GRID CONNECTIONS: CHARGING AND DISCHARGING SCENARIOS

The integration of EVs into the electrical grid introduces a dynamic and somewhat unpredictable element, characterized by the randomness associated with connecting these vehicles to the grid in both charging and discharging scenarios. This unpredictability arises from several factors. Firstly, in the charging context, EV owners exhibit varying behaviors and preferences in terms of when and how they charge their vehicles. Some may opt for overnight charging, taking advantage of off-peak electricity rates, while others might choose to charge during the day or at public charging stations. Additionally, the availability of charging infrastructure can impact the timing and frequency of EV connections, with factors such as home charging stations, workplace chargers, and public charging networks all contributing to this variability. Furthermore, the introduction of V2G technology adds another layer of complexity to this randomness.

In the discharging context, EVs have the potential to act as mobile energy storage units, capable of injecting electricity back into the grid. However, the decision to discharge power is contingent on a multitude of factors, including grid demand, grid stability, and the financial incentives offered to EV owners. This introduces an element of unpredictability, as the decision to discharge power is influenced by real-time conditions and market dynamics. Moreover, factors such as individual driving patterns, trip schedules, and user preferences further contribute to the stochastic nature of EV grid connections. For example, some users may return home from work with a significant amount of charge remaining in their vehicle, presenting an opportunity for grid discharging. Others may arrive home with a lower state of charge, prioritizing the need to charge their vehicle for upcoming trips. This variability in user behavior introduces an element of randomness, making it challenging to precisely predict when and how EVs will be connected to the grid. Overall, the randomness associated with connecting EVs to the grid underscores the need for advanced grid management strategies and technologies. These may include demand forecasting models, smart charging algorithms, and real-time communication systems between vehicles and the grid. Effectively harnessing the potential of EVs in grid operations requires a nuanced understanding of this inherent randomness and the development of adaptive solutions to ensure a reliable and stable energy ecosystem. Give subheadings for charging and discharging [108], [109].

VI. DETAILED REVIEW OF EVCS ALLOCATION

Numerous pieces of research within existing literature have delved into the allocation of energy sources in distribution systems that lack EVCS. These studies have employed a variety of objective functions and optimization methodologies. However, there is a noticeable dearth of literature concerning the allocation of EVCS, as the research in this particular area is still in its preliminary stages. Only a limited number of investigations have tackled the challenge of EVCS allocation while considering energy sources. Furthermore, a significant body of scholarly work exists that pertains to the simultaneous installation of EVCS alongside DGs and devices like DSTATCOM/capacitors. A comprehensive overview of recent contributions in the realm of EVCS planning is presented in Table 1 to 6 [43], [44], [45], [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125], [126], [127], [128], [129], [130], [131], [132], [133], [134], [135], [136], [137], [138], [139], [140], [141], [142], [143], [144], [145], [146], [147], [148], [149], [150], [151], [152], [153], [154], [155], [156], [157], [158], [159], [160], [161], [162], [163], [164], [165], [166], [167], [168], [169], [170], [171], [172], [173], [174], [175], [176], [177], [178], [179], [180], [181], [182], [183], [184], [185], [186], [187], [188], [189], [190], [191], [192], [193], [194], [195], [196], [197], [198], [199], [200], [201], [202], [203], [204], [205], [206], [207]. This review encompasses diverse aspects such as the incorporation of DG, Capacitors, Network Reconfiguration (NR), BESS, protective devices, and DSTATCOM across various types of distribution systems. The review also encompasses a wide array of optimization techniques and objective functions.

Numerous strategies have been employed to determine the optimal solution for sizing and locating EVCS. A comparative analysis, presented in Table 1-6, highlights various optimization methods used in addressing the challenges of EVCS siting and sizing. Furthermore, several studies have explored diverse approaches to effectively place EVCS. These methodologies hinge on the choice of objective functions, utilization of solution techniques, consideration of experimental setups and constraints, as well as integration of energy sources. Further, this comprehensive research article provides an in-depth visual representation of EVCS allocation strategies, meticulously examined across Figures 8 to 13. These figures encapsulate insights gleaned from a diverse array of sources, encompassing the electrical grid (Figure 8) [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125], [126], [127], [128], [129], [130], [131], [132], [133], [134], [135], [136], [137], [138], [139], [140], DG (Figure 9) [43], [44], [45], [141], [142], [143], [144], [145], [146], [147], [148], [149], [150], [151], [152], [153], [154], [155], [156], [157], [158], [159], [160], [161], [162], [163], [164], [165], [166], [167], [168], [169], [170], [171], [172], [173], [174], DG coupled with ESS (Figure 10) [175], [176], [177], [178], [179], [180], [181], [182], [183], [184], [185], [186], [187], [188], [189], [190], [191], as well as capacitors and DG (Figure 11) [192], [193], [194], [195], [196], [197], [198]. Additionally, the analysis extends to DFACTS and DG (Figure 12) [199], [200], [201], [202], and delves into protective devices alongside supplementary energy sources, in tandem with NR (Figure 13) [203], [204], [205], [206], [207], all meticulously cited within a range of recent publications. Within this comprehensive overview, several salient observations emerge. A primary emphasis lies in the leveraging of DG and the electrical grid to seamlessly integrate EVCS, thereby minimizing its impact on the distribution system. Conversely, there exists a discernible gap in the exploration of alternative energy sources, indicating a potential avenue for further investigation. A notable temporal trend reveals that the publications analyzed primarily originate from the recent past, attesting to the burgeoning interest in EVCS allocation strategies. Further scrutiny unveils a prevalent reliance on evolutionary algorithms, underscoring their efficacy as optimization tools in this domain. In terms of experimental setups, standardized test systems take precedence over real-time counterparts, a phenomenon attributed to their widespread availability and ease of implementation. Moreover, a recurring theme emerges in the form of a steadfast commitment to power loss mitigation as the paramount objective function. Notably, the chosen forums for dissemination predominantly include distinguished platforms such as IEEE and Elsevier, attesting to the rigorous peer-review process undergone by these contributions. Surprisingly, environmental and reliability objectives, while crucial in the broader context, receive relatively scant attention within the reviewed literature. Overall, this article constitutes an invaluable resource, offering a nuanced and comprehensive understanding of the dynamic landscape of EVCS allocation research, replete with trends, methodologies, and areas ripe for future exploration. It serves as an indispensable compass for researchers and industry practitioners navigating this evolving terrain.

Upon a comprehensive review of optimization research endeavors in this domain, certain gaps emerge in the current body of work.

- Most studies investigated one or two techniques for placing EVCSs in areas where it is not recommended for real-world situations. The framing of problems for appropriate CS placements is equally significant for CS owners, DS operators, and EV consumers.
- EV load modelling does not account for fluctuations in EVCS load on the DS caused by unpredictability in EV user behavior.
- Demand-side management (DSM) and V2G schemes have been ignored in determining suitable EVCS placements.
- The integration of RES is not included in formulating the EVCS placement problem.
- The authors do not incorporate charging schedules with problem formulation of EVCS ideal placement.
- Most authors positioned the charging station (high-speed charging) based on cost functions while neglecting the charging station's impact.
- Variations in daylight load, as well as changes in environmental factors such as temperature, irradiance, and wind speed, which may impact DGs like as solar PV and wind turbines, are not taken into account.
- Frequent charging and draining might shorten the life of an EV battery. As a result, using BESS as an energy storage backup and then selling electricity to the building instead of continually draining the EV battery will enhance battery longevity.
- Uncoordinated EV charging might result in a peak load on a DS.
- The conventional PSO method used for optimal sizing has various issues, such as looking for the ideal value, particles becoming caught in local minima, and increasing the number of iterations required.
- The suggested eco-charging systems (which include PV, ESS, and the electrical grid) make the environment less durable and sustainable. They can exacerbate the intermittent issue produced by PV and wind.
- Performing energy trading between Vehicle-to-Vehicle (V2V) and V2G can help to prevent peak demand on the grid and encourage depot owners to participate in the energy reserve market.
- EV loads located further away from the service transformer experience more voltage dips than those closer to the service transformer.
- A more systematic approach to charging station location difficulties, considering EV users' activity-based behavior, has yet to be examined.
- The reliance on CO_2 emissions and the protection and security of power system components are not considered when evaluating system reliability.

VII. CASE STUDY

The proposed methodology is used to a typical IEEE 33-bus RDS for the optimization of the placement and sizing of various DERs to demonstrate its effectiveness. These resources include RDGs like solar and wind, as well as capacitors, DSTATCOM, BESS, and EVCS. The usual challenge of allocating EVCS throughout the distribution network is depicted in Figure 14 utilizing a combination of distribution load flow analysis and optimization approaches. A nature-inspired algorithms known as the bald eagle search algorithm (BESA) [208] and cuckoo search algorithm [209] are used for allocating energy sources in the RDS optimally. The BESA and the CSA offer distinct advantages over traditional methods like PSO in the context of EVCS allocation. BESA excels at handling complex and nonlinear optimization challenges, thanks to its intelligent balance of exploration and exploitation. This makes it highly suitable for optimizing EVCS placement within extensive solution spaces. CSA, inspired by the breeding behavior of cuckoos, demonstrates a remarkable ability to combine global exploration and local exploitation. It proves effective in identifying optimal charging station locations, particularly in scenarios with diverse constraints and objectives. Both BESA and CSA exhibit robustness when dealing with intricate allocation tasks, showcasing their potential to surpass PSO and other algorithms for EVCS planning. This method helps to determine the best locations and capacity for various energy sources. The computational framework makes use of MATLAB to create a power flow algorithm tailored to the distribution system. This makes it easier to evaluate the RDS's base case power losses and bus voltage profiles. The research takes into account three various types of EVs, each with a different battery capacity ranging from 20 to 16 kWh. These EVs' charging behaviour includes both G2V and V2G operations. Furthermore, the EVs expected to arrive at the charging station would have various SOC levels. The charging station is intended to accommodate up to 100 EVs, adding 966 kW to the system's power consumption. To meet distribution system limits, the best configuration contains a maximum of two EVCS units, each with multiple charging ports. The primary goal is to incorporate the EVCS units into the current distribution infrastructure in a way that improves both operational efficiency and system stability.

A. FORMULATION OF THE RESEARCH PROBLEM

The Backward/Forward Sweep (BFS) technique has gained popularity for its effectiveness in conducting power flow analysis in RDS, as stated in reference [210]. The simplicity, speed, and less memory requirement for processing, as well as the computational and robust convergence in the RDS solution, are the essential features of this power flow analysis. Figure 15 demonstrates the single line diagram of RDS with energy sources and EVCS.

The calculation for the bus voltage at t+1 is determined by the equation:

$$V_{t+1} = V_t - I(R_{t,t+1} + jX_{t,t+1}) \tag{21}$$

TABLE 1. Review of the literature for efficient EVCS allocation in the distribution system.

Ref. No	Year	Technique/Method	Objective Function	Sources of Energy	Test Systems	Outcomes/Findings/Future Scope
111	2012	Modified primal dual interior point algorithm	To mitigate the total cost associated with EVCS	Grid	IEEE 123-bus DS	Future research might systematically investigate related issues such as EV fleet dispersion, traffic scenarios, and charging demand patterns.
112	2013	Fuzzy control-based optimization technique	Enhancement of voltage profile	Grid	Practical Guwahati DS	It has been noticed that V2G installation has enhanced the node's voltage profile and aided in peak shaving and valley filling.
113	2013	Cross entropy algorithm	Reducing power losses and voltage deviations	Grid	IEEE 33-bus RDS & 25-bus traffic network system	The study found that the suggested strategy successfully achieved appropriate EVCS development plans while enhancing power system operating economics and voltage profiles.
114	2013	Evolutionary algorithm	Maximization of economic profit	Grid	Modified IEEE 15-bus and 43-bus RDS	As battery technology continues to improve and governments implement additional stimulus measures, the cost of batteries and other necessary equipment is expected to decrease. This would make battery stations a more viable option for energy storage.
115	2014	Ordinal optimization algorithm	Minimization of the fixed investment cost of EVCS	Grid	IEEE 54-bus DS	By comparing the mode with V2G characteristics of EV and that without V2G, V2G features may effectively lower the DS's operational expenses.
116	2015	Fuzzy TOPSIS method	Optimizing environmental criteria, economic criteria & societal criteria	Grid	Practical Changping, Beijing DS	In the coming years, a computer-based application system could be developed by researchers to expedite the implementation of the fuzzy TOPSIS approach for selecting suitable sites for EVCS.
117	2017	Hybrid genetic algorithm and particle swarm optimization-based algorithm	Optimizing the real power loss reduction index & voltage profile improvement index	Grid	Practical Allahabad DS	Future development will concentrate on V2G charger functionality and the long-term smart design of Allahabad's fast charging infrastructure.
118	2018	Grey wolf optimization algorithm	Optimization of load variance and total cost	Grid	38-bus distribution network	With this method, high EV penetration may be accomplished while maintaining a competitive advantage in load variation and charging costs.
119	2018	Mixed-integer linear programming	Minimization of investment costs	Grid	Coupled traffic electric network	Numerical investigations have shown that the suggested method may give a global optimum planning solution for connected Traffic electric networks while using only a small amount of computational effort.
120	2018	A modified convex relaxation technique	Minimizing the total system energy cost	Grid	IEEE 15-bus DS	Additional sparsification of the communication structure will be required in future work, which may be performed utilizing the alternate direction multiplier approach.
121	2019	Double-layered intelligent energy management approach	Minimization of the daily total cost incurred for PEV & system power loss	Grid	IEEE 33-bus RDS	The suggested DIEM solution for PEV integration in DS is also not an unpalatable prospect for PEV owners.
122	2019	Genetic algorithm	Minimization of the total social cost	Grid	Practical distribution network of Nanjing, China	The proper placement of EVCSs is critical to the development of EVs. It will not only lower building costs but will also optimize the EV industry's operation mode.

TABLE 1. ***(Continued.)*** **Review of the literature for efficient EVCS allocation in the distribution system.**

123	2020	Genetic algorithm	Minimization of power loss and node voltage excursion	Grid	IEEE 33-bus RDS	Optimal scheduling of EV charging and discharging, reactive compensation, active power loss, and the danger of node voltage exceeding limits are all addressed simultaneously.
124	2020	Grey wolf optimizer, whale optimization algorithm and water cycle algorithm	Enhancing the network reliability	Grid	9-bus, 33-bus & 69-bus RDSs	In the future, improved competition over resources (COR) via the disruptive operator idea may be advocated to improve and accelerate approach performance.
125	2020	Teaching Learning Based Optimization	Real power loss and average voltage deviation index are minimized, while voltage stability index is maximized.	Grid	IEEE 33-bus and 69-bus RDSs	The optimal/smart charging feature of EVs can also significantly increase system performance, which is being researched as a future scope of this study.
126	2021	Differential Evolution and HHO techniques.	Minimization of the energy loss, voltage deviation, and land cost	Grid	IEEE 33-bus RDS	This study did not take into account traffic congestion, which has an impact on the vehicle's SOC.
127	2021	Grey wolf optimization algorithm	Enhancing the net profit under both budget and routing constraints.	Grid	Washington D.C. transportation network	More progress might be made by taking into account the various types and sizes of charging stations, charging rates for each type, and the unpredictable SOC level.
128	2021	Chicken Swarm Optimization and TLBO algorithms	Mitigation of overall cost associated with the establishment of EVCS	Grid	IEEE 33-bus RDS	Future work should focus on optimizing the placement of EV charging and switching stations, building V2G enabled charging stations, and running the planning system in real time.
129	2021	Grey wolf optimization algorithm	Controlling the Transportation Energy Loss Cost & Power Loss Cost	Grid	IEEE 34-bus RDS	EVs are garnering the attention of government organizations and the automotive industry because to their lower CO_2 emissions, simple maintenance, and low operating costs.
130	2021	Non-dominated sorting genetic algorithm	Minimization of network and loss & Maximization of utilization factor	Grid	IEEE 33-bus RDS	When the number of EVCSs is extended beyond two for user convenience, the maximum utilization of any EVCS is found to be relatively low.
131	2022	Grey wolf optimization algorithm	Enhancing the reliability	Grid	IEEE 69-bus RDS	Because of the great demand for electrical energy, modelling and distributing EVCS in the DS is difficult.
132	2022	Particle Swarm Optimization	Mitigation of power loss	Grid	IEEE 33-bus RDS	It is preferable to analyze the appropriate allocation of Energy management techniques in the system for the grid's dependable functioning during peak demands.
133	2022	Particle Swarm Optimization	Maximizing the captured charging demands, minimization of the total cost of electricity and the time consumed for charging and load variance of the power grid	Grid	IEEE 33-bus RDS	Further study subjects include cooperative control of many vehicles using multi-agent systems and the optimization problem using the weighted modularity optimizations technique.
134	2022	Particle Swarm Optimization	Mitigation of cost incurred due to energy losses	Grid	IEEE 37-bus RDS	The research is critical in reducing the overhead costs caused by the rise in power consumption caused by EV.
135	2022	Particle Swarm Optimization	Reduction of load fluctuation	Grid	IEEE 34-bus RDS	Future research should focus on analyzing EV charging and discharging procedures, as well as the proportion of various EV user types.

TABLE 1. ***(Continued.)*** **Review of the literature for efficient EVCS allocation in the distribution system.**

136	2022	Genetic algorithm	Minimization of the construction cost of charging stations	Grid	The practical DS in Ireland	These countries will take longer to electrify their automobiles. As a result, the government must raise investment to meet the desired target within a realistic time frame.
137	2022	Newton Raphson method	Optimization of voltage imbalance and power losses	Grid	IEEE 34-bus RDS	Future research may be conducted utilizing direct current networks and RES and then evaluated on various distribution test systems.
138	2022	Mixed-integer linear programming	Minimizing the total number of EVCSs in the system	Grid	The practical DS in Turkey	This study will be enhanced in the future by including DSO and EVCS interactions.
139	2023	Non-dominated sorting genetic algorithm	Increasing profit from parking lot construction while reducing energy consumption	Grid	IEEE 69-bus RDS	The usage of PV resources with EVCS at the same time can increase network utilization and save costs.
140	2023	Particle Swarm Optimization	Reduction of power loss and voltage deviations	Grid	IEEE 33-bus RDS	In the future, the researcher might examine the system for different EV models and more excellent charger ratings.
141	2023	Pareto method	Mitigation the cost of EVCS construction and active power losses.	Grid	IEEE 37-bus RDS & 25-node transport system	The data indicate that charging stations are suitably distributed across the city, allowing EVs to approach the nearest station in their position with a minimal amount of charge remaining and undertake successful excursions.

The magnitudes of the bus voltages for nodes $t+1$ and t are denoted by V_{t+1} and V_t, respectively. The link between nodes t and $t+1$ has a resistance and reactance represented by $R_{t,t+1}$ and $X_{t,t+1}$.

The division current I is determined using equation (22).

$$I = [BIBC][i] \tag{22}$$

The term 'BIBC' refers to a matrix that describes how injecting current into a particular bus affects the current flow in the branches connected to it.

$$\mathbf{i_{t+1}} = \frac{(\mathbf{P_{t+1}} + \mathbf{jQ_{t+1}})^*}{\mathbf{V_t}} \tag{23}$$

The third equation expresses the actual and imaginary power consumption at node $t+1$, labeled as Q_{t+1} and P_{t+1} correspondingly, along with the electrical current injected at node $t+1$, represented as i_{t+1}.

Equations are employed to determine the actual and reactive power losses in a system, as given below.

$$P_{loss}(t, t+1) = \left(\frac{P^2_{t,t+1} + Q^2_{t,t+1}}{|V_t|^2}\right) R_{t,t+1} \tag{24}$$

$$Q_{loss}(t, t+1) = \left(\frac{P^2_{t,t+1} + Q^2_{t,t+1}}{|V_t|^2}\right) X_{t,t+1} \tag{25}$$

Equations (24) and (25) describe the transfer of actual power and reactive power, respectively, between nodes at t and t+1. These power flows are denoted by the variables $P_{t,t+1}$& $Q_{t,t+1}$.

Therefore, the sum of branch power losses provides a comprehensive measure of the total losses of the system.

$$P_{T,Loss} = \sum\nolimits_{t=1}^{nb} P_{Loss}(t, t+1) \tag{26}$$

The number of branches is denoted by nb in the above equation.

B. DISTRIBUTION SYSTEM LOAD MODELING WITH EVCS

EVCSs impose an extra burden on the distribution grid. Equation (27) can be employed for computing the cumulative demand on the distribution system following the incorporation of EVCSs.

$$P_{Load} = \sum\nolimits_{t=1}^{nb} P_{avilable,t+1} + P_{EVCS(t+1)}) \tag{27}$$

In the context provided, P_{Load} signifies the collective load within the system. $P_{avilable,t+1}$ indicates to the existing load available at the bus during the $t+1$, while $P_{EVCS(t+1)}$ represents the load from EVCS connected to the same bus. The data essential for determining the energy demand of EVCS load during the charging process is sourced from reference [211]. The calculation of energy required for battery charging is conducted utilizing (28) and (29). The subsequent paragraphs present the various models for EVCS:

$$P_{EVCS(t+1)} = n * B_c * S_c \tag{28}$$

$$S_c = 100 - \text{SOC current status} \tag{29}$$

TABLE 2. Review of the literature for efficient EVCS and DG allocation in the distribution system.

Ref. No	Year	Technique/Method	Objective Function	Sources of Energy	Test Systems	Outcomes/Findings/Future Scope
142	2011	Monte Carlo simulation embedded with genetic algorithm	DGs' investment, operating, and maintenance costs, as well as network loss costs, must be reduced.	RDG	IEEE 37-bus DS	The proper placement and sizing of DGs might have a significant positive impact on the DS.
143	2015	Particle Swarm Optimization	Improvising the voltage stability	RDG	IEEE 30-bus DS	PV integration in a DS can enable more many EV integrations with fewer grid effects.
144	2015	Multi-period optimization	Minimization of operating cost	DG	84-bus DS	The coordinated scheduling of EVs and RDGs helps offset the negative consequences of renewable generation unpredictability.
145	2017	Hybrid genetic algorithm and particle swarm optimization-based algorithm	Reduction of power losses, voltage fluctuations, charging and demand supplying costs, and EV battery cost	RDG	IEEE 33-bus RDS	According to the findings of this study, combining EVs as active power sources with RDG in DS can reduce losses, voltage variations, and system operator and subscriber costs.
146	2017	Hybrid genetic algorithm and particle swarm optimization-based algorithm	Mitigation of system power loss	RDG	Roy Billinton DS	Although RDGs can improve DS operation, unanticipated large RDG and EV parking lot penetration in future power systems may cause technical issues such as loss rise.
147	2018	Hybrid genetic algorithm and particle swarm optimization-based algorithm	Minimizing the voltage fluctuations, load fluctuations & capacity of the ESS in EVCS	RDG	IEEE 33-bus RDS	Accuracy in energy management improves safe and predictable power scheduling, accelerates renewable integration, and maximizes EV emission reduction impacts.
148	2018	Expected Energy Not Charged technique	Improving the reliability of the system	RDG	11kV practical DS	In addition to the good and negative effects of EVs on system dependability, EV owners are affected by system breakdowns and unscheduled discharge. It is entirely sensible to consider EV dependability.
149	2019	Mixed integer second-order cone programming	Optimization of extra traffic cost in dispatches	DG	Practical urban area coupled with the 33-bus RDS	Future research will fully reflect the uncertainties in EV owners' decision-making, and the joint planning model of DGs and EVCSs will be broadened to achieve better practical value.
150	2019	Joint planning algorithm	Optimizing the deployment & operation costs and associated greenhouse gas emissions	DG	38-bus distribution network	The combined planning approach meets the technological restrictions of microgrids for electricity flow, sustainability, and dependability.
151	2020	Stochastic Fuzzy Chance Constrained Programming	Controlling the power loss and voltage	RDG	IEEE 33-bus RDS	The proposed optimization model of collaborative control of power loss and voltage variation improves the efficacy and speed of problem-solving in optimization.
152	2020	Bi-level programming model	To maximize its overall financial performance.	DG	IEEE 33-bus & 69-bus RDSs and an actual regional 30-bus DS	This approach can lead to an increase in the capacity of DG and EVCSs beyond what the dependable system can offer.
153	2020	Harries Hawk Optimization and Teaching-Learning Based Optimization algorithms	To minimize actual power losses, the goal is to optimize the system	DG	IEEE 33-bus and 69-bus RDSs	The connection of a substantial amount of EVCSs to the grid can lead to higher power losses and voltage fluctuations at buses located far away from power sources within the system.

TABLE 2. ***(Continued.)*** **Review of the literature for efficient EVCS and DG allocation in the distribution system.**

154	2020	Particle Swarm Optimization and Butterfly Optimization algorithms	Optimizing the power loss reduction and voltage improvement	DG	IEEE 33-bus RDS	Most practical optimization issues are multi-objective, making them challenging to solve using standard methodologies.
155	2020	PSO	Minimization of the branch/line losses	DG	Unbalanced IEEE 19-bus and IEEE 25-bus DS	In the future, the suggested work may be expanded by reconfiguring the imbalanced system in conjunction with EVCS and DGs.
156	2020	PSO	Keeping installation costs, losses, and distribution transformer loading to a minimum.	RDG	Practical DS National University of Sciences and Technology in Pakistan	The analysis of the effect of PV on voltage profile revealed that distributed PV generation may be able to maintain voltage profile despite the presence of EVCSs on DS commercial feeders.
157	2021	Loss sensitivity factor and GOA	Minimizing the power loss	DG	IEEE 69-bus RDS	The collected findings clearly show that smart charging paired with LSF and GOA delivers superior outcomes in terms of power loss and significantly enhances system performance.
158	2021	Mixed-integer linear programming model	Reduction of investment and operational costs	RDG	24-bus distribution system	The findings showed that increasing RDG investments reduces CO_2 emissions. However, lowering CO_2 emissions raises costs, demonstrating the tradeoff between cost and emission reduction.
159	2021	Hybrid of GWO and PSO algorithms	To reduce the amount of power lost in the network, ensure that the voltage profile remains within the necessary limits, and improve the voltage stability index.	DG	IEEE-33 bus and IEEE-69 RDS	To evaluate the reliability of the power system, factors such as the impact of CO2 emissions, safeguarding measures for system components, and overall security can be considered.
160	2021	Improved chicken swarm optimization	To optimize the voltage profile, minimize power loss, and decrease costs	RDG	IEEE 33-bus RDS	The increasing number of on-road EVs has prompted severe worries for the DS's voltage stability.
161	2021	Harris Hawk Optimization Algorithm	Minimization of the energy loss and enhancing the voltage profile	RDG	IEEE 33-bus RDS	BESS can be linked in the future to schedule the electricity generated by solar DGs.
162	2021	Enhanced grasshopper optimization algorithm	Reducing the power loss	DG	IEEE 33-bus RDS	If EV owners plan their vehicles in accordance with the system consumption pattern, they can earn money through V2G mode.
163	2022	Political Optimization Algorithm	Reduction of power loss and enhancement of voltage profile	RDG	Indian 28-bus DS	The simultaneous allocation of RDGs and EVCS enhanced the voltage profile and reduced uncertainty in DS when compared to a single allocation technique.
164	2022	Stochastic second-order conic programming	Minimizing the losses and voltage deviation	RDG	Modified IEEE 15-bus DS	The reported study contributed to resolving uncertainty problems in ADN planning, resulting in advances in the design of future cheap and dependable energy systems.
165	2022	Particle Swarm Optimization	Mitigation of the power losses	DG	IEEE 15, 33, 69, and 85- bus RDSs	Using various types of DGs and EVCSs in a grid reduces power losses and improves the voltage profile. When EVCS additionally serves as a DG source, the loss reduction increases.
166	2022	Harris Hawk Optimization Algorithm	Minimizing the power losses	RDG	IEEE 25-bus Unbalanced RDS	Future research might continue the optimization problem for a hybrid DG system with several DG units and battery storage.

TABLE 2. ***(Continued.)*** **Review of the literature for efficient EVCS and DG allocation in the distribution system.**

167	2022	A hybrid of GWO and PSO algorithms	Minimizing the land cost and maximizing the EVs flow for fast-charging stations placement	DG	IEEE 34-bus RDS	This research will help the grid integrate EVs, boost the EV population, minimize carbon emissions, and encourage investors to build FCS.
168	2022	The improved bald eagle search algorithm	Optimizing the actual power loss, reactive power loss, and investment cost	RDG	IEEE 34-bus RDS	Future studies might incorporate alternative power management techniques, including EVs into the grid and V2H EVCS features to improve DS performance.
169	2022	Particle Swarm Optimization	Mitigation the active and reactive power losses & Reducing the average voltage deviation	RDG	IEEE 33-bus RDS	In the future, the EVs' driving distance and the EV batteries' charge level will be considered while allocating EVCSs.
170	2022	Arithmetic Optimization Algorithm	Lessening the losses & improving the bus voltage level	DG	IEEE 33-bus RDS	The future scope is broadened by considering the same EV as a load and DG, with charging and discharging behavior determined by the systems off and peak load times.
171	2022	Firefly algorithm	Reducing power loss and maintaining a good voltage profile at each bus	RDG	IEEE 69-bus RDS	EVs are charged using smart charging technologies during off-peak hours. The findings indicate that utilizing an intelligent charging strategy and integrating DGs with EVs minimized power losses more efficiently.
172	2022	Multiple optimization algorithms	Obtaining the lowest line loss, voltage deviation, and static voltage stability margin possible	RDG	IEEE 33-bus RDS	The DS model with new energy and EVs is intended to demonstrate the possibility of managing reactive power in various types of DS.
173	2022	Dragonfly algorithm	Minimization of voltage deviations, energy losses, and EVs owners' dissatisfaction	RDG	IEEE 69-bus RDS	Depending on how much reactive power is injected or absorbed into/from the DS, the power factor may be leading or trailing.
174	2023	Monte Carlo Simulation Method	Reducing the losses and voltage deviation	DG	IEEE 33-bus RDS	Future research areas include analysing the effects of the association between various sources of uncertainty and the possibility of unanticipated overloading of the system.
175	2023	Particle Swarm Optimization	Minimization of voltage drop and THD	DG	IEEE 33-bus RDS	THD was shown to be lower during peak hours and greater during off-peak hours after evaluating EV charging times.
176	2023	Arithmetic optimization algorithm	Minimization of network loss	DG	IEEE 33-bus RDS	This study is being expanded with power management and EV patterns for 24hr horizons such as G2V and V2G by merging RDGs and EVCS in the same node.
177	2023	Differential Evolution and Harris Hawks Optimization	Optimization of Loss reduction, voltage deviation, EV charging services maximization, Overall cost investment reduction	RDG	IEEE 33-bus RDS	This work may be expanded to include a reliability analysis and network expansion needs.
178	2023	Modified teaching-learning-based optimization	Voltage stability, reliability, the power loss index, and cost are all factors to consider.	RDG	IEEE 33-bus and 123-bus RDSs	There are various opportunities to do more research by completing a techno-economic appraisal of DC-MG-based EVCSs when connected to the utility grid.

In the given context, the symbol B_c corresponds to the energy capacity of the battery in kWh, while S_c pertains to the requisite charging quantity as a SOC value. Furthermore, n symbolizes the count of EVs under consideration.

TABLE 3. Review of the literature for efficient EVCS, DG and ESS allocation in the distribution system.

Ref. No	Year	Technique/Method	Objective Function	Sources of Energy	Test Systems	Outcomes/Findings/Future Scope
179	2016	Novel optimization algorithm	Minimization of energy cost and the storage cost	ESS	Definite charging station	The implementation of a storage system in an EVCS can not only reduce station costs but also restrict the increase in network peak demand.
180	2017	Comprehensive optimization model	Minimization of losses and maximization of DG, EV charging station & ESS capacity	RDG & ESS	Alibeykoy and Hadimkoy DS in Istanbul, Turkey	Load flexibility via demand response techniques may be considered in the future.
181	2017	Self-adaptive hybrid optimization algorithm	Minimizing the operating cost of EVCS	RDG & ESS	Practical DS in Singapore	The cost of EVCS operation is decreased based on load dispersion throughout the day and energy market volatility.
182	2018	Whale optimiser algorithm	Minimization of energy losses and improvement of voltage profile of the grid	DG & ESS	IEEE 33-bus & 69-bus RDS	The presented approach may be expanded to account for CO_2 emissions and energy costs associated with renewable RDG-based electricity generation.
183	2019	Multi-agent particle swarm optimization algorithm	Minimizing the cost of electricity index	RDG & ESS	Industrial park in Shanghai, China	With the fast growth of information technology, additional battery charging solutions, such as Wi-Fi and µBeam over the air charging, will be investigated in future studies.
184	2020	Particle Swarm Optimization	Minimization of distribution losses	RDG & ESS	Standard solar PV-powered micro-grid network	In the future, researchers may investigate the potential benefits of employing multi-objective functions to optimize power flow, as well as performing sensitivity analysis to assess the robustness of the solutions to significant variations in the aggregate capacity of EV battery storage.
185	2021	Harris Hawks Optimization and Grey Wolf Optimization algorithms	Reduction of energy loss, voltage deviation index, and investment	RDG & ESS	IEEE 33-bus RDS	The technique created is generalized and applied to an overlaid network. This, however, applies to every network and realistic circumstance.
186	2021	Hybrid soccer league competition and pattern search algorithm	Reducing the power loss and increasing the voltage level	RDG & ESS	IEEE 33-bus and 85-bus RDSs	The locations and sizes of ESSs are also studied in a time-changing simulation for each period, covering both charging and discharging operations.
187	2021	Coyote optimization algorithm	Mitigation of real power loss and voltage deviation index	RDG & ESS	IEEE 33-bus RDS	Because EV load penetrations and PV system generations are often stochastic, precise ESS sizing is required, considering its transient behavior during charging and discharging times.
188	2022	Flow capturing location model	Minimization of the total annual operating cost of the system	RDG & ESS	IEEE 33-bus RDS and 25-bus transportation system	RDG equipment efficiently increases voltage level, while ESS equipment has the impact of peak-load reduction and valley filling, which enhances system voltage stability.
189	2022	Hybrid crow search algorithm, along with the particle swarm optimization	Maximizing the profit of the EVCS	RDG & ESS	Utility grid	Maximum net profit is realized with extensive modeling of EVCSs supplied by hybrid grid-RDGs (PV, mini-hydro, and wind).
190	2022	Reinforcement Learning based algorithm	To enhance power efficiency and minimize expenses associated with voltage stability, voltage variation, setup, and running costs, as	RDG & ESS	IEEE 33-bus and 118-bus RDSs	The present planning procedures in planning frameworks did not consider the proportional effect of different allotted units.

TABLE 3. *(Continued.)* **Review of the literature for efficient EVCS, DG and ESS allocation in the distribution system.**

			well as discharge expenses, it is essential to optimize power loss.			
191	2022	Gorilla Troop Optimizer algorithm	Minimization of power loss and total voltage deviation	RDG & ESS	108-bus distribution system	EVCSs are evaluated based on their daily profile, which is determined by the owner's behavior.
192	2022	Salp swarm algorithm	Total net present cost (TNPC), levelized cost of energy (LCOE), and reliability	RDG & ESS	The practical northwest region of Delhi, India	Future study is required to understand the effects of a battery's charging/discharging cycles on its longevity and energy consumption.
193	2022	Multi-course teaching learning-based multi-objective optimization	Optimizing the voltage, power loss, and loading capabilities	RDG & ESS	IEEE 69-bus RDS	Future work will focus on pricing, economic analysis, and optimal operational management for 'cloud storage services.
194	2023	Two-stage optimization technique	Improving the power quality and optimizing the net power	RDG & ESS	IEEE 33-bus RDS	The necessity for optimum EVCS allocation, replacing traditional transport systems with electric ones, and the modernization of power infrastructure.
195	2023	Chaotic student psychology-based optimization algorithm	Controlling the active power loss, voltage profile, total voltage deviation, cost of energy loss, and total operating cost	RDG & ESS	IEEE 33-bus and practical Brazil 136-bus RDS	This technique is being investigated for future scope for the simultaneous allocation of real power DGs, shunt capacitors, and EVCS/EVBSS(s) in the RDS for CP, IL, RES, and COM load models.

C. FORMULATION OF INNOVATIVE CHARGING AND DISCHARGING STRATEGY FOR EVS

Generally, EV users will charge their vehicles immediately after they return home. This method is termed as traditional charging technique (TCT) in this article. The TCT may not be beneficial as it leads to a high power loss, dip in voltage profile, low stability and may possible to maloperation in the network due to congestion. So, the proposed method should be beneficial to charge the EVs (V2G) during off-peak hours and supply power to the grid (G2V) during peak hours. Therefore, the EVs scheduling strategy is formulated in such a way to ensure the priority-based demand-sensitive charging and discharging of EVs. This method is called as innovative charging technique (ICT). This model ensures effective load management in such a way that a stable voltage profile and minimal power loss are achieved. In this method, the utility and EV users will have a mutual interaction about the system demand, and further strategy on improving the system performance is implemented.

Traditionally, EV owners tend to charge their vehicles immediately upon returning home, a practice referred to as the Traditional Charging Technique (TCT) in this discourse. However, this conventional approach may prove to be less advantageous, giving rise to issues such as substantial power wastage, voltage profile disturbances, reduced overall grid stability, and even the potential for operational glitches within the network due to congestion problems. To address these challenges, a fresh methodology is proposed, focusing on the charging and discharging sequence for EVs, known as the Innovative Charging Technique (ICT). The core concept behind ICT involves orchestrating the EVs' energy replenishment (V2G) during periods of lower demand and subsequently channeling power back to the grid (Grid-to-Vehicle or G2V) during peak load hours. This revamped EV scheduling strategy is meticulously designed to prioritize demand-responsive charging and discharging of EVs, thus ensuring an optimized energy flow. By adopting this innovative approach, effective load management is achieved, resulting in a consistently stable voltage profile, and a marked reduction in power losses. A key feature of this strategy entails a collaborative engagement between the utility provider and EV users to align with the system's energy requirements. Moreover, continuous feedback and enhancements to the system's performance are integral components of this model. A visual representation of the envisaged innovative charging and discharging strategy for EVs is depicted in Figure 16.

The methodology for scheduling considers Peak Envelope-to-Average Power Ratio (PEPAR) of the system load demand. PEPAR is defined as the ratio of the peak power (the highest instantaneous power level) to the average power (the mean power level over time) of a signal. The main objective for scheduling EVs is to minimize the PEPAR, which is represented as follows:

$$PEPAR = P_D^{Peak} \Big/ P_D^{Avg} \tag{30}$$

The terms P_D^{Peak} and P_D^{Avg} refer to the peak demand and average demand of the system, respectively. The determination

TABLE 4. Review of the literature for efficient EVCS and capacitor allocation in the distribution system.

Ref. No	Year	Technique/Method	Objective Function	Sources of Energy	Test Systems	Outcomes/Findings/Future Scope
196	2020	Grasshopper optimization algorithm	Enhance the power factor of the substation, minimize real power loss, and improve the voltage profile.	Capacitor & DG	51-bus DS & 69-bus distribution networks	Charging stations may experience fluctuations in node voltages due to the impact of transient battery charging loads. However, during steady-state charging, DGs and capacitors can help regulate node voltages to appropriate levels.
197	2021	A hybrid of GWO and PSO algorithms	Reducing the power loss and enhancing the net profit	Capacitor	IEEE-33 bus and 34-bus RDSs	Capacitors are used closer to the EVCS and at the ends of feeds to improve voltage profile and loss by supplying some reactive power.
198	2022	Improved mixed real and binary vector-based swarm optimization algorithm	Minimizing the operation cost	Capacitor	IEEE 69-bus and 119-bus RDSs	The influence of EV unpredictability was mitigated by regulated loads, resulting in a considerable reduction in transformer tap altering and shunt switching activities.
199	2022	Bear smell search algorithm	Controlling the power factor, re-generation, power losses, and voltage specifications	Capacitor & DG	51-bus distribution network	As the complexity of optimization issues grows, this technique suffers from slow convergence, increasing computing time.
200	2022	Particle Swarm Optimization	Optimization of voltage profile, lessen active power loss reduces cost associated	Capacitor & DG	IEEE 34-bus RDS	Power losses and overall energy costs are reduced when EVCS, DG, and capacitors are effectively arranged.
201	2022	Marine Predator Algorithm	Minimization of the power loss and maximization of the voltage profile	Capacitor & DG	Practical 83-bus Taiwan DS	The optimal mix of DGs and EVs in the DS enhances the system's overall performance by reducing loss and improving the voltage profile and VSI.
202	2022	The hybrid of GWO and PSO algorithms	Minimizing the active power loss costs, voltage deviations, FCE development costs, EV energy consumption costs, and DG costs	Capacitor & DG	IEEE 118-bus RDS	The suggested solution outperforms stage-wise component placement in terms of lower active power loss and EV user costs while maintaining a superior voltage profile.

of whether to charge or discharge is predicated on the amplitude of the power ratio ($\boldsymbol{P_{ratio}}$), which can be expressed as:

$$\mathbf{P_{ratio}} = \mathbf{P_D(t)} \Big/ \mathbf{P_D^{Avg}} \tag{31}$$

Taking into account two limitations is highly crucial. First, it is imperative to ensure that the scheduled EVs never take on negative values. Second, the allocation of EVs in the new time step must not exceed the quantity of EVs present at the initial step.

$$\sum\nolimits_{i=1}^{n} EV_{DP(i-j)} = n_{EV} \tag{32}$$

In this context, the label "DP" signifies various commuting behaviors associated with the EVs. The term $EV_{DP(i-j)}$ denotes the count of EVs categorized as "DP" designated for transfer from the i^{th} hour to the j^{th} hour. Meanwhile, $EV_{DP(i-j)}$ stands for the overall tally of accessible EVs intended for time allocation. Steps to be followed for innovative charging algorithm.

- ➢ The innovative charging algorithm initiates by gathering data such as vehicle type, quantity of vehicles slated for charging, SoC for each vehicle, and the projected system demand until the subsequent journeys.
- ➢ Subsequently, the system calculates PEPAR and $\boldsymbol{P_{ratio}}$, both with and without integration of EVs for every hour. If the $\boldsymbol{P_{ratio}}$ for a specific hour falls below the mean power demand ($\mathbf{P_D^{Avg}}$), the V2G mode is activated.
- ➢ Conversely, if the P_{ratio} surpasses the average power demand, EVs are permitted to inject power back into the grid, considering their available SoC.
- ➢ These hourly insights are then fed into the CSA algorithm, which determines the optimal sizing of energy sources.

TABLE 5. Review of the literature for efficient EVCS and DFACTS allocation in the distribution system.

Ref. No	Year	Technique/Method	Objective Function	Sources of Energy	Test Systems	Outcomes/Findings/Future Scope
203	2019	Flower pollination algorithm	Minimization of the power loss and improvising the voltage profile	DG & DSTATCOM	IEEE 69-bus RDS	Many users prefer to charge their PEVs right away after arriving home. In such instances, DSTATCOM plays a vital role since it considerably reduces the cost of wasted electricity.
204	2022	Fuzzy-Based optimization algorithm	Reduction of real power loss, enhancement of power factor and bus voltage	DG & DSTATCOM	IEEE 69-bus RDS	The transient battery charging load effects the EVCS node voltages, and with the help of DG and DSTATCOM, the node voltage maintains tolerable values during steady-state charging.
205	2022	African Vulture Optimization Algorithm	Optimizing the actual power loss index, voltage deviation index, and voltage stability index	DG & DSTATCOM	IEEE 33-bus and 69-bus RDSs	The integration of EVCSs on the electric grid necessitates extra grid power, resulting in increased power losses and voltage variation.
206	2023	Two-stage GA-PSO	Minimizing the losses, Improving VSI & Increasing network load	RDG, ESS & SVC	IEEE 33-bus RDS	It is possible that the introduction of EVs and the construction of charging stations would impair the network's technical characteristics.

TABLE 6. Review of the literature for efficient EVCS, protective devices and other energy sources allocation along with NR in the distribution system.

Ref. No	Year	Technique/Method	Objective Function	Sources of Energy	Test Systems	Outcomes/Findings/Future Scope
207	2019	Hierarchical optimization method	Improving the reliability of the system	RDG & Protective devices	IEEE 33-bus & 69-bus RDS	The test findings demonstrated that the distribution of protective devices has a more significant impact on system dependability than DG or charging station allocation.
208	2019	Genetic algorithm	Minimization of real power loss	NR	IEEE 69-bus & 118-bus RDSs	The authors are currently attempting to expand on the technique given in this research and to solve the problem of EVs scheduling and DFR as a multi-objective optimization problem.
209	2022	Adaptive dynamic planning mechanism	Reduction of power loss, enhancement of voltage stability improvement, and voltage deviation reduction	RDG, NR & ESS	15-bus, IEEE 69-bus and 118-bus distribution networks	Future work will concentrate on reducing the complexity of the planning mechanism while also adding additional unit types and constraints to monitor the complexity's increase.
210	2022	Binary Bat Algorithm	Minimization of active power loss	NR, DG & DSTATCOM	IEEE 33-bus RDS	Future research will include modelling and developing a dynamic and multi-objective stochastic model to deal with the uncertainties of RES and load in simultaneous NR and DG allocation difficulties while taking the geographical location of the real DS into account.
211	2022	Flower Pollination Algorithm	At various load factors, minimizing investment, peak loss, and annual energy loss costs.	NR	123-bus and 51-bus RDS	Future studies may include further case studies using smart grid technology for optimal sizing and allocation of commercial charging stations with the assistance of ESS, RDGs, and demand response approaches.

➢ Upon reaching the desired SoC for the EVs and confirming their readiness for the upcoming trips, the process concludes.

D. OBJECTIVE FUNCTION

In the proposed method, we have primarily focused on a single objective function, which centers on the reduction of

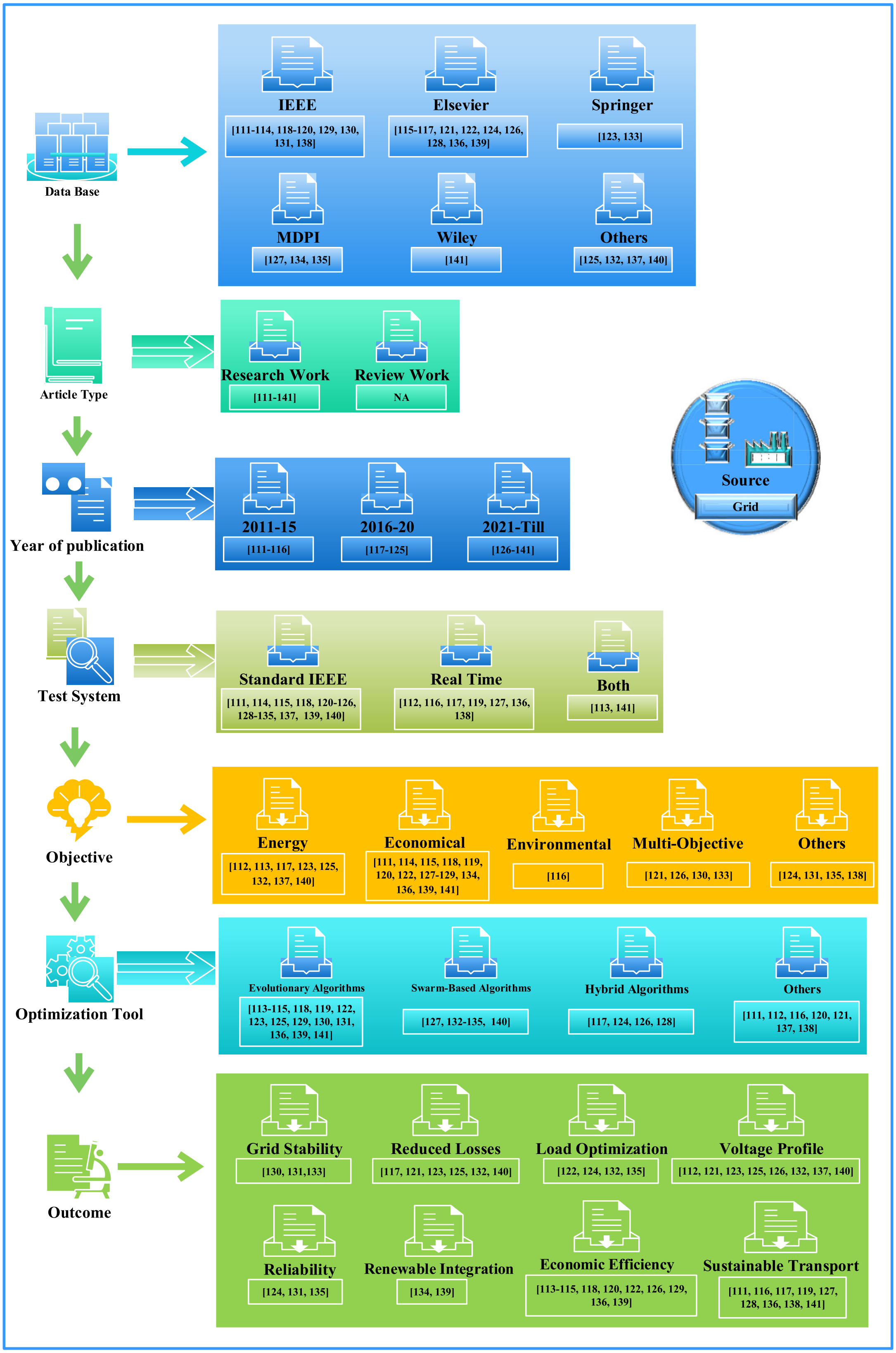

FIGURE 8. Review methodologies for EVCS integration with grid.

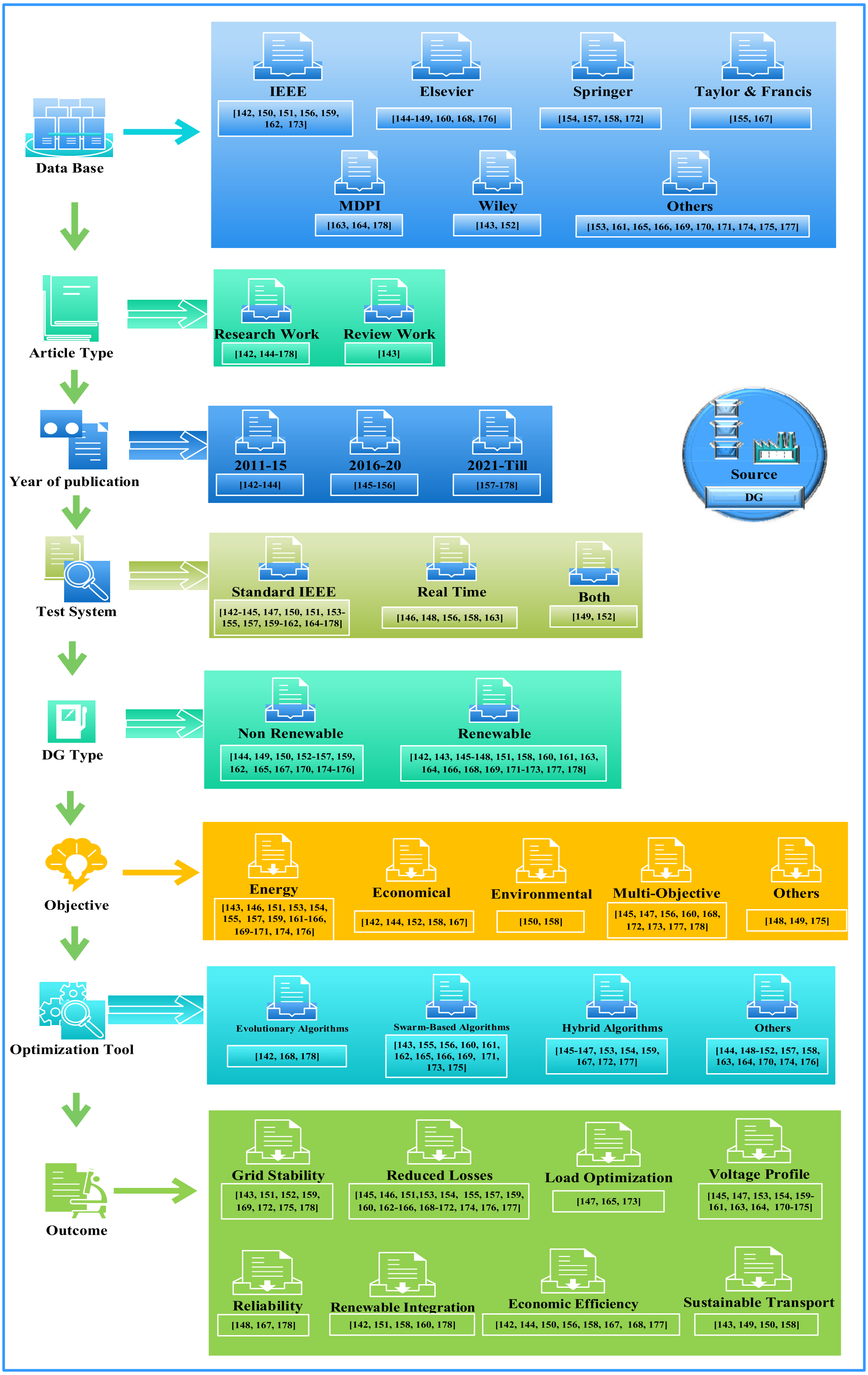

FIGURE 9. Review methodologies for EVCS integration with DG.

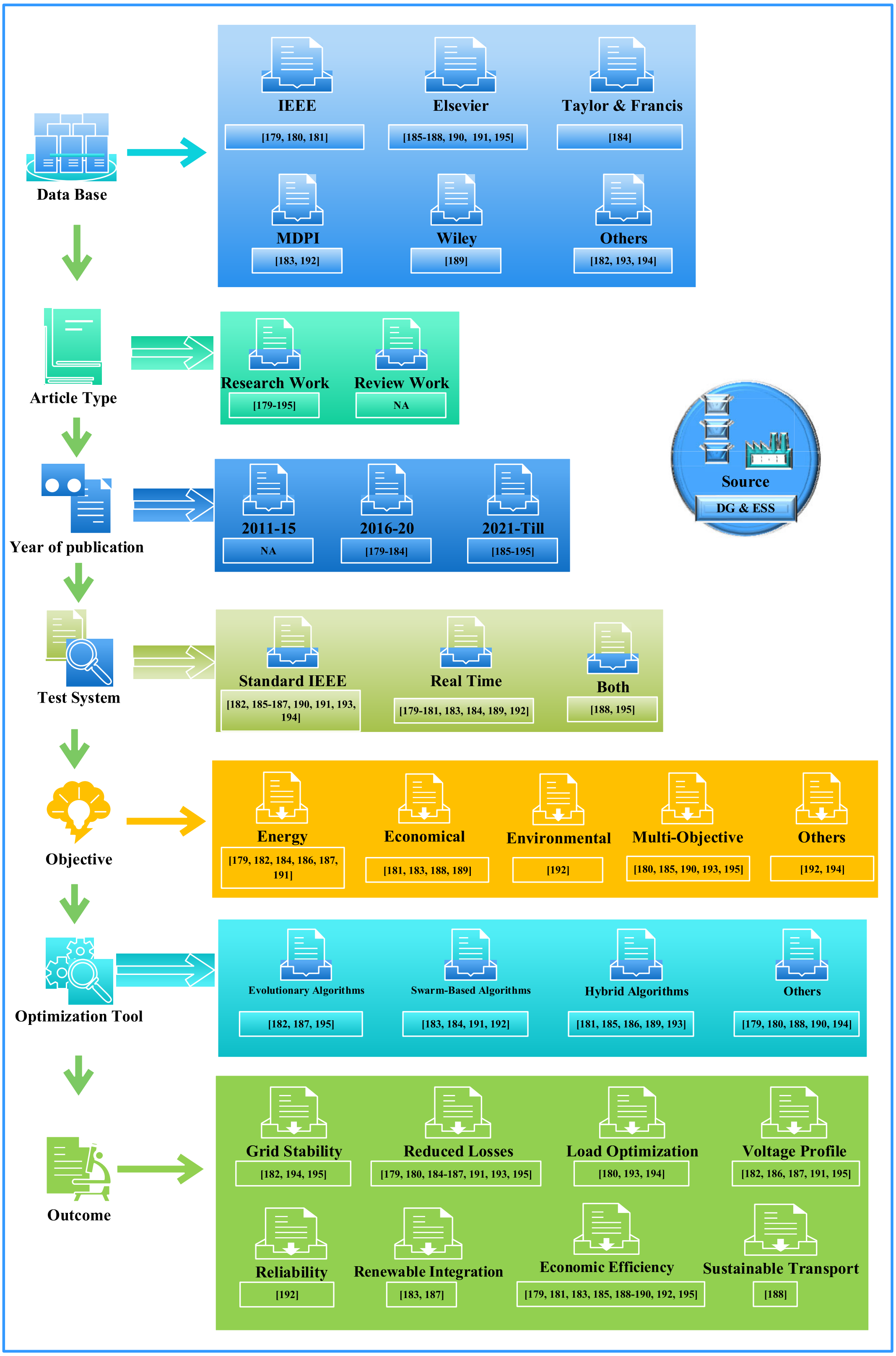

FIGURE 10. Review methodologies for EVCS integration with DG and ESS.

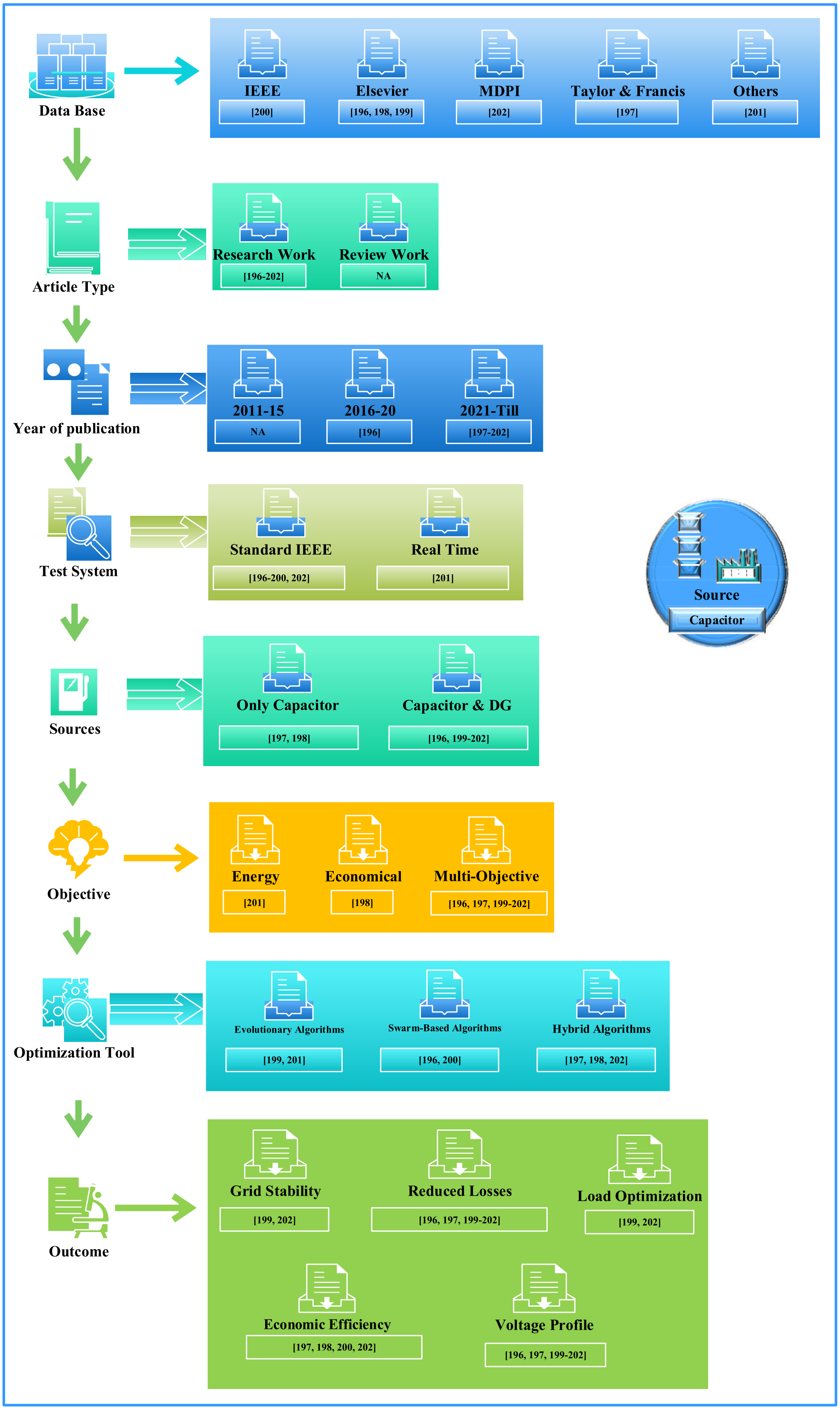

FIGURE 11. Review methodologies for EVCS integration with capacitor.

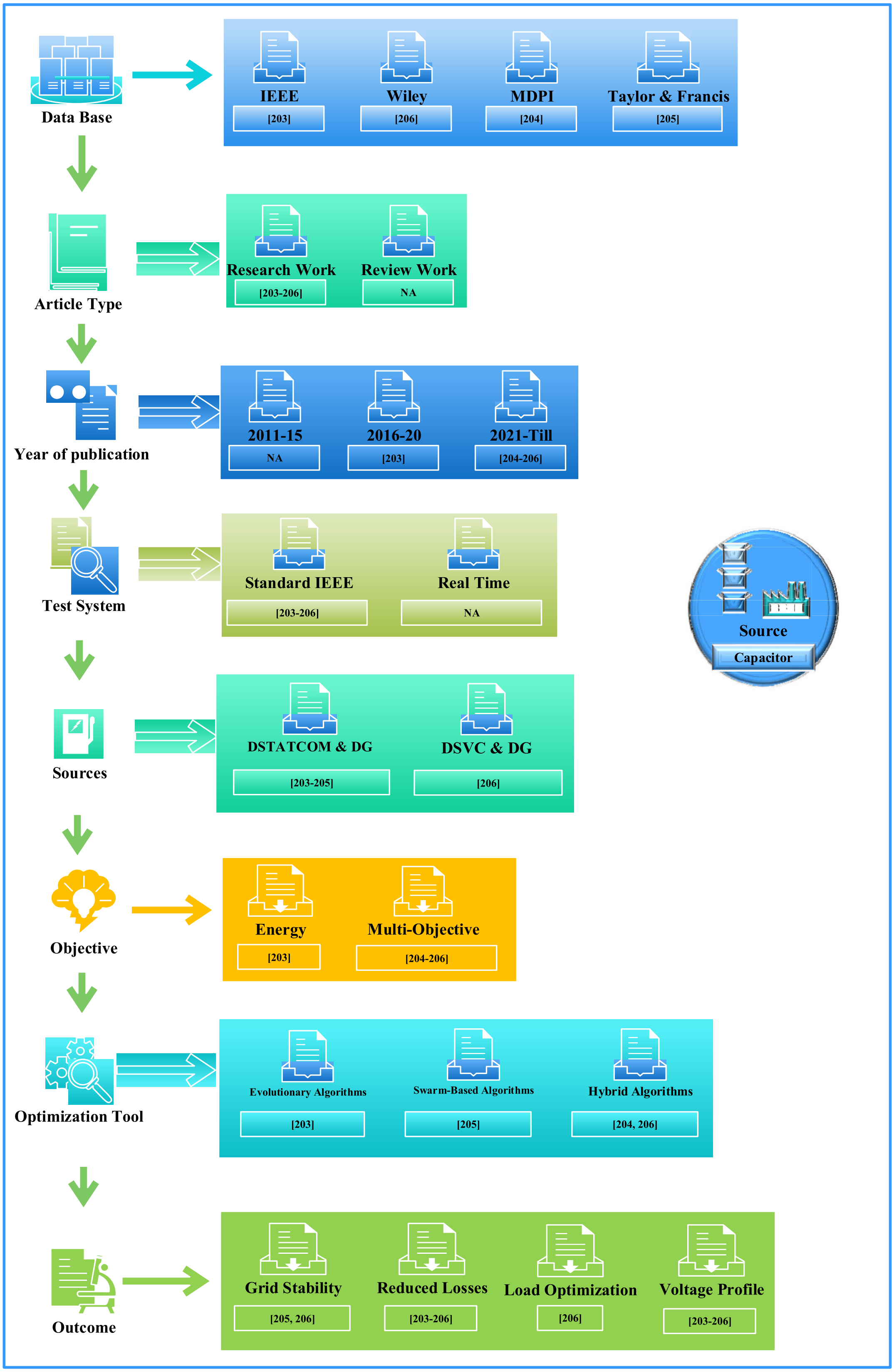

FIGURE 12. Review methodologies for EVCS integration with DFACTS.

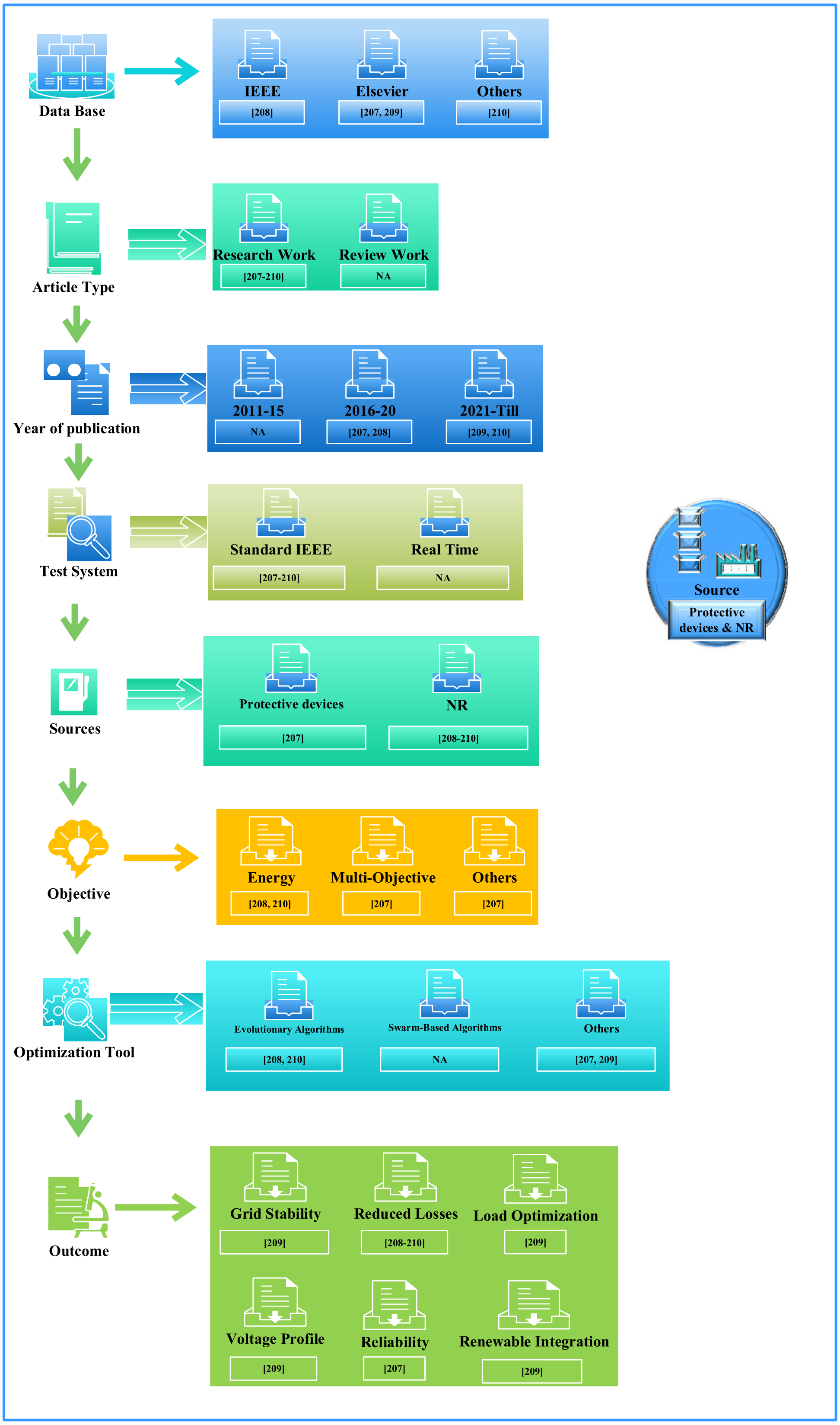

FIGURE 13. Review methodologies for EVCS integration with protective devices and NR.

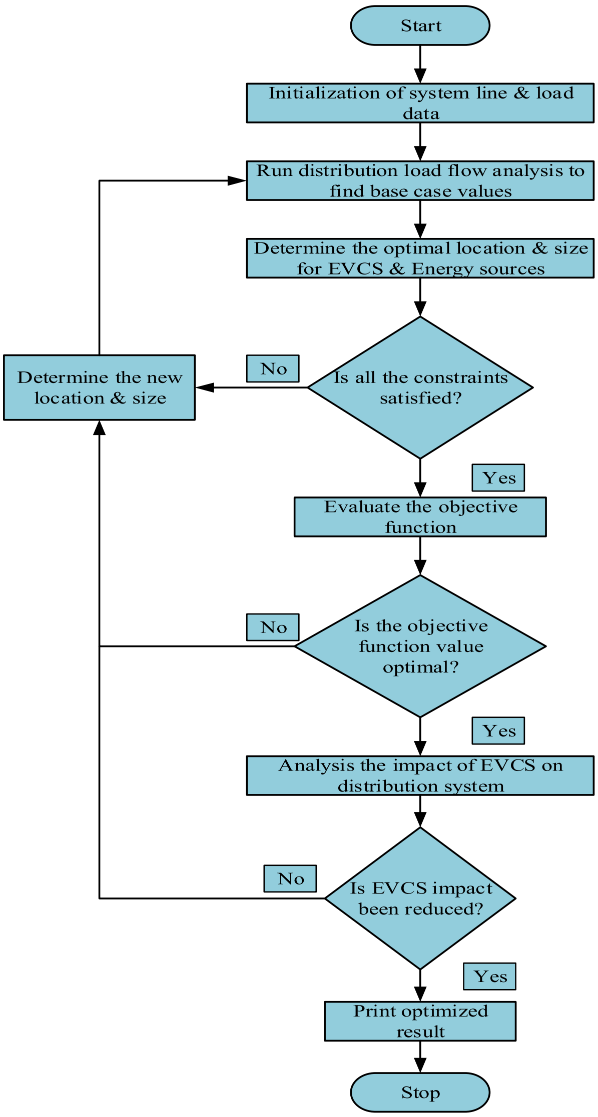

FIGURE 14. General EVCS allocation problem.

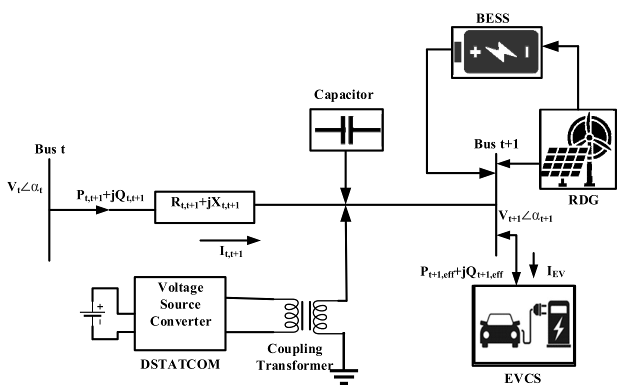

FIGURE 15. Single line diagram of RDS with energy sources and EVCS.

power losses within the RDS. While this concentration on power loss reduction is expected to yield cascading benefits across a range of interconnected objectives, we acknowledge

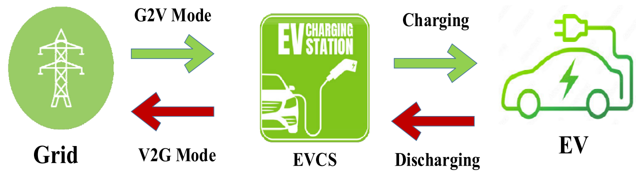

FIGURE 16. Proposed innovative charging and discharging strategy for EVs.

that a multi-objective approach could offer a more comprehensive optimization strategy. It is important to note that our emphasis on minimizing power losses inherently encompasses a synergy of multiple aspects, including improved voltage profiles, enhanced system stability, optimized operating costs, increased power factor, and elevated power quality. Although these dimensions have not been explicitly treated as separate objectives in our current study, they are poised to be positively influenced as natural outcomes of our primary goal. Nonetheless, we recognize the potential of multi-objective optimization as an avenue for further exploration. By delving into the intricate interplay between power loss reduction and the aforementioned objectives, future researchers have the opportunity to uncover nuanced trade-offs, synergies, and compromises. A multi-objective framework has the potential to provide a more holistic understanding of the complex dynamics at play and can lead to a more nuanced and comprehensive optimization methodology. In addition, we acknowledge that our research, while laying a foundational groundwork, has identified certain gaps and unexplored areas within the existing literature. We invite and encourage future scholars to venture into these uncharted territories. By addressing these unexplored aspects, future researchers can contribute to the advancement of knowledge in this field, enriching our collective understanding and pushing the boundaries of research in exciting new directions.

The primary goal of this case study is to illustrate the integration of EVCS with commonly utilized energy sources in the RDS. When EVCS is used in the power network, it causes more significant power loss and a poor voltage profile. As a result, energy sources are strategically located at appropriate distribution nodes to offset higher losses. The energy sources allocation method ensures that proper voltage ranges are maintained for each bus. As a result, the goal function is designed to reduce power loss, which reduces total annual energy loss costs, optimizes net savings, and improves the voltage profile of the RDS while remaining within the subject restrictions. The objective function's mathematical formulation is provided by,

$$\boldsymbol{Minimize}(\boldsymbol{F}) = \boldsymbol{Min}(\boldsymbol{P}_{\boldsymbol{T},\boldsymbol{Loss}}) \tag{33}$$

where $\boldsymbol{P}_{\boldsymbol{T},\boldsymbol{Loss}}$ is the total power loss of the RDS.

The following ten scenarios have been considered for IEEE 33-bus RDS.

Scenario-I: Without Compensation

Scenario-II: With EVCS (G2V-Mode)

Scenario-III: With EVCS (V2G-Mode)
Scenario-IV: With EVCS & Capacitor
Scenario-V: With EVCS & DSTATCOM
Scenario-VI: With EVCS & RDG (Only Solar)
Scenario-VII: With EVCS & RDG (Only Wind)
Scenario-VIII: With EVCS, RDGs (Both Solar & Wind)
Scenario-IX: With EVCS, RDG & BESS
Scenario-X: With EVCS, Capacitor, DSTATCOM, RDG & BESS

E. NUMERICAL RESULTS

The load and line data are sourced from reference [212] for the considered test system IEEE 33-bus system. For this particular system, the active and reactive power demands stand at 3.72 MW and 2.3 MVAr, respectively, while the line voltage measures 12.66 kV. The original power loss within the system, without any compensation, amounts to 210.98 kW as calculated within the RDS. To establish the base bus voltages and power distribution across the lines within the test system, we employ the direct approach distribution load flow method described in reference [213]. In this configuration, a single energy source is utilized in conjunction with the EVCS to minimize its impact on the overall RDS. For a visual representation of the IEEE 33-bus RDS, refer to Figure 17.

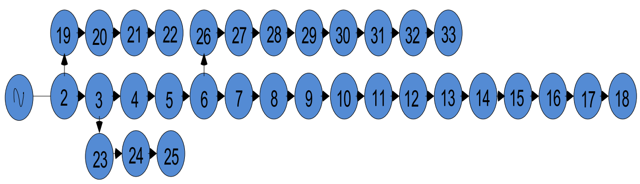

FIGURE 17. IEEE 33-bus test system.

1) SCENARIO-I: WITHOUT COMPENSATION

There is no deployment of energy sources, such as capacitors, DGs, or DSTATCOMs, along the feeder in this scenario to manage voltage levels. As a result of power losses, voltage levels might decrease dramatically near the end of the feeder, resulting in lower voltage levels for consumers further away from the substation. This can lead to operational, financial, stability, and power quality issues in DS. To address these concerns, utilities may consider integrating RES into the RDS.

A distribution load flow analysis was conducted on a RDS under the condition of existing loads and the absence of any energy sources. The power flow algorithm was applied within this framework. The study revealed that the bus with the lowest voltage registered at 0.9037p.u. In this setup, no energy sources were integrated, and the real power loss amounted to 210.98 kW, accompanied by a reactive power loss of 143.13 kVAr. Additionally, the minimum VSI value observed was 0.6610 p.u. Table 7 presents the outcomes of a performance evaluation carried out on an IEEE 33-bus system. Various energy sources were considered, and allocations for EVCS were investigated to gauge their impact.

2) SCENARIO-II: WITH EVCS (G2V-MODE)

When an EV is linked to a charging station in G2V mode, it receives power from the grid to charge its battery. This mode is also known as "charging mode" or "grid mode." The charging station works as a bridge between the electrical grid and the EV in this mode. The station is linked to the grid and receives power, which is then converted to the voltage and current levels required by the vehicle's battery. The charging station also connects to the vehicle, guaranteeing a safe and efficient charging procedure.

Operating EVCSs in G2V mode leads to an increase in power losses, particularly if their placement within the system is not optimized. The introduction of an additional load of 1932 kW from two EVCSs, each with a capacity of 966 kW, contributes to this effect. Strategic installation of these EVCSs at the 2nd and 19th buses of the RDS utilizes the G2V capability. Consequently, power losses elevate from an initial value of 210.98 kW to 224.18 kW. Moreover, the influence extends to the voltage profiles of the buses. The system's lowest voltage experiences a reduction from 0.9037 p.u. to 0.9025 p.u. Importantly, positioning the EVCSs within the RDS has an adverse impact on voltage stability, further emphasizing the significance of optimal placement.

3) SCENARIO-III: WITH EVCS (V2G-MODE)

The proposed ICT is implemented in this scenario-III. A V2G mode charging station allows the EV's battery to discharge energy back to the grid during times of high demand or to offer backup power during power outages. This is known as bi-directional charging. This is also known as "discharging mode" or "vehicle mode." Overall, V2G charging stations can potentially increase grid efficiency by lowering peak demand, boosting the usage of RES, and providing a stable backup power supply. Using the ICT in V2G facility, two EVCSs are advantageously situated in the RDS (2nd and 19th buses). The EV (V2G mode) injects energy into the system to restore the system after it has failed. Power loss was reduced from 210.98kW to 204.11kW after installing EVs in RDS in V2G mode. As a result, the bus voltage magnitudes and overall system stability are enhanced. The system's V_{min} is raised from 0.9037p.u to 0.9050p.u. Using EVCSs as load in ICT in V2G mode reduces power losses significantly and helps the RDS during system breakdowns. Furthermore, putting the EVCS in the RDS reduces the voltage stability of the system. However, V2G technology is still in its early phases and requires further study and testing.

Figures 18 and 19 compare the base case actual power loss and bus voltage magnitudes of the IEEE 33-bus with two EVCS modes (V2G & G2V) using proposed innovative charging technique. G2V mode increases RDS demand and can result in power loss if the EVCS cannot handle the increased load and is not installed correctly. After installing EVCS in G2V mode on RDS, the power loss rose from 210.98kW to 224.18kW. Additionally, the voltage profile of each bus is changed. V2G mode, on the other hand, can

TABLE 7. Performance of IEEE 33-bus system under different scenarios.

Scenarios		Items	BESA	CSA
Scenario-I	Without Compensation	P_{loss} (kW)	210.98	210.98
		Q_{loss} (kVAr)	143.13	143.13
		V_{min} (p.u)	0.9037	0.9037
		VSI_{min}(p.u)	0.6610	0.6610
Scenario-II	With EVCS (G2V-Mode)	EVCS size in kW (Location)	966 (2) 966 (19)	966 (2) 966 (19)
		P_{loss} (kW)	224.18	224.18
		Q_{loss} (kVAr)	150.79	150.79
		V_{min} (p.u)	0.9025	0.9025
		VSI_{min}(p.u)	0.6573	0.6573
Scenario-III	With EVCS (V2G-Mode)	EVCS size in kW (Location)	966 (2) 966 (19)	966 (2) 966 (19)
		P_{loss} (kW)	204.11	204.11
		Q_{loss} (kVAr)	139.58	139.58
		V_{min} (p.u)	0.905	0.905
		VSI_{min}(p.u)	0.6647	0.6647
Scenario-IV	With EVCS & Capacitor	EVCS size in kW (Location)	966 (2) 966 (19)	966 (2) 966 (19)
		Capacitor size in kVAr (Location)	720 (13)	1020 (18)
		P_{loss} (kW)	194.74	216.50
		% P_{loss} Reduction	13.13	3.42
		Q_{loss} (kVAr)	131.46	162.54
		V_{min} (p.u)	0.9222	0.9202
		VSI_{min}(p.u)	0.7152	0.7075
Scenario-V	With EVCS & DSTATCOM	EVCS size in kW (Location)	966 (2) 966 (19)	966 (2) 966 (19)
		DSTATCOM size in kVAr (Location)	1250 (30)	1720 (26)
		P_{loss} (kW)	164.25	174.38
		% P_{loss} Reduction	26.73	22.21
		Q_{loss} (kVAr)	111.34	119.74
		V_{min} (p.u)	0.9148	0.9108
		VSI_{min}(p.u)	0.6943	0.6838
Scenario-VI	With EVCS & RDG (Only Solar)	EVCS size in kW (Location)	966 (2) 966 (19)	966 (2) 966 (19)
		RDG (Solar) size in kW (Location)	1200 (13)	850 (18)
		P_{loss} (kW)	139.58	156.67
		% P_{loss} Reduction	37.74	30.11
		Q_{loss} (kVAr)	93.45	107.28
		V_{min} (p.u)	0.9334	0.9282
		VSI_{min}(p.u)	0.7508	0.7341
Scenario-VII	With EVCS & RDG (Only Wind)	EVCS size in kW (Location)	966 (2) 966 (19)	966 (2) 966 (19)
		RDG (Wind) size in kW (Location)	1500 (30)	2400 (26)
		P_{loss} (kW)	80.49	86.13
		% P_{loss} Reduction	64.09	61.58
		Q_{loss} (kVAr)	60.73	68.67
		V_{min} (p.u)	0.9409	0.9382
		VSI_{min}(p.u)	0.7777	0.7652
Scenario-VIII	With EVCS, RDGs (Both Solar & Wind)	EVCS size in kW (Location)	966 (2) 966 (19)	966 (2) 966 (19)
		RDG (Solar) size in kW (Location)	840 (13)	510 (18)
		RDG (Wind) size in kW (Location)	1140 (30)	1930 (26)
		P_{loss} (kW)	43.87	58.64
		% P_{loss} Reduction	80.43	73.84
		Q_{loss} (kVAr)	31.09	45.35
		V_{min} (p.u)	0.9781	0.9706
		VSI_{min}(p.u)	0.9089	0.8794
Scenario-IX	With EVCS, RDG & BESS	EVCS size in kW (Location)	966 (2) 966 (19)	966 (2) 966 (19)
		RDG (Solar) size in kW (Location)	780 (13)	510 (18)
		RDG (Wind) size in kW (Location)	1040 (30)	1020 (26)
		BESS size in kW (Location)	1070 (24)	910 (27)
		P_{loss} (kW)	28.05	57.17
		% P_{loss} Reduction	87.49	74.51
		Q_{loss} (kVAr)	21.26	44.58

TABLE 7. *(Continued.)* Performance of IEEE 33-bus system under different scenarios.

Scenario-X	With EVCS, Capacitor, DSTATCOM, RDG & BESS	EVCS size in kW (Location)	966 (2) 966 (19)	966 (2) 966 (19)
		Capacitor size in kVAr (Location)	400 (13)	240 (18)
		DSTATCOM size in kVAr (Location)	930 (30)	280 (26)
		RDG (Solar) size in kW (Location)	780 (13)	500 (18)
		RDG (Wind) size in kW (Location)	1040 (30)	1090 (26)
		BESS size in kW (Location)	1070 (24)	810 (27)
		P_{loss} (kW)	20.61	53.69
		% P_{loss} Reduction	90.81	76.05
		Q_{loss} (kVAr)	15.53	41.64
		V_{min} (p.u)	0.9908	0.9713
		VSI_{min}(p.u)	0.9595	0.8821

TABLE 8. Effect on real power loss due to EVCS under different scenarios (IV to X).

Items	**Scenarios**													
	IV		**V**		**VI**		**VII**		**VIII**		**IX**		**X**	
	BESA	**CSA**	**BESA**	**CSA**	**BESA**	**CSA**	**BESA**	**CSA**	**BESA**	**CSA**	**BESA**	**CSA**	**BESA**	**CSA**
P_{loss} (kW)	194.74	216.50	164.25	174.38	139.58	156.67	80.49	86.13	43.87	58.64	28.05	57.17	20.61	53.69
% P_{loss} Reduction	13.13	3.42	26.73	22.21	37.74	30.11	64.09	61.58	80.43	73.84	87.49	74.51	90.81	76.05

lessen the requirement for extra power production and aid in reducing system power loss. According to Figures 18 and 19, V2G mode using proposed ICT on IEEE 33-bus RDS provides higher power loss mitigation and bus voltage magnitude enrichment than G2V mode.

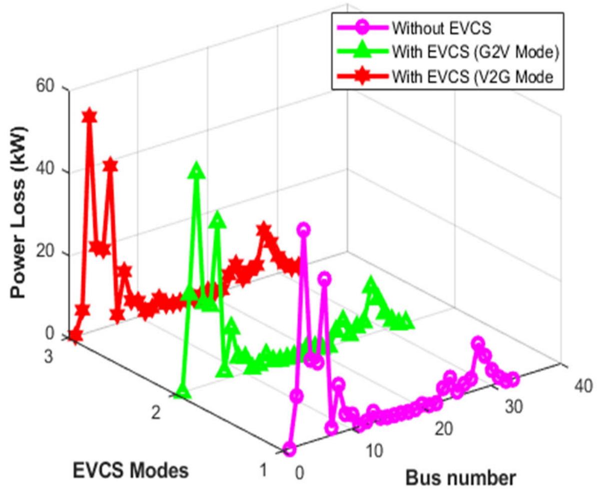

FIGURE 18. Comparison of real power loss with different EVCS modes using proposed innovative charging technique.

4) SCENARIO-IV: WITH EVCS & CAPACITOR

The integration of capacitors into the RDS presents an effective solution for mitigating power loss and voltage fluctuations stemming from EVCS. This strategic deployment of capacitors not only enhances the stability and reliability of the electrical grid, especially during periods of high EV charging demand, but also yields tangible benefits. By incorporating capacitors to counterbalance the impact of EVCSs on the RDS, significant reductions in power loss are

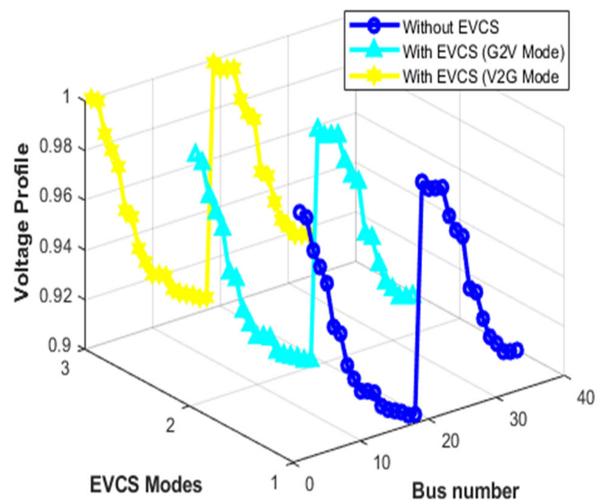

FIGURE 19. Comparison of voltage profile values with different EVCS modes using proposed innovative charging technique.

achieved, decreasing from 224.18kW to 194.74kW. Furthermore, this approach yields an increase in VSI from 0.6573p.u to 0.7152p.u, along with a noteworthy elevation in the minimum bus voltage, rising from 0.9025p.u to 0.9222p.u.

5) SCENARIO-V: WITH EVCS & DSTATCOM

The installation of EVCS in conjunction with DSTATCOMs in the RDS can provide substantial benefits such as enhanced power quality, decreased power losses, and higher voltage profile. When two EVCSs are concurrently integrated into IEEE 33-bus RDS in collaboration with DSTATCOM, actual power loss is reduced from 224.18kW to 164.25kW, VSI is increased to 0.6943p.u from 0.6573p.u, and the minimal bus voltage is increased to 0.9148p.u from 0.9025p.u. This contributes to voltage stability and lowers power losses in the

RDS. Furthermore, providing reactive power assistance to the grid during periods of low output helps offset the impact of intermittent RES like wind and solar power.

6) SCENARIO-VI: WITH EVCS & RDG (ONLY SOLAR)

Integrating EVCSs and solar-powered DG systems into RDS can benefit the grid and the users. Customers can utilize solar panels to generate their electricity, lessening their reliance on the grid and potentially saving money on their energy costs. Overall, including EVCS and solar-powered DG systems in DS may assist in minimizing power losses, boosting efficiency, and promoting the use of clean energy. At the 13^{th} slot, a solar-based renewable DG is appropriately positioned and scaled using BESA. The power loss is reduced from 224.18kW to 139.58kW as a consequence. It also improves voltage profiles and voltage stability on DS.

7) SCENARIO-VII: WITH EVCS & RDG (ONLY WIND)

When EVs are charged using RDGs such as wind power, the demand for fossil fuels is reduced, as are greenhouse gas emissions. This also promotes sustainability and reduces our dependency on non-RES. Power losses in the RDS can be reduced by combining wind-based RDG with EVCS. In this scenario, one wind-based DG is appropriately positioned and scaled at the 30^{th} position using BESA. The power loss is reduced from 224.18kW to 80.49kW as a consequence.

8) SCENARIO-VIII: WITH EVCS, RDG (BOTH SOLAR & WIND)

Renewable DG systems based on solar and wind can be deployed at various places in the DS to generate electricity locally. This can aid in lowering power losses by supplying electricity directly to local loads and minimizing the amount of power that must be transported over long distances. The extra electricity produced by these devices may also be utilized to charge EVs at charging stations. In the scenario, solar and wind-powered DGs are optimally positioned on the 13^{th} and 30^{th} sites to maximize the advantages of EVCS on RDS. According to the simulation findings, power loss is reduced from 224.18kW to 43.87kW, which is minimal when compared to placing the solar and wind-based DGs separately using EVCS. Furthermore, the minimal bus voltage is raised from 0.9025p.u to 0.9781p.u. Multiple RDGs appropriate location and sizing, such as bus voltage, also boost VSI. As a result, when EVCS is integrated into an RDS with solar and wind-based RDGs, the system's performance is less influenced by EV charging.

9) SCENARIO-IX: WITH EVCS, RDGS & BESS

An EVCS powered by RDG, such as solar and wind, in conjunction with a BESS, can efficiently reduce power loss in the RDS. A BESS can be utilized to store excess power generated by RDGs during low-demand periods and then release it during high-demand periods. This helps to balance power supply and demand, reducing pressure on the RDS. To mitigate the charging impact of EVCSs, solar and wind-based RDGs, and BESSs are connected with EVCSs at ideal spots on the RDS. Consequently, the power loss is reduced from 224.18kW to 28.05kW, the VSI is increased to 0.9071p.u from 0.6573p.u, and the minimum voltage is raised to 0.9775p.u from 0.9025p.u. Furthermore, the voltage profile of each bus is kept within the permissible range of voltage stability.

10) SCENARIO-X: WITH EVCS, CAPACITOR, DSTATCOM, RDG & BESS

The EVCS is equipped with Capacitor, DSTATCOM, RDG, and BESS to maximize the benefits of energy sources on DS. To mitigate the charging impact of EVs, two RDGs (Solar->13^{th} & Wind->30^{th} buses), a capacitor (13^{th} bus), DSTATCOM (30^{th} bus), and BESS (24^{th} bus) are collaboratively incorporated on the RDS at ideal places and sizes. Consequently, the power loss is reduced from 224.18kW to 20.61kW, the VSI is raised from 0.6573p.u to 0.9595p.u, and the minimum voltage is increased from 0.9025p.u to 0.9908p.u. Furthermore, the voltage profile of each bus is kept within the permissible range of voltage stability. As seen in Tables 7, this scenario has the most significant decrease in power loss and voltage deviation, as well as the maximum improvement in VSI.

F. EFFECT OF EVCS ON SYSTEM LOSS

Power loss difficulties arise due to the installation of EVCS to the 33-bus RDS. In the 33-bus system, the base case active and reactive power losses are determined to be 210.98kW and 143.13kVAr, respectively. When two EVCS are optimally put at the bus's second and nineteenth places, the power loss increases by 224.18kW. It is advised that EV users install many EVCS on their journey to boost the widespread adoption of EVs. It is recognized that the inclusion of EVCS is necessary for the survival of EVs but harms the health of the power RDS. As a result, a trade-off must be made between power system health and charging infrastructure. To lessen the charging impact of EVs, energy sources are incorporated. On the other hand, the usage of energy sources on optimum buses compensates for the power loss difficulties.

In this situation, the ideal placement of a 720kW capacitor at bus 13 resulted in an actual power loss of 194.74kW. When DSTATCOM is positioned on bus 30, it has a capacity of 1250kW and a decreased loss of 164.25kW. Also, when solar and wind-powered DGs with capacities of 840kW and 1140kW are put at bus numbers 13 and 30, respectively, the loss is decreased to 43.87 kW. The power loss values are reduced to 30.16kW from 224.18kW when EVCS and all energy sources (Scenario-X) are arranged sequentially in a 33-bus RDS, as shown in Table 7 and 8. Figure 20 depicts the actual and reactive power loss figures for all cases. Figure 20 illustrates the real power loss of an IEEE 33-bus system in all scenarios evaluated for each bus. According to Table 7 and Figures 20 and 21, Scenario-X provides significant real and reactive power loss mitigation and bus voltage magnitude augmentation in 33-bus RDS compared to other scenarios.

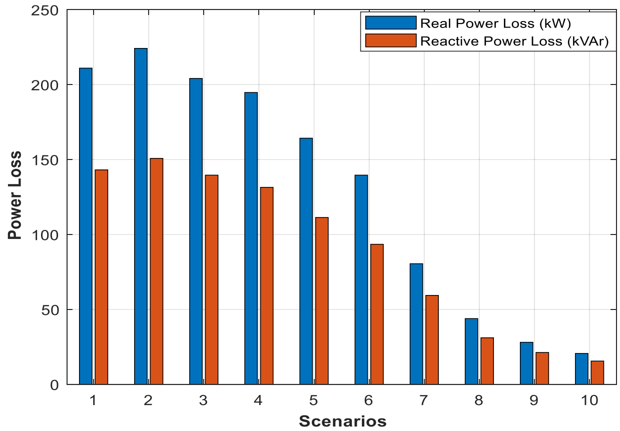

FIGURE 20. Comparison of real & reactive power loss values with different scenarios.

The influence of EV charging load on RDS performance is investigated using a capacitor, RDG, DSTATCOM, and BESS integration. According to Tables 7 and Figure 21, the highest power loss reduction in the RDS may be accomplished when all compensators are ideally located (Scenario-X). Table 8 also demonstrates the effect of EVCS on real power loss in different scenarios (IV to X) for an IEEE 33-bus system.

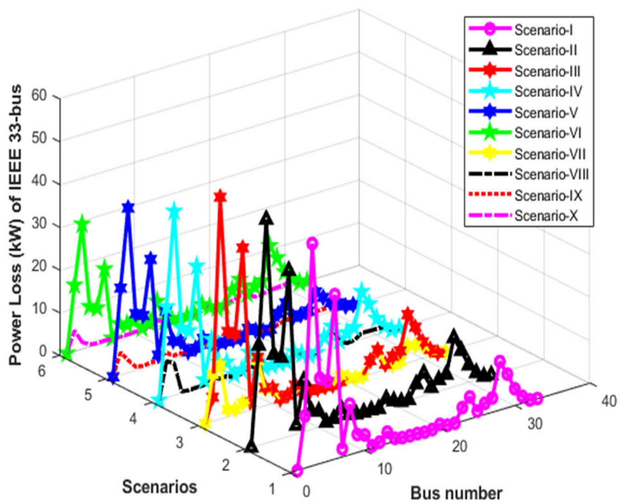

FIGURE 21. Real power loss of IEEE 33-bus system.

G. EFFECT OF EVCS ON SYSTEM VOLTAGE PROFILE

Incorporating EVCS into the network introduces challenges such as system losses, which have a negative impact on both voltage profiles and VSI. The voltage stability and profile of the system experience degradation with the rise in EV loads. To counter these disruptions, it is essential to strategically integrate pertinent energy sources at specific nodes within the RDS. The 33-bus system's voltage profile under different scenarios, involving the installation of multiple EVCS units and energy sources, is illustrated in Figure 16. Similar to the findings depicted, it is evident that as the charging

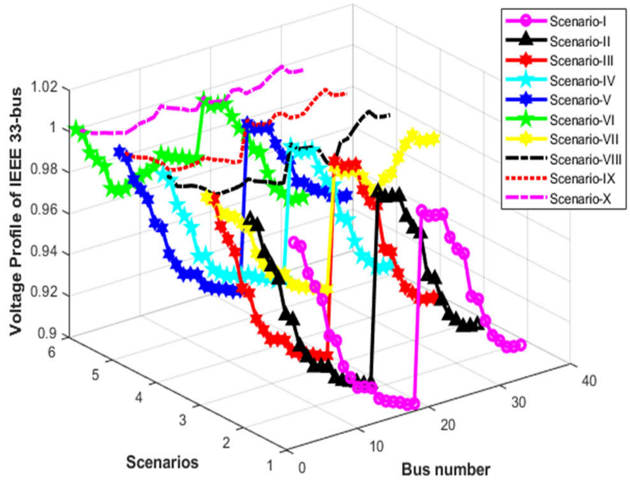

FIGURE 22. Voltage profile of IEEE 33-bus system.

load increases, the voltage at individual buses continues to decrease. An interesting observation arises from the optimal placement of a 1932kW EVCS on buses 2 and 19, which leads to a collective reduction in the voltage profile of the entire system.

Furthermore, as the number of EVCS grows, the voltage profile degrades. To guarantee that the system operates properly, energy sources and EVCS are integrated into the RDS. The integration of energy source units has a favorable influence on the system's voltage profile. Figure 22 depicts the improvement in voltage profile after combining all energy sources using EVCS. Voltages on all buses fluctuate due to real and reactive power losses in the RDS. As a result, real power assistance is necessary to reduce real power losses, which improves voltage levels by reducing I2R losses. It has also been noted that bus voltages improve when multiple energy sources are positioned together. Furthermore, the kind, size, and placement of energy sources influence voltage profile improvement. Table 7 shows that when all energy sources are combined on a 33-bus system, the minimum voltage rises to 0.9908p.u from 0.9025p.u, as seen in Figure 22.

H. EFFECT OF EVCS ON SYSTEM STABILITY

Adding EVCS and energy sources to the RDS affects both the voltage stability index and the voltage profile. Figure 23 depicts the VSI findings for the 33-bus system achieved for all situations. VSI is 0.6610p.u., in the base case (before adding EVCSs and energy sources). When two EVCS of capacity 1932kW are ideally put at bus numbers 2 and 19, it falls to 0.6573p.u. The incorporation of RES into RDS improves the VSI. As shown in Figure 23, VSI increases when more energy sources are optimally located in the RDS. When all energy sources are used, the VSI rises to 0.9595p.u from 0.6573p.u.

I. COMPARATIVE ANALYSIS

Further, to demonstrate the effectiveness of the proposed approach, the authors constructed the objective function using

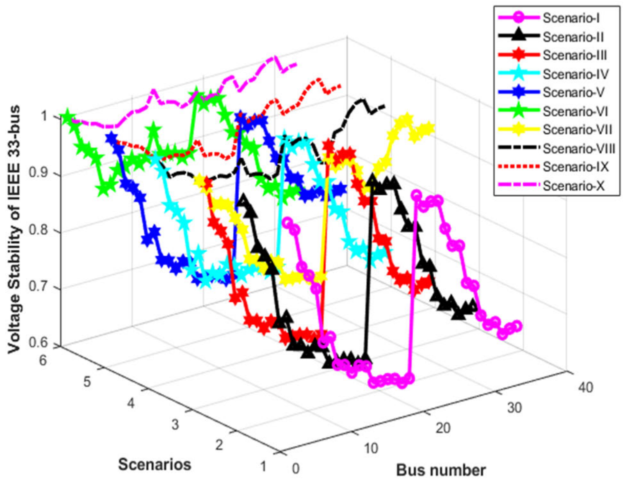

FIGURE 23. Voltage stability of IEEE 33-bus system.

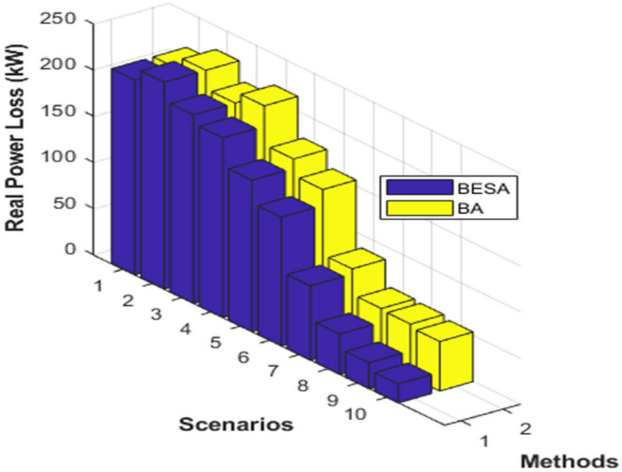

FIGURE 24. Comparison of real power loss under various scenarios using BESA and CSA.

two algorithms: proposed BESA and CSA. Since there is no literature on distribution systems using proposed considered cases for IEEE 33-bus RDS, the authors used the above algorithms to construct the same objective function. They compared the results of CSA to the proposed BESA. Tables 7 compares various parameters for IEEE 33-bus RDS using presented and existing approaches. To validate the supremacy of the proposed method objective, the performance of system under different scenarios with objective function as real power loss is compared with CSA and tabulated in Table 8 for both IEEE 33 bus RDS. Figure 24 shows the comparison of real power loss under various scenarios using BESA and CSA. From the Figure 24, Tables 7 and 8, the proposed BESA has provided a significant decrease in power loss compared to CSA in all scenarios. The BESA-based optimization strategy is found to be more effective than CSA technique in improving voltage profiles. Furthermore, VSI_{min} values were improved in all scenarios compared to CSA based approach. The findings suggest that the BESA is capable of solving complex and real time power system problems. Future researchers are recommended to use the BESA as a robust optimization tools for resolving intricate engineering real time problems. The problem of combined allocation of all the energy sources in the RDS, with EVCS, has been effectively addressed through the proposed BESA and CSA optimizations. This solution ensures the RDS operates reliably and efficiently.

VIII. CONCLUSION

Finally, as EV usage grows, EVCS allocation in distribution networks is a crucial issue that must be addressed. Various approaches for allocating EVCSs in DS have been proposed, including optimization models, heuristic algorithms, and machine learning techniques. The objective of this article was to provide a complete assessment of the kinds, technologies, energy sources, test methods, problems, difficulties, issues, and possibilities encountered in the optimal installation and sizing of EVCS in DS. For this case study, an IEEE 33-bus RDS was used. Various scenarios with various energy sources have been evaluated to minimize DS power loss. The simulation findings showed that combining energy sources with EVCS resulted in more significant power loss reduction and voltage profile enhancement than combining energy sources independently on the DS.

Finally, the approach will be determined by the DS's particular characteristics and the allocation process's aims. Factors like as the quantity and placement of EVCSs, the capacity of the DS, EV charging trends, and the availability of RES must all be considered. Overall, good EVCS placement in DS may aid in expanding the EV industry and contribute to a more sustainable future. Overall, the influence of EVCSs on the DS is determined by various factors, including the system's unique features, charging method, and management measures. EVCSs may be incorporated into the grid to maximize their advantages while minimizing their negative consequences with proper design and management. The G2V and V2G modes of EVCSs have the potential to play an essential role in the future of the electrical grid and the transition to a more sustainable energy system. Further, it can also be understood that the EV owners may generate revenues by V2G mode if they can schedule their vehicles as per the system using proposed innovative charging technique.

IX. FUTURE SCOPE/DIRECTION/RECOMMENDATIONS

Electric vehicles are becoming increasingly popular as the world progresses towards a more sustainable and environmentally friendly future. As EVs become more popular worldwide, so does the need for EVCSs. According to the International Energy Agency, over 145 million EVs will be on the road worldwide by 2030. This implies that EVCS will be in high demand in the following years. As a result, the need for EVCS is rapidly increasing.

The future of EVCS allocation in DS looks bright. The responsibility of DNO is to ensure enough energy infrastructure to accommodate the rising demand for EVCS. This involves providing enough capacity is available in the DS to enable the installation and operation of EVCS. Furthermore, DSOs must guarantee that EVCS are situated in areas where EV customers may readily reach them.

Future research can concentrate on the scope and recommendations for allocating EVCSs in DS listed below:

- ✓ ***Optimal location allocation:*** The arrangement of EVCSs in DS should be optimized to reduce the cost of charging infrastructure while ensuring that EV owners have accessible charging facilities. Researchers in the future can utilize optimization techniques to find the best position and size of charging stations. The optimization method may consider parameters such as the quantity of EVs in a given region, EV charging habits, and DS capacity. This research will assist utilities in determining the most cost-effective sites for charging station installation and the ideal number and EVCSs to deploy.
- ✓ ***Smart charging:*** Smart charging technology can optimize the charging process while reducing the strain on the DS. Smart charging technology may modify the charging rate of EVCS based on renewable energy supply, grid load, and other factors. Researchers in the future might look at the possible benefits of adopting smart charging technologies to allocate EVCSs in DS.
- ✓ ***Multi-objective optimization of EVCS allocation:*** Future studies should concentrate on establishing a multi-objective optimization strategy that considers multiple criteria such as EVCS location, capacity, cost, and environmental effect. This will aid in optimizing EVCS allocation in DS while balancing numerous objectives.
- ✓ ***Dynamic allocation of EVCSs:*** As EVs become more popular, the demand for EVCSs will change throughout the day. Researchers should concentrate on creating a dynamic allocation system that can adapt EVCS allocation in real-time to account for variations in demand.
- ✓ ***Dynamic pricing:*** Dynamic pricing techniques can be implemented by DSOs to encourage EV owners to charge their vehicles during off-peak hours. This can assist in balancing the DS's load and preventing the need for costly modifications.
- ✓ ***Load management:*** Load management strategies can also be used by researchers to control the power demand from EVCS. They can, for example, limit the number of vehicles charging at any given moment or lower the charging fee during busy hours.
- ✓ ***Collaborative planning:*** Future academics can provide recommendations to DSOs, who can then collaborate with other stakeholders, such as towns and companies, to determine the best areas for EVCS. This can aid in ensuring that EVCS are placed in areas where they are most required and are conveniently accessible to EV users.
- ✓ ***Demand forecasting:*** Future studies should focus on establishing realistic forecasting models to estimate EVCS demand in various places. These models can consider aspects like the quantity of EVs in the region, the rate of EV adoption growth, and the availability of charging infrastructure. This can assist utilities in planning for essential infrastructure modifications and ensuring that the grid can manage the increased demand.
- ✓ ***Renewable energy integration:*** As the utilization of RES grows, future researchers may look into integrating EVCS with RES like solar and wind power. Future researchers can concentrate on creating models and algorithms that optimize the integration of RES into EVCSs. Integrating RES into EV charging infrastructure can help to lower the transportation sector's carbon footprint.
- ✓ ***Interoperability and standardization:*** Interoperability and standardization are critical for creating a dependable and efficient EV charging infrastructure. Future research might examine the influence of various charging techniques and standards on EVCS allocation in DS.
- ✓ ***Distribution system planning:*** Future scholars might examine how EVCS affects DS planning. This involves assessing the best sites for EVCS based on DS capacity and load demand, both present and anticipated.
- ✓ ***Charging behavior analysis:*** Researchers can examine EV users' charging habits, such as setting patterns, sites, and preferred charging periods. This can influence EVCS design and implementation, ensuring that they fulfill the demands of EV owners.
- ✓ ***Energy management systems:*** Future studies might consider using energy management systems (EMS) to optimize EV charging. An EMS can assist in balancing the DS's load and reducing the impact of EV charging on the grid.
- ✓ ***Advanced Charging Technologies:*** Advanced charging technologies, such as wireless charging, rapid charging, and V2G charging, can be developed by researchers. These innovations will improve the user experience of EVs while reducing grid load. Wireless charging technology will allow EVs to charge without cords while fast-charging technology will minimize charging time. The V2G technology will enable EVs to discharge energy back to the grid as needed, assisting in grid stabilization.
- ✓ ***EV Infrastructure Planning:*** Researchers may use data-driven methodologies to analyze EV adoption patterns and forecast future demand for charging infrastructure. This research will assist utilities in planning and deploying EV charging infrastructure to meet expected demand. This planning approach will limit the danger of overbuilding or underbuilding charging infrastructure, hence optimizing charging infrastructure investment.
- ✓ ***Smart grid integration:*** Researchers can look at integrating EVCSs with smart grids to optimize their functioning and reduce their effect on the grid. This may include employing advanced control systems, such as demand response, to manage the charging load and guarantee that it is in sync with the grid's capacity.
- ✓ ***Energy storage integration:*** Integrating energy storage systems with EVCSs can supply backup power during high-demand hours or a power outage. Researchers may

look at the best scale and positioning of energy storage systems about EVCSs to guarantee they can supply dependable and efficient backup power.

✓ ***Environmental Sustainability in EVCS Allocation:*** Environmental considerations play a pivotal role in the allocation of EVCS, ensuring a sustainable and eco-friendly charging infrastructure. This involves integrating renewable energy sources like solar or wind power through eco-charging systems (which include PV, ESS, and the electrical grid), strategically placing charging stations to prevent grid overload, and prioritizing high-efficiency charging equipment to minimize energy wastage. Additionally, it entails avoiding sensitive environmental areas, adhering to urban planning regulations, and conducting comprehensive life cycle assessments of EVCS installations. Proper waste management and community engagement further contribute to environmental sustainability. Moreover, long-term scalability and adaptability to evolving environmental standards are crucial factors in ensuring the lasting eco-friendliness of EVCS infrastructure. By addressing these considerations, stakeholders can contribute to a greener and more sustainable transportation ecosystem.

The future scope of EVCS allocation in DS is promising. DSOs will play a critical role in ensuring adequate infrastructure to serve the rising demand for EVs. DSOs may optimize the use of existing infrastructure and reduce the need for costly upgrades by implementing smart charging, dynamic pricing, load control, and collaborative planning initiatives. Future research can concentrate on creating creative strategies to efficiently allocate EVCSs in DS while guaranteeing grid dependability and stability. This study is critical for the effective integration of EVs into the transportation system and the transition to a more sustainable future. Researchers should also concentrate on developing methodologies for integrating EVCSs into DS, optimizing their allocation, evaluating their impact on DS, integrating RES, and standardizing EVCSs to ensure interoperability and compatibility.

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T. YUVARAJ received the B.E. degree in electrical and electronics engineering and the M.E. degree in power electronics and drives from Anna University, Chennai, India, in 2011 and 2013, respectively, and the Ph.D. degree from VIT University, Vellore, India, in 2017. He is currently an Associate Professor with the Department of Electrical and Electronics Engineering and a Research Member of the Centre for Computational Modeling, Chennai Institute of Technology, Chennai. He has published more than 70 papers in Web of Science/Scopus-indexed journals. His research interests include power system optimization, allocation of distributed energy resources, electric vehicle technology, power system resilience, and renewable energy. He is a member of IET and IAENG. He has served as a reviewer for various reputed journals, such as IEEE, Elsevier, Springer, Taylor and Francis, and Interscience journals.

K. R. DEVABALAJI received the bachelor's degree in electrical and electronics engineering and the master's degree in power electronics drives from Anna University, Chennai, India, in 2011 and 2013, respectively, and the Ph.D. degree from the Vellore Institute of Technology, Vellore, India, in 2016. He is currently an Associate Professor with the Department of Electrical and Electronics Engineering, Aarupadai Veedu Institute of Technology, Vinayaka Mission's Research Foundation, Chennai. He has published several research articles in reputed journals. He has more than 10 years of teaching and research experience. He has visited Thailand, Singapore, Indonesia, and the U.K. to present research papers, funded proposals, and collaborative research activities. His research interests include renewable energy systems, power systems, and power electronics and drives.

J. ANISH KUMAR received the B.E. degree in electrical and electronics engineering from Manonmaniam Sundaranar University, in 2003, and the M.E. and Ph.D. degrees in applied electronics from Anna University, Chennai, in 2005 and 2023, respectively. He is currently an Assistant Professor (SG) with the Department of Electrical and Electronics Engineering, Saveetha Engineering College, Chennai. He has published articles in Scopus/SCI indexed journals His research interests include embedded systems, the Internet of Things, power electronics, and robotics.

SUDHAKAR BABU THANIKANTI (Senior Member, IEEE) received the B.Tech. degree from Jawaharlal Nehru Technological University, Ananthapur, India, in 2009, the M.Tech. degree in power electronics and industrial drives from Anna University, Chennai, India, in 2011, and the Ph.D. degree from VIT University, Vellore, India, in 2017. He has completed a Postdoctoral Research Fellowship with the Department of Electrical Power Engineering, Institute of Power Engineering, University Tenaga Nasional (UNITEN), Malaysia. He was with the Department of Electrical and Electronic Engineering Science, University of Johannesburg, as a Senior Research Associate. He is currently a Senior Research Associate with the Department of Electrical and Electronic Engineering Science, University of Johannesburg, and an Associate Professor with the Department of Electrical and Electronics Engineering, Chaitanya Bharati Institute of Technology, Hyderabad. He has published more than 140 research articles in various renowned international journals. His research interests include the design and implementation of solar PV systems, renewable energy resources, power management for hybrid energy systems, storage systems, fuel cell technologies, electric vehicles, and smart grids. He has been acting as an Editorial Board Member and a Reviewer of various reputed journals, such as the IEEE, IEEE Access, IET, Elsevier, and Taylor and Francis.

NNAMDI I. NWULU (Senior Member, IEEE) is currently a Full Professor with the Department of Electrical and Electronic Engineering Science, University of Johannesburg, and the Director of the Centre for Cyber Physical Food, Energy and Water Systems (CCP-FEWS). His research interests include the application of digital technologies, mathematical optimization techniques, and machine learning algorithms in food, energy, and water systems. He is a Professional Engineer registered with the Engineering Council of South Africa (ECSA), a Senior Member of the South African Institute of Electrical Engineers (SMSAIEE), and a Y-Rated Researcher by the National Research Foundation of South Africa. He is the Editor-in-Chief of the *Journal of Digital Food Energy and Water Systems* (JDFEWS) and an Associate Editor of *IET Renewable Power Generation* (IET-RPG) and *African Journal of Science, Technology, Innovation and Development* (AJSTID).