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Techno-economic Evaluation of Renewable Energy Microgrids for EV Charging Applications

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ABSTRACT

This research performs an economic and technological assessment of a renewable energy system optimized by Self adaptive grey wolf optimizer (SA-GWO) which enables sustainable EV charging in microgrids. While reducing the cost of operations and hence carbon emissions from EV charging infrastructure, the combination of solar panels and wind turbines with storage units helps lessen the reliance on the primary power grid. Optimal system architecture consists of renewable energy component sizes together with storage facilities and energy management systems to enable sustainable, dependable and affordable EV charging. Operating inside an optimized framework, the SA-GWO controls optimization parameters to enable suitable exploitation-exploration balances that produce optimal solutions for reducing system energy losses while minimizing operational expenses, thus maximizing system reliability. Technical needs for operational effectiveness and logistical dependability as well as financial concerns (including capital expenses, maintenance costs and financial returns) are handled by this optimizing system. In this study, SA-GWO was used to achieve microgrid design goals with improved energy system efficiency, environmental responsibility, economic sustainability and grid independence. In future transportation systems, SA-GWO will be a useful tool for both environmental sustainability and expansion of EV market. This paper combines the ideas of renewable energy-based microgrid, battery-powered automobile charging and SA-GWO with energy storage systems.

Keywords: Renewable energy-based microgrid; Electric vehicle charging; Self-adaptive grey wolf optimizer.

1. INTRODUCTION

Growing global attention to sustainability combined with environmental preservation has driven a shift towards the adoption of electric vehicles (EV) and energy production from renewable sources. Conventional energy systems, which are heavily reliant on fossil fuels, have proven economically unsustainable and environmentally damaging, failing to meet the increasing energy needs of countries.

Such a scenario demands for innovative solutions to integrate renewable energy sources (RESs) into modern energy systems, especially in applications like electric vehicle charging, where reliability and sustainability are essential (Aljehane and Mansour, 2022). In response to these challenges, renewable energy-based microgrids have emerged as a promising approach, offering localized, efficient and sustainable supply and distribution of energy (Lin *et al*. 2022).

Compared to vehicles powered by petroleum and other fossil fuels, electric vehicles offer a promising solution for reducing pollution and greenhouse gas emissions, while also decreasing dependence on fossil fuels. As a result, EVs are gaining widespread adoption globally. Rapid growth of EVs has placed significant stress on existing energy infrastructure, raising concerns about grid stability and the carbon footprint of electricity generation. Most conventional EV charging stations rely on the central power grid, which, in most parts of the world remains predominantly reliant on non-renewable energy sources (Li *et al*. 2022). This reliance weakens the environmental benefits of EVs, and emphasizes the need for greener charging solutions. Possible constraints of purchasing electrical vehicles is shown in Fig. 1.

To address these concerns, renewable energy-based microgrids, powered by solar photovoltaic (PV) systems, wind turbines and energy storage systems, offer an ideal solution to provide sustainable, decentralized and grid-independent EV charging. Designing such a system requires a careful balance of technical, economic, and environmental considerations.

From a technical point of view, the microgrid system must be reliable, stable and efficient, even amid fluctuations in both energy supply and demand. Economically, the system should minimize initial capital investment, operational costs and long-term maintenance costs while maximizing return on investment (ROI). Environmentally, it should significantly reduce greenhouse gas emissions, increase renewable energy utilization and contribute meaningfully to global sustainability goals (Abubakr *et al*. 2022).

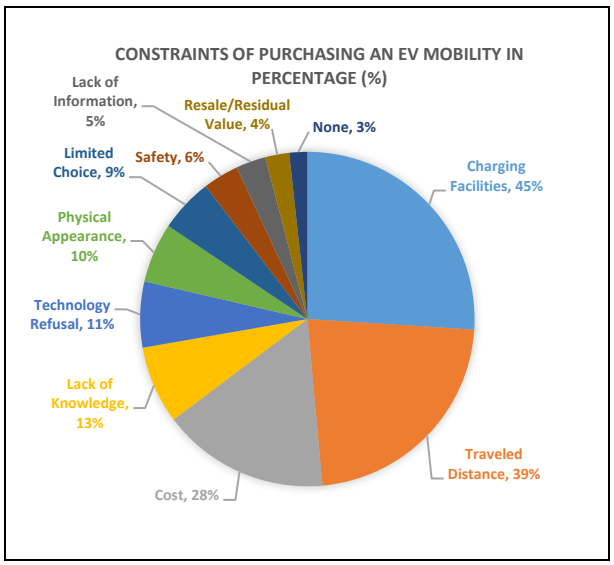


Fig. 1: Possible constraints of purchasing an EV mobility

In order to effectively handle the essential complexity of microgrid configuration and servicing, a sophisticated and flexible optimization framework is essential. Electric vehicles have been progressing due to the exponential rise in sustainable use of energy and efforts to reduce greenhouse gas (GHG) emissions (Akhtar *et al*. 2021). It is imperative to consider the integration of RESs between various other variables in order to deal with emission issues and support infrastructure. There is a global notion that transition to EVs will enhance the quality of life with less pollution. In recent years, the global EV market has shown rapid growth, with approximately 14 million sales in 2023. The overall share of EVs in the total number of automobile sales was barely below 4% in 2020; however, it reached about 18% by the year 2023 (Aljehane and Mansour, 2022). The annual growth rate was above 20%, by the end of 2024 with more than one in every five cars sold globally. This marks clear process towards realization of Net Zero Emission target by 2050.

The electric vehicle charging stations (EVCS) serve to support this global expansion by providing electric power at affordable prices and environmentally friendly electricity from the grid as well as the RESs. These stations are widespread so that the user can travel long distances with a reliable assurance of access to the charging facilities. National policies, incentives and increasing price competition improve EV sales. However, efforts are needed in future to decrease costs and to improve range per charge (Attaianese *et al.* 2023).

Despite the wide expansion of EVCSs, grid stability and efficiency are affected by both technical and economic challenges caused by the growth in EV charging without planning. Harmonic distortion, voltage fluctuations, and increased peak load demands of electrical grid strain the grid and raise its operational costs, constituting major key problems (Beyazıt, and Taşcıkaraoğlu, 2023). Furthermore, battery storage systems (BSS) are very important in the provision of power when the solar energy is low. Despite this, the energy density and storage capacity of traditional batteries are presently quite limiting, and in particular inappropriate for long time periods of low energy interval generation. These issues emphasize the need for advanced, scalable energy storage solutions to maintain stable and efficient operations of EVCS. Integration of renewable energy sources into microgrids introduces a number of technical challenges, including variability in generation of energy due to the change in weather conditions, intermittency of solar and wind resources, and requirement of effective storage and management of energy. It has been shown that self-adaptive grey wolf optimization (SA-GWO) is a self-adjusting technique that enhances the efficiency and reliability of renewables based microgrids and addresses the difficulties inherent in determining increasing solar energy components, determining the ideal location for storing renewable energy, and managing the energy storing systems. Similarly, the infrastructure requirements and economic costs involved with the self-sustaining microgrid system needed for charging electric vehicles have a major qualitative impact on these systems scalability and check system profitability. The high initial investment and underwhelming ROI for customers leads to the unfeasibility of renewable energy microgrid systems (Chaurasiya and Singh, 2022).

This study shows the potential of advanced optimization methodologies to improve economic viability by minimizing installation and operation costs, maximizing system performance and ROI by establishing SA-GWO. Furthermore, the integration of EV charge in RE-based microgrids has substantial environmental advantages, which support the development of a sustainable energy future, the reduction of fossil fuel dependence, and the mitigation of GHG emissions (Ebrahimi and Rastegar, 2023).

1.1 Key Challenges and Opportunities

Developing a microgrid infrastructure for EV charging requires effective integration of financial, technical, and environmental components (Gogoi *et al.* 2024).

Even in the face of energy fluctuation and high demand, the system must be technically reliable, stable, and efficient. The microgrid should be economically viable in terms concerning its minimum initial capital investment, operational costs, and long term maintenance costs, while simultaneously optimizing ROI (Haegel and Kurtz, 2021).

Table 1. Technical, economic, and environmental aspects

Aspect	Key Challenges	Opportunities
Technical	Ensuring system reliability and stability under variable energy generation.	Leverage advanced control systems for enhanced grid stability and demand-response strategies.
	Managing efficiency during fluctuating energy demands.	Integrate energy storage systems to buffer energy fluctuations.
	Balancing supply and demand in real time.	Utilize predictive analytics for energy demand forecasting.
Economic	High initial capital investments for infrastructure.	Decrease costs through modular and scalable designs.
	Minimizing operational and maintenance costs.	Explore innovative financing models like public-private partnerships.
	Achieving a favourable ROI	Incentives for renewable energy adoption and carbon credits.
Environmental	Reducing GHG emissions effectively.	Maximize renewable energy integration to support sustainability goals.
	Ensuring environmental compliance and mitigating impacts.	Promote eco-friendly initiatives and certifications.
	Overcoming resistance to renewable adoption due to skepticism or lack of awareness.	Raise public awareness and enhance community engagement in green energy initiatives.

Table 2. Summary of research projects using hybrid systems for simulation

Ref.	Grid Infrastructure	Optimization Methods	Applications	Merits	Demerits
Iqbal *et al.* (2022)	WT/PV/Battery	Genetic Algorithm, PSO, Multi-objective PSO, and HOMER	Energy generation optimization	Efficient and reliable	Limited scalability
Jaganath *et al.* (2023)	PV/WT/Battery	HOMER, GAMS	Microgrid optimization	Cost-effective	Weather dependency
Liu *et al.* (2023)	DG/PV/WT/ Micro/Hydro	HOMER	Rural electrification	Versatile energy sources	High initial costs
Lu *et al.* (2023)	Biogas generator/PV/DG/WT/ Battery	HOMER	Decentralized grids	Environmentally friendly	Limited biogas availability
Mishra *et al.* (2023)	PV/DG	Crow Search Algorithm	Standalone systems	Enhanced accuracy	Computational complexity
Kumar *et al.* (2023)	PV/WT/DG/ Battery	HOMER	Renewable energy integration	Reduced grid dependency	High capital investment
Lenka *et al.* (2024)	Battery/PV/WT/ Hydrogen storage	Simulated annealing, Hybrid search, Harmony search	Long-term storage	High energy density	High hydrogen costs
Haegel and Kurtz, (2021)	Fuel Cell /PV/WT/Biogas Generator	HOMER	Sustainable charging	Low emissions	Complex setup
Li *et al.* (2022)	Battery /PV/WT/DG/ Biogas Generator	HOMER , Artificial Bee Colony (ABC), PSO	Grid resilience	Optimized resource use	Algorithm complexity
Lamedica *et al.* (2023)	PV/WT/Battery	HOMER	Urban microgrids	Reliable backup power	Weather variability

Integration of EV charging stations into microgrids amplifies benefits by avoiding transportation systems (Huang *et al.* 2023). By integrating hydrogen technology into hybrid energy storage systems can enhance storage capacity compared to conventional batteries. This innovative method increases energy efficiency and reliability and agrees with renewable energy alternatives in the energy storage infrastructure. Hybrid systems that combine BSS and H_2 technology can make EVCS cost effective with limited grid dependence. Not only does this relieve grid stress, but it provides EVCS as a suitable and sustainable replacement from

traditional gas stations (Huang *et al.* 2024). Table 1 shows key challenges and opportunities in developing a microgrid infrastructure.

The use of renewable energy source in modern power system is necessary to suppress GHG emissions and achieve the sustainable energy goals. This integration is driven up by RES incentive policies. Typically, these policies are divided into two types, i.e., price based and the quantity based. Feed in tariff (FIT) and price-based policy are those based on purchased energy at a predetermined price (fixed or variable) over a specified period. These policies promoting RES adoption are widely in place in most of the countries as they are simple and effective (Iqbal *et al.* 2022). On the other hand, quantity-based policies stipulate targets for the renewable energy source capacity, while energy prices are determined by market supply and demand dynamics. There are many studies on the effects on RES incentive policies. For example, the leader-follower method was employed to explore how incentive mechanism affects the penetration rate of PV systems in China. Thus, it is important to incorporate incentive policies to encourage the use of diesel generators (DGs) and RES as means to address power demand in generation expansion planning studies (Jaganath *et al.* 2023). Table 2 lists different research projects using hybrid systems for simulation.

Moreover, financial mechanisms that increase the use of electrical energy storage systems in power grids have been proposed. Yet, there are critical gaps in existing research that pertain to practical implementation in developing countries. Many studies simultaneously overlook both the net present cost (NPC) and CO_2 reduction, as well as the practical feasibility of incentive policies. This paper fills in the gaps by planning a microgrid that runs on renewable energy sources. It also shows three new, scalable incentive programs that can be used by both developed and emerging countries. These policies incorporate NPC, CO_2 emissions, and technical feasibility to make it applicable in real systems (Kumar *et al.* 2023).

The focus of this study is on the techno-economic analysis of the EV charging stations and include the following key points.

- With increase in electricity demand for EV infrastructure, it mitigates grid stability issues.
- The sector of transport may have less pollution if more people buy electric vehicles.
- The study of techno-economic analysis is beneficial for the renewable energy-based EV infrastructures. EV charging stations make the ecosystem and environment clean.

2. MODELLING OF SYSTEM COMPONENTS

2.1 Solar Photovoltaic (SPV) Component

Modelling solar panels involves reproducing their electrical and performance characteristics under certain conditions such as sunlight intensity, temperature, and panel orientation. The electrical behaviour of solar panels is mostly simplified using the single diode model, which includes features such as photocurrent produced by sunlight, a diode representing the current-voltage curve and series and shunt resistances that reduce overall efficiency.

Output power for a solar panel is directly proportional to the temperature, although, in general, efficiency diminishes at higher temperatures. A temperature coefficient is suggested to represent this effect. Moreover, the output of a solar panel depends greatly on the angle of incidence of sunlight, which varies over both daily and seasonal cycles (Lamedica *et al.* 2023). The performance parameters of solar PV model can be assessed on the basis of formulation as depicted below (equations (1)-(9)).

The output power of the SPV system after the inverter at time t is given by:

$$P_{SPV(AC)}(t) = P_{\text{SPV (out)}}(t) \times \eta_{\text{inverter}} \quad \ldots (1)$$

The DC power output from the SPV system at time t is expressed as:

$$P_{SPV(\text{ out })}(t) = FF_A(t) \times i_{\text{short}}(t) \times v_{\text{open}}(t) \quad \ldots (2)$$

The short-circuit current at time t is calculated as:

$$i_{\text{short}}(t) = \frac{SR}{1000}\left[i_{\text{short },STC} + C_I(T_{SM}(t) - 25)\right] \ldots (3)$$

The open-circuit voltage at time t is expressed as:

$$v_{\text{open}}(t) = v_{\text{open },STC} + C_V[T_{SM}(t) - 25] \quad \ldots (4)$$

The actual fill factor at time t, $FF_A(t)$, is given by:

$$FF_A(t) = FF_i(t) \times [1 - R_s(t)] \quad \ldots (5)$$

The ideal fill factor at time t is calculated as:

$$FF_i(t) = \frac{v_{\text{open },0}(t) - \ln\left[v_{\text{open },0}(t) + 0.72\right]}{v_{\text{open },0}(t) + 1} \quad \ldots (6)$$

The thermal voltage normalized open-circuit voltage is given by:

$$v_{\text{open},0}(t) = v_{\text{open}}(t) \times \frac{Q}{N \times K[T_{SM}(t)+273.15]} \quad \ldots (7)$$

$$R_s(t) = R_S \times \frac{i_{\text{short}}(t)}{v_{\text{open}}(t)} \quad \ldots (8)$$

Equation (8) relates $R_S(t)$ to the standard series resistance (R_S), the short-circuit current ($i_{short}(t)$), and the open-circuit voltage ($v_{open}(t)$). Here, $T_{SM}(t)$ depends on the ambient temperature ($T_{amb}(t)$), the solar radiation (SR), and the nominal operating cell temperature (T_{nom}) adjusted by a factor of 0.8. $T_{SM}(t)$ is determined as:

$$T_{SM}(t) = T_{\text{amb}}(t) + SR\frac{(T_{\text{nom.}}-20)}{.8} \quad \ldots (9)$$

2.2 Wind Turbine Component

The power curve is the key feature of a wind turbine model, and it connects the wind speed to the power output of the turbine. A range of methods can be devised for estimating the power output. A typical approach incorporates the Betz Limit and the turbine's power coefficient (Cp), which defines how effective a turbine is at converting wind energy into mechanical work. Real turbines have lower efficiencies because of mechanical losses and design limitations. The theoretical maximum power extractable from the wind is 59.3%, known as the Betz limit. The resulting equation (10) shows the total power the wind turbine makes (Lu *et al.* 2023). Equations (11) and (12) are related to power output.

$$\text{Cp} = \frac{\text{Mechanical Power Output}}{\text{Cut-in wind speed}} \quad \ldots (10)$$

Cut-in wind speed, rated wind speed and cut-out wind speed are the factors affecting the efficiency with which a wind turbine works. Altitude and temperature influence the wind turbine performance because lower temperature and higher altitude lower the air density, leading to lower power generation (Mishra *et al.*2023). Performance is also closely related to the turbine's design, specifically the length of blades and the efficiency of generator.

$$P_{\text{mech}}(V_{\text{wind}}, \omega_{\text{rotor}}) = \frac{1}{2} \times \rho \times V_{\text{wind}}^3 \times C_p(\lambda, \theta) \quad \ldots (11)$$

The density of air is given by ρ, and the area moved by the wind turbine rotor blades is given by A_s. V_{wind} indicates the speed of the wind (important factor in figuring out the power output). The power coefficient C_p is not a straight line and is determined by the pitch angle and the tip speed ratio.

$$\lambda = \frac{\omega_{\text{rotor}} \times GR \times r_{\text{rotor}}}{V_{\text{wind}}} \quad \ldots (12)$$

ω_{rotor} stands for the speed of the generator's rotor, and GR stands for the gear ratio. R_{rotor} stands for the rotor radius, which is obtained at the turbine edges.

$$C_p(V_{\text{wind}}, \omega_{\text{rotor}}, \theta) = C_1\left(C_2\frac{1}{\alpha} - C_3\theta - C_4\theta^x - C_5\right) \times \exp\left(\frac{-C_6}{\alpha}\right) \quad \ldots (13)$$

Also, C_1 through C_6 and x are fixed values that are found through numerical calculations, as explained in a previous study (Mishra *et al.* 2021). Equation (14) adjusts α given in equation (13) by accounting for the combined effects of λ and θ, including non-linear behaviour at higher pitch angles.

$$\frac{1}{\alpha} = \frac{1}{(\lambda+0.08\theta)} - \frac{0.035}{1+\theta^3} \quad \ldots (14)$$

$$P_{WTG} = \begin{cases} 0; & 0 \le V \le V_{\text{cin}} \text{ or } V \ge V_{\text{cout}} \\ P_{WTG,\text{rated}} \times \left(\frac{V - V_{\text{cin}}}{v_{\text{rated}} - V_{\text{cin}}}\right); & V_{\text{cin}} \le V \le v_{\text{rated}} \\ P_{WTG,\text{rated}}; & v_{\text{rated}} \le V \le V_{\text{cout}} \end{cases} \quad \ldots (15)$$

where P_{WTG} = output wind turbine generator power, $P_{WTG,\text{rated}}$ = rated output wind turbine generator power, v_{rated} = rated wind speed (equation (15)) (Nair and Shukla, 2023).

2.3 Battery Storage System (BSS)

The power output of lithium-ion battery system by Freqcon Company is competitively in line with other products in the same industry. In this case, 'dispatch' means giving out the BSS resources and going into more detail about what the task needs. The BSS dispatch method starts to keep an eye on the busiest times. When the peak load is higher than what Wind Turbine Generator (WTG) and SPV can handle, the BSS empties. When peak load is lower than the Wind Turbine Generator and Solar Photovoltaic system can handle, surplus energy is directed towards charging the Battery Storage System (BSS). In neutral mode, the BSS remains connected to the distribution system, providing system support. The State of Charge (SOC) determines BSS operational mode. The battery power and energy parameters are defined as follows:

The DC charging/discharging power of the battery over a given time interval Δt is represented as $P_{Battery(DC)}(t)$ in watts (W). The energy stored in the battery is denoted by $E_{Battery}(t)$ and is measured in watt-hours (Wh) (equation 16).

$$P_{\text{Battery }(DC)}(t) = \frac{E_{\text{Battery }}(t) - E_{\text{Battery }}(t-\Delta t)}{\Delta t} \quad \ldots (16)$$

The AC power corresponding to the charged or discharged state of the battery is given by $P_{Battery(AC)}(t)$. The overall efficiency of the battery is represented by $\eta_{Battery}$, while the inverter power factor is indicated as $PF_{Inverter}$ (equation (17)).

$$P_{\text{Battery }(AC)}(t) = \begin{cases} \frac{P_{\text{Battary }(DC)}(t)}{\eta_{\text{Battary}}}; P_{\text{Battery }(DC)}(t) > 0 \\ P_{\text{Battery }(DC)}(t) \times \eta_{\text{Battery}} \times PF_{\text{Inverter}}; \text{ Otherwise} \end{cases} \quad \ldots (17)$$

The SOC of the battery at any time t is denoted by SOC (t). The charging efficiency of the battery is represented by $\eta_{Charging}$. The battery capacity, expressed in ampere-hours (Ah), is denoted as $C_{Battery}$, while the nominal voltage of the battery is represented as V in volts (V) (equation (18)) (Padhy and Sahu, 2023).

$$\text{SOC}(t) = SOC(t-\Delta t) + \eta_{\text{Charging}} \times \frac{P_{\text{Battery }(DC)}(t)}{C_{\text{Battery}} \times V} \times \Delta t \quad \ldots (18)$$

3. METHODOLOGY

The use of batteries to store energy has become essential for enhancing the dependability and effectiveness of these charging stations, ensuring a stable electricity supply during variations in renewable energy output (Pandey *et al*. 2024).

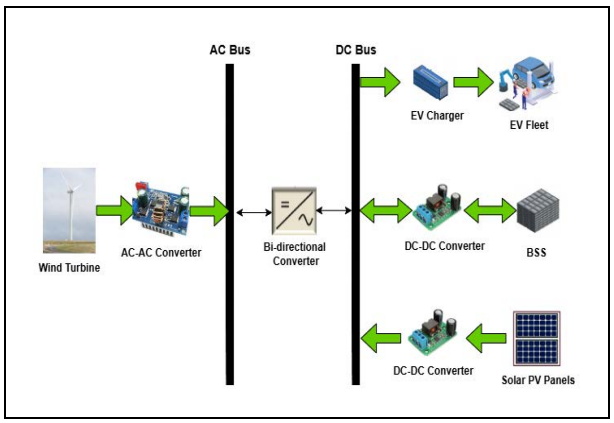


Fig. 2: Model of renewable energy-based microgrid with EV charging load

Fig. 2 shows the model of the Renewable energy-based microgrid with EV charging load (Panigrahi, Sharma and Singh, 2022). The system is enhanced by the SA-GWO and comprises a combination of solar photovoltaics, wind turbines, and energy storage solutions. The objective is to ascertain the optimal arrangement of these components to ensure a cost-efficient and reliable energy supply, while concurrently reducing the environmental impact of traditional grid electricity. The study focuses on multi-objective optimization, incorporating both technical and economic goals. The technical aspects include the optimization of system efficiency, the minimization of energy losses, and the assurance of reliable energy supply (Pham et al. 2023). The economic objectives are to reduce installation costs, operational expenditures, and enhance ROI. To do this, the SA-GWO algorithm is employed to dynamically adjust essential optimization parameters. The algorithm efficiently converges to an optimal solution for microgrid design by employing a self-adaptive strategy that considers various limitations.

The analysis indicates that the SA-GWO based optimization method yields a balanced microgrid design that is economically feasible and environmentally friendly by optimizing the dimensions and arrangement of renewable energy components and energy storage systems (Shih and Pantic, 2023). The method significantly diminishes reliance on the main power grid, enhances energy efficiency, and lowers carbon emissions. The findings highlight the capability of this method to accelerate the integration of EVs and attain enduring sustainability goals within the transportation industry.

3.1 Objective Functions and Related Constraints

3.1.1 Total Net Present Cost (TNPC)

Minimising TNPC is a very important part of figuring out if the suggested hybrid system can be made to work and be profitable. The parameter keeps track of the initial costs of equipment, installation, and maintenance. Reducing TNPC is important for more than just the money it brings in. As per the proposed model, designers should pick the final solution that fits their needs and tastes the best from the Pareto optimal set of solutions generated by it. This process ensures total efficiency of the system, cost-effectiveness and reliability (Singh and Kumar, 2023).

$$Obj\ 1 = Min\ (TNPC) \quad \ldots (19)$$

$$Obj\ 2 = Min\ (LPSP) \quad \ldots (20)$$

Subject to:

$$\begin{cases} N_x^{min} \le N_x \le N_x^{max}, x \in \{PV, WT, BAT\} \\ \left(P_{pv}(t) + P_{WT}(t) \pm C_{Bat}(t)\right) \times \text{ Time step} \ge \frac{P_{EVCS}(t) \times \text{Timestep}}{\eta_{inv}} \\ C_{Bat,min} \le C_{Bat}(t) \le C_{Bat,max} \end{cases} \quad \ldots (21)$$

3.2 Installation Cost of EVCSs

Operational and installation expenses of EVCSs can be reduced as defined by equations (22)-(27).

In consideration with slow and fast CSs:

$$Obj\ 3 = Min\ (Cost\ of\ EVCSs) \quad \ldots (22)$$

$$Cost = C_{operation} + C_{installation} \quad \ldots (23)$$

$$C_{operation} = \left\{\left\{\sum_{j=1}^{m} F_j \times f_j \times \left(CP_{fast}\right)\right\} + \left\{\sum_{j=1}^{m} S_j \times s_j \times (CP_{slow})\right\}\right\} \quad \ldots (24)$$

$$C_{installation} = \left\{\left\{\sum_{j=1}^{m} F_j \times f_j \times \left(C_{fast}\right)\right\} + \left\{\sum_{j=1}^{m} S_j \times s_j \times (C_{slow})\right\}\right\} \quad \ldots (25)$$

It is to be noted that, the cost of operation and installation depends on quantity of charging points and infrastructure, intake of power and electricity cost per unit.

In instance with fast CS:

$$C_{operation} = \left\{\sum_{j=1}^{m} F_j \times f_j \times \left(CP_{fast}\right)\right\} \times P_{elec} \ldots (26)$$

$$C_{installation} = \left\{\sum_{j=1}^{m} F_j \times f_j \times \left(C_{fast}\right)\right\} \quad \ldots (27),$$

where the number of EV charging facilities for slow and rapid charging is denoted by s_j and f_j, while the quantity of EV charging infrastructure for slow and fast is represented as S_j and F_j, respectively. Cost of installation is defined as C_{fast} andC_{slow}, power intake is specified as CP_{slow} and CP_{fast}. Moreover, cost per unit is signified as P_{elec}.

4. EXPERIMENTAL METHODS

Three optimisation methods are used in this study: Particle Swarm Optimisation (PSO), Grey Wolf Optimisation (GWO), and a hybrid called Simulated Annealing-Grey Wolf Optimisation (SA-GWO). These are used to make planning EV charging stations (EVCS) more efficient and cost-effective. Each method is used to find the best values for important factors like the average cost, the needed charging capacity, and the cost of fast and slow charging stations. Using these optimisation methods, the study aims to find the best way to lower spending costs while still making sure there is enough charging infrastructure to meet the growing demand for charging electric vehicles. By comparing PSO, GWO, and SA-GWO, we can see how well they do at keeping costs low, charging capacity high, and finding the best mix between performance and cost-effectiveness (Solis and Carrasco, 2022).

The SA-GWO algorithm performs better than the Grey Wolf Optimisation (GWO) algorithm. It is a population-based optimisation algorithm that is based upon the way grey wolves hunt and how they live together in the wild. The improvement (self-adaptation) allows the algorithm to dynamically adjust certain parameters during the optimization process, helping it achieve better exploration and exploitation balance in solving optimization problems.

4.1 Particle Swarm Optimization (PSO)

Particle Swarm Optimisation is a metaheuristic optimisation method that is based on how birds and fish act together. It is often used to find the best way to optimise complex, multidimensional functions in engineering and computer science tasks (Su *et al.* 2021). It is a population-based stochastic optimisation method that moves a group of possible answers, called particles, through the search space to find the best one.

$$v_i = Wv_i + c_1 r_1\left(P_{best,i} - x_i\right) + c_2 r_2\left(G_{\text{best}} - x_i\right) \quad \ldots (28)$$

$$x_i = x_i + v_i \quad \ldots (29)$$

Where,

v_i - Velocity of the ith particle
xi - Position of the i^{th} particle
$P_{\text{best,i}}$ - Personal best of the ith particle
G_{best} - Global best
r_1 and r_2 - Random numbers
c_1 and c_2 - Acceleration Coefficients
W - Inertia weight

4.2 Grey Wolf Optimization (GWO)

In the original GWO algorithm, the grey wolves in the population are classified into four categories:

- Alpha (α): The best solution (wolf) in the population, guiding the search.
- Beta (β): The second-best solution, assisting in refining the search.
- Delta (δ): The third-best solution, still helpful for guiding the search but to a lesser degree.
- Omega (ω): All the remaining solutions are wolves in the population that are less influential.

The grey wolves simulate the hunting process by encircling, attacking, and chasing their prey. The search area will be examined in keeping with the position

of the alpha, beta, and delta factors. The algorithm continuously determines the optimal location for the wolves by adjusting their proximity to the alpha, beta, and delta.

Grey Wolf Optimizer algorithm

Step 1: Initialize the random population X_i(for i=1,2,…,n)
Step 2: Set up the settings for the algorithm: a, A, and C
Step 3: Evaluate the fitness value of all search agents
Step 4: Identify the three fittest search agents:

- X_α = Fittest member (Leader)
- X_β = Second fittest member
- X_δ = Third fittest member

Step 5: While (k< max iterations)

- Apply the position update eq. for modifying every member in the field of search space.
- End for
- Set parameters a, A, and C
- Evaluate each search agent fitness values
- k=k+1; update the values of X_α, X_β, and X_δ.

Step 6: End the While loop
Step 7: Return X_α

5. SELF ADAPTIVE MECHANISM IN SA-GWO

The Self-Adaptive Grey Wolf Optimization method builds upon the original GWO technique by automatically self-adjusting relevant parameters during the searching process, making it more efficient. It can address numerous optimization problems, such as the optimal assortment of solar photovoltaic units, wind turbines, and battery storage needed to satisfy microgrid energy demands at minimal costs. In contrast, the degree of auxiliary performance is restated because of ability to expand the boundaries of systematization, exploration and to focus on the sophisticated objective functions, as is the case for energy systems. By virtue of this self-adaptation, SA-GWO improves GWO integration by automatic tuning of some parameters of the model associated with the processes of exploration and exploitation (Wang *et al.* 2023). The most important parameters are:

1. Exploration coefficient (A): This is the parameter that decides how much the wolves can restrict themselves to a specific range. Low values facilitate localized searches, whereas high values promote extensive exploration.

2. Exploitation coefficient (C): This determines how much the wolves can restrain themselves from using new areas or solutions related to the present spent region. Eagles with lower C values begin exploring other unfamiliar regions, while those with larger values can approach the more familiar solutions.

The parameters, A and C, autonomously modify in SA-GWO during the optimization process, leading to improved convergence towards the optimal solution. Fig. 3 shows the flowchart of SA-GWO (Raut and Patel, 2023).

Table 3. Analysis of PSO, GWO, SA-GWO, GA and DE methods

Method	PV (kW)	WT (units)	Battery (units)	LPSP (%)	LCOE (₹/kWh)	TNPC (₹)
PSO	224	1	6	0.94	22.1154	4,86,17,554
GWO	213	1	6	0.86	22.6484	4,95,56,208
SA-GWO	202	1	5	0.63	23.7718	5,27,72,248
GA	210	1	6	0.85	22.3286	5,02,48,698
DE	205	1	5	0.68	23.329	5,16,95,424

Algorithm: Self Adaptive Grey Wolf Optimizer (predicated on the standard GWO)

Step 1*:* Initialize Parameters

- Initialize the grey wolf population parameter, X_i where i=1,2,…,N
- Set a=2, and compute the wolf population parameter A and C using Equation (1)
- Calculate the average fitness value by evaluating each search agent's fitness.
- Identify the three best search agents:
- X_α = Top search engine
- X_β = Second- Top search engine
- X_δ = Third- Top search engine

Step 2: Compute the moving average of fitness values over the last w iterations

Step 3: Exploration Phase

For t ≤ Full Exploration Time:

- Update the positions of the search agents using Equations (1) and (2).
- Update parameters A, C, and the leader wolf X_α, X_β, and Xu.
- Compute the fitness of all search agents and update F^-
- Compute the moving average of fitness values using Equation (3).

Step 4: Adaptive Strategy for Convergence

While ($a>\delta$ **or** $F^- < F_{movavg} - \epsilon$):

- Update the positions of the search agents using Equations (1) and (2).
- **If** $F^- \geq F_{movavg} - \epsilon$, reduce the exploration parameter: $a=\Upsilon_a$
- Update A, C, and the leader wolf X_α , X_β , X_δ
- Compute the fitness of all search agents and update F^-
- Compute the moving average of fitness values using Equation (3).

Step 5: Return Optimal Solution

Step 6: Return Xα as the best solution.

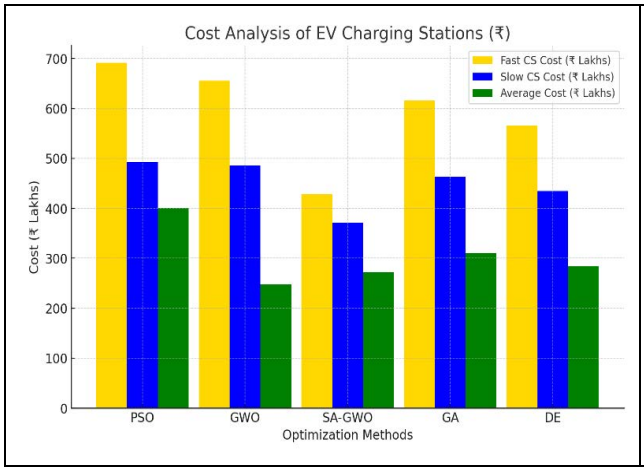


Fig. 4: Cost analysis of EV charging stations using different optimization methods (₹ lakhs)

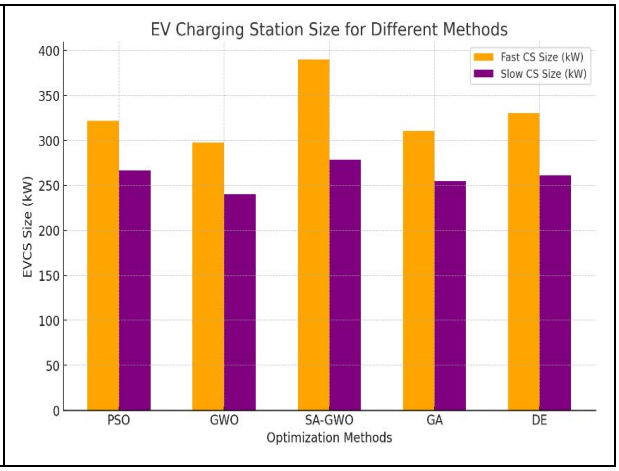


Fig. 5: Comparison of EV charging station sizes (kw) for different optimization methods

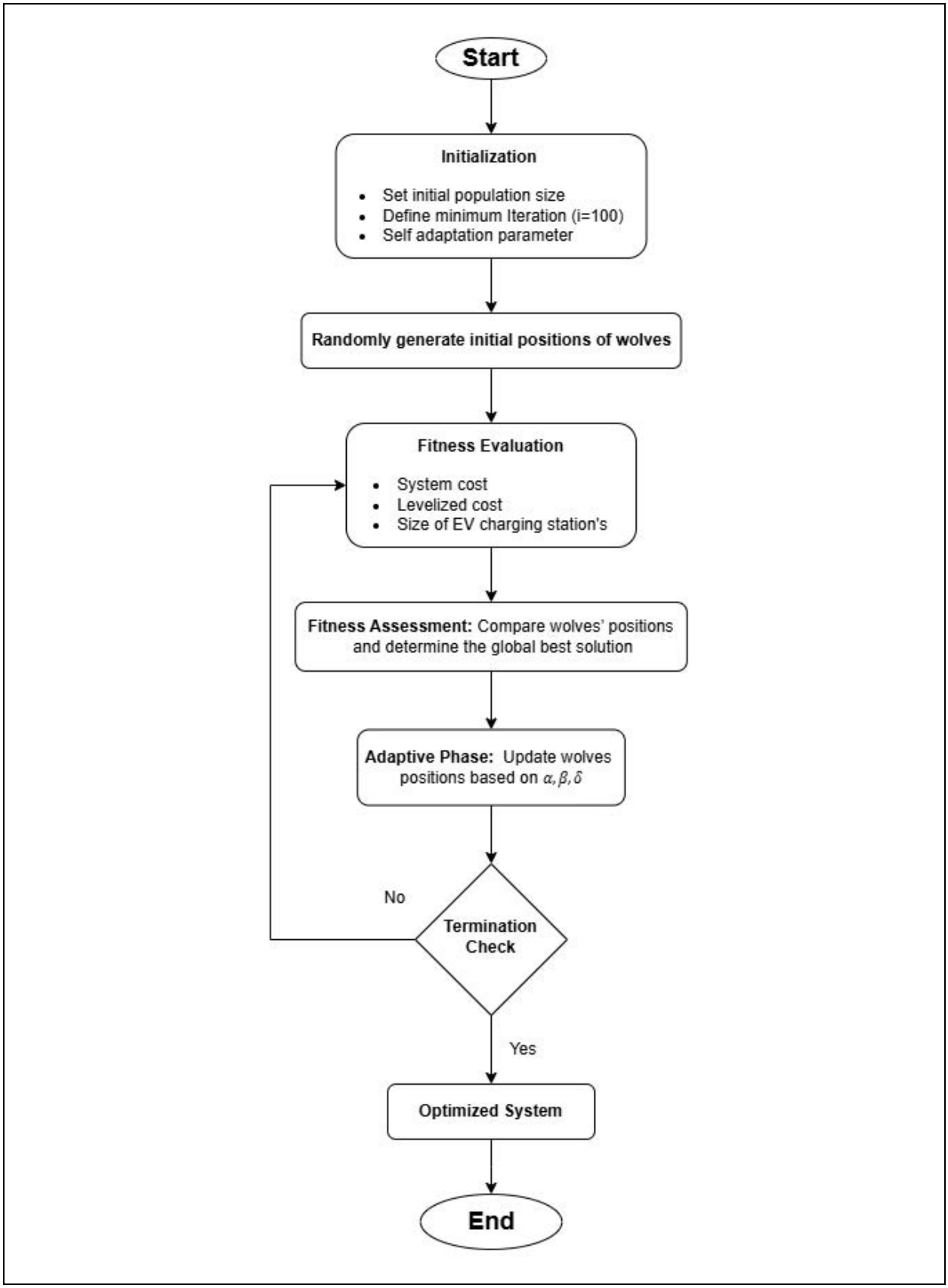


Fig. 3: Flowchart of self adaptive grey wolf optimizer

Initialization of Population and Parameters in GWO for Microgrid Control

Initialize:
n_wolves = number of wolves (population size)
max_iter = maximum number of iterations
dim = 3 (decision variables: Solar PV, Wind Turbine, Battery)
wolves_position = random positions of wolves within bounds [0, 20]
alpha_position = [0, 0, 0] (initial best positions)
beta_position = [0, 0, 0] (second best positions)
delta_position = [0, 0, 0] (third best positions)
alpha_score = infinity
beta_score = infinity
delta_score = infinity
W = 0.5 (initial exploration weight)
A = random between [-2, 2] (exploration coefficient)
C = random between [0, 2] (exploitation coefficient)

For each iteration t from 1 to max_iter:
For each wolf i in population:
fitness_value = calculate_fitness(wolves_position[i])

If fitness_value < alpha_score:
alpha_score = fitness_value
alpha_position = wolves_position[i]

Else if fitness_value < beta_score:
beta_score = fitness_value
beta_position = wolves_position[i]

Else if fitness_value < delta_score:
delta_score = fitness_value
delta_position = wolves_position[i]

For each wolf i in population:
Calculate new position of the wolf i:
A = self-adaptive value (could be adjusted during search)
C = self-adaptive value (could be adjusted during search)
new_position = alpha_position - A * |C * alpha_position - wolves_position[i]|
Clip the new_position within the valid bounds (0 to 20 units)

Update wolves_position[i] with the new_position

Update A and C dynamically for self-adaptation:
- Update A (exploration) and C (exploitation) based on iteration number

After max_iter iterations:
Output the optimal solution:
- The alpha_position represents the optimal number of Solar PV, Wind Turbine, and Battery units
- The corresponding alpha_score represents the total cost

6. RESULTS

The results show that the study analyzed PSO, GWO, and SA-GWO, along with Genetic Algorithm (GA) and Differential Evolution (DE) methods. GA achieved a PV capacity of 210 kW and a battery requirement of 6 units, with a low LPSP of 0.85%. DE achieved a lower PV requirement and battery count, with a higher LCOE.

.The photovoltaic capacity used by PSO is the largest at 224 kW, followed by GWO at 213 kW and SA-GWO at 202 kW. This shows that the hybrid optimisation approach in SA-GWO lowers the PV capacity needs. All

three ways use one wind turbine (WT), which suggests they all depend on wind energy in the same way. However, the holding capacity of the batteries varies. The algorithms PSO and GWO need 6 battery units, but SA-GWO needs only 5. This means that SA-GWO uses less energy. Loss of Power Supply Probability (LPSP %) shows how reliable a system is. SA-GWO has the lowest LPSP of 0.63%, which means it has the lowest risk of power outages (Yang et al. 2022). GWO comes in second with 0.86%, and PSO has the highest LPSP at 0.94%, which means that power cuts are a little more likely. All of them provide a stable power source, but SA-GWO provides the most stable system performance. Table 3 provides the comparative analysis of different methods studied.

PSO is the most cost-effective method from an economic point of view, with the lowest levelized Cost of Energy (LCOE) of ₹22.1154 ₹/kWh and the lowest TNPC of ₹4, 86, 17,554 ₹/kWh. Even though GWO is a little more expensive, it has an LCOE of ₹22.6484 ₹/kWh and a TNPC of ₹4, 95, 56,208 ₹/kWh. That being said, SA-GWO is the most reliable way, but it also costs the most, with an LCOE of ₹23.7718 ₹/kWh and a TNPC of ₹5, 27, 72,248 ₹/kWh (Shah et al. 2023). This means that the higher cost of SA-GWO's improved stability is more likely to be the case. At the end of the day, system priorities determine which way is best. acceptable for the power supply.

When it comes to saving money, PSO is the best choice because it has the lowest LCOE and TNPC, respectively making it the least expensive option. Although it costs more, SA-GWO is the best choice if system dependability is the most important thing. It has the lowest LPSP. Because GWO strikes a good mix between price and dependability, it can be used in situations where a stable power supply is needed but price is an issue. To make the best choice for the energy system, the end choice should take into account available funds, the amount of energy needed, and the level of risk that is.

6.1 Cost Objective for EV Charging Stations

The study employs two advanced optimization algorithms: SA-GWO (Self Adaptive Grey Wolf Optimizer) and GWO (Grey Wolf Optimizer) to accomplish this optimization. The cost-effectiveness of EVCS installations inside the grid is dependent on the use of these algorithms to minimize the total expenses related to the placement and sizing of the EVCSs (Zhang and Wu 2023). The objective function represents the costs involved in each scenario or solution, including installation expenses of the charging stations and the operational costs within the distribution system. The precise cost estimates for different configurations of EVCSs are presented in the results of these optimization techniques, as shown in Table 4. It has been shown in table that both the SA-GWO and GWO methods have been used with different sets of fast and slow charging points in the distribution system. The most cost-effective method will be found by comparing the prices of various technologies, taking into account factors like the size of the charging station, the amount of energy used, and how well it connects to the power grid.

Table 4. Cost analysis of EVCS based on power loss

Method	Fast CSs (₹)	Slow CSs (₹)	Average Cost (₹)	Fast CSs Size (KW)	Slow CSs Size (KW)
PSO	691.5224	492.7954	400.6684	321.78	267
GWO	655.8114	486.1288	247.6892	297.6	240
SA-GWO	428.3188	370.8286	272.2318	389.87	278.65
GA	616.0086	463.0622	310.4028	310.45	255
DE	565.595	434.8132	283.4576	330.12	260.87

Fig. 4 shows the cost analysis of EV charging stations using different optimization methods (₹ Lakhs) and Fig. 5 shows the comparison of EVCS Sizes (kW) for different optimization methods.

While SA-GWO is the most cost-effective method, both fast charging stations (52.234 crore INR) and slow charging stations (45.223 crore INR) have the lowest prices, giving the method an average cost of 33.199 crore INR. GWO, on the other hand, costs more. Its fast-charging stations cost 79.977 crore INR and its slow charging stations cost 59.284 crore INR, for a total of 30.206 crore INR. On the other hand, PSO has the highest prices. Fast charging stations cost 84.332 crore INR, and slow charging stations cost 60.197 crore INR. This means that PSO has the highest average cost of 48.862 crore INR. Fig. 6 shows the comparative bar charts for NPC, LCOE, LPSP and renewable fraction. When it comes to the size of the EVCSs, SA-GWO has the highest fast charging power (389.87 kW), followed by PSO (321.78 kW) and GWO (297.6 kW). Slow charging stations need at least 267 kW to work, while

GWO and PSO only need 240 kW and 278.65 kW, respectively. This means that SA-GWO allows for a higher filling capacity while keeping costs low. This makes it the most effective and efficient method. The table above compares the results of PSO, GWO, and SA-GWO in finding the best NPC. It shows that there are big differences in how well they work and whether they are financially viable. The results show that SA-GWO is the fastest and most effective optimisation method. It only takes 36 iterations to reach the optimised NPC, which is a lot less time than GWO (59 iterations) and PSO (77 iterations). This shows how well the hybrid SA-GWO method works. It combines the exploration power of Simulated Annealing with the exploitation power of Grey Wolf Optimisation, which speeds up the process of finding the best solutions.

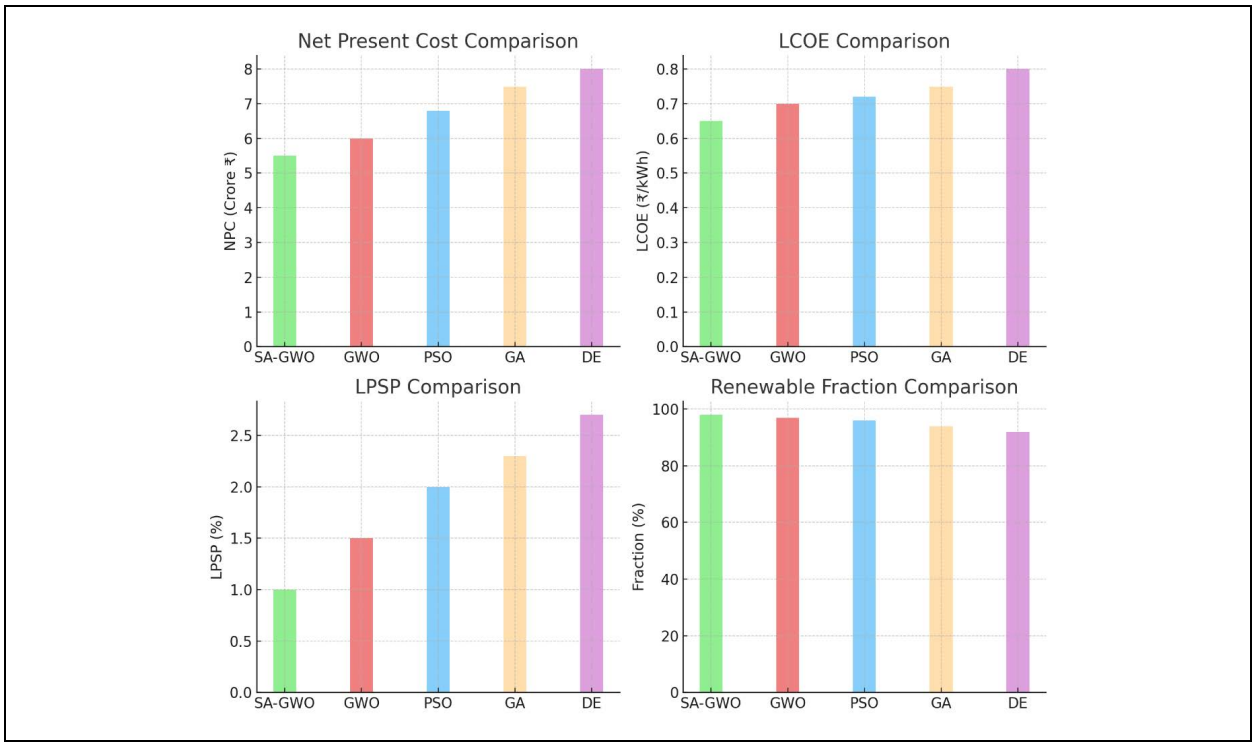


Fig. 6: Comparative bar charts: NPC, LCOE, LPSP and renewable fraction

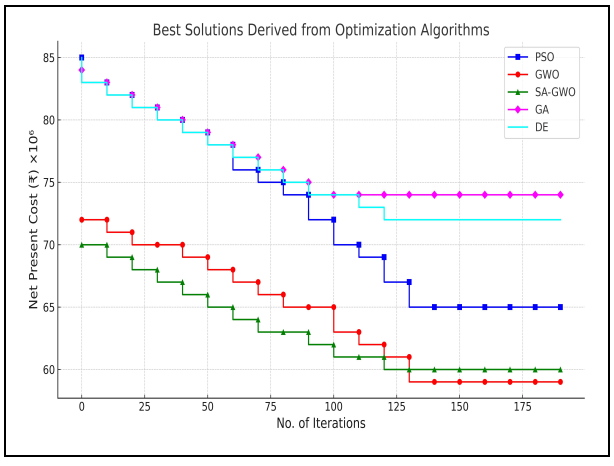


Fig. 7: Best solutions derived from SA-GWO optimization

In terms of economic performance, SA-GWO not only achieves the fastest convergence but also results in the lowest costs for both fast and slow charging stations, making it the most cost-effective solution. While GWO offers a balanced approach, converging in fewer iterations than PSO while maintaining moderate cost efficiency, PSO, despite its ability to support larger charging capacities, requires the most iterations (77) and incurs the highest cost as shown in Fig. 7 which provides the best solutions derived from SA-GWO optimization.

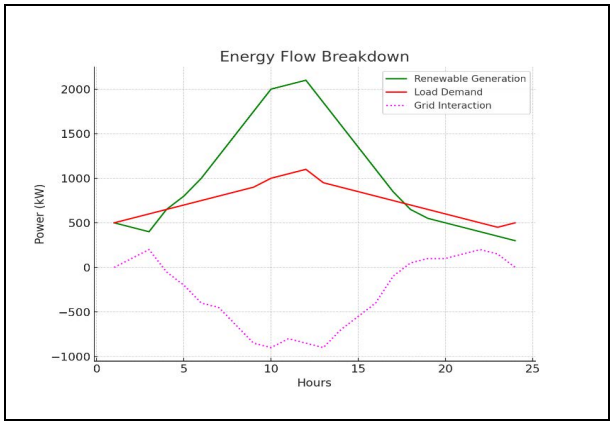


Fig. 8: Energy flow breakdown between renewable energy generation, load demand, and the grid

Fig. 8 shows an energy flow breakdown between renewable energy generation, load demand, and the grid provides a comprehensive understanding of the relationship between renewable energy generation, load demand, and the grid. The renewable generation curve fluctuates in response to the availability of solar and wind energy, whereas the load demand curve remains relatively stable. The grid interaction line, which demonstrates minimal dependence on the main grid, exemplifies the self-sustainability of the optimised microgrid system.

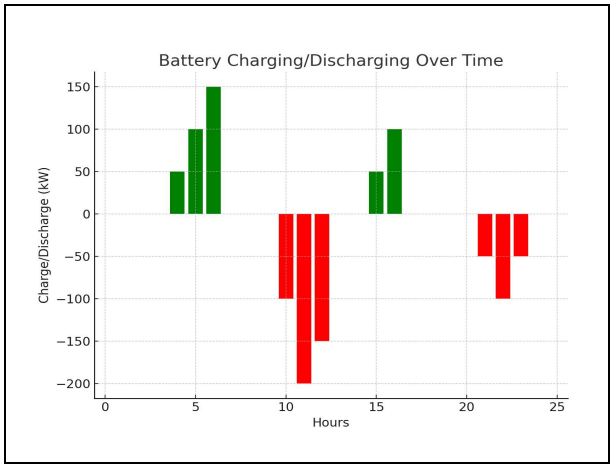


Fig. 9: 24-Hour battery charging and discharging

The bar chart (Fig. 9) depicts the battery's charge (green bars) and depleting (red bars) activities throughout a day. It illustrates the dynamic nature of battery utilisation by storing surplus renewable energy during periods of low demand and supplying energy during peak demand. The chart emphasises the optimised battery dispatch strategy that ensures grid stability and efficient energy utilisation.

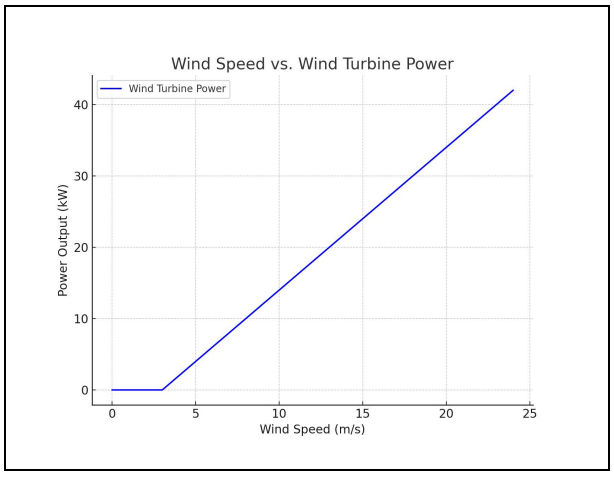


Fig. 10: Wind turbine power *vs.* wind speed

The graph of wind turbine power output demonstrates the correlation between wind speed and power as shown in Fig. 10. The critical role of wind conditions in energy generation is illustrated by the fact that the power generated by the turbine increases as the wind speed increases. This graph aids in the optimisation of wind turbine placement and capacity to guarantee consistent energy production.

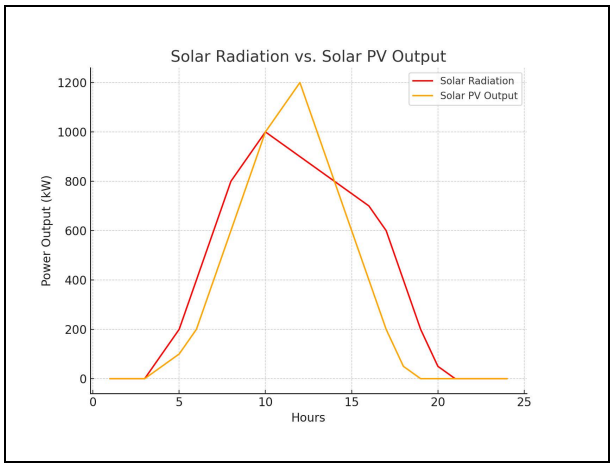


Fig. 11: Solar PV output *vs.* Solar radiation

This graph underscores the direct correlation between the power output of solar PV systems and solar radiation. The output is in accordance with the radiation pattern as shown in Fig. 11, with a peak in the afternoon when sunlight is most intense. This correlation underscores the importance of solar radiation forecasting in the optimisation of the operation of solar PV systems within the microgrid.

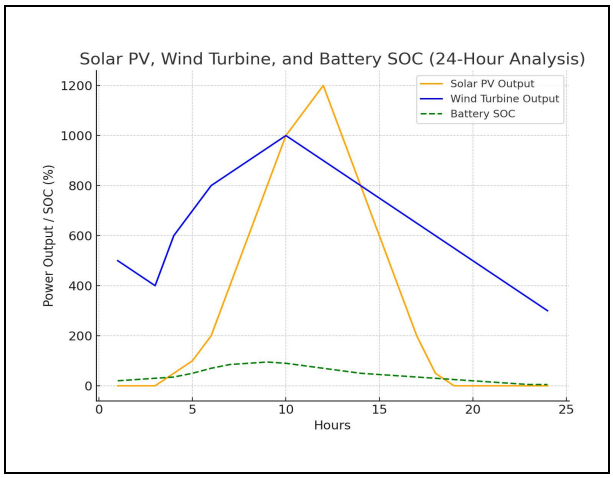


Fig. 12: Solar PV, wind turbine, and battery soc (24-hour analysis)

The hourly performance of solar PV systems, wind generators, and the battery's state of charge (SOC) is depicted in this graph over the course of 24 hours as shown in Fig. 12. While the solar PV output reaches its optimum during midday, when the intensity of sunlight is at its highest, the wind turbine output fluctuates throughout the day in accordance with the wind speed.

The battery SOC graph, which illustrates periods of charging and discharging, preserves the energy equilibrium within the system. This analysis demonstrates the effective collaboration between renewable energy sources and battery storage in meeting energy demands.

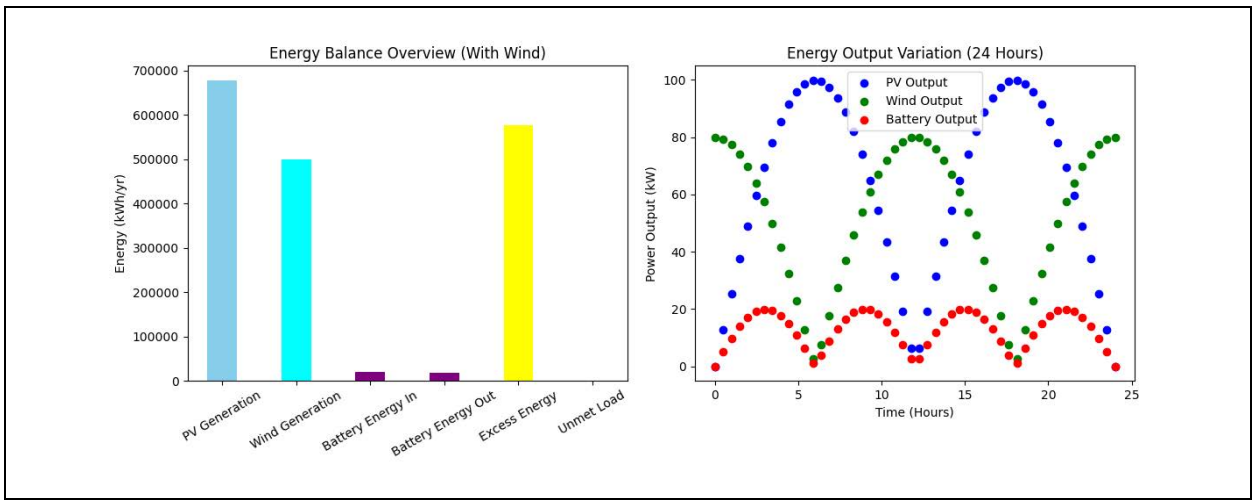


Fig. 13: Energy balance overview and energy output variation (24 hours)

Photovoltaic energy production (Blue Dots) peaks around midday, indicating maximum solar radiation intensity, whereas wind output (Green Dots) changes with wind speed in the 24-hour energy output variation analysis. Red dots signify battery charging and discharging for energy balance as shown in Fig. 13. Solar, wind, and battery storage balance energy make investment planning vital since capital expenditures contribute most to system costs. To reliably supply energy from PV, wind, and battery storage, hybrid renewable energy systems need resource forecasting, cost optimisation, and energy management.

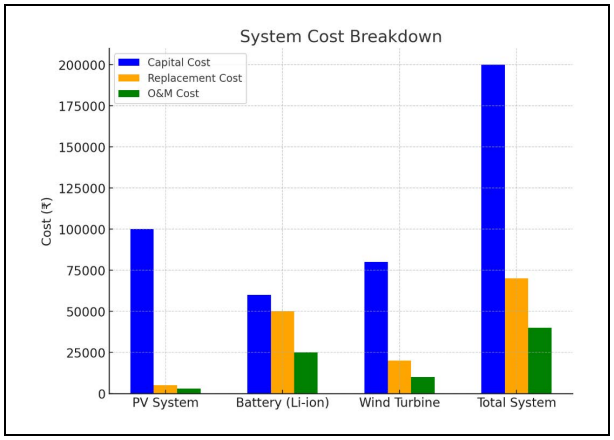


Fig. 14: System cost breakdown

The PV systems cost most, followed by wind turbines and batteries. Capital investments account for most RES costs, requiring long-term financial planning. The energy balance overview shows 700,000 kWh/year of PV generation and much lower for wind generation as shown in Fig. 14. Battery charging and discharging help balance energy supply and demand. When excess energy is high, it must be either stored or utilized effectively. Conversely, when unmet load is low, it indicates that the renewable energy system is efficiently meeting the demand.

7. CONCLUSION

The comparison of PSO, GWO, and SA-GWO reveals the balance between minimizing EVCS costs, ensuring system reliability and managing infrastructure scale. The findings show that SA-GWO is the most cost-effective approach. It has the lowest costs for both fast and slow charging stations, along with the highest charging capacities (389.87 kW for fast charging and 278.65 kW for slow charging). This shows that SA-GWO's hybrid optimization strategy supports both smooth business operations and system efficiency.

Particle swarm optimisation provides slightly higher charging capacities than GWO but is significantly more expensive. The fastest charging station costs 722.151×105 INR, with an average cost of 418.569×105 INR. This approach demands more money to support bigger facilities. However, GWO is a good compromise between price and performance, delivering moderate charging speeds at a lower cost than PSO, but higher than SA-GWO. Overall, SA-GWO stands out as the most balanced choice, combining low costs with high charging capability. GWO may be suitable for scenarios considering a balance between the funding cost and the size of the charging infrastructure. PSO is less cost-effective, but remains an option when high-capacity EVCS is necessary. These results help people to make informed decisions in selecting optimal EVCS

installation strategies while taking into account costs and service reliability.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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