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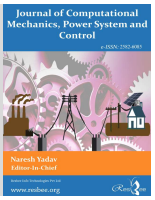

Detecting the Grid-connected Solar-Wind Hybrid System's Least Levelized Cost of Electricity (LCOE) with an Electric Vehicle Charging Station Using a DREAM Optimization Algorithm

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Abstract: Nowadays, Electric Vehicles (EVs) are a growing technology in India, and they need more power for driving EVs. Due to the requirement for excess power, the grid is used to provide a massive amount of power for EVs. By sharing tap line capacity and other interconnection cost components, hybridizing systems may lower transmission costs. To address the need for electricity, this paper proposes a grid-connected PV-Wind hybrid model withan EV Charging Station (EVCS). The integration of renewable sources is intended to reduce dependency on traditional grid supply and improve system sustainability. Similarly, this model's recommended configuration has been competitively examined to meet both the shopping complex's electrical load consumption and EV charging requirements. The primary objective of the paper is to lessen the isolated system's Levelized Cost of Electricity (LCOE). Moreover, the DREAM Optimization Algorithm (DOA) is used in this process tooptimize the controller which is used in the model. The cost-effectiveness of the outcomes produced by the two approaches has been examined. The MATLAB simulation platform is used to perform the proposed model's function to get the result. In this analysis, the suggested DOA-based grid-connected hybrid system with EVCS obtained a value of 0.0241 at 18kW of grid capacity; however, other approaches, including ABC, PSO, GA, and WOA, attained values of 0.0218, 0.0225, 0.0280, and 0.0251, respectively. These comparative results highlight the varying efficiencies of different optimization algorithms under similar operational conditions. Furthermore, the results demonstrate that using more complex algorithms, like DOA, produces more optimal solutions than other current approaches.

Keywords: Electric Vehicles; Solar Photovoltaic; Wind Installations; Levelized Cost of Electricity; Optimization Technique

Nomenclature

Abbreviation	Description
DOA	DREAM Optimization Algorithm
PSO	Particle Swarm Optimization
WOA	Whale Optimization Algorithm
RESs	Renewable Energy Sources
WTs	Wind Turbines
PV	Photovoltaic
TNPC	Total Net Present Cost
NPC	Net Present Cost
GA	Genetic Algorithm
EMS	Energy Management Systems
FiT	Feed-in Tariff
SPV	Solar Photovoltaic
FC-PV	Fuel Cell–Solar Photovoltaic
HRES	Hybrid Renewable Energy System
HES	Hybrid Energy System
ABC	Artificial Bee Colony
HMS	Hybrid Microgrid System
POA	Pufferfish Optimization Algorithm
COE	Cost of Energy
LPSP	Lack of Power Supply Probability
LCOE	Levelized Cost of Energy
EVCS	Electric Vehicle Charging Station
2DE-MC	Differential Evolution Markov Chain
SOC	State Of Charge
SR	Reduction Factor
GHG	Greenhouse Gas
CO_2	Carbon Dioxide
V2G	Vehicle-To-Grid
MSSA	Modified Salp Swarm Algorithm
SSA	Salp Swarm Algorithm

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1. Introduction

Globally, the advancement of renewable energy is now a positive trend. This shift is largely driven by the urgent global need to reduce dependence on fossil fuels and transition toward sustainable alternatives. Consequently, there is an increasing desire for the creation of sources of renewable and clean energy [1]. Solar and wind energy have been used extensively in recent years [2]. For instance, WT and PV power installed capacities in China now exceed by 184 GW and 175 GW, respectively, incorporating around 9.7% and 9.2% of the nation's total installed capacity [3]. However, because of the non-linearity of system parts and the unpredictability of the new energy system outputs, it is extremely challenging to ensure the safe and cost-effective functioning of grids while entirely using the new energy system. According to the research, HRES is more reliable and economical than single-source systems. To increase dependability, WT and PV modules must be incorporated into an HRES [4]. The complementary nature of wind and solar generation helps reduce output fluctuations and enhances overall system stability. The reliability of this system can be further improved by incorporating energy storage devices or backup power sources. Moreover, energy storage devices can reduce system energy losses and store any excess energy.

Government subsidies like FiT have a major impact on the size and design of a hybrid power system [5]. These incentives often encourage investors to adopt renewable-based hybrid systems by reducing the initial financial burden. However, independent electricity buying by customers is heavily influenced by economic factors, such as NPC and LCOE. The reduction of overall GHG emissions, particularly CO2 emissions, is the primary environmental goal of such systems. Numerous studies have suggested strategies and methods for sizing optimization in hybrid energy systems [6]. A comprehensive examination of the ideal HRES size is provided, taking into account economic goals such as NPC, beginning capital, and system payback duration [7]. The data on energy values and the weather are crucial for optimizing HES costs. Similarly, a quantitative control strategy to lower the HES energy cost is put forth using this concept. It is discussed how multi-objective optimization utilizing meta-heuristic methodologies has definite advantages over linear programming and the iterative method. Meta-heuristic algorithms provide more flexible search capabilities, enabling them to handle the complex, nonlinear characteristics of hybrid systems. Over the years, other multi-objective methods for HES optimization have also been put forth, using factors such as technical, economic, environmental, and sociopolitical goals [8].

However, the EV market's explosive expansion has some difficulties, especially when it comes to the distribution networks' ability to satisfy demand. The increased penetration of EVs introduces unpredictable load variations that can strain existing power infrastructure. Research has examined how EV deployment affects energy distribution networks and demand. However, these models are used to create EV demand profiles based on variables like charging characteristics and driving habits [9]. The RESs had a great chance to build power from renewable energy that can allow EV charging while maintaining grid stability. Similarly, reducing CO_2 emissions and increasing energy output from renewable sources are the main goals of efforts to incorporate renewable energy into the electrical grid [10]. However, the hybrid power systems at EVCS incorporated fuel cells, WT, and SPV panels to create a clean energy-dependent grid. Such combinations enable continuous power availability even when individual resources experience intermittency. A revolutionary stage in EMS is represented by the move to smart grids and hybrid power systems, which integrate large-scale renewable resources into decentralized networks.

To determine the LCOE, the study suggested a grid-connected hybrid system with EVCS. A techno-economic assessment and optimization process is a key component of this approach. The typical price for producing one unit of energy (kWh) over the system's duration is known as the LCOE. LCOE serves as a universal benchmark that simplifies comparing diverse energy generation technologies. Furthermore, because it allows researchers and system designers to compare various topologies, energy sources, and management systems on a consistent economic basis, determining the least LCOE is crucial. Since solar PV, WTs, grid connections, and charging infrastructure are all part of hybrid renewable systems, each of these technologies has its own cost structure and generation pattern. As a result, LCOE functions using a consistent economic metric for choosing the most economical combination. This metric also guides policymakers in formulating incentives that promote the adoption of cost-effective renewable solutions.The optimization technique is utilized in this process to identify the LCOE. Thus, the proposed model is the most economical, dependable, and efficient system configuration, and it also has the effecicient operation strategy.

The work is systematized as follows: Section 2 explains the literature review of current LCOE detection in grid-connected hybrid systems. Section 3 provides the proposed methodology for LCOE detection in grid-connected hybrid systems. The results and discussion of the conventional and suggested methods for the LCOE detection model are offered in Section 4. Section 5 gives the work's conclusion.

2. Literature Survey

2.1 Related Work

Many studies have concentrated on applying sophisticated meta-heuristic algorithms to optimize hybrid systems for the purpose of decreasing the LCOE. These algorithms allow researchers to explore large search spaces efficiently and identify optimal or near-optimal configurations for hybrid renewable systems.The following list of recent studies demonstrates the effectiveness of numerous optimization algorithms.

In 2020, Singh et al. [11] demonstrated a grid-connected solar-wind hybrid system to satisfy a small shopping centre'sfor university campus in India. Also, an EVCS becomes a component of the system. Economic analysis was carried out for the suggested design in order to supply both the retail complex's electrical load needs and the EV charging requirements. The study highlighted how hybrid configurations can effectively support commercial structures with variable load profiles. The recommended approach-maintained power interchange between the utility grid and other system components while considering the cost of the energy that was bought and supplied to the utility grid. According to the results, the LCOE and LPSP of the proposed system were determined to be 0.038 $/kWh and 0.19%, respectively, with a renewable percentage of 0.87. These outcomes confirm the economic viability of hybrid systems when supported by appropriate control mechanisms. It was discovered that a reliable and cost-effective system was produced when load demands and renewable power generation were appropriately controlled.

In 2022, Nishanthy et al. [12] evaluated the environmental elements and techno-economic aspects of charging stations for hybrid solar wind vehicles along India's Southern Tamil Nadu highway. Sensitivity analysis was carried out in order to build a charging station in the following highway locations: Sattur, Tirunelveli, Kayathar, Virudhunagar, and Madurai. The sites were chosen where solar and wind abilities would be in opposition to each other. This ensured that the hybrid systems could compensate for intermittency by leveraging complementary renewable potentials. The hybrid optimization method for electrical renewable sources was used in the development and optimization. Also, Madurai generates 70% more electrical energy than other chosen areas when economic research was taken into consideration. In addition, the system's performance analysis was examined, and the results were more dependable and practical when taking into account both technical and economic research. Such findings emphasize the importance of location-specific resource assessment in hybrid charging infrastructure planning.

In 2020, Singh et al. [13] suggested a hybrid energy system based on FC-PV to offer a tiny community centre in India with electricity. PV panels, a hydrogen storage tank, a fuel cell, and an electrolyzer were used in the system's development. This architecture allowed long-term energy storage through hydrogen, enhancing system reliability during low-solar-output periods. Also, ratings for PV and hydrogen system components were determined through cost optimization. The objective was to decrease this isolated system's LCOE. This optimization was carried out using an ABC in both the HOMER software and another tool. The cost-effectiveness of the outcomes produced by the two approaches was evaluated. Lastly, IEC 61850 interoperable communication was used to give operational details for an FC-PV hybrid system. This ensured standardized and seamless communication between system components, improving operational efficiency.

In 2024, Bilal et al. [14]investigated the environmental and techno-economic feasibility of PEV on-grid charging. The technology was created to make it simpler for different energy system components and the grid network to exchange power. The approach emphasized the importance of synergy between distributed energy resources and electric mobility demands.The location'sconflicting solar and wind potential ensures a variety of renewable energy opportunities. The hours that PEVs were charged vary by area. By reducing the system objectives, such as COE and the TNPC, the POA, the modeloptimizes system factor sizing while ensuring an LPSP within a suitable range. The results showed that a grid-tied system combining WT and SPV panels was the optimal solution for PEV charging stations.

In 2022, Bilal et al. [15]offered various hybrid energy system configurations to supply the power needs of the EVCS. The three prospective configurations were examined for their intellectual, financial, and environmental feasibility using meta-heuristic approaches. The use of multiple algorithms provided a robust comparison to identify the most effective configuration. The goal of the optimization technique was to maximize LCOE and the overall net present cost while maintaining a certain level of power supply likelihood. The MSSA performed better than the SSA and grey wolf optimization in terms of computing time.

2.2 Problem Statement

This section represents the advantages and the limitations of the grid-connected solar-wind hybrid system's LCOE detection. Understanding these factors is crucial in identifying research gaps and

developing more efficient hybrid system designs. First, Paper [11] provided benefits such as grid support and reliable power. The increased expense and technological difficulties in managing energy storage and integration were the drawbacks. These issues indicate that improving storage technologies could significantly enhance system performance. The hybrid optimization model presented in Paper [12] had benefits like lower emissions and less reliance on the grid, but it also had drawbacks like high initial installation costs, potential unreliability due to weather fluctuations, and the requirement for a sizable amount of land for the WT and PV panels. Similarly, the main drawbacks of an FC-PV-based hybrid energy system were the high initial costs of the fuel cell and electrolyzer and the complexity of system management, but it has the benefit of a dependable, emission-free power supply [13]. Furthermore, the Paper [14] offered grid stabilization, lower electricity costs, and less of an impact on the environment. However, this strategy had drawbacks including the unpredictability of renewable energy sources, the requirement for complex grid infrastructure, and possible security problemed with smart technologies. These concerns highlight the importance of resilient system design and cybersecurity considerations in modern hybrid systems. Paper [15] suggested a hybrid energy system structure with the advantages of reduced costs, improved user convenience, grid stability, and environmental benefits. High initial implementation costs, potential AI constraints like scalability and data quality problems, and difficulties integrating with current infrastructure are drawbacks.

3. Proposed Methodology for the Minimization of LCOE in the Grid-Connected Hybrid System

This model proposed that the RES, like solar PV and WTs, can be integrated into a grid-connected solar-wind hybrid system with an EVCS. Integrating multiple renewable sources allows the system to compensate for intermittency and create a more stable power output profile. In this case, the grid and EV charging loads are supplied with steady electricity. However, with optimization, they reduce costs and increase dependability. The main goal of the research is to achieve techno-economic feasibility by finding out the best structure and operational strategy for the system's parts. This includes selecting the proper PV panel, WT, and power converter capacities, as well as the control plan for energy exchange with the grid. Appropriate sizing of each component plays a critical role in ensuring both cost-effectiveness and technical reliability. The optimization process's primary goal is to reduce the LCOE while simultaneously improving grid stability, renewable energy use, and system dependability.

The microgrid works by collecting renewable energy from the WT and PV panels, passing it through AC/DC converters, and then feeding the AC and DC buses. This conversion stage ensures compatibility between different power sources and the loads they serve. To effectively satisfy charging demand, the EVCS uses regulated energy from the DC bus. Similarly, to find the most cost-effective and dependable power dispatch, a central microgrid controller that has been improved with the DREAM optimization algorithm continuously evaluates generation, load situations, and system states. In this optimization process, the DREAM enables the controller to determine the best time to start the diesel generator and how much support it should provide when renewable power declines. This reduces unnecessary generator operation and minimizes fuel consumption, leading to both economic and environmental benefits. In order to preserve equilibrium, DREAM selects the optimal times to import or export power, which involves the PCC utility system likewise. Thus, this optimization algorithm ensures optimal renewable usage, minimal fuel consumption, and stability through continuous multi-objective optimization. Its multi-objective nature allows it to consider competing priorities, such as cost, reliability, and environmental constraints, simultaneously. In the end, the load receives consistent, continuous power from all synchronized sources. Fig 1 shows the schematic diagram of the proposed grid connected hybrid system with EVCS.

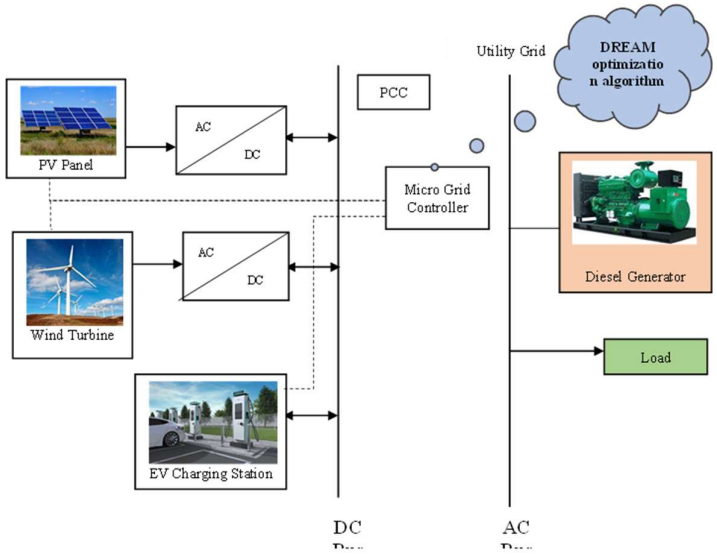

Fig. 1. *Schematic diagram of the proposed grid connected hybrid system with EVCS*

3.1. EV Charging Station

The charging station consists of EVs, a dual converter, and charging stations [11]. This combination enables flexible charging modes and ensures compatibility with varying EV battery specifications. The microgrid controller helps in controlling the power flow at certain times. The SOC can be used to charge EVs. This explains the remaining charge % of the battery. Monitoring SOC is essential for optimizing charging duration and preventing battery degradation. Eqs. (1) and (2) provide a mathematical description of the practical limitations on EV charging.

$$SOC_{\min} \le SOC(t) \le SOC_{\max} \tag{1}$$

$$C_{rate}(t) \le C_{rate}^{\max} \tag{2}$$

where $SOC(t)$, $SOC_{\max}$, and $SOC_{\min}$ are the current, maximum, and minimum SOC values of specific EV at a particular time t; however, $C_{rate}^{\max}$ and $C_{rate}(t)$ are the maximum allowed charging rate and present charging rate of EVs, respectively. These constraints ensure that EV charging remains within safe operational boundaries to protect both the vehicle and the system. Eq. (3) determines the EVs' power at the charging station at any given time t.

$$P_{EV}(t) = \frac{E_{\max} \cdot SOC(t)}{100\Delta t} \tag{3}$$

The most important element in determining the difference in EV charging needs is comparing SOC with SOC_{cr}, which is critical SOC.This comparison helps the controller identify when fast charging or load balancing strategies are required. In this study, a level 2 charger with the benefits of simple and easy charging for 20 EVs at a charging station is examined.

3.2. GRID-CONNECTED PV/ WIND SYSTEM

A PV panel [13] uses sunlight to produce electricity. Its energy output strongly depends on seasonal and daily variations in irradiation. However, other variables, such as temperature and radiation from the sun could affect a PV panel's output. Eq. (4) provides the power generated by a single PV panel $P_{sol}(t)$ at any particular time.

$$P_{sol}(t) = \frac{P_m S_m(t)}{1000}[1 + \alpha_p(T_{cell} - 25^{\circ})] \tag{4}$$

where T_{cell} is the cell temperature, the temperature coefficient of power is P, the rating of a single PV module is denoted as P_m, and $S_m(t)$ represents the solar radiation at that time t.This equation highlights how PV efficiency declines with increasing temperature, a critical factor in system modeling.
Eq. (5) computes the total power produced by all PV panels $P_{PV}(t)$.

$$P_{PV}(t) = N_{PV} P_{sol}(t) \tag{5}$$

where N_{PV} is a selection variable that represents the total number of PV panels [1,13].

Modelling WTs: Modelling WTs helps in understanding the wind system's static and dynamic behaviour. Eq. (6) provides the power output of a WT $P(t)$.

$$P(t) = \frac{1}{2}\rho\pi R^2 C_P(\lambda,\beta)V_v^3 \tag{6}$$

3.3. Power Converter

At the charging station, EVs receive DC power from PV panels and WTs [7]. Nevertheless, the converters are required to send electricity to the grid, meet load demand, or do both. The maximum grid sales $P_{gs}^{\max}$ and buying capacity $P_{gp}^{\max}$ are taken into consideration while choosing the converter's size. Proper converter sizing prevents bottlenecks and ensures seamless bidirectional power exchange. Eqs. (7) and (8) compute the rated power of the rectifier $P_{inv}(t)$ and the inverter $P_{rect}(t)$:

$$P_{inv}(t) = P_{gs}^{\max} / \eta_{inv} \tag{7}$$

$$P_{rect}(t) = P_{gp}^{\max}\eta_{rect} \tag{8}$$

where η_{rect} and η_{inv} are the efficiency values of the rectifier and inverter, respectively.

3.4. Diesel Generator

To increase the operational stability of the HMS, a diesel generator is linked with the AC bus is used as an additional or backup supply [8]. This backup source is especially useful during periods of low renewable generation. This approach offers secure operation against power fluctuation in the case of irregular load demand. The generator's fuel consumption $q(t)$ is represented by Eq. (9):

$$q(t) = aP(t) + bP_{rated} \tag{9}$$

where a and b are the fuel consumption coefficients, and their respective values are regarded as 0.246 and 0.08415. These coefficients reflect the relationship between power output and fuel usage, which is essential for accurate cost modeling. Additionally, the diesel generator's output power for a specific time instant is indicated by $P(t)$, while the rated power is shown by P_{rated}. However, Eq. (10) provides the relationship that can be used to express diesel generator net efficiency T.

$$\eta_T = \eta_B \times \eta_G \tag{10}$$

where B denotes the thermal brake efficiency and G is the generator's efficiency.

4. DREAM Optimization Algorithm

The improved DE-MC algorithm is the basis of the DOA [14]. Its hybrid nature enhances convergence speed and solution diversity. The DE method is included in the Markov chain calculation process after the algorithm is used for the sampling practices to gather parameter sample information in line with the suggested distribution of the samples. The DOA improves the DE-MC in the following ways: (1) Adaptive random subspace sampling technology replaces the sampling, (2) The crossover probability in the initialization step of the DREAM algorithm can be adaptively changed. (3) The DREAM algorithm incorporates the execution of useless chains. These enhancements enable the algorithm to avoid premature convergence and explore the solution space more thoroughly.
For each Markov chain, Eq. (11) produces a probable transition.

$$z^i = x^i + (1_d + e)\gamma(\delta,d')\left[\sum_{j=1}^{\delta} x^{r_1(j)} - \sum_{n=1}^{\delta} x^{r_2(n)}\right] + \varepsilon \tag{11}$$

where γ is the scaling factor, z^i is the individual variance, and the model parameter is typically $\frac{\gamma^{1/4}2.38}{(2\delta d)0.5}$; e and ε are both small numbers that are created at random, $r_1(j)$ and $r_2(n)$ are the serial numbers of randomly chosen parallel chains, δ which indicate how many parallel chains were utilized to create the candidate sample; $\gamma(\delta,d0)$ is the scale factor; the parameters' acceptance probability $\alpha(x^i,z^i)$ and probability distribution $\pi(z^i)$, and y relate to the model's observed outcome, are provided in Eq. (12):

$$\alpha(x^i,z^i) = \begin{cases} \min\left(\dfrac{p(z^i \mid y)}{p(x^i \mid y)},1\right), & p(x^i \mid y) > 0 \\ 1, & p(x^i \mid y) = 0 \end{cases} \tag{12}$$

Make a decision on acceptance z^i or rejection z^i based on the acceptance likelihood $\alpha(x^i,z^i)$. The new candidate sample is accepted $\alpha(x^i,z^i)u$; if not, it is rejected. Put an end to the N parallel Markov chains' t

-generation evolution. This iterative process ensures the algorithm gradually converges toward optimal parameter values.

To determine whether the Markov chain has converged, utilize the sampling points of the final 50% of every Markov chain to calculate SR, which is provided in Eq. (13).

$$S_R = \sqrt{\frac{g-1}{g} + \frac{q+1}{q \cdot g} \cdot \frac{B}{W}} \tag{13}$$

In the above equation, each Markov chain's evolution algebra is represented in g, $\frac{B}{W}$ is the average of the variance of q Markov chains, and q is the number of Markov chains utilized for the evaluation and W is the variance of the average of Markov chains. Evaluating convergence is critical to guarantee that the optimization results are stable and reliable.

Thus, the grid-connected hybrid system with an EVSC habits the DREAM optimization algorithm to intelligently coordinate grid interaction, power generation, and storage. This coordination helps balance competing objectives such as cost, reliability, and energy efficiency. It maximizes renewable penetration while minimizing operating costs, optimizes the real-time dispatch of solar and wind energy, and determines when to activate the diesel engine or seek grid backup. Also, DREAM controls the demand for EV charging by anticipating changes in load and effectively distributing power. This predictive capability enhances system flexibility and prevents unnecessary strain on the grid. All things considered, it improves system dependability, lowers fuel usage, maintains bus voltage stability, and ensures smooth energy transfer to all linked loads.

5. Result and Discussion

The simulation outcomes of the suggested DOA-based grid-connected hybrid system with EVCS to determine the LCOE are displayed in this section. Additionally, the simulation setup was designed to capture transient behaviors and steady-state performance under varying renewable and load conditions to ensure robustness of the proposed approach. To evaluate the model's performance, a simulation framework was created with MATLAB/Simulink 2021b. The proposed DOA-based system is contrasted with existing ABC, PSO, GA, and WOA. The results to evaluate how well DOA produces the greatest outcomes are strongly correlated with the performance of the ABC, PSO, GA, and WOA. These benchmark algorithms were selected due to their widespread use in hybrid energy system optimization studies and their ability to provide a fair comparative baseline. The simulation model analyses the variation of LCOE and the convergence of the suggested algorithm over existing algorithms.

Two essential components of a grid-connected system are its maximum buying and selling capacities, sometimes referred to as grid power exchange capacities. These parameters significantly influence the overall energy management strategy, especially during periods of high renewable variability. The impact of grid capacity versus LCOE is assessed in order to examine how the suggested system operates. Initially, the maximum grid buying capacity is kept at 10kW while the grid sales capacity fluctuates in order to calculate LCOE. The fluctuation of maximum grid sales and buying capabilities with LCOE is shown in Fig. 2.

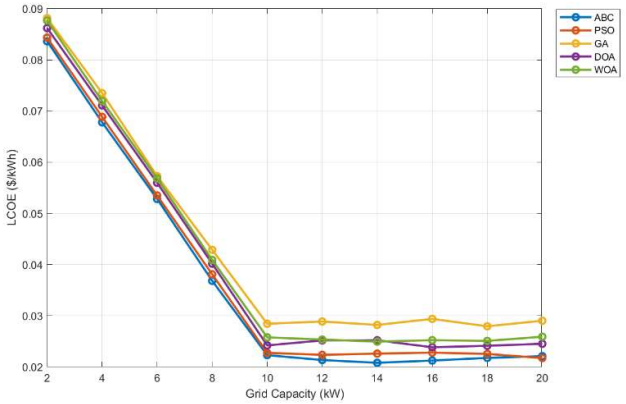

Fig. 2. *Fluctuation of maximum grid sales and buying capabilities with LCOE*

Table 1. *Comparison of the proposed DOA method with the existing method at various grid capacities*

GridCapacity_kW	ABC [16]	PSO [17]	GA [18]	WOA [19]	Proposed DOA
2	0.0836	0.0843	0.0882	0.0877	0.0862
4	0.0678	0.0689	0.0735	0.0720	0.0711
6	0.0528	0.0535	0.0573	0.0568	0.0560
8	0.0368	0.0381	0.0429	0.0409	0.0402
10	0.0223	0.0228	0.0284	0.0258	0.0242
12	0.0213	0.0224	0.0289	0.0254	0.0252
14	0.0208	0.0226	0.0282	0.0250	0.0252
16	0.0213	0.0228	0.0294	0.0252	0.0238
18	0.0218	0.0225	0.0280	0.0251	0.0241
20	0.0221	0.0217	0.0290	0.0259	0.0245

Table 1 shows the comparison of the DOA method with the existing method at various grid capacities. The table clearly indicates that system performance improves consistently as the grid capacity increases, demonstrating the scalability of the proposed optimization approach. In this study, the proposed DOA-based grid-connected hybrid system with EVCS achieved the value of 0.0241, likewise, other methods, including ABC, PSO, GA, and WOA, attained the value of 0.0218, 0.0225, 0.0280 and 0.0251, respectively, at 18kW of grid capacity.

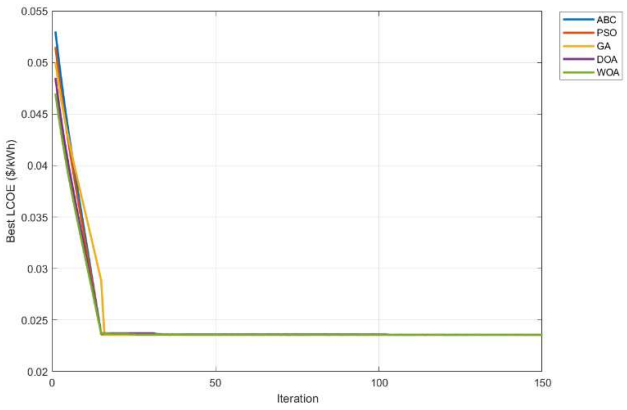

Fig. 3. *Comparison of convergence characteristics of the proposed DOA over other existing algorithms*

Fig. 3 shows the proposed and existing algorithms-based models convergence analysis, which are visible in the initial ten rounds. The fast convergence of DOA during early iterations indicates a strong ability to escape local minima, which is a common limitation in traditional population-based algorithms. In this analysis, the proposed DOA-based grid-connected PV system achieved the value of 0.0242, however, existing algorithm-based grid-connected PV systemssuch as ABC, PSO, GA, and WOA obtained the values of 0.0223, 0.0228, 0.0284, and 0.0258, respectively. This indicates that DOA not only provides improved optimization accuracy but also enhances stability during the iterative search process. Thus, the proposed DOA-based grid-connected PV system attained higher energy conversion efficiency and improved dynamic performance compared to conventional control strategies.

6. Conclusion

This study concluded that the cost of supplying electricity to an EVCS was found to be significantly decreased by combining solar and wind resources in a grid-connected hybrid structure. This reduction is especially important as EV adoption continues to accelerate, increasing the need for sustainable and low-cost charging solutions. In this model, the architectural components of the system were effectively adjusted using the DREAM optimization algorithm to produce the lowest feasible LCOE while maintaining operational limitations and system dependability. The adaptability of the DREAM algorithm allowed it to handle nonlinear interactions among system components more efficiently than traditional optimization approaches. When compared to non-optimized hybrid systems, the optimization results indicate that a balanced combination of solar PV generating, wind power, and grid support provides the lowest LCOE. The DOA frequently converged toward cost-optimal solutions without compromising technical performance for demonstrating its exceptional efficacy in navigating the search field. Its rapid convergence also implies reduced computational effort, which is advantageous for large-scale or real-time applications. The

evaluation of the suggested DOA approach contrast to the current approach at different grid capacities was analysed. In this analysis, the suggested DOA-based grid-connected hybrid system with EVCS received a value of 0.0241 at 18kW of grid capacity, however, other methods such as ABC, PSO, GA, and WOA, obtained values of 0.0218, 0.0225, 0.0280, and 0.0251, respectively. Similarly, the suggested optimization framework specified as an excellent method for establishing cost-effective renewable-based charging infrastructure. Thus, this model demonstrated the economic feasibility of hybrid renewable models for addressing the growing demand for EVs and helped to achieve wider decarbonization objectives. By integrating multiple renewable sources with intelligent control, the system supports long-term sustainability and aligns with global clean energy transition goals. To further improve cost effectiveness and system resilience, future work may expand the model to incorporate battery energy storage, V2G interactions, and real-time adaptive control.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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