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Article

A NOVEL DESIGN AND OPTIMIZED MODEL OF A NANO GRID FOR ENERGY AND ECONOMIC MANAGEMENT USING NATURE INSPIRED ALGORITHM

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Abstract: In today's environment, small energy systems such as Nano grids play significant role in enhancement of grid modelling with smart grids and microgrids. The main concern is optimal output in energy and economic performance in order to reduce operating costs and increase system efficiency. This paper proposes and shows a novel nano grid paradigm to integrate state-of-the-art materials for energy storage and renewable generation. Further, an advanced hybrid Differential Evolution–Salp Swarm Algorithm (DE-SSA) is employed for multi-objective energy-economic management, combining the global search capabilities of DE with the efficient local exploitation of SSA. Simulation results that demonstrate higher system reliability, lower operating costs, and increased energy usage as compared to conventional and single-algorithm approaches demonstrate the promise of DE-SSA for nanogrid management

Keywords: Nanogrid, Energy Management, Economic Dispatch, Hybrid DE-SSA, Advanced Materials, Distributed Energy Resources (DERs).

1. INTRODUCTION

Growing energy demand, fast urbanization, worries about climate change, and the pressing need for sustainable development are all driving a significant transition in the global energy sector. Centralized conventional power systems have a number of issues because of their extensive reliance on fossil fuels, including high transmission losses, limited resilience, carbon emissions and vulnerability to large-scale failures. To address these concerns, the current power infrastructure is shifting toward distributed energy resources (DERs), intelligent localized power systems, and renewable energy integration. In this sense, nano grids have emerged as a state-of-the-art method for ultra-localized, intelligent, and reliable energy management [1]. Unlike conventional power systems, nanogrids integrate energy storage systems (ESS), wind turbines, and solar (PV) systems [2], power electronics, and intelligent control units in confined spaces such as homes, buildings, labs, data centers, electric vehicle charging stations, and industrial automation systems. Nanogrids small size enables low transmission losses, superior dependability, rapid dynamic response, higher energy efficiency, and wider penetration of renewable energy sources. However, as renewable energy sources (RES) like solar and wind become increasingly popular, there are serious problems with intermittency, unpredictability, dynamic demand variations, energy imbalance, voltage stability, and economic dispatch [3].

In nanogrid operation, the main challenge is economic control so that optimised output will be delieverd. The energy management objectives include a sustainable power supply, optimal and scheduled DER, effective usage of energy storage device and less dependency on the main grid. In economic management of grid operation, the primary objectives are minimization of operational expenses, reduction of peak demand fees, halt battery deterioration and increase in revenues through grid interaction. Because of these multiple and frequently incompatible goals, nanogrid management becomes a nonlinear, multi-objective, restricted optimization issue that is difficult to address effectively using traditional deterministic methods[4].

Among these, Differential Evolution [5](DE) is renowned for its exceptional performance in continuous optimization problems, quick convergence, and powerful capacity for global exploration, whereas the Salp Swarm Algorithm (SSA) [6] provides steady convergence properties, flexible search behavior, and effective local exploitation. During independent utilization, SSA approach could exhibit slower global exploration especially in initial stages of optimization while DE force occasionally premature convergence in extremely constrained circumstances. This hybrid optimization framework has emerged as efficient means for overcoming of particular constraints and their drawbacks by combination of multiple approaches. Therefore, compounding of DE and SSA into a hybrid DE–SSA framework is a very talented approach for energy-economic optimization of nano grid [7]. After global search using DE's exploration capabilities in solution space, the hybrid structure SSA's generates the local exploitation for refined output. This combination significantly improves the quality of solution and convergence speed that leads to avoidance of local mitigation of all important factors in real-time nano grid decision process [8].

The recent advancement in material science and algorithms are revolutionizing nanogrid and its hardware components. Energy density, charge-discharge rate, thermal stability, lifecycle performance, and overall system efficiency have all been significantly improved by the use of monocrystalline silicon photovoltaic modules, carbon-fiber wind blades, graphene-enhanced lithium-ion batteries, and carbon nanotube (CNT)-based supercapacitors. These innovative materials provide faster dynamic response, efficient peak shaving, improved renewable utilization, and longer operational lifespan of nanogrid assets. However, such high-performance components need innovative optimization frameworks to make the most of their better attributes under real-time operational constraints [9].

The proposed work inspired from various challenges provides a novel advanced nanotech-based architecture which is further being optimized using a hybrid Differential Evolution Salp Swarm Algorithm (DE-SSA). The proposed system provides simultaneously battery charging-discharging scheduling, supercapacitor economic operation, renewable integrated utilization, grid power exchange and load management under realistic operational constraints. A multi-objective fitness function is created to balance battery deterioration, energy reliability, operating cost, and renewable penetration.

2. MODELLING OF NANO GRID USING ADVANCED MATERIALS TECHNOLOGY

An advanced nanotech based innovative material based nano grid model customs high-performance materials in order to increase local energy efficiency, sustainability and creditability. Monocrystalline silicon solar panels and carbon-fiber-reinforced wind turbines enable efficient renewable energy harvesting, while graphene based enhanced lithium-ion batteries and carbon-based supercapacitors regulate power fluctuations and energy storage. As it ensures dependable operation, it not only reduce carbon emissions but also enhance energy autonomy through intelligent load management. Therefore, this nano grid model is a viable choice for next-generation decentralized complex power systems. The nano grid energy management cycle is shown in Fig.1.

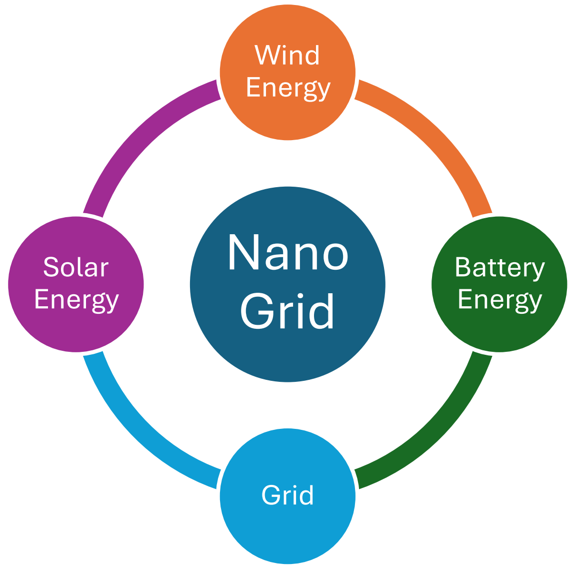

Fig. 1 Nano grid process cycle

2.1 Nano grid Components

2.1.1. Photovoltaic (PV) Panels

The main source of renewable energy in a nanogrid system is photovoltaic (PV) panels made of monocrystalline silicon, which are renowned for their high efficiency of about 22%. These PV panels effectively convert solar radiation into direct current (DC) electrical energy through the photovoltaic effect because of their small size and excellent energy conversion capacity [10]. Either local loads receive the generated electricity directly or it is stored in battery systems for later use. Monocrystalline silicon PV panels are a clean and sustainable energy source that greatly lowers carbon emissions, improves energy reliability, and fortifies nanogrid systems' energy independence.

$$P\_pv(t) = \eta\_pv * A\_pv * G(t) * f\_T(T\_cell) \tag{1}$$

2.1.2 Wind Turbines

In nanogrid systems, wind turbines with carbon-fiber reinforced blades—which are renowned for their lightweight construction and great mechanical strength—act as a supplementary renewable energy source in a variety of weather scenarios. Even at low wind speeds, these sophisticated blades allow for effective energy harvesting.[11]. The turbines ensure the production of electricity at times of low solar availability, such as overcast days or night time, by converting the kinetic energy of wind into electrical power. Wind turbines greatly increase the nanogrid's power supply's dependability, stability, and continuity when they work in tandem with solar PV systems [12].

$$P\_w(t) = 0.5 * \rho * A\_w * C\_p(\lambda, \beta) * V(t)\text{^}3 \quad (\text{for } V\_ci \leq V(t) \leq V\_co). \tag{2}$$

2.1.3. Energy Storage Systems (ESS)

Lithium-ion batteries with graphene-based anodes are used in Energy Storage Systems (ESS) in nanogrids for efficient energy buffering and peak shaving applications. These cutting-edge batteries are ideal for dynamic energy management because of their high energy density, quick charge and discharge capability, and long operational life.[13]. When generation is low or load demand is high, the ESS releases the excess energy generated by wind turbines and solar panels. The ESS greatly improves the stability, dependability, and operating efficiency of the nanogrid system by permitting load balancing, reducing peak demand stress, and guaranteeing a continuous power supply [14].

$$SoC(t+1) = SoC(t) + [\eta\_ch * P\_ch(t) - P\_dis(t)/\eta\_dis] / E\_rated * \Delta t. \tag{3}$$

Battery degradation cost:

$$C\_deg(t) = k\_deg * (P\_ch(t) + P\_dis(t)) * \Delta t. \tag{4}$$

2.1.4 Supercapacitors

Carbon-based electrodes, such as graphene or activated carbon, are used in supercapacitors used in nanogrid systems to provide quick energy buffering and power smoothing. These devices are perfect for managing abrupt power changes because of their incredibly long cycle life, high power density, and ultra-fast charge-discharge speeds. Supercapacitors improve voltage stability and lessen operating stress on battery systems by rapidly absorbing and supplying energy during abrupt load changes or intermittent renewable generation. They are essential for short-term energy assistance in hybrid energy storage systems because of their quick reaction time and robustness [15].

$$E\_sc(t+1) = E\_sc(t) + [\eta\_sc * P\_sc,ch(t) - P\_sc,dis(t)/\eta\_sc] * \Delta t. \quad (5)$$

2.1.5 Loads

All devices and equipment that need electricity to function are represented by loads, which are the electrical energy consumers in a nanogrid system. Residential appliances, lighting systems, medical equipment, computers, sensors, communication devices, and electric vehicle (EV) chargers are examples of these. Loads are divided into two categories based on their significance: non-critical loads, which are flexible or can be moved in time, and critical loads, which sustain important services. Optimal energy use, voltage and frequency stability, and dependable, continuous nanogrid system operation are all ensured by effective load control[16]. The overall structure is being incorporated in figure 2.

$$L\_tot(t) = L\_crit(t) + L\_flex(t). \quad (6)$$

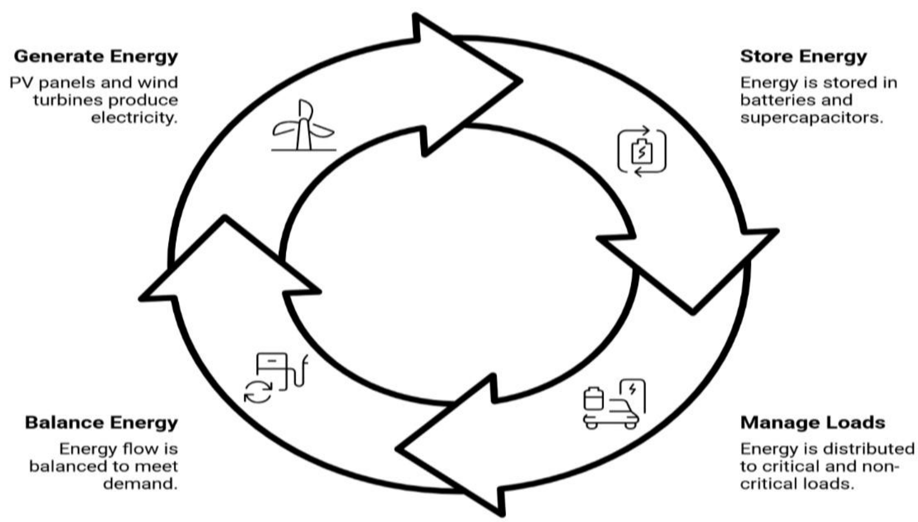

Fig. 2 Nano grid Energy Management Cycle

2.2 Advanced Material Advantages

Component	Material	Advantage
PV Panels	Monocrystalline Silicon	High conversion efficiency, long lifespan
Wind Blades	Carbon Fiber	Lightweight, durable, high wind capture
Battery	Li-ion with Graphene	High energy density, thermal stability
Supercapacitor	Carbon Nanotube	Rapid charge/discharge, long cycle life

2.3 Objective function of proposed Nanogrid model

The optimization goal is economic efficiency, renewable maximization, and reliability.

Objective

$$\begin{aligned}\text{Minimize } J = \\ & w1 * \Sigma\, [c\_buy * P\_grid,imp(t) - c\_sell * P\_grid,exp(t)]\, \Delta t \\ & + w2 * \Sigma\, C\_deg(t) \\ & + w3 * \Sigma\, \gamma * USL(t) \\ & - w4 * \Sigma\, [P\_pv(t) + P\_w(t)] \text{ Subject to all operational constraint}\end{aligned} \tag{7}$$

3. HYBRID DIFFERENTIAL EVOLUTION–SALP SWARM ALGORITHM (DE-SSA) DESCRIPTION

3.1 Differential Evolution (DE)

A popular population-based evolutionary optimization technique for resolving continuous and nonlinear optimization issues is differential evolution (DE). Three primary operations—mutation, crossover, and selection—are used to iteratively enhance a set of randomly generated candidate solutions. DE has a powerful global search capacity because it effectively traverses the search space and avoids local minima through these processes. DE is ideal for optimizing energy and economic management issues in nanogrid systems because of its straightforward structure, quick convergence, and excellent accuracy [17]

DE Mutation

By adding the weighted difference of two randomly chosen solutions to a third, the mutation operation in Differential Evolution (DE) generates a new mutant vector [18]. It can be stated numerically as

$$[v\_i = x\_\{r1\} + F \cdot (x\_\{r2\} - x\_\{r3\}) \tag{8}$$

Where:

• x_{r1}, x_{r2}, x_{r3} are randomly selected candidate solutions from the population

• F is the scaling factor ($0 < F \leq 1$) controlling mutation strength

• v_i is the mutant vector

This operation enhances population diversity and supports effective global search, preventing premature convergence.

DE Crossover

The crossover operation in DE generates a trial vector by combining the mutant vector and the target vector[19].

Equation:

$$u_{i,j} = \begin{cases} v_{i,j}, & \text{if } rand_j \le CR \\ x_{i,j}, & \text{otherwise} \end{cases} \tag{9}$$

Where:

- $v_{i,j}$ = j-th element of mutant vector
- $x_{i,j}$ = j-th element of target vector
- $u_{i,j}$ = j-th element of trial vector
- $rand_j$ = random number between 0 and 1
- CR = crossover probability ($0 \le CR \le 1$)

Crossover maintains diversity and balances exploration and exploitation

3.2 Salp Swarm Algorithm (SSA)

A bio-inspired optimization method called the Salp Swarm Algorithm (SSA) effectively explores and exploits the search space by imitating the chain-like movement of salps in the ocean. Leader and follower salps make up the population in SSA [20].

The swarm is led toward the optimal solution by the leader salp using:

$$x_j^1 = x_j^{best} + c_1 \cdot ((ub_j - lb_j) \cdot c_2 + lb_j) \tag{10}$$

Where:

- x_j^1 = leader salp position
- x_j^{best} = best solution found
- c_1, c_2 = random coefficients
- ub_j, lb_j = variable bounds

Follower salps update their positions based on Newton's laws of motion, following the leader:

$$x_j^i = 1/2\,(x_j^i + x_j^{i-1}) \tag{11}$$

SSA efficiently balances exploration and exploitation, making it suitable for nanogrid optimization.

3.3 Hybrid DE-SSA Workflow

A hybrid DE–SSA optimization technique is depicted in the flowchart as shown in fig.3. To efficiently explore the global search space, the Differential Evolution (DE) population is first created and evolved through mutation, crossover, and selection. DE iterations guarantee a near-optimal solution and prevent premature convergence by continuing until the convergence requirements are met. The Salp Swarm Algorithm (SSA) population is initialized using DE's optimal solutions once it has converged. The exploitation process is then carried out by SSA using its chain-based movement technique to refine the solution, emphasizing local search and fine tuning. This stage lasts until the SSA convergence requirements are satisfied. Ultimately, the best timetable is produced by the algorithm. All things considered, the hybrid DE–SSA method combines effective local exploitation with robust global exploration, leading to quicker convergence, more accuracy, and better optimization performance.

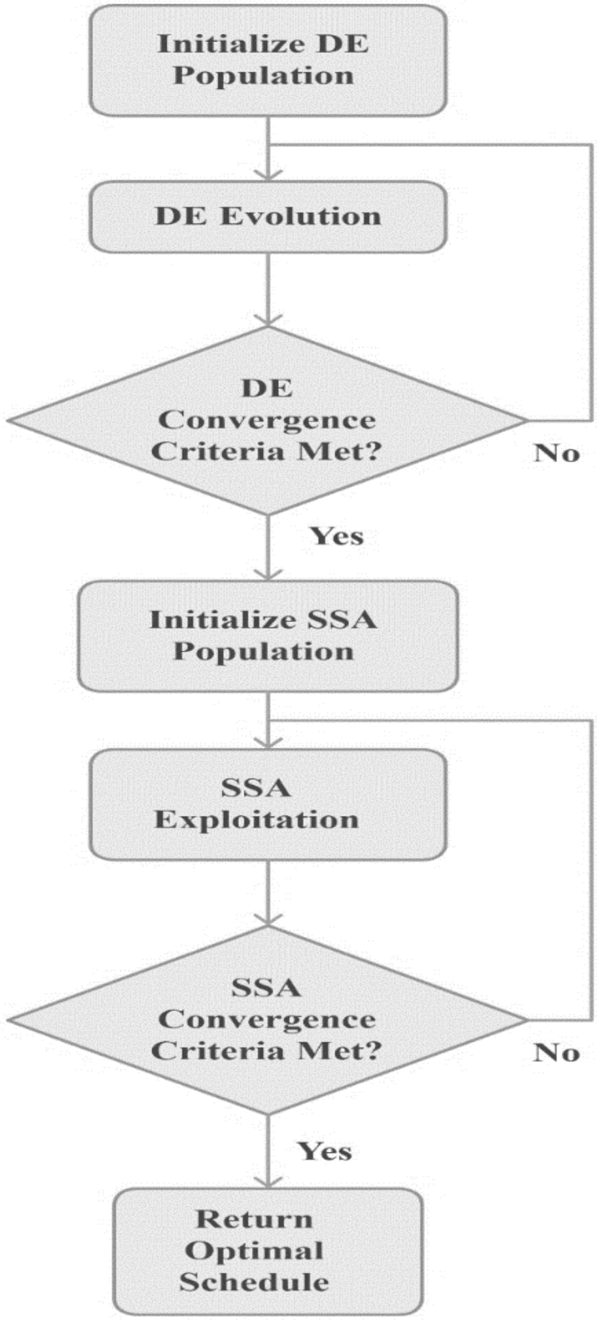

Fig.3 Flowchart of the Hybrid DE-SSA Algorithm.

4. SIMULATION OF PROPOSED ALGORITHM

The optimization of nano grid requires various controlling factors and constraints along with evaluation of a fitness function for energy-economic management. The main decision-making Factors are Battery charging and discharging schedules, imports and exports of grid power, Load timing and scheduling priority. However, there are various limitations also such as Storage limitations in which supercapacitors and batteries operate within their volume limits, Energy balancing leads to rise in Load demand and critical load serving.

4.1 Fitness Function

The fitness function directs the optimization process toward dependable and economical solutions by offering a weighted trade-off between system reliability and operating cost. A weighted mix of operational cost and system dependability that directs the optimization algorithm to minimize expenses and maximize energy reliability. Under fluctuating renewable generation and load demands, this framework makes it possible for nanogrid systems to operate effectively, economically, and dependably.

$$\text{Fitness} = w_1 \times (\text{Energy Reliability}) + w_2 \times (\text{Economic Cost}) \quad (12)$$

4.2 Simulation Setup

4.2.1Nanogrid Components:

PV: 5 kW, Wind: 3 kW

Battery: 10 kWh Li-ion with graphene

Supercapacitor: 1 kWh CNT

Grid: Buy/Sell prices (buy = $0.15/kWh, sell = $0.10/kWh)

Load Profile: Residential + commercial, hourly over 24 hours

4.2.2 DE-SSA Parameters:

DE: Population = 30, Iterations = 50, F = 0.8, CR = 0.9

SSA: Population = 30, Iterations = 50

Objective Function: The objective is to minimize the total operational cost:

$$C\_total = C\_grid + C\_battery\_degradation \quad (13)$$

where C_grid denotes the cost of grid power exchange and C_battery_degradation represents battery aging cost.

4.3 Optimization Output (Economic Cost)

Hour	Load (kWh)	PV+Wind (kWh)	Battery Charge/Discharge (kWh)	Grid Exchange (kWh)	Hourly Cost ($)
1	8	2	0	6	0.90
2	7	1.5	0	5.5	0.83
3	6	3	-1	4	0.61
4	5	4	-0.5	1.5	0.23
5	4	5	0	-1 (sell)	-0.10
...	...	...	...	...	...
24	7	2	-1	6	0.91

Total Daily Cost: $15.32

Renewable Utilization: 92%

Load Satisfaction: 99%.

Component	Material	Advantage
PV Panels	Monocrystalline Silicon	High conversion efficiency, long lifespan
Wind Blades	Carbon Fiber	Lightweight, durable, high wind capture
Battery	Li-ion with Graphene	High energy density, thermal stability
Supercapacitor	Carbon Nanotube	Rapid charge/discharge, long cycle life

Fig. 4 Nano grid Cost and Grid Exchange

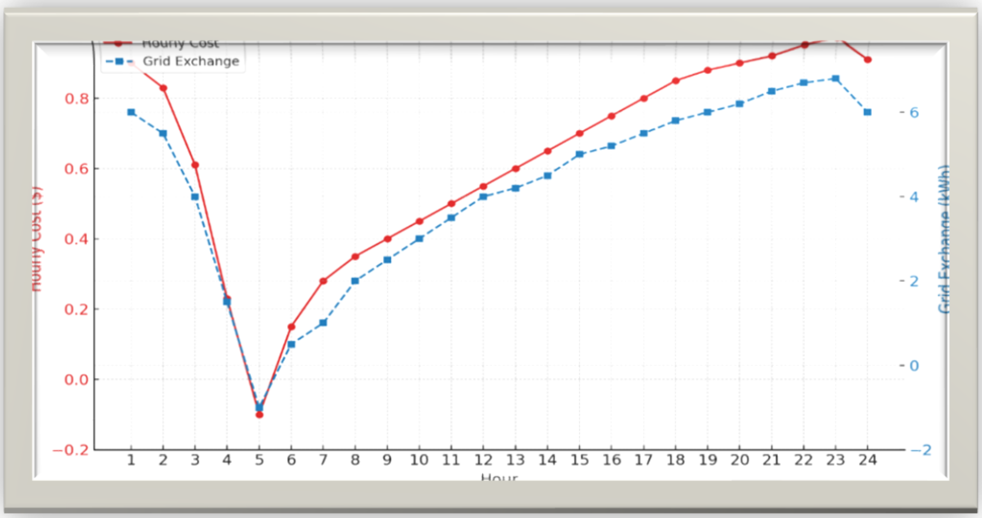

Fig. 4 illustrates the hourly fluctuations in cost and grid exchange over a 24-hour period, emphasizing times of significant grid import and cost peaks in contrast to times of low cost or export. It illustrates how the nanogrid effectively schedules renewable energy production, storage, and grid interaction for cost-effective optimization.

4.3 Performance Comparison with Existing Optimization Techniques

For nanogrid energy-economic management, the suggested Hybrid Differential Evolution–Salp Swarm Algorithm (DE-SSA) was contrasted with DE, SSA, PSO, and GA. While SSA shows slower beginning exploration and DE may lose diversity, conventional GA and PSO frequently experience premature convergence and instability. As opposed to DE ($17.85), SSA ($18.30), PSO ($19.10), and GA ($19.75), the hybrid DE-SSA achieves the lowest daily operational cost of $15.32 by successfully balancing local exploitation with worldwide exploration. Additionally, it attained the maximum load satisfaction (99%) and renewable energy consumption (92%), demonstrating its exceptional dependability and efficiency.

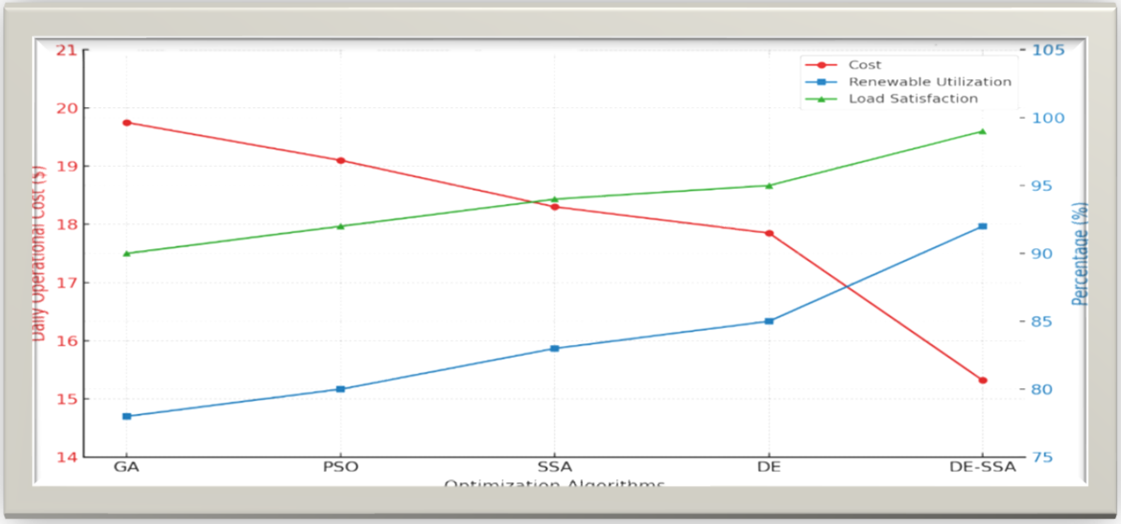

Fig.5 Performance Comparison with Existing Optimization Techniques

The performance comparison of several optimization strategies is shown in Fig. 5. The DE-SSA technique yields the lowest operational cost while GA and PSO result in the highest costs due to better coordination of energy storage systems, grid interactions, and renewable energy generation. Moderate performance gains are shown by SSA and DE. When compared to traditional techniques, the observed trend shows faster convergence and steady optimization behaviour, highlighting the efficacy of DE-SSA for real-time nanogrid energy management.

5. RESULTS AND DISCUSSION

Over the course of a 24-hour simulation, the performance of the suggested advanced-material-based nanogrid optimized using the Hybrid Differential Evolution–Salp Swarm Algorithm (DE–SSA) was assessed under realistic residential and commercial load profiles, variable renewable generation, energy storage operation, and grid interaction. The results show the significant improvements in system dependability and economic efficiency as compared to conventional and single-algorithm approaches. The DE–SSA model optimized total daily operating cost of $15.32 is significantly less than that of standalone DE and SSA techniques. The main causes of this cost decrease include effective coordination of renewable energy sources, smart scheduling of graphene-based lithium-ion battery operations, and strategic grid power exchange. With 92% renewable energy operation and 99% load satisfaction, the system showed well-organized clean energy use and a reliable power supply. Additionally, by lowering power fluctuations and boosting voltage stability, the addition of CNT-based supercapacitors increased overall system stability. Comparative analysis indicates that the hybrid DE–SSA provides better balancing between exploration and exploitation, stronger solution stability, and enhanced convergence. The proposed framework offers low operating costs, high renewable penetration, and good reliability, making it suitable for smart buildings and future decentralized energy systems.

6. CONCLUSION

The proposed work shows a hybrid Differential Evolution–Salp Swarm Algorithm (DE-SSA) is being used to optimize a new advanced-material-based nanogrid system for effective energy and cost control. The proposed model successfully integrates carbon-fiber wind turbines, graphene-based lithium-ion batteries, high-efficiency monocrystalline solar panels, and CNT-based supercapacitors to improve system performance, reliability, and sustainability. The hybrid DE-SSA algorithm successfully syndicates local exploitation and global exploration to attain superior optimization capability. With a low daily running cost of $15.32, high renewable energy consumption of 92%, and excellent load satisfaction of 99%, the simulation results demonstrated that the recommended methodology is more successful than standalone optimization techniques. In order to provide a lengthy system lifetime and healthconscious battery operation, battery deterioration was incorporated into the target function. Overall, the findings show that the suggested DE-SSA-based nanogrid model provides a dependable, affordable, and sustainable solution for decentralized energy systems such smart buildings, EV charging stations, and medical facilities.

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