IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 5 July 2024, accepted 29 July 2024, date of publication 5 August 2024, date of current version 26 August 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3438456

RESEARCH ARTICLE

Optimizing Radial Distribution System With Distributed Generation and EV Charging: A Spotted Hyena Approach

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ABSTRACT Ensuring reliability and resilience in radial distribution systems (RDS) is essential for consistent electricity delivery and rapid recovery from disruptions, particularly with the rise of electric vehicles (EVs). This study investigates the impact of EV charging stations (EVCS) on RDS performance, focusing on reliability, resilience, power loss, and voltage stability. We conducted two key studies: (i) enhancing reliability with distributed generation (DG) and EVCS in grid-to-vehicle mode, and (ii) enhancing resilience with DG and EVCS in vehicle-to-grid mode. Using the spotted hyena optimizer algorithm (SHOA), we formulated objective functions to improve RDS performance, comparing results with the cuckoo search algorithm (CSA). Testing on the IEEE 69 bus system demonstrated that SHOA significantly improves reliability and resilience, offering a robust solution for optimizing RDS amidst evolving energy demands.

INDEX TERMS Spotted hyena optimizer algorithm, distributed generation, electric vehicle charging station, radial distribution system.

I. INTRODUCTION

The global surge in electric vehicle (EV) adoption has highlighted the need for electric vehicle charging stations (EVCSs) to support clean transportation. While EVCS proliferation brings benefits, it poses challenges to the radial distribution system (RDS) [1]. This research assesses the effects of EVCS on power loss, voltage stability, and the reliability of RDS. The imperative to reduce greenhouse gas emissions and enhance energy independence drives the shift to electric mobility, leading to exponential EVCS deployment and increased grid load [2]. EVCS integration raises concerns about power losses in the RDS due to high EV charging currents, impacting system efficiency. Understanding these losses is crucial for sustainable charging infrastructure design. Additionally, EVCS operation can affect RDS voltage stability, potentially causing fluctuations and drops during peak demand. Stable voltage is essential for electricity supply quality for both EVs and non-EV customers [3].

Reliability is impacted by EVCS integration, with added load straining distribution equipment in densely populated areas, raising failure rates. Maintaining the dependability of RDS is essential for ensuring a continuous power supply to all customers. As EVCS deployment grows, methodically addressing these challenges is essential for seamless EV integration, requiring innovative technology to enhance power distribution, voltage stability, and overall RDS reliability [4], [5]. Distributed generation (DG) strategically placed in high EVCS demand or voltage unstable areas helps balance load distribution, reducing power losses. DG units with voltage regulation stabilize supply to EVCS. Smart grid tech and dynamic allocation algorithms optimize DG

The associate editor coordinating the review of this manuscript and approving it for publication was Junho Hong.

placement, enhancing reliability. Integrating energy storage smooths power demand fluctuations, crucial for addressing EV charging spikes. DG deployment optimizes RDS performance amid growing EVCS presence [6].

Resilience is a critical measure of a power system's ability to recover from significant disruptions like accidents, deliberate attacks, or natural disasters. Such events can cause multiple line faults, some taking hours or days to fix. Electric utilities strive to maintain service to as much load as possible while minimizing the costs of load shedding, a key resilience metric. Enhancing resilience encompasses three primary strategies. Firstly, strengthening distribution poles along essential lines mitigates the risk of breakage during severe weather events. Secondly, building additional normally open tie lines enables system operators to restore power to isolated feeders by reconfiguring the network during faults. Thirdly, increasing distributed energy resources (DERs) deployment, forming microgrids (MGs) within the faulted RDS buses, significantly boosts system resilience [7], [8], [9].

II. LITERATURE REVIEW

The deployment of EVCS within power distribution networks is a critical area of research due to its impact on grid stability, reliability, and resilience. This literature review examines the multifaceted aspects of EVCS allocation, integrating reliability and resilience studies to provide a comprehensive overview of current methodologies, challenges, and advancements in the field.

A. LITERATURE REVIEW ON EVCS ALLOCATION

Research on EVCS allocation focuses on optimizing the location and sizing of EVCSs to ensure efficient utilization of the power grid while meeting the growing demand for electric vehicle charging. Studies explore various optimization algorithms, such as particle swarm optimization (PSO) and genetic algorithms (GA), to address factors like power loss minimization, voltage stability, and cost-effectiveness.

The research focused on a hybrid preference-based EVCS location problem, considering multiple optimization preferences of distribution network operators, charge station owners, and electric vehicle users. The problem was formulated by an uncertain mixed-integer programming model, introducing significant computational complexity through the use of Type-2 fuzzy variables [10]. A system comprising a solar photovoltaic (PV) array, battery energy storage system (BESS), diesel generator set, and grid-based EVCS for continuous charging in islanded, grid-connected, and DG set-connected modes was presented. The assumption of ideal conditions for seamless switching and consistent DG performance may not have accounted for real-world fluctuations and complexities [11].

SCOPE is a revolutionary multi-objective framework that combines optimization goals such as decreasing real power loss, lowering bus voltage fluctuation, maximizing system voltage stability, lowering system operating expenses, and reducing CO_2 emissions. However, it relied on simulated driving patterns and V2G capabilities over a 24-hour horizon, potentially not accurately capturing real-world EV usage variability [12]. The hybrid genetic algorithm and particle swarm optimization (GA-PSO) were presented for the optimal allocation of plug-in EVCS (PEVCS) in the RDS with DG in high volumes and appropriately put on selected network buses. The hybrid GA-PSO algorithm may have involved significant computational complexity and longer processing times [13].

The slime mould algorithm (SMA) and other optimization methods were utilized to determine the best positioning and scaling of RDG/DSTATCOM/EVCS/BESS within the RDS, as demonstrated on IEEE 33-bus and 69-bus systems. The reliance on stochastic processes and unpredictable motions may have resulted in irregular convergence behavior and prolonged processing times, with incorrect placement and sizing potentially affecting RDS performance [14].

The modeling of EVCSs affected by EV owner behavior in a power distribution network was studied, as well as the appropriate location and size of EVCSs to decrease their negative effects on the network, including as network losses and voltage variations in the presence of uncertain loads. The probabilistic model was studied using the Monte Carlo simulation (MCS) approach. Future research could have analyzed the impacts of correlation between different sources of uncertainties and the possibility of sudden overloading of the system [15].

The developed PSO algorithm was proposed for the optimal placement of EVCS in the RDS. The performance of PSO may have been influenced by factors such as parameter settings and problem formulation, potentially affecting the accuracy and efficiency of the results [16]. The integration of DG and DSTATCOM using BESA for minimizing the impact of EVCS in distribution systems considering load uncertainty and load variation was proposed, though the load variation was not considered for EVCS [17]. A hybrid method to effectively manage energy in EVCS and distribution systems was proposed, consolidating shell game optimization (SGO) and recalling-enhanced recurrent neural network (SGO-RERNN) techniques. The comparison with existing systems may have been limited by differences in implementation details and evaluation criteria, potentially impacting the generalizability of the findings [18]. Using BESA for power loss mitigation and net savings showed improvements in power loss reduction and VSI enhancement in the distribution system, although BESA may have only been suitable for certain optimization problems, particularly those with well-defined fitness functions and continuous search spaces [19].

B. LITERATURE REVIEW ON EVCS WITH RELIABILITY STUDY

Incorporating reliability studies into EVCS planning involves assessing the impact of EVCS on the overall reliability of the power distribution network. This includes evaluating the likelihood of system failures, downtime, and the robustness of the grid in accommodating additional loads from EVCS. Research in this area often utilizes probabilistic models and reliability indices to quantify and enhance the reliability of RDS integrated with EVCS.

A novel strategy for obtaining the optimal location of EVCS/EVBSSs in the RDS was proposed, investigating their impact on various network parameters. However, the study assumed perfect integration of renewable DGs with battery energy storage, which may not always be achievable in practice [20]. A hybrid technique, combining golden jackal optimization (GJO) and random forest algorithms (RFA), named the GJO–RFA technique, was presented to address EV allocation and assignment problems. Assumptions made regarding the number of charging ports and FCS capacity may not fully capture real-world deployment complexities [21]. Research aimed at modeling and optimizing hydrogen-fuel-cell-based distributed generation (HFC-DG) to minimize the effects of EVCSs in RDS. However, ideal conditions were assumed, neglecting practical challenges such as equipment failures and regulatory constraints [22].

An AI approach, hybrid GWO-PSO, was proposed to investigate suitable nodes for EVCS and DGs in a balanced distribution system considering reliability. Limitations include the stochastic approach employed to model EV load and the focus on conventional DGs instead of renewable-based ones [23]. The impact of PEV charging and discharging on reliability was analyzed for two areas, showing improvements in EENS and SAIDI with PEV and DGs. However, the study did not consider the integration of transportation and RDS as a test system [24]. Investigations into the effect of EVCS loads on network parameters were conducted on the IEEE 33-bus test system. Results indicated that the system could withstand placement of fast charging stations at strong buses, but placement at weak buses hampered system operation [25].

The GABC algorithm was implemented to minimize total active power loss through DG and shunt capacitor placement simultaneously, effectively reducing total annual cost and improving voltage profile. However, the study's generalizability may be limited by its focus on specific optimization techniques [26]. A multi-year expansion planning strategy for distribution networks was presented to enable increasing penetrations of plug-in electric vehicles, with an emphasis on the temporal aspects of charging loads and their reliability implications. However, potential uncertainties and complexities associated with PEV integration and RDS planning may not be fully captured [27].

C. LITERATURE REVIEW ON EVCS WITH RESILIENCE STUDY

Resilience studies related to EVCS focus on the ability of the power distribution network to withstand and recover from extreme events, such as natural disasters and cyberattacks. This includes developing strategies for resilient planning and operation of EVCS, such as the integration of DERs and mobile energy resources (MERs). Studies often employ advanced optimization frameworks and scenario-based analyses to enhance the resilience of distribution networks with EVCS.

A decision-making framework was proposed to enhance seismic resilience by modifying importance measures and applying fault tree analysis. However, reliance on assumptions and simplifications in modeling seismic hazards and system vulnerabilities may limit its scalability and generalizability [28]. Resilience analysis focused on moderate and severe damage under varying weather conditions, evaluating microgrid performance with different levels of DERs and demand. While demonstrating potential to enhance distribution grid resilience, ongoing technological advancements and increased prosumer engagement may further contribute to a cleaner, more resilient energy future [29]. A proposed framework for resilience enhancement in pre-attack and post-detection stages utilized optimal placement of DERs and power network reconfiguration. Limitations include assumptions about specific cyberattack scenarios, potentially overlooking a full spectrum of potential threats [30].

A probabilistic framework was proposed for assessing ice storm resilience in power distribution systems, evaluating fragility modeling and resilience enhancement strategies. Generalizability beyond the specific context of the Oklahoma power distribution network may be a concern [31]. An investment method, utilizing sectionalizing switches and DERs, was proposed for resilience enhancement. Further research is needed to validate its robustness and applicability across diverse distribution system scenarios [32]. A methodology integrating microgrids, DERs, and line hardening was proposed to improve resilience in extreme operating situations. Investigation of DERs' ability to maintain the distribution system over extended periods and incorporating additional resilience metrics are suggested for future research [33].

An integrated simulation framework was proposed to model PDS resilience against extreme winds, considering tree fragility and system restoration. Future work could refine tree failure modeling and consider dynamic effects in PDS component failure estimation [34]. A multistage, dynamic, and resilient RDS expansion planning framework was presented, relying on specific assumptions regarding hurricane occurrence and vulnerability. This may not fully capture the variability and complexity of real-world extreme weather events across different regions [35]. An optimal framework for resilience-oriented design in distribution networks was proposed, minimizing investment and repair costs. However, reliance on specific assumptions and simplifications in problem conversion may limit its applicability to real-world scenarios [36]. Challenges and advantages of networked MGs to improve power distribution system resilience were discussed, with a focus on managing DERs. Limitations include the lack of consideration for hybrid renewable energy systems [37].

A two-stage resilient restoration model utilizing EVs and MERs was proposed for distribution systems. However, accurate pre-disaster placement of charging and repair stations may not fully account for unpredictable damage from extreme weather events [8]. The proposed method for profit sharing between distribution networks and the private sector during extreme weather conditions considers uncertainties like weather-induced outages and EV conditions. However, its effectiveness may be limited by predicting weather-induced outages and EV initial conditions accurately [9].

D. LITERATURE REVIEW ON RELIABILITY AND RESILIENCE STUDY

The combined study of reliability and resilience in power distribution systems, without specific focus on EVCS, provides insights into the overall robustness of the grid. Research in this area typically includes probabilistic resilience assessment models, generalized fragility models for system components, and strategies to improve both reliability and resilience. Challenges such as data dependency, computational complexity, and evolving operational requirements are commonly addressed to ensure practical applicability in real-world scenarios.

An article discussed the combined reliability and resilience study in power systems without EVCS. The authors presented a probabilistic resilience assessment model and a generalized fragility model for distribution system components to improve reliability and resilience [38]. However, reliance on historical data and detailed component characteristics may limit applicability in scenarios with incomplete information. Focusing on past events and current system status for resiliency evaluation might not fully address the dynamic nature of distribution system operations and planning needs. Thus, practical implementation could face challenges in real-world settings with limited data availability and evolving operational requirements. Despite its comprehensive approach, challenges associated with computational complexity and algorithm selection affected the feasibility and scalability of this framework in real-world applications.

In the literature spanning studies [10] through [38], several challenges arise in applying optimization techniques to distribution network planning and management, particularly concerning the allocation of DG and EVCS, resilience, and reliability. Scalability issues with optimization algorithms are prominent, especially for large-scale distribution networks and complex optimization objectives. Additionally, recurring challenges include computational complexity, convergence issues, and sensitivity to initial conditions. Several studies also highlight complexities in parameter tuning and dilemmas in algorithm selection. These challenges underscore the intricacy of optimizing distribution networks and emphasize the importance of careful consideration during implementation. Addressing these challenges is vital for enhancing the robustness and efficacy of optimization processes in distribution network planning and management.

E. LITERATURE REVIEW ON SHOA

The SHOA offers promising solutions to the challenges encountered in optimizing distribution networks. With its scalability, robust convergence properties, insensitivity to initial conditions, and simplicity in parameter tuning, SHOA addresses key hurdles such as computational complexity, convergence issues, sensitivity to initial conditions, and algorithm selection dilemmas. By leveraging SHOA's capabilities, practitioners can enhance the efficiency and reliability of optimization processes in distribution network planning and management, contributing to the overall resilience and reliability of distribution systems. Extensive exploration of the literature underscores the SHOA as a leading meta-heuristic method for optimizing various allocation problems in distribution networks. Across various studies, SHOA consistently demonstrates remarkable effectiveness and superiority over other techniques [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50]. In [39], SHOA's ability is evident in solving complex design problems, yielding near-optimal solutions for tasks like optical buffer and airfoil design. Similarly, [40] showcases SHOA's superiority over established algorithms like PSO, ABC, ICA, and GWO, affirming its robustness and capability in handling complex optimization tasks, such as matching complicated images. Moreover, [41] illustrates SHOA's efficiency and cost-effectiveness in economic dispatch, achieving better convergence speed and lower computational cost compared to CSA and BBO. Practical applications in [42] demonstrate SHOA's effectiveness in wind energy resource allocation for loss reduction and voltage profile enhancement, further solidifying its credibility.

SHOA's versatility shines in tasks ranging from resolving the traveling salesman problem [43] to optimizing PID parameters in AVR systems [44] and determining optimal power flow in microgrids with renewable energy resources [45]. Additionally, SHOA's effectiveness in DG allocation with network reconfiguration was highlighted in [46], where it outperformed PSO and DE methods. This further emphasizes SHOA's practical applicability and superiority over conventional optimization techniques in real-world scenarios.

Moreover, SHOA's adaptability is showcased in [47], where it effectively enforces a two-stage controller, acquiring controller gains and parameters. Additionally, SHOA excels in tasks like determining the optimal size and location of capacitors [48] and resolving complicated nonlinear physical world tasks [49].

Recent studies consistently emphasize SHOA's high optimization power and convergence rate compared to conventional meta-heuristic algorithms [50], positioning it as the preferred method for optimization problems in distribution networks. Its ability to address critical aspects such as resilience, reliability, and optimal resource allocation underscores its indispensability in achieving optimization objectives. Through its advanced optimization capabilities, SHOA

TABLE 1. Summary of literature on EVCS allocation with reliability and resilience studies.

Ref. No	Year	EVCS	Reliability	Resilience	Technique	Findings
[10]	2024	√	×	×	General algebraic modeling system	Significant computational complexity with Type-2 fuzzy variables.
[11]	2024	√	×	×	United supervision system	Assumption of ideal conditions may not reflect real-world fluctuations.
[12]	2024	√	×	×	Improved Bald Eagle Search Algorithm	Reliance on simulated driving patterns may not capture real-world EV behavior.
[13]	2023	√	×	×	Hybrid GA-PSO	Hybrid GA-PSO algorithm may have significant computational complexity.
[14]	2023	√	×	×	Slime mould algorithm	Improper placement and sizing of components can impact RDS performance.
[15]	2023	√	×	×	Monte Carlo simulation method	Future research could explore correlation between uncertainties and system overloading.
[16]	2023	√	×	×	PSO	PSO performance influenced by parameter settings and problem formulation.
[17]	2023	√	×	×	Bald eagle search algorithm	Load variation considered for DG and DSTATCOM, not for EVCS.
[18]	2023	√	×	×	Shell game optimization	Comparison with existing systems may be limited by differences in implementation details.
[19]	2023	√	×	×	Bald eagle search algorithm	BESA may only be suitable for some optimization problems.
[20]	2024	√	√	×	Chaotic student psychology based optimization	Constant current load modeling for EV chargers oversimplifies actual charging behavior.
[21]	2024	√	√	×	Hybrid GJO–RFA	Assumptions about factors like charging ports and FCS capacity may not fully capture real-world complexities.
[22]	2023	√	√	×	Spotted hyena optimizer algorithm	Ideal conditions assumed, neglecting practical challenges like equipment failures and grid constraints.
[23]	2021	√	√	×	Hybrid GWO-PSO	Stochastic approach used to model EV load may not fully capture real-world dynamics; focus on conventional DGs.
[24]	2018	√	√	×	Monte Carlo simulation method	No change in SAIFI observed, while EENS and SAIDI improved with PEV and DGs.
[25]	2018	√	√	×	GA and VRP index	FCS placement at weak buses hampers smooth operation of the power system.
[26]	2017	√	√	×	Gbest-guided Artificial Bee Colony	GABC algorithm exhibits superior global searching ability compared to ABC.
[27]	2017	√	√	×	Dual-stage optimization model	Study may not fully capture all uncertainties and complexities of PEV integration and distribution system planning.
[28]	2024	√	×	√	PSO	Scalability and generalizability of method to diverse distribution system configurations and seismic scenarios require further investigation.
[29]	2024	√	×	√	SMA	Cleaner, more resilient energy future achievable with technological advancements and increased prosumer engagement.
[30]	2023	√	×	√	ODPS and OID technique	Specific cyberattack scenarios assumed may not encompass full spectrum of potential threats.

TABLE 1. ***(Continued.)*** **Summary of literature on EVCS allocation with reliability and resilience studies.**

[31]	2023	√	×	√	Probabilistic framework	Generalizability of findings beyond specific context of Oklahoma power distribution network may be limited.
[32]	2023	√	×	√	Stochastic decisions making method	Validation needed to assess robustness and applicability across diverse scenarios.
[33]	2023	√	×	√	Bald eagle search algorithm	Future work needed to investigate DERs' ability to maintain system resilience.
[34]	2023	√	×	√	Tree Fragility Modeling	Improvement opportunities include considering failures of branches and refining RDS component failure estimation models.
[35]	2022	√	×	√	Hurricane occurrence model	Reliance on specific assumptions about hurricane occurrences and vulnerability index may limit applicability.
[36]	2021	√	×	√	Mixed integer linear programming	Unpredictable nature of extreme weather events and their impact on distribution network.
[37]	2020	√	×	√	Networked microgrid	Lack of consideration for hybrid renewable energy in the study.
[8]	2024	√	×	√	Nonlinear programming model	Two-stage resilient restoration model heavily relies on accurate pre-disaster station placement.
[9]	2023	√	×	√	Two-stage genetic algorithm	Proposed method's effectiveness limited by accuracy of predicting weather-induced outages and initial EV conditions.
[38]	2018	√	√	√	Graph theory	Practical applicability limited by reliance on historical data, computational complexity, and algorithm selection.
Proposed Method	-	√	√	√	SHOA	-

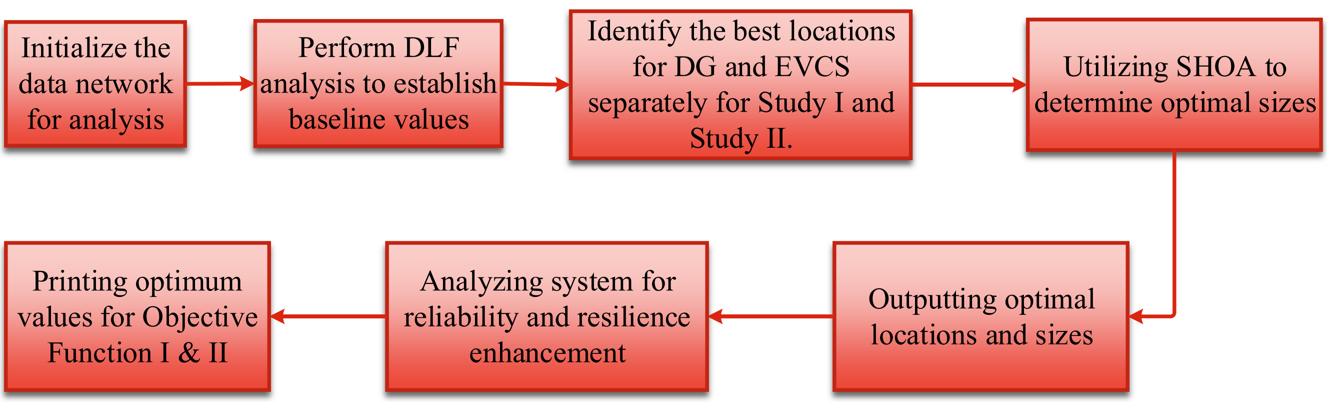

FIGURE 1. **The layout of the proposed technique.**

overcomes challenges related to scalability, computational complexity, convergence issues, and sensitivity to initial conditions, thereby facilitating the improvement of reliability and resilience in distribution systems. By leveraging SHOA's strengths, practitioners can enhance the robustness and efficiency of optimization processes, ultimately contributing to the resilience and reliability of distribution networks.

Table 1 summarizes the methodologies and main findings of studies investigating EVCS within the context of reliability and resilience in distribution systems. The examination of previous literatures [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], and [38] reveals several gaps in understanding resilience and reliability enhancement through DG and EVCS allocation in RDS.

- Previous literature tends to focus on either reliability or resilience enhancement individually in RDS, resulting in a lack of comprehensive approaches that address both aspects simultaneously. Very few studies have considered the combination of reliability and resilience enhancement in the RDS, highlighting a critical research gap in understanding how these aspects interact and influence overall system performance.
- Existing studies predominantly rely on conventional optimization methods for DG and EVCS allocation in RDS, neglecting the potential benefits of advanced optimization techniques. Exploring advanced optimization techniques could enhance the efficiency and effectiveness of allocation strategies.
- There is a gap in the comprehensive assessment of the impact of integrating DG and EVCS on RDS reliability and resilience. Thorough impact assessments are needed to understand the implications of these components on key performance metrics such as voltage stability and power losses.
- The absence of comparative analysis hinders the identification of optimal allocation strategies for enhancing RDS reliability and resilience. Comparative studies are essential to evaluate the effectiveness of different allocation approaches.
- The literature lacks innovative resilience measurement methods tailored to the unique characteristics of RDS. Developing novel resilience measurement methods could provide more accurate assessments of resilience performance.
- Comprehensive resilience measurement techniques that encompass factors like timing schemes for microgrid recovery and post-disaster recovery strategies are lacking.
- Research on post-disaster recovery strategies specifically designed for RDS resilience enhancement is limited. Effective post-disaster recovery strategies tailored to RDS challenges are crucial for improving overall system resilience.
- Challenges such as scalability, computational complexity, convergence issues, sensitivity to initial conditions, parameter tuning complexities, and algorithm selection dilemmas in optimization techniques for distribution network planning and management need to be addressed. Improving the efficiency and robustness of optimization processes is essential for enhancing RDS performance.

This work stands out by not only addressing the resilience and reliability challenges in the RDS but also by tackling the limitations observed in existing literature. Through this comprehensive approach, the study offers the following major contributions:

- This study makes a significant advancement by simultaneously addressing reliability and resilience enhancement in RDS, a critical aspect often overlooked in previous research. Few studies have explored this problem, highlighting the novelty and impact of our contribution.
- New methodologies utilizing the SHOA are presented for determining the optimal size and location of DG and EVCS. These methods offer robust solutions to improve the reliability and resilience of RDS.
- While most articles focused on EVCS in G2V mode, our work extends this by including EVCS operating in V2G mode alongside DG units in the RDS. This novel approach explores bidirectional energy flow between EVs and the grid, enhancing network versatility and resilience.
- A comprehensive examination of the impact of EVCS loads and DG on both consumer and energy-oriented reliability indices provides valuable insights into system performance.
- Analyzing the impact of EVCS loads on voltage stability and power in the RDS sheds light on the issues of incorporating them into the network.
- A comparative investigation of the proposed SHOA with the CSA regarding the effects of EV charging loads on various distribution network metrics, such as voltage stability, reliability, and power losses, offers a comprehensive understanding of the implications of EV integration.
- Introduction of a new resilience measurement method combined with a timing scheme for MG recovery offers a robust framework for enhancing resilience performance within the distribution network.
- Enablement of the development of post-disaster recovery strategies aimed at enhancing resilience performance within the RDS further enhances the overall resilience of the system.
- Addressing the absence of comprehensive resilience measurement techniques, which should include considerations such as timing schemes for microgrid recovery and post-disaster recovery strategies.
- Multiple faults have been considered in the RDS during resilience analysis, indicating a robust approach to resilience assessment.

This comprehensive research endeavor aims to thoroughly examine and quantify the impact of EVCSs on the reliability and resilience of the RDS. The study seeks to demonstrate that effective minimization of EVCS influence on the system can be achieved through optimal allocation of DG. Its outcomes are expected to enrich our understanding of strategically designing, operating, and upgrading the RDS to accommodate the growing demand for EV charging while maintaining a stable and reliable power supply, as assessed by the SHOA technique. Acknowledging the crucial importance of understanding the effects of EVCS on power loss, voltage stability, reliability, and resilience, this research is of great significance to utilities, policymakers, and stakeholders involved in the planning, management, and expansion of charging infrastructure. The proposed method is systematically examined through two distinct case studies, focusing on enhancing reliability and resilience in the RDS through EVCS and DG utilization.

Figure 1 illustrates the proposed technique for optimizing a system involving data networks, DG, and EVCS, with a focus on enhancing reliability and resilience. The technique begins with the initialization of the data network, followed by a distribution load flow analysis to establish base case values. Subsequently, optimal locations for DG and EVCS are determined separately for two distinct studies, likely based on different criteria. The ideal sizes of DG and EVCS are then determined using SHOA, a specific optimization approach. The technique outputs the best sites and capacities for DG and EVCS. Further analysis using SHOA assesses the system's reliability and resilience, identifying areas for enhancement. Finally, the optimum values for objective functions I & II, representing the optimization criteria, are presented. While Figure 1 provides an overview of the technique, additional description in the research would enhance understanding by providing more detailed explanations of each step and its implementation.

To validate the efficiency of the planned SHOA, a comparison is made with the cuckoo search algorithm (CSA) in both case studies. The findings highlight the superior capability of SHOA in identifying optimal locations within the IEEE 69-RDS, resulting in enhanced reliability and resilience compared to CSA. Further, this research significantly contributes to advancing strategies for integrating EVCSs into distribution systems while safe guarding the reliability and resilience of the overall power supply network.

III. PROBLEM FORMULATION

The distribution load flow (DLF) approach, as outlined in [51] and [52], is utilized to determine the actual and reactive power losses, as well as the voltage at specific branches within a RDS. Figure 2 illustrates a streamlined the one-line diagram of RDS with DG and EVCS, providing an overview of its layout and components.

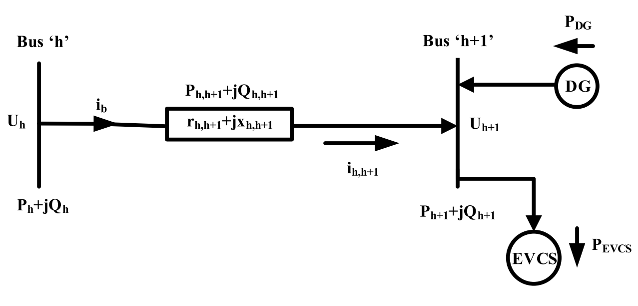

FIGURE 2. One-line diagram of RDS with DG and EVCS.

The voltage at node '*h+1*' is given by the following expression:

$$U_{h+1} = U_h - i_b(r_{h,h+1} + jx_{h,h+1}) \tag{1}$$

Here, U_h and U_{h+1} denote the bus voltage at buses '*h*' and '*h+1*' respectively. The term $(r_{h,h+1} + jx_{h,h+1})$ denotes the impedance of the line linking branches '*h*' and '*h+1*'.

$$i_b = [bibc]\,[i_h] \tag{2}$$

where i_b signifies the current flowing through the branch.

The current injected at node '*h*' is calculated as:

$$i_h = \frac{(P_h + jQ_h)^*}{U_h} \tag{3}$$

The variables P_h, which represents the real power load at bus '*h*'; Q_h, indicating the reactive power load at bus '*h*'; and i_h, denoting the current injected at node '*h*'.

The real power loss in the line between nodes '*h*' and '*h+1*' is expressed as:

$$P_{loss}\,(h, h+1) = \left(\frac{P^2_{h,h+1} + Q^2_{h,h+1}}{|U_h|^2}\right) * r_{h,h+1} \tag{4}$$

Similarly, the reactive power loss in the line between nodes 'h' and 'h+1' is given by:

$$Q_{loss}\,(h, h+1) = \left(\frac{P^2_{h,h+1} + Q^2_{h,h+1}}{|U_h|^2}\right) * x_{h,h+1} \tag{5}$$

The system loss after EVCS assignment is determined through load flow analysis. To obtain the total real power loss of the system, the losses across all branches are summed:

$$P^{Total}_{loss} = \sum_{h=1}^{N} P_{loss}\,(h, h+1) \tag{6}$$

In a RDS, the voltage stability index (VSI) is a metric used to assess the system's ability to maintain voltage levels within acceptable limits under varying operating conditions. It provides insights into the system's voltage stability, indicating how close the system is to voltage collapse or instability [53].

The VSI is typically calculated for individual nodes or buses within the distribution system. It is often expressed as a dimensionless quantity ranging from 0 to 1, where a VSI value closer to 1 indicates better voltage stability and a lower risk of voltage collapse, while a value closer to 0 indicates poorer stability and a higher risk of voltage collapse. The formula for calculating the VSI at node 'h' in a RDS is given by:

$$\begin{aligned} VSI\,(h) = \{&|U_h|^4 - 4\left|P_{h,h+1} * x_{h,h+1} - Q_{h,h+1} * r_{h,h+1}\right|^2 \\ &- 4[P_{h,h+1} * r_{h,h+1} - Q_{h,h+1} * x_{h,h+1}]\,|U_h|^2 \end{aligned} \tag{7}$$

A. DEVELOPMENT OF RELIABILITY MATRICES

Reliability indices serve as quantitative metrics to evaluate the performance and reliability of a power distribution system. These metrics offer valuable insights into the system's capability to consistently deliver electricity and fulfill customer needs. Among the commonly used reliability indices in power distribution systems are the system average interruption duration index (SAIDI), system average interruption frequency index (SAIFI), and customer average interruption duration index (CAIDI) [24], [25]. These critical reliability indices, namely SAIDI, SAIFI, and CAIDI, are expressed mathematically as follows:

$$SAIFI = \frac{\sum_{i}^{Nl} F_{r(h)} N_{c(h)}}{\sum_{i}^{Nl} N_{c(h)}} \tag{8}$$

$$SAIDI = \frac{\sum_{i}^{Nl} O_{p(h)} N_{c(h)}}{\sum_{i}^{Nl} N_{c(i)}} \tag{9}$$

$$CAIDI = \frac{\sum_{h}^{Nl} O_{p(h)} N_{c(h)}}{\sum_{h}^{Nl} F_{r(h)} N_{c(h)}} \tag{10}$$

Here, $O_{p(h)}$ represents the outage period of bus 'h', $F_{r(h)}$ is the failure rate of bus 'h', Nl is the number of load points, $N_{c(h)}$ is the total number of customers.

1) OBJECTIVE FUNCTION-I

The various reliability indices for the objective function is given in the below equation (11):

$$R_{reliability} = \sigma_1 \left(\frac{SAIFI_{loss}^{after}}{SAIFI_{loss}^{before}} \right) + \sigma_2 \left(\frac{SAIDI_{loss}^{after}}{SAIDI_{loss}^{before}} \right) + \sigma_3 \left(\frac{CAIDI_{loss}^{after}}{CAIDI_{loss}^{before}} \right) \tag{11}$$

The variables $\text{SAIFI}_{\text{loss}}^{\text{before}}$ and $\text{SAIFI}_{\text{loss}}^{\text{after}}$ represent the SAIFI values before and after the implementation of charging stations, respectively. Similar conventions apply to SAIDI and CAIDI. In equation (11), the weights assigned to SAIFI, SAIDI, and CAIDI are denoted as σ_1, σ_2 and σ_3, respectively. These weights are usually distributed uniformly across all values.

The initial objective function (OF_1) in the proposed approach, relying on the reliability index, can be articulated as follows:

$$OF_1 = Minimize \left[R_{reliability} \right] \tag{12}$$

Improving the system's reliability involves minimizing the OF_1 as described in equation (12).

B. DEVELOPMENT OF RESILIENCE MATRICES FOR COST EVALUATION

1) ENERGY NOT SUPPLIED ASSESSMENT

To gauge the extent of energy not supplied (ENS) during adverse weather conditions, we utilize the following expression:

$$ENS = \sum_{\tau=1}^{24} (\tau * P_l) \tag{13}$$

Here, ENS quantifies the number of nodes experiencing energy unavailability amidst challenging weather events.

2) REVENUE GENERATION ANALYSIS

The equation representing the revenue generated by RDS operators through energy sales is as follows:

$$R_g = \left[\sum_{\tau=1}^{24} (\tau * P_t) \right] * \varepsilon \tag{14}$$

$$R_g = ENS * \varepsilon \tag{15}$$

where ε denotes the cost of energy and P_t represents the total load of the system at time τ.

3) REVENUE LOSS CALCULATION

The computation of revenue loss incurred by the distribution network operator can be expressed as follows:

$$R_l = R_g - \left[\left(\sum_{\tau=1}^{\tau_f} \tau * P_t \right) * \varepsilon \right] \tag{16}$$

Here, R_l represents the cost attributed to outages, while τ_f signifies the duration of faults.

4) RESILIENCE INDEX DETERMINATION

To assess the resilience index (R_{index}) of a system in the aftermath of a catastrophic incident, we employ a method outlined in equation (18). This involves computing the inverse of the system's loss in performance (ΔP_l). This approach facilitates a conceptual gauge of resilience, with values spanning from 0 to infinity. A resilience index of infinity denotes flawless resilience, signifying no decline in performance subsequent to an extreme occurrence. Conversely, a resilience index of 0 indicates deficient resilience, implying an incapacity to endure or immediate collapse following a severe event.

$$\Delta P_l = \frac{P_t - P_a}{P_a} \tag{17}$$

$$R_{index} = \frac{1}{\nabla P_l} \tag{18}$$

In this equation, P_t represents the total load in the system after the event, while P_a denotes the active load.

5) OBJECTIVE FUNCTION-II

The second objective function is to enhance the resilience index of the RDS.

$$OF_2 = Maximize \left(\sum_{c=1}^{T_c} R_{index}(c) \right) \tag{19}$$

C. CONSTRAINTS OF THE RDS

The optimal distribution of EVCS in the RDS is subject to the following constraints:

1) LIMITS OF POWER GENERATION

The limits of power generation, also known as equality constraints, can be mathematically expressed as follows:

$$P_{loss}^{Total} + \sum P_{D(h)} + \sum P_{EVCS(h)} = \sum P_{RDS} + \sum P_{DG(h)} \tag{20}$$

The power demand at bus 'h' is represented as P_D, while P_{RDS} denotes the power generated by the RDS, and P_{EVCS} signifies the power taken by the EVCS.

2) LIMITS OF BUS VOLTAGE

Ensuring that the bus voltage remains within acceptable ranges at each bus is essential, as defined by:

$$U_{h,min} \leq |U_h| \leq U_{h,max} \tag{21}$$

The voltage at each bus is constrained by minimum and maximum limits, denoted as $U_{h,min}$ and $U_{h,max}$ respectively.

3) LIMITS OF REAL POWER

DGs must supply real power at each optimized bus within the defined minimum and maximum constraints.

$$P_{DG(h)}^{min} \leq P_{DG(h)} \leq P_{DG(h)}^{max} \tag{22}$$

Here, the lower real power limits P_{DG}^{min} indicate the minimum thresholds for the compensated bus 'h', while the upper real power limits P_{DG}^{max} denote the maximum thresholds for the compensated bus 'h'.

IV. SPOTTED HYENA OPTIMIZER ALGORITHM

A. OVERVIEW OF SHOA

Spotted hyenas, named for their fur markings, share social traits with humans. They're large carnivores found in African and Asian forests, grasslands, and plains, living up to 12 years in the wild and 25 in captivity. There are four species—spotted, striped, brown, and Aardwolf—each with unique traits. Spotted hyenas, known for their intelligence and social skills, live in clans where females dominate. They emit laughter-like sounds to communicate food discoveries and use social cues to navigate relationships. The SHOA mimics their hunting and social behaviors in mathematical models [54].

1) ENCIRCLING PREY

Spotted hyenas can adjust their locations based on the bait, determining the optimal response. The mathematical model for this phenomenon is presented below.

$$X^{HP} = \left|\beta * \alpha^{P}(m) - \alpha^{H}(m)\right| \tag{23}$$

$$\alpha^{H}(m+1) = \alpha^{P}(m) - \gamma * X^{HP} \tag{24}$$

In the equation, X^{HP} represents the distance between the prey and the spotted hyena, α^H denotes the position vector of the hyena, and α^P signifies the position vector of the prey. The variable 'h' represents the current iteration, while β and γ are coefficient vectors. This relationship can be expressed as follows:

$$\beta = 2\alpha_{R1} \tag{25}$$

$$\gamma = 2n * \alpha_{R2} - n \tag{26}$$

$$n = 5 - (iter * \left(\frac{5}{iter_{max}}\right)) \tag{27}$$

In this scenario, the variable '$iter$' spans from 0 to the maximum iteration count denoted as $iter_{max}$. In this context, α_{R1} and α_{R2} represent random vectors within the range of [0,1], and 'n'' can be linearly decreased from 5 to 0.

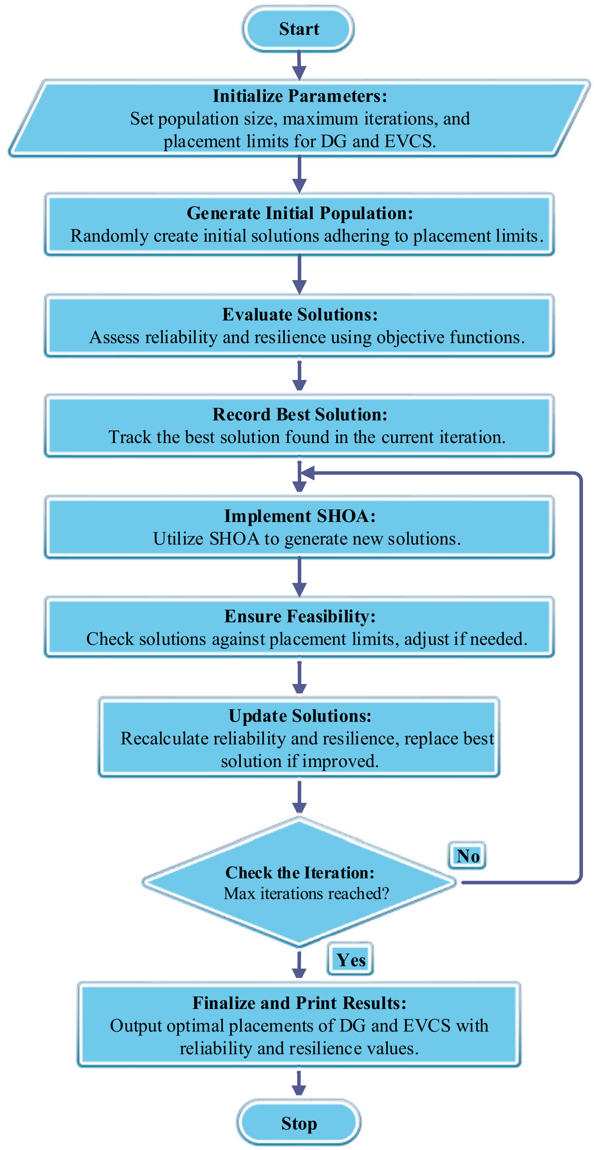

FIGURE 3. Implementation of SHOA for the proposed work.

2) HUNTING

The hunting strategy implemented in the proposed SHOA unfolds as follows:

$$X^{HP} = \left|\beta * \alpha_{finest}^{P}(m) - \alpha_{finest}^{H}(m))\right| \tag{28}$$

$$\alpha_{finest}^{P}(m) = \alpha_{finest}^{P}(m) - \gamma * X^{HP} \tag{29}$$

$$Y^{H} = \alpha_{finest}^{H} + \alpha_{finest+1}^{H} + \ldots\ldots\ldots\ldots\alpha_{finest+N^{H}}^{H} \tag{30}$$

where α_{finest}^{P} represents the best position of the spotted hyena, and α_{finest}^{H} is the best position of the prey. Meanwhile, the variable N^H denotes the total number of spotted hyenas and is determined as follows:

$$N^{H} = \epsilon^{N}(\alpha_{finest}^{P}, \alpha_{finest+1}^{P}, \alpha_{finest+1}^{P}, \ldots\ldots\ldots\ldots(\alpha_{finest+G}^{P}) \tag{31}$$

In this scenario, G denotes a random vector ranging from 1 to 0.5, N signifies the total count of responses, encompassing all potential candidate responses, and ϵ^N represents the collection of N^H optimal responses.

3) ATTACKING PREY (EXPLOITATION)

Given the aforementioned relationships, the mathematical expression for attacking the prey can be formulated as follows:

$$\alpha^H (S+1) = \epsilon^N / N^H \tag{32}$$

The updated position of $\alpha^H (S+1)$ retains the best position and adjusts the position of the other agents relative to the best search agent's position.

4) SEARCH FOR PREY (EXPLORATION)

Equation (24) indicates that the variable E must be adjusted to be either greater or smaller than 1 to yield the correct solution. Another crucial element of the SHOA is vector β, which facilitates exploration. Vector β comprises random values that assign random weights to the prey, as described in Eq. (25). To emphasize the algorithm's random nature, let's suppose that vector $\beta > 1$ is prioritized over $\beta < 1$ to highlight the distance effect.

B. IMPLEMENTATION OF SHOA FOR THE PROPOSED WORK

To implement SHOA for the proposed problem-solving, adhere to the following steps:

1. ***Initialize parameters:*** Begin by setting up parameters such as population size, maximum number of iterations, and constraints for DG and EVCS placement within the RDS.
2. ***Generate initial population:*** Create an initial population of potential solutions randomly, ensuring they adhere to the defined placement limits.
3. ***Evaluate solutions:*** Assess each solution's reliability and resilience using objective functions tailored to the problem, considering factors like system stability and ability to handle disruptions.
4. ***Record best solution:*** Keep track of the best solution found in the current iteration, representing the optimal placement of DG and EVCS based on the evaluated objective functions.
5. ***Implement SHOA:*** Utilize the SHOA to generate a new set of potential solutions. This involves a combination of optimization techniques to explore the search space effectively.
6. ***Ensure feasibility:*** Check the newly generated solutions against the predefined limits for DG and EVCS placement, adjusting them if needed to maintain feasibility.
7. ***Update solutions:*** Recalculate reliability and resilience values for the new solutions. Replace the previous best solution if an improvement is observed, and continue iterating to find better solutions.
8. ***Iterate:*** Repeat steps 5 to 7 until the maximum number of iterations is reached or convergence is achieved.
9. ***Finalize and print results:*** Once the optimization process concludes, print the final results including the optimal placements of DG and EVCS within the RDS, along with their corresponding reliability and resilience values.

This description outlines a structured approach to implementing SHOA for the proposed work, with the aim of enhancing understanding. It breaks down the steps depicted in Figure 3 to provide clarity and facilitate comprehension of the process of the proposed approach. Through this flowchart, the implementation of SHOA becomes more accessible, ensuring that each step is clearly defined and understood.

V. CASE STUDY RESULTS AND DISCUSSION

In the realm of distribution systems, both reliability and resilience enhancement play crucial roles in ensuring the smooth and uninterrupted delivery of electricity to consumers. Reliability enhancement focuses on metrics, which measure the frequency and duration of power interruptions experienced by consumers. Improving reliability is essential because it directly impacts customer satisfaction, operational efficiency, and economic productivity. A reliable distribution system ensures that consumers receive consistent and uninterrupted electricity, thereby minimizing inconvenience, financial losses, and potential safety hazards associated with power outages.

On the other hand, resilience enhancement is equally important, especially in the face of increasing challenges posed by extreme weather events, cyber threats, and other disruptions. Resilience refers to the ability of a distribution system to withstand and recover from disturbances swiftly, ensuring minimal downtime and rapid restoration of service. Enhancing resilience involves deploying measures and technologies that can quickly detect, isolate, and mitigate disruptions, as well as adapt to changing conditions to maintain continuous operation. By bolstering resilience, distribution systems can minimize the impact of disruptions, enhance grid stability, and ensure reliable electricity supply even under adverse conditions. Therefore, both reliability enhancement and resilience enhancement are critical aspects of ensuring the overall effectiveness and performance of distribution systems, ultimately benefiting consumers, businesses, and society as a whole.In this proposed work, two studies were examined:

(i) Case Study-I (Reliability enhancement), and
(ii) Case Study-II (Resilience enhancement)

A. CASE STUDY-I (RELIABILITY ENHANCEMENT)

In the first case study-I, the reliability enhancement. The simulation outcomes for the 69-bus IEEE test system, focusing on optimal EVCS placement using SHOA [54] and CSA [55], are summarized. The studied system is a large scale RDS with 69 buses and 68 branches, as illustrated in Figure 4. Line and bus data are sourced from reference [56]. Set at

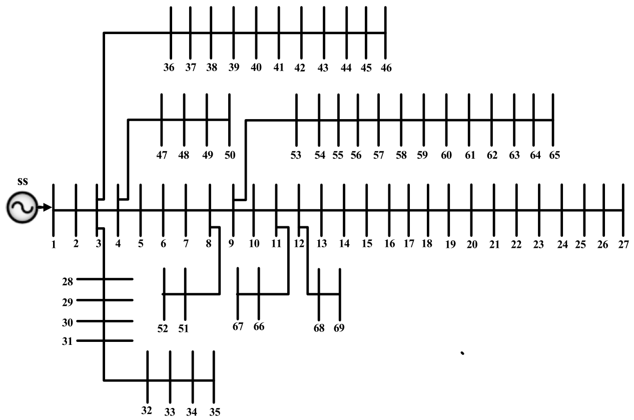

FIGURE 4. Schematic diagram of IEEE 69-bus RDS.

TABLE 2. Optimal size and location of EVCS and DG.

Cases	Device	Size (kW) and Site	
		SHOA	CSA
One EVCS	EVCS	1675.5 (7)	1675.5 (7)
Two EVCS	EVCSs	1675.5 (7) 1675.5 (30)	1675.5 (7) 1675.5 (30)
Two EVCSs & DGs	EVCSs	1675.5 (7) 1675.5 (30)	1675.5 (7) 1675.5 (30)
	DGs	900 (11) 1750 (60)	900 (11) 1750 (60)

100MVA and 12.66kV, the base values include total real and reactive power loads of 3.80 MW and 2.69 MVAr. This study categorizes EVCS locations, considering three EVCSs, each with a power rating of 975 kW for average charging ports, or potentially 1675.5 kW for the maximum number of charging ports, aligning with the specified maximum EVCS demand in reference [57].

The IEEE 69-bus RDS was used to analyses power loss, voltage stability, and reliability in the EVCS (in G2V mode) allocation problem. Table 2 presents the findings of sizing and siting for all of the several cases tested using SHOA and CSA, offering full insights into the functioning of the 69-bus system.

Table 3 shows the comparison of various results of reliability index in 69-bus RDS. From the Table 3, the comparison between the base case and scenarios with EVCS alone (Cases I to III) serves as a foundational benchmark for evaluating the performance of the SHOA and the CSA. Since the locations for EVCS are consistent across both approaches, any discrepancies in the reliability indices (SAIFI, SAIDI, and CAIDI) between SHOA and CSA in these cases can be attributed to the optimization algorithms themselves.

Case IV introduces a more complex scenario where both EVCSs and DGs are considered, and the allocation of DGs is determined by the optimization algorithms. Here, variations in reliability indices between the proposed SHOA and the existing CSA-based methods showcase the effectiveness of SHOA in optimizing the allocation of DGs to enhance system reliability.

This comparative assessment offers valuable perspectives on SHOA's performance in optimizing DG allocation alongside EVCSs, showcasing its potential benefits compared to established optimization methods like CSA. By showcasing SHOA's impact on reliability indices across diverse system setups, our research enhances comprehension of SHOA's effectiveness in improving system reliability and resilience.

1) CASE-I: BASE CASE

In the initial scenario, devoid of any supplementary EVCS or DG installations, both SHOA and CSA methodologies yield indistinguishable reliability metrics. The SAIFI maintains a constant value of 2.4795, signifying the average interruptions experienced per customer. Similarly, both the SAIDI and the CAIDI remain consistent at 77.6787 and 31.3283, respectively, representing the average duration of interruptions per customer and per interruption.

2) CASE-II: ONE EVCS

The introduction of a solitary EVCS brings about minor alterations in the reliability metrics across both SHOA and CSA paradigms. SAIFI experiences a marginal uptick to 2.4827, indicating a slight increase in the average interruptions per customer. Correspondingly, SAIDI exhibits a slight elevation to 79.6953, reflecting a minor augmentation in the average interruption duration per customer. Consequently, CAIDI also undergoes a marginal rise to 31.8805, depicting the average interruption duration per interruption.

3) CASE-III: TWO EVCS

By incorporating two additional EVCSs into the system, both SHOA and CSA approaches demonstrate a notable improvement in reliability metrics. SAIFI escalates to 2.4998, reflecting a heightened average frequency of interruptions per customer compared to previous scenarios. Similarly, SAIDI rises to 81.9982, indicating an extended average duration of interruptions per customer. Consequently, CAIDI also experiences an increase, reaching 32.6239, denoting a longer average interruption duration per interruption.

4) CASE-III: TWO EVCS AND DG

In the scenario involving two EVCSs and DGs, there are variations between the reliability parameters under the SHOA and CSA metrics. Under the SHOA metric, SAIFI decreases to 2.3931 compared to the previous scenarios, suggesting a slightly lower average number of interruptions per customer. However, SAIDI remains relatively stable at 78.0023, with a slight decrease compared to the two EVCS scenario. As a result, CAIDI decreases marginally to 31.0161. Conversely, under the CSA metric, SAIFI increases to 2.4254, SAIDI rises to 79.2154, and CAIDI increases to 32.4265, indicating a slightly higher level of interruptions compared to the SHOA metric, potentially due to different calculation methodologies or considerations of critical system components.

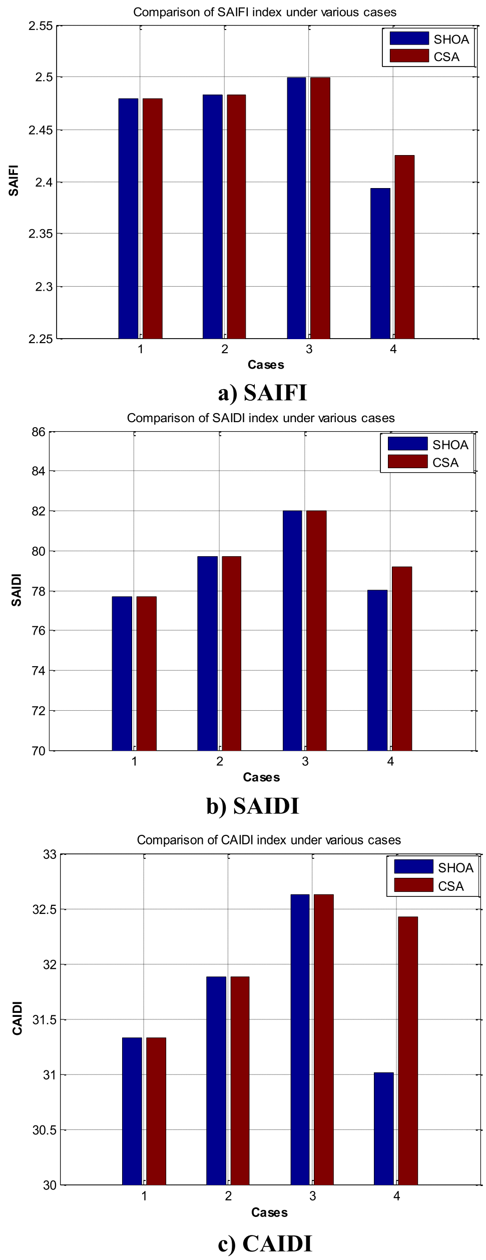

FIGURE 5. Impact of EVCS Integration on Reliability Indices.

TABLE 3. Results of reliability index in 69-bus RDS.

Cases	SAIFI		SAIDI		CAIDI	
	SHOA	CSA	SHOA	CSA	SHOA	CSA
Base Case	2.4795	2.4795	77.6787	77.6787	31.3283	31.3283
One EVCS	2.4827	2.4827	79.6953	79.6953	31.8805	31.8805
Two EVCS	2.4998	2.4998	81.9982	81.9982	32.6239	32.6239
Two EVCSs & DGs	2.3931	2.4254	78.0023	79.2154	31.0161	32.4265

The inclusion of two EVCS loads significantly affects the reliability of the 69-bus RDS. Table 3 illustrates the negative impacts of charging loads on customer-centric reliability metrics. With the introduction of EVCS, metrics like SAIFI, SAIDI, and CAIDI show noticeable increases compared to the base case values, indicating a decrease in system reliability. Additionally, the integration of DGs contributes to the enhancement of reliability index values. Figure 5 (a-c) visually represents these effects on various reliability indicators within the 69-bus RDS. Moreover, the integration of DGs plays a pivotal role in sustaining the reliability of the power network by injecting energy and mitigating power losses.

5) ANALYSIS ON SYSTEM POWER LOSS, VOLTAGE AND STABILITY

The proposed methodology not only improves reliability but also effectively addresses power loss, voltage, and stability concerns within the power distribution system. Table 5 presents a comparative assessment of system power loss, voltage stability, and bus voltage under various scenarios, employing both the SHOA and CSA metrics. This comparison sheds light on the effects of EVCS and DGs on power distribution system performance.

Initially, the 69-bus system registers power losses of 225 kW and 102.19 kVAr, which escalate with the introduction of EVCS. For instance, strategically placing one EVCS at the 7th bus increases real power loss to 292.56 kW, while further installations lead to a power loss of 301.39 kW. In dealing with the increasing presence of EVs, integrating EVCS poses a delicate balance between supporting EV adoption and maintaining power system stability. DGs are introduced to mitigate EVCS effects, notably reducing power loss after their incorporation into the system. The superiority of the SHOA-based approach in loss reduction, particularly evident in case-IV, underscores its efficacy over the existing CSA approach.

Integration of EVCS also impacts the system's voltage profile, significantly affecting the VSI. Prior to EVCS integration, the VSI measures at 0.6822 p.u., decreasing as EVCS charging loads are introduced. Optimal placement of DGs leads to an increase in VSI, addressing stability concerns. However, increasing EVCS numbers adversely affects both VSI and bus voltage within the distribution system, as evidenced by the VSI results across all cases.

Figures 6 and 7 depict the distribution of power loss and VSI profile across each bus within the 69-bus system under different scenarios, including the presence of EVCS and DGs. This visualization offers insights into the impact of EVCS and DGs on system power loss and stability. Through strategic placement of DGs and careful consideration of EVCS locations, the proposed method optimizes system performance while supporting EV integration and enhancing system stability and reliability.

The convergence reliability of an algorithm significantly impacts its efficiency in reaching the global optimum solution. Figure 8 presents the convergence comparison of OF-I among different algorithms in Case-IV. With objective function values of 0.9855 for SHOA and 1.0099 for

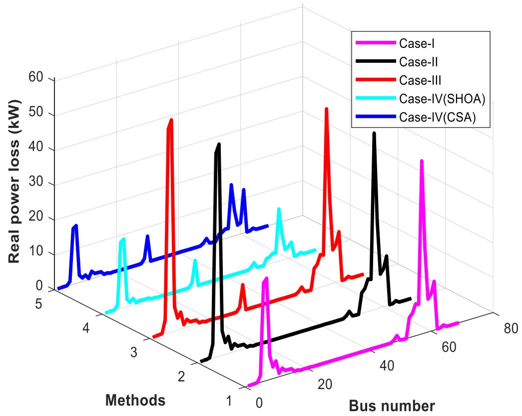

FIGURE 6. Power loss on each bus under various cases.

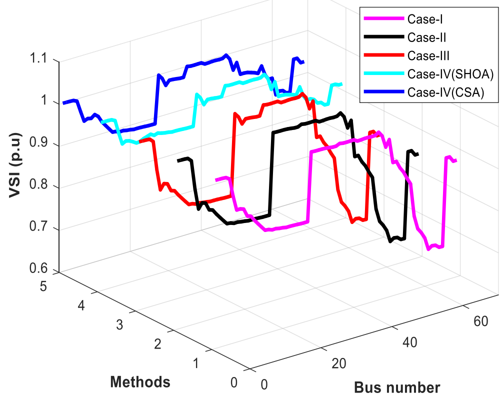

FIGURE 7. VSI on each bus under various cases.

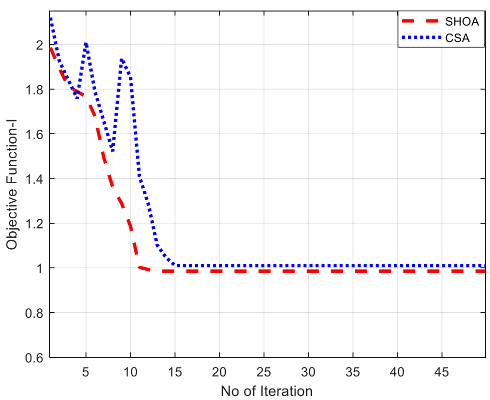

FIGURE 8. Convergence comparison of objective function-I among different algorithms in Case-IV.

CSA, calculated through equation (11), the analysis reveals a decrease in the reliability index, indicative of enhanced system reliability. Remarkably, SHOA achieves convergence to the optimal objective value in only thirteen iterations, surpassing CSA's sixteen iterations, thus demonstrating its superior speed. SHOA's distinguishing feature lies in its exceptional convergence rate, balancing stability and rapidity while effectively exploring near-global solutions for optimal reliability indexes during DG and EVCS allocation. Consistently maintaining swift convergence, SHOA excels in both speed and efficiency. Additionally, SHOA simplifies parameter tuning processes and provides comprehensive solutions to algorithm selection dilemmas, making it a valuable tool for enhancing optimization processes in distribution network planning and management.

TABLE 4. Comparative results system power loss, voltage and stability.

Cases	Power loss (kW)		VSI_{min} (p.u)		V_{min} (p.u)	
	SHOA	CSA	SHOA	CSA	SHOA	CSA
Base Case	225	225	0.6822	0.6822	0.9090	0.9090
One EVCS	292.56	292.56	0.6551	0.6551	0.8998	0.8998
Two EVCS	301.39	301.39	0.6550	0.6550	0.8998	0.8998
Two EVCSs & DGs	102.65	107.64	0.8833	0.8658	0.9696	0.9648

Table 4 compares the IEEE 69-bus system's power loss, VSI_{min}, and V_{min} using the SHOA and CSA across different scenarios for Study-I. In the base case, both algorithms yield identical results with a power loss of 225 kW, VSI_{min} of 0.6822 p.u, and V_{min} of 0.9090 p.u. Adding one EVCS increases the power loss to 292.56 kW and decreases VSI_{min} to 0.6551 p.u and V_{min} to 0.8998 p.u for both algorithms. With two EVCS, power loss further rises to 301.39 kW, and VSI_{min} and V_{min} remain unchanged at 0.6550 p.u and 0.8998 p.u, respectively, for both SHOA and CSA. However, integrating two EVCS and DGs significantly reduces power loss to 102.65 kW with SHOA and 107.64 kW with CSA, improves VSI_{min} to 0.8833 p.u (SHOA) and 0.8658 p.u (CSA), and raises V_{min} to 0.9696 p.u (SHOA) and 0.9648 p.u (CSA). This demonstrates that SHOA provides slightly better performance in reducing power loss and enhancing voltage stability compared to CSA.

B. CASE STUDY-II (RESILIENCE ENHANCEMENT)

Case Study-II explores a proposed approach for establishing microgrids within a modified version of the IEEE 69-bus RDS. The study investigates three distinct scenarios over a 24-hour period, encompassing a 4-hour outage triggered by a natural disaster. ENS costs are determined using a fixed energy rate, while outage costs are computed based on a predefined value per hour. The primary objective is to minimize costs while concurrently enhancing system resilience through the strategic allocation of DG and EVCS in V2G mode.

Microgrids are strategically positioned along the system's feeders to bolster resilience, with three microgrids strategically placed. Test system data, including load adjustments and microgrid placements, are sourced and adjusted accordingly. The aim is to assess the impact of microgrids, DG, and EVCS on resilience during natural disasters. Assuming a simulated storm event causing moderate system damage, a 4-hour outage from 12 p.m. to 4 p.m. is considered. Sizing of DG and EVCS resources within microgrids is determined using the

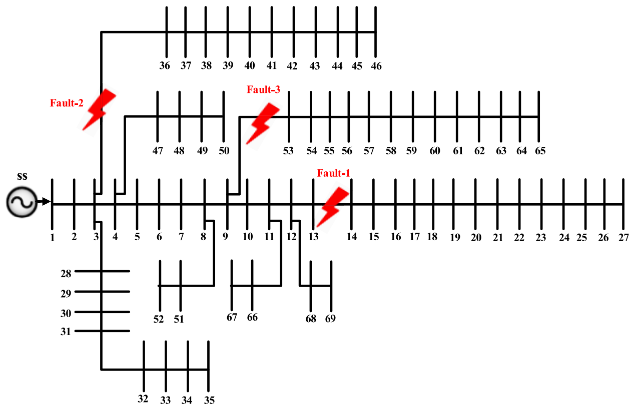

FIGURE 9. Layout of the 69-bus system under Case-I without DG/EVCS.

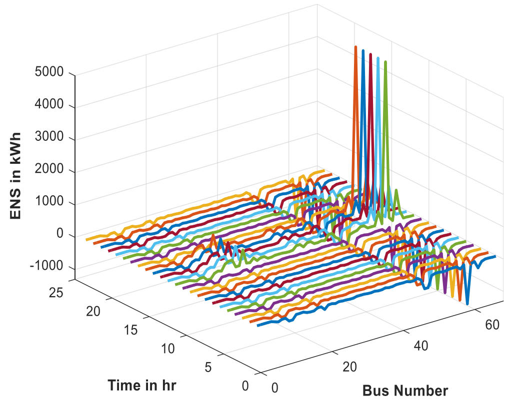

FIGURE 10. ENS profile of the 69-bus system under Case-I without DG/EVCS.

SHOA. Minimizing ENS and optimizing load recovery during emergencies are crucial for enhancing system resilience, with ENS costs calculated based on a fixed energy rate of 0.16 USD/kWh [33].

The case studies are conducted under the following assumptions:

- All DGs within MGs continue to operate following the event.
- Line repairs are expected to take 4 hours, scheduled from 12 p.m. to 4 p.m.
- All line repairs occur simultaneously.
- Fault locations and MG formations remain consistent across all cases to enable comparison.
- EVCS operate in V2G mode.
- Adequate repair crews are available to address all damaged lines.
- All (DGs) within microgrids remain operational after the event.

Three distinct cases are analyzed within a modified standard IEEE 69-bus RDS. These case studies are conducted to evaluate the influence of DG and EVCS on bolstering system resilience across different fault scenarios.

- Case-1: Fault without any DG/EVCS.
- Case-2: Fault with only DG.
- Case-3: Fault with DG and EVCS.

1) CASE-I: FAULT WITHOUT ANY DG/EVCS

Case-I evaluates the 69-bus test system's performance without DG and EVCS. A fault at 12 p.m. causes a 4-hour outage affecting buses 14-27, 36-46, and 53-65, interrupting approximately 2248.04 kW of load. This results in a high ENS value of 8992.16 kWh and a resilience index of 0.691, indicating system vulnerability due to the absence of backup systems. This scenario highlights the risk of power supply interruptions during faults. To enhance system reliability and address these vulnerabilities, integrating DG and EVCS is proposed. Using EVCS in V2G mode can provide power and reduce ENS during outages. Incorporating DG and EVCS ensures a continuous power supply, minimizing disruptions for end users. Case-I underscores the risks of relying solely on traditional grid operations without backups, while subsequent cases will explore the benefits of DG and EVCS integration for improving system resilience.

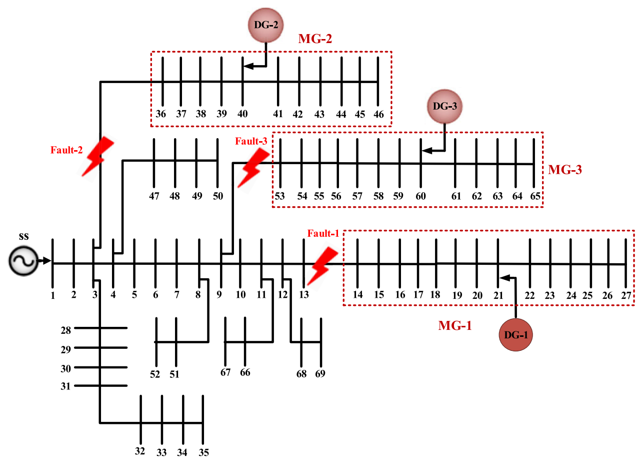

FIGURE 11. Layout of the 69-bus system under Case-II with only DG.

2) CASE-II: FAULT WITH ONLY DG

In Case-II, a microgrid is set up in the fault-affected area of buses 14-27, 36-46, and 53-65, with only DGs active and EVCS inactive. DGs are strategically placed at buses 21, 40, and 60 using the SHOA. The updated IEEE 69-RDS configuration with these DGs is shown in Figure 11. Table 5 lists the load requirements for each bus, and Table 6 details the optimal DG locations and capacities. The DGs effectively meet the 2248.04 kW load demand of the faulted buses despite inactive EVCS. Figure 12 shows a reduced ENS profile compared to Case-I. The resilience index improves to 2.493, highlighting the enhanced system resilience from DG integration.

TABLE 5. Load demands for individual buses within the microgrid.

Microgrid Number	Bus Number	Load Demand	Microgrid Number	Bus Number	Load Demand
I	14	8	II	41	1.2
I	15	0	II	42	0
I	16	46	II	43	6
I	17	60	II	44	0
I	18	60	II	45	39.22
I	19	0	II	46	39.22
I	20	1	III	53	4.35
I	21	114	III	54	26.4
I	22	5	III	55	24
I	23	0	III	56	0
I	24	28	III	57	0
I	25	0	III	58	0
I	26	14	III	59	100
I	27	14	III	60	0
II	36	26	III	61	1244
II	37	26	III	62	32
II	38	0	III	63	0
II	39	24	III	64	227
II	40	24	III	65	59

TABLE 6. DG and EVCS allocation for MG.

MG	Device	Site	Size (kW)			Power Demand (kW)
			Case-I	Case-II	Case-III	
MG-1	DG	21	--	216	216	350
	EVCS (V2G)	21	--	--	120	
MG-2	DG	40	--	124	124	185.64
	EVCS (V2G)	40	--	--	62	
MG-3	DG	60	--	820	820	1712.4
	EVCS (V2G)	60	--	--	425	

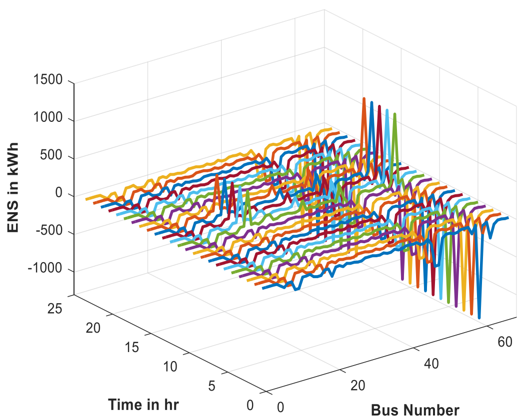

FIGURE 12. ENS profile of the 69-bus system under Case-II with only DG.

3) CASE-III: FAULT WITH DG AND EVCS

In Case-III, the activation of both DG and EVCS contributes to the bolstering of resilience. Illustrated in Figure 13 is the seamless integration of DG and EVCS resources into the 69-bus system, guaranteeing continuous power provision. With EVs functioning in V2G mode, they serve as backup power sources during outages. The incorporation of EVs and

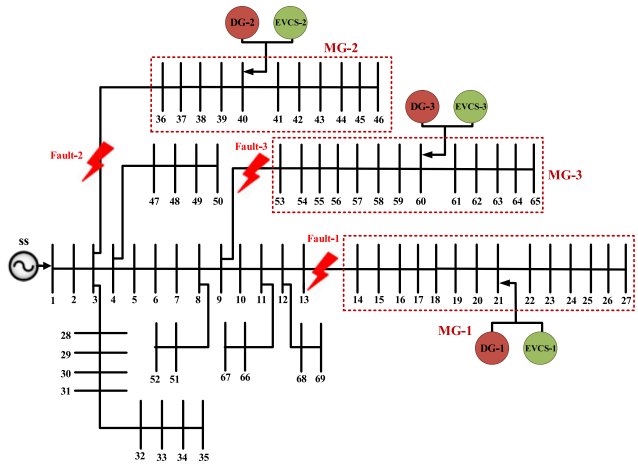

FIGURE 13. Layout of the 69-bus system under Case-III with DG and EVCS.

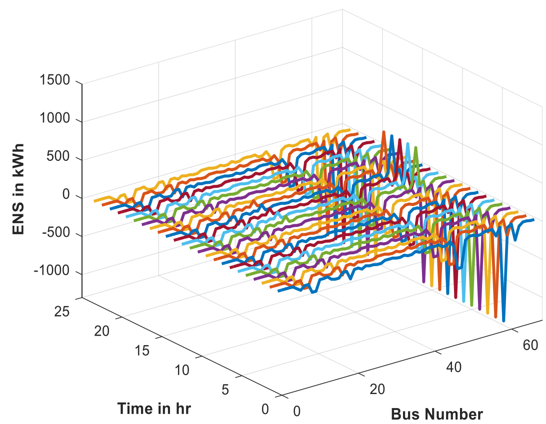

FIGURE 14. ENS profile of the 69-bus system under Case-III with DG and EVCS.

DGs within the microgrid brings forth numerous advantages, encompassing energy storage, load redistribution, and the assimilation of renewable energy sources, thereby fortifying grid reliability and sustainability.

Fig. 14 depicts the ENS profile of the 69-bus system during Case-III, where both DG and EVCS are operational. Despite potential challenges, the system exhibits notable resilience, as evidenced by an ENS value of 1924.16 kWh. This value underscores the successful management of energy supply disruptions. Such resilience is achievable through the efficient deployment of DG and EVCS, guaranteeing uninterrupted power provision and minimizing the adverse effects of faults and interruptions on consumers. Furthermore, in Case-III, the resilience value significantly increases from 0.691 to 6.906, underscoring the enhanced resilience achieved through the integration of both DG and EVCS resources within the MG. This integrated approach effectively mitigates disruptions and ensures continuous power supply during fault scenarios.

A thorough comparative analysis was undertaken to assess the efficacy of established algorithms in addressing resilience issues, with a focus on CSA, conducted under consistent conditions. Table 7 offers a comparative evaluation of resilience metrics for the IEEE 69-bus system, comparing the performance of SHOA and CSA across all examined scenarios. The comparison reveals the differences in ENS, revenue generation, revenue loss, and resilience index between SHOA and CSA methodologies for each case. Common fault area in the RDS is chosen for both SHOA and CSA for comparison purpose.

The comparative analysis between SHOA and CSA highlights SHOA's superiority in enhancing the resilience and reliability of the RDS. Across all evaluated parameters, SHOA consistently outperforms CSA, notably in reducing ENS and increasing the R_{index}. Figure 15 illustrates the comparison of ENS across various algorithms for the 69-bus system, offering insights into each algorithm's efficacy in minimizing energy supply disruptions during fault scenarios. Similarly, Figure 16 depicts the comparison of R_{index} across different algorithms for the 69-bus system, enabling stakeholders to assess the effectiveness of each algorithm in maintaining system resilience and reliability.

This indicates SHOA's effectiveness in minimizing disruptions and ensuring continuous energy supply during fault scenarios. For instance, in Case-III, SHOA achieves a remarkable reduction in ENS to 1924.16 kWh, significantly outperforming CSA's higher ENS value of 2600.16 kWh. This substantial difference underscores the critical role of SHOA in maintaining grid stability and reliability under adverse conditions. Moreover, SHOA consistently yields higher R_{index} values across all cases, highlighting its ability to enhance the system's ability to withstand and recover from disruptions. Notably, the R_{index} value of 6.906 attained by SHOA in Case-III signifies its exceptional capability in mitigating disruptions and ensuring grid reliability, whereas CSA falls short with a lower R_{index} value of 6.123. In essence, the comprehensive analysis emphasizes SHOA as a superior approach for bolstering system resilience and minimizing energy disruptions compared to CSA, underscoring its significance in ensuring the robustness and reliability of power RDS.

Fig. 17 illustrates a comparative analysis of convergence trends between SHOA and CSA concerning objective function-II (Case-III). Objective function values of 6.906 for SHOA and 6.123 for CSA, calculated using equation (19), indicate improved system resilience. Significantly, SHOA attains convergence to the optimum impartial value in just eleven iterations, surpassing CSA's fifteen iterations, demonstrating its superior speed. SHOA's unique characteristic lies in its remarkable convergence rate, striking a balance between stability and rapidity while efficiently exploring near-global solutions for optimal resilience indexes during DG and EVCS allocation. Consistently maintaining rapid convergence, SHOA excels in both speed and efficiency. Moreover, SHOA simplifies parameter tuning processes and offers comprehensive solutions to algorithm selection dilemmas, making it a valuable asset for optimizing distribution network planning and management.

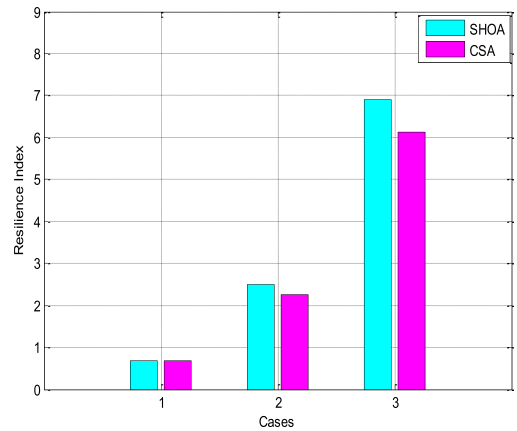

FIGURE 15. Comparison of ENS across different algorithms for the 69-bus system.

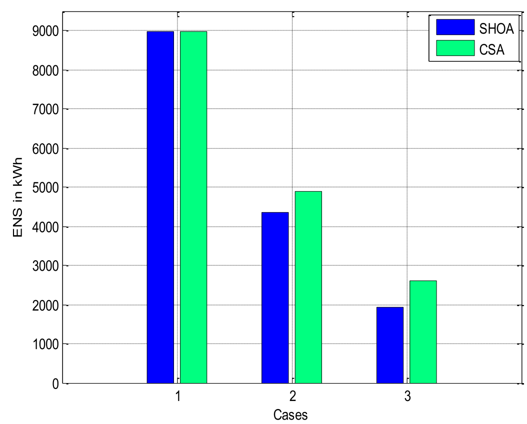

FIGURE 16. Comparison of resilience index across different algorithms for the 69-bus system.

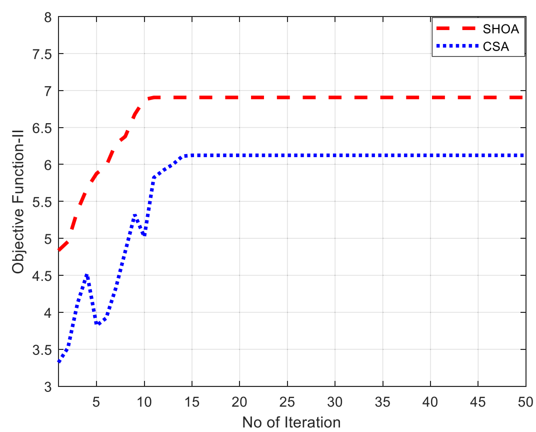

FIGURE 17. Convergence comparison of objective function-II among different algorithms in Case-III.

Table 7 presents a comparative analysis of the resilience metrics for the IEEE 69-bus system under the SHOA and the CSA across three cases for Study-I. In Case-I, both SHOA and CSA show identical results with an ENS of

TABLE 7. Comparison of resilience metrics analysis of IEEE 69-bus system under SHOA and CSA.

Cases	ENS (kWh)		Revenue Generation (USD)		Revenue Loss (USD)		Resilience Index	
	SHOA	CSA	SHOA	CSA	SHOA	CSA	SHOA	CSA
Case-I	8992.16	8992.16	12163.2	12163.2	2432.64	2432.64	0.691	0.691
Case-II	4352.16	4896.16	12905.6	12818.6	1690.24	1777.28	2.493	2.269
Case-III	1924.16	2600.16	13294.08	13185.9	1301.76	1409.92	6.906	6.123

8992.16 kWh, revenue generation of $12,163.2, revenue loss of $2432.64, and a resilience index of 0.691, indicating no improvement with the base configuration. In Case-II, SHOA performs better with an ENS of 4352.16 kWh compared to CSA's 4896.16 kWh, generating $12,905.6 in revenue versus CSA's $12,818.6, and showing a lower revenue loss ($1690.24 vs. $1777.28). The resilience index for SHOA is higher at 2.493 compared to CSA's 2.269, highlighting SHOA's superior performance in enhancing system resilience. In Case-III, SHOA again outperforms CSA with an ENS of 1924.16 kWh against 2600.16 kWh, higher revenue generation ($13,294.08 vs. $13,185.9), and lower revenue loss ($1301.76 vs. $1409.92). The resilience index for SHOA is significantly higher at 6.906 compared to CSA's 6.123, demonstrating the effectiveness of SHOA in improving system resilience and efficiency.

VI. CONCLUSION AND FUTURE WORK

This study examined the impact of EVCS on RDS, focusing on enhancing reliability and resilience through analysis of the IEEE 69-bus RDS. Factors such as power loss, voltage stability, and bus voltage were considered. Our findings highlighted the importance of proactive measures and advanced optimization algorithms, like SHOA, for optimal EVCS placement and improved RDS performance. Comparisons with CSA demonstrated the effectiveness of our approach. The study also emphasized the need for infrastructure upgrades and smart charging strategies to ensure a reliable power supply for EVs. By addressing challenges and solutions related to EVCS integration, this research offers valuable insights for optimizing charging infrastructure and strengthening RDS resilience.

To further enhance the reliability and resilience of electrical RDS, future work should focus on:

Renewable energy integration: Enhancing coordination between renewable energy generation and EV charging to maximize clean energy utilization.

Vehicle-to-everything (V2X) technology: Enhancing bidirectional power flow control and scheduling algorithms to enable efficient energy exchange between vehicles and the grid.

Dynamic pricing and incentives: Exploring mechanisms to effectively manage peak demand and optimize charging patterns through dynamic pricing strategies and incentive programs.

Grid-interactive charging: Developing standards and infrastructure for seamless integration of grid-interactive charging technology to support grid stability and reliability.

Collaborative planning: Ensuring effective stakeholder coordination through collaborative planning and policy development.

Resilience modeling: Developing techniques to evaluate RDS resilience with EVCS and other DERs.

Resilience metrics: Standardizing metrics for quantitative assessment and strategy comparison.

Advanced control systems: Exploring predictive analytics and autonomous control algorithms for real-time management.

Policy frameworks: Incorporating resilience considerations into regulatory guidelines and investment decisions.

Grid hardening: Implementing measures like undergrounding power lines and strategic equipment placement to withstand extreme weather and disturbances.

Addressing these areas can significantly enhance RDS reliability and resilience, ensuring a more sustainable and reliable electricity supply for communities and consumers.

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