

Research paper

Smart grid management: Integrating hybrid intelligent algorithms for microgrid energy optimization

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ABSTRACT

The increasing global demand for power drives the need for advancements in generation, control, and supply technologies. While bulk power generation remains cost-effective, it depends on transmission and distribution systems for delivery. Integrating distributed generators into the grid enhances reliability and direct power supply to consumers. Micro Grids (MGs) are a promising solution, offering smoother and more reliable operations. This study explores MGs, incorporating the latest loads and distributed generators to minimize operating costs for electrical power providers. This work utilizes intelligent algorithms, including the Firefly algorithm, Spider Monkey Optimization (SMO), and a hybrid approach combining both. The Firefly algorithm, inspired by swarm intelligence, mimics fireflies' light emission to optimize solutions. SMO, based on spider monkeys' social behavior, balances exploration and exploitation to achieve optimal results. A novel hybrid algorithm is developed to minimize MG operating costs by combining SMO's exploration with the Firefly algorithm's neighborhood optimization; enhancing navigation through the complex constraint solution space of MGs. Case studies on a modified IEEE 33-bus test feeder are conducted. The study compares three metaheuristic methods with non-convex solution spaces to MG operational algorithms. The results demonstrate the hybrid method's efficacy in determining the optimal location and size of real and reactive power support devices for MG operation. Numerical results show the hybrid algorithm's superiority over existing methods, reducing operating costs by 7.5 %, real power loss by 36.5 %, and reactive power loss by 1.7 %, and voltage deviation by 16.895. By considering MG constraints, the hybrid algorithm consistently delivers better outcomes, optimizing operating costs and ensuring efficient power supply. This study presents a novel MG optimization approach, enhancing future energy systems with improved solutions.

1. Introduction

1.1. Background

A microgrid (MG) is an independent energy system catering to a specific area, such as a college campus, hospital complex, business center, or neighbourhood (Alsharif, 2017a; Venkatesan et al., 2021a). It relies on various distributed energy sources like solar panels, wind

turbines, combined heat and power, and generators (AlQaisy et al., 2022; Alsharif, 2017b; Venkatesan et al., 2021b; Chandrasekaran et al., 2021). Clean energy microgrids offer localized energy generation and distribution, ensuring consistency, affordability, reliability, flexibility, and resilience (Jia et al., 2021). During power disruptions, a microgrid can continue supplying electricity to local customers, operating either as an island or integrated with the main grid, thereby facilitating quicker system response and recovery.

Microgrids enhance energy efficiency and reduce losses during

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Abbreviations and nomenclatures

k	Battery Bank	β	attractiveness of a firefly
$C_k(P_k(t))$	Cost function of DESD in (\$/h) at the t^{th} hour	β_0	initial attractiveness
$C_j(P_j(t))$	Cost function of DG in (\$/h) at the t^{th} hour	γ	absorption coefficient
$C_{\text{grid}}(P_{\text{grid}}(t))$	Cost of utility grid in (\$/h) at the t^{th} hour	r	distance between fireflies
j	Diesel generator	DG	Distributed Generators
t	Hour	DLF	Distributed Load flow
$P_j^{\min}, P_j^{\max}$	Minimum and maximum real power generation of the j^{th} DG generator	DESD	Distribution of Energy Storage Devices
C_j^U	Start-up/shutdown cost	DSTATCOM	Distribution Static Compensator
$C_j^U(t)$	Startup/shutdown cost (\$/h) of generated DG power kW at the t^{th} hour	FA	Firefly Algorithm
N_{bus}	Total number of buses	FBS	Forward and Backward Sweep
$P_{T,\text{loss}}, Q_{T,\text{loss}}$	Total real and reactive power losses in kW and kVAR	GLDP	Global Leader Decision Phase
V_u	Voltage magnitude at the sending end node (u) in p.u	GLLP	Global Leader Learning Phase
$P_{\text{grid}}(t), Q_{\text{grid}}(t)$	real and reactive power taken from the utility grid	GLP	Global Leader Phase
$P_j(t), Q_j(t)$	jth DG real and reactive power generation	LLP	Local Leader Phase
$P_{k1}(t), P_{k2}(t)$	the real power generation of PV and wind energy source	LSF	Loss Sensitive Factor
$P_{T,\text{loss}}(t), Q_{T,\text{loss}}(t)$	total real and reactive power loss	MG	Microgrid
$P_D(t), Q_D(t)$	real and reactive power demand of the MG	NR	Newton-Raphson
SoCj	State of Charge of the jth distributed energy storage	OPF	Optimal Power Flow
DoDj	Depth of Discharge of the jth distributed energy storage	PV	Photo Voltaic
		PEV	Plug-In Electric Vehicle
		RDN	Radial Distribution Network
		SMO	Spider Monkey Optimization
		GLP	Global Leader Phase

transmission and distribution (Bakr et al., 2020). Localized power generation also boosts community resilience during extreme weather events, enhances public safety, and minimizes economic losses and infrastructure failure incidents (Jiang et al., 2020). Municipalities and customers utilizing renewable energy sources can benefit from "net metering," whereby excess energy generated can be sold back to utility companies or offset against energy costs (Alsharif, 2017a). Microgrid operation involves load flow analysis and calculating operating costs to determine the optimal procedure based on decision authority. This optimization problem can be tackled using Linear Programming (LP), Nonlinear Programming (NLP), Quadratic Programming (QP), Newton-based solutions, and Interior Point (IP) methods (Zhao et al., 2019). LP utilizes the simplex method, while NLP employs techniques like Lagrange multiplier and sequential unconstrained minimization. QP, a form of NLP, employs sensitivity-based methods, while various techniques such as the gradient method, Newton-based solutions, and Kuhn-Tucker conditions are commonly used (Chen et al., 2022).

Recent research and literature explore the use of intelligent algorithms to minimize operational costs in microgrids (Wang et al., 2020). Popular algorithms include Genetic Algorithm (GA), Simulated Annealing (SA), Ant Colony Algorithm (ACA), Bee Algorithm (BA), Differential Evolution (DE), Particle Swarm Optimization (PSO), Harmony Search (HS), and Firefly Algorithm (FA) (Chen et al., 2021). GA, developed in the 1960s, mimics biological evolution and offers advantages in solving complex optimization problems and parallelism. FA emulates fireflies' social behaviour to find optimal solutions, while Spider Monkey Optimization (SMO) leverages spider monkeys' intelligent behaviour. PSO is inspired by the flocking behaviour of birds traveling long distances across continents.

1.2. Literature Review

In this section, we present a compilation of research papers focused on addressing the operational challenges of microgrids (MG). These papers are categorized based on the optimization techniques employed into two main groups: conventional optimization approaches and intelligent optimization techniques.

1.2.1. Conventional optimization techniques

Conventional optimization techniques have played a significant role in the evolution of power systems optimization. The seminal work of Carpentier in 1962 introduced the concept of optimal power flow, laying the groundwork for subsequent research (Carpentier, 1962). Dommel and Tinney expanded on this by employing Newton's power flow and various optimization methods to minimize generating costs and losses (Dommel and Tinney, 1968). Further advancements were made by researchers like Billinton and Sachdeva in 1972, who utilized nonlinear programming (NLP) techniques to optimize real and reactive power generation for hydrothermal plants (Billinton and Sachdeva, 1972).

Subsequent researchers, such as Alsac and Stott (Alsac and Stott, 1973), enhanced these methods by introducing new constraints for steady-state security, setting a benchmark for future studies. Despite convergence issues in larger systems, Housos and Irisarri (Housos and Irisarri, 1982) introduced techniques based on sparse matrices. Momoh (Momoh, 1986) introduced the Extended Kuhn Tucker conditions algorithm, validated on larger systems. Baran and Wu (Baran and Wu, 1989) proposed simplified distribution flow methods targeting power loss reduction, particularly focusing on radial feeder configurations. Li et al (Li et al., 2008). addressed load variations using the Karush–Kuhn–Tucker conditions, accommodating uncertainties and correlations. Advancements continued with Capitanescu and Wehenkel (Capitanescu and Wehenkel, 2010) utilizing MILP for efficient control with minimal load curtailment. Molzahn et al (Molzahn et al., 2013). introduced semidefinite programming for large power systems, overcoming challenges posed by sparse matrices. Welcong et al (Welcong et al., 2014). developed a two-stage methodology for microgrid optimization, integrating renewable sources and energy storage devices.

Recent studies by Mu et al (Mu et al., 2019). have delved into adaptive dynamic programming to enhance frequency stability and optimize energy storage device usage. These advancements underscore a trajectory towards more sophisticated optimization techniques tailored for modern power systems, promising enhanced efficiency, stability, and integration of renewable resources.

Table 1
Comparative study of literature.

Study	Optimization Techniques	Objective	Results	Merits	Disadvantages
Mu et al. (2019)	Adaptive Dynamic Programming	Frequency stability and optimize energy storage	Enhanced frequency stability and energy storage optimization	Advanced adaptive methods	Complexity in implementation
Ju et al. (2018)	Genetic Algorithms	Energy scheduling based on demand response	Efficient PV generation and storage utilization	Leveraged demand response	Specific to PV systems
Song et al. (2019)	Intelligent Algorithms	Optimize military microgrid operations	Minimized operational costs with effective load-shifting	Multi-agent optimization	Application-specific
Vinayagam et al. (2018)	Particle Swarm Optimization	Islanded microgrid power management	Ensured smooth coordination between DGs and load variations	Effective for islanded systems	May not generalize to all microgrid types
Roselyn et al. (2020)	Adaptive Neuro-Fuzzy Systems	Reconfigurable microgrids for power balance and frequency regulation	Utilized adaptive neuro-fuzzy systems for switching operations	Enhanced adaptability	Complexity in fuzzy systems
Naik et al. (2021)	Butterfly Optimization	Standalone microgrid optimization	Optimized standalone microgrids	Innovative optimization approach	Limited application scenarios
Arumugam and Kuppan (2021)	Hybrid Optimization Techniques	Grid-connected microgrid operation	Minimized operational costs alongside renewable energy integration	Comprehensive hybrid approach	Implementation complexity
Lekvan et al. (2021)	Genetic Algorithm, Intelligent Water Drop	Optimal DG placement	Improved voltage regulation and minimized losses	Novel algorithm combination	Complexity in algorithm integration
Pramila and Chandramohan (2021)	Heuristic Algorithms	DG planning with improved power quality	Optimal sizing and placement of DGs	Enhanced power quality	Complexity in heuristic methods
Bala and Ghosh (2019)	Swarm Intelligence Algorithms	DG optimization	Integrated conventional methods with swarm intelligence	Comprehensive two-stage methodology	Complexity in integration
M. Talaat et al. (2023)	Artificial Intelligence (AI), Particle Swarm Optimization (PSO), Artificial Neural Networks (ANN)	Improve integration of RESs, reduce total cost, improve grid performance	Improved operation accuracy and prediction control, NMSE of 1.10 % in 3367.50 s	Enhanced reliability and sustainability, effective cost reduction, fast convergence rate of PSO	Intermittent and unstable nature of RESs, complexity of integration schemes
Fayyazi et al. (2023)	Machine Learning, Intelligent Controllers, Data-Driven Control, Optimization Systems	Effective energy management in hydrogen fuel cell vehicles and fuel cell hybrid electric vehicles	Improved prediction, control, and energy management; effective V2X communication	Reduced greenhouse gas emissions, enhanced sustainability, advanced control strategies	Complexity in energy management, reliance on advanced AI techniques
Joey Li et al. (2023)	Artificial Intelligence (AI), Big Data, Internet of Things (IoT), Blockchain	Provide a holistic view of integrable IT for smart energy management	Enhanced energy forecasting, resource scheduling, and energy trading	Improved performance and utilization of energy resources, efficient data transmission and storage, seamless integration of technologies	Requires immense data volumes, complexity in integration and deployment
Takialddin et al. (2024)	Artificial Intelligence (AI), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Fuzzy Neural Inference-based Controller	Improve energy generation and management in PV systems under varying climatic conditions	Enhanced energy regulation and management, continuous power supply with battery integration	Improved energy quality, effective optimization of energy output, robust performance under variable conditions	Susceptibility to meteorological fluctuations, complexity in controller design and implementation
Temidayo Oladosu et al. (2024)	Artificial Intelligence (AI)-Based Algorithms, Multi-Objective-Based Algorithm, Reinforcement Learning Algorithm, Hybridizations	Enhance performance and cost-effectiveness of HFCEVs	Improved performance optimization, competitive cost edge over BEVs and fossil fuel vehicles	Effective handling of multi-objective systems, advanced control and EMS strategies	Computational complexity, challenges in retrofitting existing systems

1.2.2. Intelligent optimization algorithms

The exploration of optimization techniques in power systems has seen dynamic advancements, with various methodologies tailored to specific challenges and objectives. Abido et al (Abido, 2002). emphasized the advantages of integrating hybrid wind and solar with thermal power to reduce operating costs and enhance voltage stability, employing PSO and GA algorithms for evaluation. Bakirtzis et al (Bakirtzis Anastasios et al., 2002). introduced an Enhanced Genetic Algorithm (EGA) for Optimal Power Flow (OPF), augmenting traditional GA with novel operators for improved convergence. Mirko Todorovski (Mirko and Rajicic, 2006) innovated initialization procedures for GA, optimizing operating costs by considering real power and voltage constraints.

Chandramohan et al (Chandramohan et al., 2010a). tackled distribution loss minimization using intelligent non-dominated sorting algorithms, achieving efficiency in radial distribution systems. Advancing further, Priyanka Roy and Chakrabarti (Roy and Chakrabarti, 2012) addressed power market-oriented OPF, incorporating economic load

dispatch for real and reactive power in deregulated systems. Zidan and El-Saadany (Zidan and El-Saadany, 2012) introduced probabilistic models for load demand and DG power fluctuation, optimizing wind and solar-based DGs while respecting network constraints.

Recent studies have expanded into microgrid optimization. Ju, et al (Ju et al., 2018). proposed energy scheduling based on demand response, leveraging genetic algorithms for efficient PV generation and storage device utilization. Song et al (Song et al., 2019). utilized intelligent algorithms to optimize military microgrid operations, considering shifting loads to minimize operational costs. Also, the authors suggested scheduling strategies for isolated and grid-connected microgrids, incorporating various energy sources and employing multi-agent optimization techniques. Vinayagam et al (Vinayagam et al., 2018). implemented particle swarm optimization for islanded microgrid power management, ensuring smooth coordination between DGs and load variations.

Beyond optimization, researchers have explored innovative control and protection schemes for microgrids. Some authors also proposed a

multi-agent approach for microgrid protection, ensuring smooth operation and coordination of relay systems. Roselyn et al (Roselyn et al., 2020). focused on reconfigurable microgrids for power balance and frequency regulation, utilizing adaptive neuro-fuzzy systems for switching operations.

Moreover, recent advancements have extended into standalone microgrid energy management. Naik et al (Naik et al., 2021). employed butterfly optimization for standalone microgrid optimization, while Arumugam et al (Arumugam and Kuppan, 2021). utilized hybrid optimization techniques for grid-connected microgrid operation, considering operational cost minimization alongside renewable energy integration. These diverse studies underscore ongoing efforts to enhance the efficiency, reliability, and sustainability of power systems, spanning from macro-level grid optimization to micro-level control and protection schemes.

1.2.3. Optimal sizing and location

The pursuit of optimal solutions in power system planning and management has driven the exploration of various methodologies across numerous studies. The authors investigated heuristic algorithms for capacitor placement in radial distribution networks, primarily focusing on reducing overall losses. However, these methods encountered challenges in addressing voltage instability issues, particularly in heavily loaded systems. Dehghanian et al (Dehghanian et al., 2013). introduced a multi-objective approach considering investment cost, network loss, and customer outage costs, utilizing both conventional and fuzzy-based decision-making methods for optimal DG placement. Shuaib et al (Shuaib et al., 2015). employed Loss Sensitive Analysis (LSA) and gravitational search algorithms to optimize capacitor sizing, thereby enhancing voltage regulation in distribution systems. Lekvan et al (Lekvan et al., 2021). proposed a novel algorithm combining GA and intelligent water drop techniques for optimal DG placement, to improve voltage regulation and minimize losses. Chandramohan et al (Chandramohan et al., 2010b). suggested power flow adjustments and efficient use of D-FACTS devices to manage reactive power flow and reduce reliance on bulk networks.

Advancing, Pramila, V (Pramila and Chandramohan, 2021) proposed heuristic algorithms for DG planning, emphasizing improved power quality through optimal sizing and placement. Bala and Ghosh (Bala and Ghosh, 2019) introduced a two-stage methodology integrating conventional methods with swarm intelligence algorithms for DG optimization. Furthermore, Fard et al (Hassanzadehfard and Jalilian, 2018). employed PSO for optimizing renewable energy-based DGs, considering nonlinear loads and voltage constraints. Also, the authors developed a chance constraint programming model for isolated microgrid scheduling, focusing on cost minimization and spinning reserve management. Kumar et al (Kumar et al., 2019). addressed shading issues in PV panels and proposed control schemes for optimal power generation, emphasizing unity power factor supply to the grid. A multi-objective optimization for standalone microgrid operation, balancing environmental concerns, efficiency, and economic viability. Some authors utilized GA for optimal sizing of PV and EV charging in microgrids, considering real-time power generation and load consumption. Lekvan et al (Lekvan et al., 2021). incorporated demand response for renewable energy scheduling in multi-energy microgrids, employing a hybrid framework for decision-making.

Moreover, Kannan et al (Kannan et al., 2021). utilized HOMER software for cost minimization in microgrid operation, considering various renewable energy sources and load demands. Similarly, Singh et al (Singh et al., 2021). employed HOMER software to operate wind and solar PV-based standalone microgrids economically. Finally, Huang et al (Huang et al., 2021). focused on manufacturing industry microgrids, optimizing operating costs through intelligent demand response and uncertainty management, utilizing evolutionary algorithms and branch-bound mixed-integer LP techniques. Below Table 1 provides a significant comparison of studies related to microgrid optimization,

showcasing their objectives, results, advantages, and disadvantages. It highlights the unique contributions and superior performance of the proposed hybrid algorithm in this study, demonstrating its efficiency compared to existing methods.

These studies collectively demonstrate the diverse range of methodologies employed for optimal power system planning and management, reflecting a continuous quest for efficiency, reliability, and sustainability in energy systems. Utilizing natural resources economically, such as wind energy and solar PV, while maintaining power supply quality is essential in a competitive environment. Intelligent algorithms play a crucial role in minimizing operating costs, and line losses, and maintaining voltage stability, considering multiple objectives for the best optimal solution.

1.3. Objectives and contributions

The primary objective of this research is to address the need for scheduling optimal generating patterns within a microgrid (MG) to minimize operating costs. This is achieved by focusing on the minimization of losses, which is directly proportional to power generation, thus aiding in cost reduction. Additionally, ensuring the quality of power supply is paramount, measured through voltage magnitude, with a particular emphasis on minimizing voltage deviation index.

The specific objectives of this work are outlined as follows:

- Development of Firefly Algorithm and Spider Monkey Optimization techniques to minimize operating costs, losses, and voltage deviation index within the microgrid.
- Creation of a novel Hybrid Spider Monkey Optimization - Firefly (HSMOFF) algorithm aimed at simultaneously minimizing operating costs, losses, and voltage deviation index within the microgrid.
- Achieving optimal sizing of Distributed Generators (DG) and Distributed Static Compensators (DSTATCOM) to minimize generating costs, losses, and voltage deviation index within a constrained solution space.

Intelligent algorithms, notably Spider Monkey Optimization and Firefly Algorithm, have demonstrated efficacy in solving optimization problems within radial distribution networks and microgrid energy scheduling. Leveraging the advantages of these algorithms, the proposed hybrid approach aims to enhance optimization capabilities further.

The contributions of this research are:

- Development of the novel Hybrid Spider Monkey Optimization - Firefly (HSMOFF) algorithm tailored for microgrid optimization, facilitating simultaneous minimization of operating costs, losses, and voltage deviation index.
- Optimization of DG and DSTATCOM sizing within the microgrid under constrained solution spaces, thereby optimizing generation costs, losses, and voltage deviation index.

The problem at hand is fundamentally an optimization problem, aiming to minimize operating costs, losses, and voltage deviation within the microgrid. The MG integrates renewable energy sources such as PV and wind power generation to minimize reliance on the main utility grid and reduce operating costs during renewable power availability periods. Recent developments also necessitate the consideration of electric vehicle charging stations within the MG, with distributed energy storage devices integrated as essential components. During peak hours, DGs are utilized to meet additional load demands, while reactive power support devices such as Distributed Static Compensators (DSTATCOM) are employed to improve voltage power quality within the microgrid. These considerations are integrated into the mathematical model to formulate an effective optimization strategy for microgrid operation.

2. Modelling of the system

In electrical engineering, computational solutions are essential due to the complex nature of real-time problems. This entails modeling the problem using mathematical equations, referred to as mathematical models, which are based on decision variables. These models accurately depict how the system responds to changes in independent variables, ensuring relevance and precision in real-world applications. Once the mathematical model is coded, it can be simulated on a computer, enabling a cost-effective and time-efficient analysis of system behaviour. The results obtained from simulations are validated and utilized to optimize practical electrical equipment, thereby reducing research and development costs.

In microgrid (MG) optimization, solving multi-objective problems is paramount. These objectives typically include minimizing operating costs, enhancing voltage quality, and reducing system losses. Minimizing operating costs is essential for maintaining competitive pricing while improving voltage quality enhances the performance of electrical devices and ensures customer satisfaction. Additionally, loss minimization optimizes power generation, enabling efficient meeting of demand.

The subsequent section will delve into problem formulation, aiming to comprehensively address these objectives within the microgrid optimization framework.

2.1. Objective functions

In this research, a multi-objective function is employed, with the primary objective being the minimization of operating costs. Operating costs refer to the expenditure on electrical power consumed from the large utility power grid. After the consumption of renewable power generated locally within the microgrid, any excess power requirement is fulfilled by drawing from the utility power grid. This forms the basis of the first objective function, aiming to minimize the reliance on external power sources and consequently reduce operating costs.

$$\text{Minimize } F_1 = \sum_t C_{grid}(P_{grid}(t)) + \left(\sum_j \sum_t C_j^U(t) + C_j(P_j(t)) \right) + \sum_k \sum_t C_k(P_k(t)) \quad (1)$$

Where,

$\sum_t C_{grid}(P_{grid}(t))$: cost function of grid power consumption for the time (t)

$\sum_j \sum_t C_j^U(t) + C_j(P_j(t))$: cost function of the generated DG power.

$\sum_k \sum_t C_k(P_k(t))$: Energy storage devices degrade cost function

(t)-time period,

j - jth generator,

Eq. 1 has three terms, grid power consumed cost, which is the cost function of real power consumed from the large utility grid. The second term is the generation cost of DGs, which has two parts, first, one is startup and shutdown cost and the second part is the cost function of real power generated by the DG. The third term is the cost incurred by the battery energy storage system. The battery energy storage cost is based on the charging and discharging characteristics of batteries, which create a degradation of energy storage devices. To attract customer goodwill, the quality of the power supply should be at its best. The important power quality is rated voltage for the good operation and long life of the devices. In this research, this is measured in terms of voltage deviation from the rated value and given in Eq. 2.

$$\text{Minimize } F_2 = \sqrt{\frac{\sum_{j=1}^{Nbus} (V_j - V_{rated})^2}{Nbus}} \quad (2)$$

Where,

V_j - jth bus voltage

V_{rated} - rated voltage

$Nbus$ - total number of buses

This second objective function given in Eq. 2 is the measure of the quality of voltage. The deviation between the rated value and the actual bus voltages should be as low as possible for the better quality of the voltage. Minimization of loss is equivalent to generation and helps to provide power supply to additional consumers. The reduction of loss brings the minimization of the generation or operating cost of the MG. The losses are due to the resistance and reactance in the distribution lines. There are two types of losses: real and reactive power loss, as given in Eqs. 3 and 4, respectively.

$$\text{Minimize, } F_3 = P_{T,loss} = \sum_{\substack{1 \leq v \leq Nbus \\ 1 \leq u \leq Nbus \\ u \neq v}} \frac{P_v^2 + Q_v^2}{V_u^2} \times R_{uv} \quad (3)$$

$$Q_{T,loss} = \sum_{\substack{1 \leq v \leq Nbus \\ 1 \leq u \leq Nbus \\ u \neq v}} \frac{P_v^2 + Q_v^2}{V_u^2} \times X_{uv} \quad (4)$$

Where,

$P_{T,loss}, Q_{T,loss}$ -total real and reactive power losses respectively

P_v, Q_v -receiving end real and reactive power

V_u - sending end voltage magnitude

R_{uv}, X_{uv} -resistance and reactance of the distribution line between u and v

$Nbus$ - Total number of buses

The radial distribution system comprises 'Nbus' buses and 'Nbus-1' branches. The total line loss in the branches is aggregated across the entire network to determine the overall losses in the distribution system, to minimize them. The third objective is to reduce the total real power loss in the system. These three objectives are crucial for optimizing the operation of the microgrid (MG). To streamline optimization efforts, these three objectives are consolidated into a single objective, as presented in Eq. 5.

The single objective function is

$$\text{Minimize } F = w_1 F_1 + w_2 F_2 + w_3 F_3 \quad (5)$$

Where,

w_1, w_2, w_3 are weight factors

2.2. Constraints

Engineering problems often manifest as constraint optimization problems, where solutions must adhere to certain limits and constraints. These constraints are essential for ensuring the feasibility of solutions within the given parameters. They are typically categorized into two types: equality constraints and inequality constraints.

Equality Constraints:

The constraints which are balanced on the left and right sides of the equality sign are called equality constraints. Many problems possess these equality constraints and have to be satisfied for proper operation. In this research work, the power balance equation has to be satisfied for the proper operation of the MG. The real and reactive power generation should be equal to the system's demand and losses, as shown in Eqs. 6 and 7, respectively.

$$P_{grid}(t) + \sum_j P_j(t) + \sum_{k1} P_{k1}(t) + \sum_{k2} P_{k2}(t) = P_{T,loss}(t) + P_D(t) \quad (6)$$

$$Q_{grid}(t) + \sum_j Q_j(t) = Q_{T,loss}(t) + Q_D(t) \quad (7)$$

Where,

(t)-time period

$P_{grid}(t)$, $Q_{grid}(t)$ -real and reactive power taken from the utility grid

$P_j(t)$, $Q_j(t)$ - j^{th} DG real and reactive power generation

$P_{k1}(t)$, $P_{k2}(t)$ - the real power generation of PV and wind energy source

$P_{T,loss}(t)$, $Q_{T,loss}(t)$ - total real and reactive power loss

$P_D(t)$, $Q_D(t)$ - real and reactive power demand of the MG

Inequality Constraints:

Most of the constraints in the MG are inequality constraints, the limits on decision and dependent variables are subjected to inequality constraints. The DG power generations have the lower and upper boundaries for the power generation and are given in Eqs. 8 to 11.

$$P_j^{\min} \leq P_j(t) \leq P_j^{\max} \quad (8)$$

$$Q_j^{\min} \leq Q_j(t) \leq Q_j^{\max} \quad (9)$$

$$P_{k1}^{\min} \leq P_{k1}(t) \leq P_{k1}^{\max} \quad (10)$$

$$P_{k2}^{\min} \leq P_{k2}(t) \leq P_{k2}^{\max} \quad (11)$$

In Eqs. 8 and 9 the real and reactive power generation by the DG are within the minimum and maximum limits of the j^{th} DG generator. Eq. 10 $P_{k1}(t)$ is the real power generation by the PV power generator and it has to be within its minimum and maximum limits. Eq. 11, $P_{k2}(t)$ is the real power generation, which should be within the minimum and maximum limits of the wind energy electric power generator. For battery energy storage, the state of charge and depth of discharge are important for the better life and performance of the distributed battery energy storage devices and are governed by Eqs. 12 and 13.

$$SoC_j^{\min} \leq SoC_j(t) \leq SoC_j^{\max} \quad (12)$$

$$DoD_j^{\min} \leq DoD_j(t) \leq DoD_j^{\max} \quad (13)$$

Where,

SoC_j – State of Charge of the j^{th} distributed energy storage device

DoD_j – Dept of Discharge of the j^{th} distributed energy storage device

The power quality mainly depends on the voltage magnitude and has the constraints given in Equation (2.14).

$$V_j^{\min} \leq V_j(t) \leq V_j^{\max} \quad (14)$$

where $V_j(t)$ is the t^{th} period voltage at the bus- j , it should be within its minimum and maximum limited value and given in Eq. 14.

DSTATCOM, a FACTS device designed to improve power quality, is used to increase the voltage magnitude, with the limits shown in Eq. 15.

$$Q_i^{\min} \leq Q_i(t) \leq Q_i^{\max} \quad (15)$$

In Equation (2.15) $Q_i(t)$ is the reactive power supply by the i^{th} STATCOM for the period (t). Its reactive power supply/absorption is within the minimum and maximum limits of the device.

2.3. Loss Sensitivity Factor

The location of the FACTS device is important for effective reactive power support. One of the most versatile techniques for the location of FACTS, real and reactive power support devices is the Loss Sensitivity Factor (LSF). The effective real and reactive power-supporting device locations are decided based on the loss reduction by the real/reactive power support. The location might have the best effect on loss reduction. The best location for the supporting devices is calculated as follows. Eqs. 25 and 26 give the real and reactive power losses in the line segment between buses ‘ u ’ and ‘ v ’

$$P_{uv,loss} = \frac{(P_{v,eff}^2 + Q_{v,eff}^2) \times R_{uv}}{V_u^2} \quad (16)$$

$$Q_{uv,loss} = \frac{(P_{v,eff}^2 + Q_{v,eff}^2) \times X_{uv}}{V_u^2} \quad (17)$$

where,

$P_{uv,loss}$, $Q_{uv,loss}$ -real and reactive power loss in the line segment between u and v

$P_{v,eff}$, $Q_{v,eff}$ -effective real and reactive power available at bus ‘ v ’

R_{uv} , X_{uv} -resistance and reactance of the line segment between u and v

V_u - Voltage magnitude at the bus ‘ u ’

The variation in real power loss due to reactive power support is given in Eq. 27. It is the derivative of real power loss in the line segment concerning reactive power availability in the receiving end bus.

$$\frac{\partial P_{uv,loss}}{\partial Q_{v,eff}} = \frac{2 \times Q_{v,eff} \times R_{uv}}{V_u^2} \quad (18)$$

The variation of reactive power loss due to reactive power injection is given in Eq. 28. It is the derivative of reactive power loss in the line segment concerning reactive power availability in the receiving end bus.

$$\frac{\partial Q_{uv,loss}}{\partial Q_{v,eff}} = \frac{2 \times Q_{v,eff} \times X_{uv}}{V_u^2} \quad (19)$$

Eq. 27 is the LSF; the value of LSF is calculated for all the buses. After the LSF calculation, it is arranged in descending order. Now the first or highest value of LSF and its corresponding bus is the best suitable for the reactive power support. The second-best location is the second value of LSF and its corresponding bus location. This LSF approach is used in the research work for the location of supporting devices. The location calculated using this LSF is simple and gives the best location for the supporting devices. This location also reduces the optimization time and provides the best effective supporting devices for real/reactive power support.

3. Proposed methodology

3.1. Firefly algorithm

This study aims to minimize the operating costs of the microgrid (MG) by optimizing control variables such as real power generation, generator bus voltages, and transformer tap positions. These control variables are subject to certain constraints, including limits on their values. The firefly algorithm (FA) is employed for optimization, where fireflies represent potential solutions to the optimization problem. These fireflies form a population and evolve based on their brightness, distance, attractiveness, and movement within the solution space. Encoding involves converting the MG optimization problem into a form suitable for the Firefly algorithm. Since FA is a maximization algorithm, whereas the MG problem is a minimization problem, the objective function is transformed by subtracting it from the largest possible value. This transformation effectively converts the minimization problem into a maximization problem, making it compatible with FA.

An appropriate fitness function, also known as brightness, is crucial for the evolution and convergence of the FA. Brightness represents the objective function value for each firefly in the population. Fireflies migrate towards brighter ones in each iteration, leading to solution improvement over successive iterations. The best firefly, also known as the global best, is determined in each iteration, contributing to overall solution quality.

When a firefly seeks a brighter one, it assesses the attractiveness of the target based on its brightness. Higher brightness leads to greater attractiveness between fireflies. However, attractiveness is influenced by natural disturbances and primarily the distance between fireflies.

Shorter distances increase attractiveness, while the absorption coefficient accounts for declining attraction due to absorption components in nature. Eq. 29 represents a monotonically decreasing function that governs the behaviour of fireflies when they fail to find brighter ones. In such cases, fireflies randomly explore the search space in pursuit of an optimal solution.

$$\beta = \beta_0 \exp(-\gamma r^2) \quad (20)$$

Where,

β -attractiveness of a firefly

β_0 -initial attractiveness

γ -absorption coefficient

r -distance between fireflies

Distance between fireflies A and B is calculated using Cartesian distance as given by Eq. 30.

$$r_{AB} = \|A - B\| = \sqrt{\sum_{k=1}^D (A - B)^2} \quad (21)$$

In the above equation, k is the dimension and for 2-dimensional solution space, the distance between A and B fireflies may be calculated as follows using Eq. (31)

$$r_{AB} = \sqrt{(x_A - x_B)^2 + (y_A - y_B)^2} \quad (22)$$

r_{AB} is the distance between fireflies. (x_A, y_A) is the position of firefly A and (x_B, y_B) is the position of firefly B in the 2-dimensional space. Movement of the 'A' firefly toward the 'B' brighter firefly is based on attractiveness and the distance between them is indicated in Eq. 32.

$$x_i^{k+1} = x_i^k + \beta_0 \exp(-\gamma r^2) * (x_j^k - x_i^k) + \alpha * \varepsilon_i^k \quad (23)$$

Where the left side first term is the initial position of i^{th} firefly, the second term gives attractiveness towards j^{th} firefly and the third term introduces random movement in i^{th} firefly. Initial attractiveness β_0 is taken as 1.0; absorption coefficient γ is taken as 0.9. Randomizing coefficient α ranges from 0 to 1, in this work is taken as 0.2; ε_i is a randomization vector that ranges from 0 to 0.5. Fireflies move randomly and try to move towards brighter fireflies. FA improves problems' solution iteration by iteration and the iteration has to be stopped when either the problem converges or the iteration reaches its maximum value. The stopping of iteration is important to provide a solution for time complexity. In this research work, a maximum number of 200 iterations is considered as a stopping criterion.

The following is the FA algorithm for resolving the problem:

Step 1:Get input data such as 24 hours of load, wind, and solar data. Minimum and maximum limits of DG, DSTATCOM, PEV, and Battery storage.

Step 2:Initially, the location of Wind, Solar, and EV are found by LSF, thereby the position of these devices is assumed.

Step 3:Operating cost, Voltage deviation (VD), and Loss are calculated without connecting DG, DSTATCOM, and Battery storage

Step 4:Generate the initial population of fireflies $\{x_1, x_2, x_3 \dots x_{20}\}$

Step 5:Set the iteration count, $itr = 1$

Step 6:Compute the brightness of each firefly

Step 7:Set Firefly count =1

Step 8:For each firefly, find the brightest firefly and find the attractiveness between them.

Step 9:Move each firefly towards the brightest firefly and update the position of the firefly.

Step 10:Increment Firefly count, Firefly count =Firefly count +1

Step 11:Check the Firefly count, if Firefly count $\leq$ Num. of firefly, then go to step 8, else go to the next step

Step 12:Increase the Iteration count $itr = itr + 1$

Step 13:Check itr , if $itr \leq$ maximum number of iterations then go to Step-6, else go to the next step

Step 14:The brightest firefly is the required optimal solution and it can be printed as a result

The Firefly Algorithm (FA) is a powerful optimization technique utilized to tackle complex problems within microgrids (MGs). By employing the MG objective function, FA evaluates the brightness of fireflies, with attractiveness determined by both distance and brightness. Fireflies iteratively adjust their positions to move towards brighter counterparts, aiming to converge toward optimal solutions. In this section, FA is comprehensively elucidated through algorithms and flowcharts, detailing its operation and implementation. FA is characterized as an exploitation algorithm, prioritizing local search to refine solutions, while exhibiting limited divergent search behaviour.

To enhance optimization performance and achieve superior results, a hybrid approach is introduced by integrating FA with the Spider Monkey Optimization (SMO) algorithm. This hybridization capitalizes on the strengths of both FA and SMO, leveraging their complementary characteristics to address the complexities inherent in MG optimization problems. Further exploration and discussion on this hybrid algorithm are presented in subsequent chapters.

3.2. Spider monkey optimization

Spider Monkey Optimization (SMO) is a population-based optimization technique inspired by the social behaviour of spider monkeys. These monkeys, known for their adeptness in using their tails to hold branches, exhibit interesting and useful behaviour patterns. They live in groups led by an experienced female leader who directs the group to find food sources. When food is scarce, the leader divides the group into subgroups, each led by a female leader with better experience in that subgroup's area. These subgroup leaders explore food sources and fulfil their subgroup's needs. When food is abundant, subgroups merge to share resources, showcasing the spider monkey's ability to divide and search efficiently. In SMO, each subgroup member is intelligent and utilizes information from the subgroup's mentor or local leader, as well as other team members, to search for food sources. Members move based on the perceived direction of progress or remain stationary if deemed appropriate. This process, known as the local leader phase (LLP), is mathematically represented as Eq. 33.

$$M_{ij}^{\text{new}} = M_{ij} + U(0, 1) \times (MLL_j - M_{ij}) + U(0, 1) \times (M_j - M_{ij}) \quad (24)$$

where, M_i is the i^{th} spider monkey in the subgroup, 'j' - is the control variable in the M, MLL is the local leader in the subgroup, M_r is another spider monkey in the subgroup, and uniformly distributed random number is $U(0,1)$. The member of the team (spider monkey) updates its position by adding differences between the local leader and another random team member in the subgroup. By this, it imparts knowledge of team members and mentors for its food search. The position update is controlled by the perturbation rate constant, which has a value between 0 and 1. A random number for an individual team member is generated when this number is greater than or equal to the perturbation constant (PC). Then, the update may take place as given in the local leader phase pseudo code.

Pseudo code of local leader phase (LLP):

for $k = 1$ to the number of groups

for $i = 1$ to the number of members in the group

for $j = 1$ to the number of control variables

if $PC \leq U(0,1)$

$$M_{ij}^{\text{new}} = M_{ij} + U(0, 1) \times (MLL_j - M_{ij}) + U(0, 1) \times (M_j - M_{ij})$$

else

$$M_{ij}^{\text{new}} = M_{ij}$$

endif

end j-loop
end i-loop
end k-loop

All the spider monkeys communicate their position and get the location of the global leader. Based on the information of the global leader's location and subgroup team member's position, the spider monkey updates its new position or location to search for food. After the LLP, every spider monkey updates its position based on the global leader position. The equation that governs this phase is given in Eq. 34.

$$M_{ij}^{new} = M_{ij} + U(0, 1) \times (MGL_j - M_{ij}) + U(-1, 1) \times (M_{rj} - M_{ij}) \quad (25)$$

where, M_i is the i th spider monkey in the subgroup, 'j' is the control variable in the spider monkey M , MGL is the global leader, M_r is another spider monkey in the subgroup, a uniformly distributed random number between 0 and 1 is represented as $U(0,1)$ and between -1 and 1 is represented as $U(-1,1)$. In this phase, the position update is controlled by the probability variable (Pr). This variable varies from maximum to minimum to reduce the step size of the search from the start to the end of the search process. Near the end of the search process, the probability value should be less to reduce the step size and make quick convergence of the search. A random number for an individual team member is generated when this number is less than the probability variable (Pr). Then the update may take place as given in the global leader phase pseudo code. D is the number of control variables in the monkey.

Pseudo code of global leader phase (GLP):

for $k = 1$ to the number of groups
for $i = 1$ to the number of members in the group
if $U(0,1) < Pr$
j - selected randomly between 1 and D

$$M_{ij}^{new} = M_{ij} + U(0, 1) \times (MGL_j - M_{ij}) + U(-1, 1) \times (M_{rj} - M_{ij})$$

end if
end i-loop
end k-loop

During the Local Leader Phase (LLP) and Global Leader Phase (GLP) of the Spider Monkey Optimization (SMO) algorithm, all Spider Monkey positions are updated, leading to changes in their fitness within the group. In each subgroup, the fitness of individual members is evaluated, and the best-performing member is selected as the local leader. However, there are instances where updates do not occur, indicating that solutions may be trapped in local minimum points. To detect this, a variable called `local_limit_count` is used. This variable is incremented whenever there is no update in the local leader during the phase. Similarly, the position and fitness of all spider monkeys and local leaders are updated in the preceding three phases. This update also affects the fitness of the global leader, which represents the spider monkey with the highest fitness in the entire population. To address the possibility of solutions being stuck in local minimum points at the global level, a variable called `global_limit_count` is employed. Like the `local_limit_count`, this variable is incremented when there is no update in the global leader during the phase.

To overcome situations where solutions are trapped in local minima or maxima, the `local_limit_count` is compared to a maximum count value. If the `local_limit_count` reaches this maximum count, it indicates that the search is indeed locked in a local minima or maxima point. To break free from this situation, the local leader decision phase utilizes random updates of subgroup members based on the positions of global and local leaders.

Eq. 35 and 36 describe the update process for team member positions based on local and global leaders, taking into account minimum and maximum limits to ensure the validity of the updates.

$$M_{ij}^{new} = M_{ij} + U(0, 1) \times (MGL_j - M_{ij}) + U(0, 1) \times (M_{ij} - MLL_j) \quad (26)$$

$$M_{ij}^{new} = M_{ij}^{min} + U(0, 1) \times (M_{ij}^{max} - M_{ij}^{min}) \quad (27)$$

where, M_i is the i th spider monkey considered to update, 'j' is the decision variable in the spider monkey, $U(0,1)$ is the uniformly distributed random number, MGL is the global leader, and MLL is the local leader of the subgroup. M_{ij}^{min} is the minimum limit of the spider monkey and M_{ij}^{max} is the maximum limit of the spider monkey. To update the spider monkey in the LLDP, either Equation (4.3) or Equation (4.4) is used based on the random number and the perturbation constant (PC). The LLDP pseudo-code is given below for the update of spider monkeys in the subgroup. D is the number of control variables in the monkey.

Pseudo code of local leader decision phase (LLDP):

for $k = 1$ to the number of groups
for $i = 1$ to the number of members in the group
for $j = 1$ to D
if $U(0,1) \geq PC$

$$M_{ij}^{new} = M_{ij}^{min} + U(0, 1) \times (M_{ij}^{max} - M_{ij}^{min})$$

else

$$M_{ij}^{new} = M_{ij} + U(0, 1) \times (MGL_j - M_{ij}) + U(0, 1) \times (M_{ij} - MLL_j)$$

end if
end j-loop
end i-loop
end k-loop

In this phase, the `global_limit_count` is checked if it reached its maximum value. Then the global leader splits the group into two subgroups for the first time and initializes the `global_limit_count` to zero. Again, the phases are executed and the count is compared for the next time. Again, if the `global_limit_count` reaches the maximum value, then the global leader increases the subgroup number from two to three and this process extends till the maximum number of subgroups is possible. When the division of the subgroup reaches its maximum, and `global_limit_count` is also the maximum value, the global leader fusions all the subgroups into a single group. The fission and fusion of the subgroups take place in this phase. The fission is based on `global_limit_count` and the maximum number of subgroups. The maximum number of subgroups is decided based on the minimum number of spider monkeys in the subgroup. The criterion is a minimum three number of spider monkeys that may be available in the subgroup. The pseudo-code of this phase is as follows,

Pseudo code of global leader decision phase (GLDP):

If `global_limit_count` $\leq$ Maximum value of `global_limit_count`
`global_limit_count` = 0
if `number_of_group` $\leq$ Maximum number of groups
Increase one more subgroup (Fission process)
else
Combine all the subgroups into a single group (Fusion process)
end if
Update Local leaders of the subgroups
end

The above six phases are the parts of the spider monkey optimization (SMO). In the first two phases, the position of spider monkeys is updated based on the local leader and global leader positions, respectively. In the third and fourth phases, local and global leaders are updated in their respective phases if the update does not take place, then the `local_limit_count` and `global_limit_count` are increased in their respective phases. In the fifth phase (LLDP), the position of team members is updated randomly within the solution space of update based on the position of both local and global leaders. In the sixth phase (GLDP), the fission and fusion process takes place. The following steps are followed to optimize the engineering problem in the SMO algorithm.

Step 1: Encode the engineering problem into SMO
Step 2: The set of control variables of the considered problem becomes a spider monkey and the objective function becomes the fitness of the monkey
Step 3: Initialize the spider monkey population in the solution space
Step 4: Find the fitness of all the spider monkey
Step 5: Initialize the iteration count = 1
Step 6: Select the global leader that has the highest fitness among all
Step 7: Select the local leader in the subgroup which has high fitness in the subgroup
Step 8: Execute the local leader phase
Step 9: Execute the global leader phase
Step 10: Execute the local leader learning phase
Step 11: Execute the global leader learning phase
Step 12: Execute the local leader decision phase
Step 13: Execute the global leader decision phase
Step 14: Increment the iteration count by one
Step 15: If the iteration count is less than the maximum number of iterations, then go to step 8, else go to the next step
Step 16: The global leader, which consists of the best control variables, is the solution to the considered problem.

The Spider Monkey Optimization (SMO) algorithm draws inspiration from the intelligence of spider monkeys, employing a population-based search to explore the solution space effectively. The algorithm ensures thorough exploration by utilizing a population of monkeys across all dimensions, leading to enhanced optimization outcomes. Within a group of spider monkeys, the female monkey serves as the leader, guiding team members in the search for food sources. The expertise of the senior female leader is critical for the group's survival, as she effectively explores and exploits potential food sources. Groups are subdivided based on need, with each subgroup led by an experienced female leader who becomes the local leader. Among these local leaders, the best-performing one is selected as the global leader. Team members update their positions based on instructions from global, local, and other team member positions, facilitating a balanced exploration-exploitation search strategy. SMO optimization proceeds through six phases: the local leader phase, global leader phase, local leader learning phase, global leader learning phase, local leader decision phase, and global leader decision phase. These phases collectively ensure effective exploration and exploitation of the solution space. Further, next section delves into the hybridization of SMO and the Firefly Algorithm (FA) to solve engineering problems. While FA is known for its greedy exploitation approach, it further refines the search for optimized results as a subset of SMO. This hybrid approach combines the strengths of both algorithms, leveraging their complementary nature to achieve superior optimization outcomes.

3.3. Hybrid spider monkey optimization and firefly algorithm

The Spider Monkey Optimization (SMO) and Firefly Algorithm (FA) are both population-based and nature-inspired intelligent algorithms. Leveraging the strengths of both algorithms can lead to obtaining the best optimal solution. This chapter elucidates the hybrid SMO and FA algorithm. In SMO, spider monkeys utilize their four legs and tail to hold and climb trees, mimicking their natural behaviour. On the other hand, fireflies, as light-emitting insects, exhibit swarm intelligence to locate food sources. They are naturally inclined to move towards brighter spots, signifying potential food sources. Communication among fireflies occurs through rhythmic flashing lights, allowing them to assess the brightness of nearby fireflies and determine the location of potential food sources. Successful communication prompts fireflies to estimate the distance to brighter counterparts and move towards them. The hybrid SMO-FA algorithm is applied to engineering applications, consisting of two main phases. The first phase entails solving SMO optimization, which involves six phases:

Phase - I

- i. Local Leader Phase,
- ii. Global Leader Phase,
- iii. Local Leader Learning Phase,
- iv. Global Leader Learning Phase
- v. Local Leader Decision Phase and
- vi. Global Leader Decision Phase

After phase – I, the Firefly algorithm (FA) is used to fine-tune the solution using its strength of exploitation nature. The steps involved in this phase – II is as follows,

Phase - II

- i. Estimate the attractiveness of the firefly
- ii. Calculate the distance between the fireflies
- iii. Move the firefly toward the brighter firefly

A detailed explanation of these two phases is given below:

In the subgroup, the member has the intelligence to search the food source. In addition to this, it uses the mentor or local leader of the subgroup intelligence and other team members' information. The member moves if it is observed that the movement is in the right direction or else, it stays in the same place. This process of the move is called as local leader phase (LLP). This phase mathematical representation is given in Equation 37.

$$M_{ij}^{new} = M_{ij} + U(0, 1) \times (MLL_j - M_{ij}) + U(0, 1) \times (M_{rj} - M_{ij}) \quad (28)$$

where, M_i is the i th spider monkey in the subgroup, ' j '- is the control variable in the M , MLL is the local leader in the subgroup, M_r is another spider monkey in the subgroup, and uniformly distributed random number is $U(0, 1)$. The member of the team (spider monkey) updates its position by adding the difference between the local leader and another random team member in the subgroup. By this, it imparts knowledge of team members and mentors for its food search. The position update is controlled by the perturbation rate constant, which has a value between 0 and 1. A random number for an individual team member is generated when this number is greater than or equal to the perturbation constant (PC). The update may take place as given in the local leader phase pseudo code.

Pseudo code of local leader phase (LLP):

```
for k = 1 to the number of groups
for i = 1 to the number of members in the group
for j = 1 to the number of control variables
if PC ≤ U(0,1)
```

$$M_{ij}^{new} = M_{ij} + U(0, 1) \times (MLL_j - M_{ij}) + U(0, 1) \times (M_{rj} - M_{ij})$$

else

$$M_{ij}^{new} = M_{ij}$$

end if

end j-loop

end i-loop

end k-loop

All the spider monkeys communicate their position and get the location of the global leader. Based on the information of the global leader's location and subgroup team member's position, the spider monkey updates its new position or location for the search of food. After the LLP, every spider monkey updates its position based on the global leader position. The equation that governs this phase is given in Equation 38.

$$M_{ij}^{new} = M_{ij} + U(0, 1) \times (MGL_j - M_{ij}) + U(-1, 1) \times (M_{rj} - M_{ij}) \quad (29)$$

where, M_i is the i th spider monkey in the subgroup, ' j '- is the control variable in the spider monkey M , MGL is the global leader, M_r is another

spider monkey in the subgroup, a uniformly distributed random number between 0 and 1 is represented as $U(0,1)$ and between -1 and 1 is represented as $U(-1,1)$. In this phase, the position update is controlled by the probability variable (Pr). This variable varies from maximum to minimum to reduce the step size of the search from the start to the end of the search process. Near the end of the search process, the probability value should be less to reduce the step size and make quick convergence of the search. A random number for individual team members is generated when this number is less than the probability variable (Pr). Then the update may take place as given in the global leader phase pseudo code. D is the number of control variables in the monkey.

Pseudo code of global leader phase (GLP):

for k = 1 to the number of groups

for i = 1 to the number of members in the group

if $U(0,1) < \text{Pr}$

j - selected randomly between 1 and D

$$M_{ij}^{\text{new}} = M_{ij} + U(0,1) \times (MGL_j - M_{ij}) + U(-1,1) \times (M_{rj} - M_{ij})$$

end if

end i-loop

end k-loop

All the spider monkey positions are updated in the LLP and GLP, leading to fitness change in the group. The fitness of the members in each subgroup is evaluated and the best is selected as a local leader for that subgroup. Sometimes the update may not take place when the solutions get locked in the local minimum point; to identify this a variable local_limit_count is used. The value of the local_limit_count variable is incremented by one whenever there is no update in the local leader in the phase. The position and fitness of all spider monkeys and local leaders are updated in the previous three phases. This update also affects the global leader's fitness and hence the global leader needs to update that has the highest fitness in the population. Sometimes the update may not take place when the solutions get locked in the local minimum point; to identify this a variable global_limit_count is used. The value of the global_limit_count variable is incremented by one whenever there is no update in the global leader in the phase. To come out of the local minima/maxima point, the local_limit_count is compared with the maximum value of the count. If the local_limit_count value is equal to the maximum count, then it is evident that the search is locked in the local minima/maxima point. To unlock this, the local leader decision phase uses the random update of subgroup members based on the position of global and local leaders. Equations 39 and 40 give the team members' position updates based on local, and global leaders, minimum and maximum limits.

$$M_{ij}^{\text{new}} = M_{ij} + U(0,1) \times (MGL_j - M_{ij}) + U(0,1) \times (M_{ij} - MLL_j) \quad (30)$$

$$M_{ij}^{\text{new}} = M_{ij}^{\text{min}} + U(0,1) \times (M_{ij}^{\text{max}} - M_{ij}^{\text{min}}) \quad (31)$$

where, M_i is the i^{th} spider monkey considered to update, 'j' - is the decision variable in the spider monkey, $U(0,1)$ is the uniformly distributed random number, MGL is the global leader, and MLL is the local leader of the subgroup. M_{ij}^{min} is the minimum limit of the spider monkey and M_{ij}^{max} is the maximum limit of the spider monkey. To update the spider monkey in the LLDP, either Equation 39 or Equation 40 is used based on the random number and the perturbation constant (PC). The LLDP pseudo-code is given below for the update of spider monkeys in the subgroup. D is the number of control variables in the monkey.

Pseudo code of local leader decision phase (LLDP):

for k = 1 to the number of groups

for i = 1 to the number of members in the group

for j = 1 to D

if $U(0,1) \geq \text{PC}$

$$M_{ij}^{\text{new}} = M_{ij}^{\text{min}} + U(0,1) \times (M_{ij}^{\text{max}} - M_{ij}^{\text{min}})$$

else

$$M_{ij}^{\text{new}} = M_{ij} + U(0,1) \times (MGL_j - M_{ij}) + U(0,1) \times (M_{ij} - MLL_j)$$

end if

end j-loop

end i-loop

end k-loop

In this phase, the global_limit_count is checked if it has reached its maximum value. Then the global leader splits the group into two subgroups for the first time and initializes the global_limit_count to zero. Again, the phases are executed and the count is compared for the next time. Similarly, if the global_limit_count reaches the maximum value, then the global leader increases the subgroup number from two to three and this process extends till the maximum number of subgroups is possible. When the division of the subgroup reaches its maximum and global_limit_count is the maximum value, the global leader fusions all the subgroups into a single group. The fission and fusion of the subgroups take place in this phase. The fission is based on global_limit_count and the maximum number of subgroups. The maximum number of subgroups is decided based on the minimum number of spider monkeys in the subgroup. The criterion is that a minimum three number of spider monkeys may be available in the subgroup. The pseudo-code of this phase is as follows,

Pseudo code of global leader decision phase (GLDP):

if global_limit_count $\leq$ Maximum value of global_limit_count

global_limit_count = 0

if number_of_group $\leq$ Maximum number of groups

Increase one more subgroup (Fission process)

else

Combine all the subgroups into a single group (Fusion process)

end if

Update Local leaders of the subgroups

end

A firefly searches the brighter firefly more than its brightness, if it finds one, then based on the brightness of the searched firefly attractiveness is estimated. More brightness gives more attraction to the fireflies. This attractiveness is affected by the natural disturbances and mainly the distance between them. Less distance between the fireflies increases the attractiveness and vice-versa. The main reasons for the reduction in attractiveness being absorption factors in nature are implemented by using the absorption coefficient. When a firefly finds no brighter firefly, then it moves randomly and explores the search space for the optimal solution. This function is a monotonically decreasing function represented by Equation 41.

$$\beta = \beta_0 \exp(-\gamma r^2) \quad (32)$$

where,

β - attractiveness of a firefly

β_0 - initial attractiveness

γ - absorption coefficient

r - distance between fireflies

Distance between fireflies A and B is calculated using Cartesian distance as given by Equation 42.

$$r_{AB} = \|A - B\| = \sqrt{\sum_{k=1}^D (A_k - B_k)^2} \quad (33)$$

In the above Equation, k is the dimension, and for two-dimensional solution space, the distance between A and B fireflies may be calculated using Equation 43.

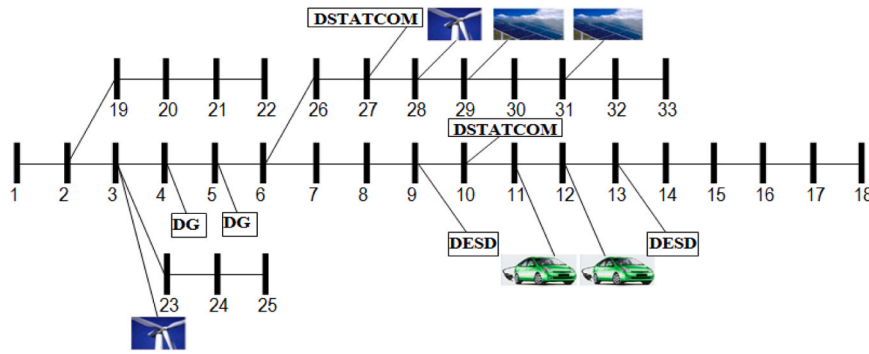


Fig. 1. 33-bus radial system.

$$r_{AB} = \sqrt{(x_A - x_B)^2 + (y_A - y_B)^2} \quad (34)$$

r_{AB} is the distance between fireflies. (x_A, y_A) is the position of firefly A and (x_B, y_B) is the position of firefly B in the 2-dimensional space. The Movement of firefly 'A' towards brighter firefly 'B' is m-based on attractiveness and distance between them as shown in Equation 44.

$$x_i^{k+1} = x_i^k + \beta_0 \exp(-\gamma r^2) * (x_j^k - x_i^k) + \alpha * e_i^k \quad (35)$$

where the left side first term is the initial position of i^{th} firefly, the second term gives attractiveness towards j^{th} firefly and the third term introduces random movement in i^{th} firefly. Initial attractiveness β_0 is taken as 1.0; absorption coefficient γ is taken as 0.9. Randomizing coefficient α ranges from 0 to 1, in this work, it is taken as 0.2; e_i is a randomization vector ranging from 0 to 0.5. These nine phases as to be executed in the iteration, at the end of these phases, the next iteration population for SMO is ready and used as the starting for the nine phases again. The algorithm steps for the implementation of this developed hybrid algorithm are given in the next section. The following steps are followed to optimize the engineering problem in the hybrid SMO - FA algorithm.

Step 1: Encode the engineering problem into SMO

Step 2: The set of control variables of the considered problem becomes a spider monkey and the objective function becomes the fitness of the monkey.

Step 3: Initialize the spider monkey population in the solution space

Step 4: Find the fitness of all the spider monkey

Step 5: Initialize the iteration count = 1

Step 6: Select the global leader that has the highest fitness among all

Step 7: Select the local leader in the subgroup which has the highest fitness in the subgroup

Step 8: Execute the local leader phase

Step 9: Execute the global leader phase

Step 10: Execute the local leader learning phase

Step 11: Execute the global leader learning phase

Step 12: Execute the local leader decision phase

Step 13: Execute the global leader decision phase

Step 14: The set of control variables in the SMO are considered as the firefly and for this population, brightness is calculated

Step 15: Set Firefly count = 1

Step 16: For each firefly find the brightest firefly and find the attractiveness between them.

Step 17: Move each firefly towards the brightest firefly and update the position of the firefly.

Step 18: Increment Firefly count, Firefly count = Firefly count + 1

Step 19: Check the Firefly count, if Firefly count $\leq$ Num. of firefly, then go to step 16, else go to the next step

Step 20: Increment the iteration count by one

Step 21: If the iteration count is less than the maximum number of iterations, then go to step 8, else go to the next step

Step 22: The brightest firefly, which consists of the best control variables, is the solution to the considered problem.

This hybrid algorithm is a combination of SMO and FA. This hybrid algorithm is divided into two main phases, the first phase is SMO and the second one is FA. In the SMO phase, six sub-phases are there and in the FA phase, three sub-phases are needed to be executed. In one iteration a total of nine sub-phases has to be executed. The population size and several control variables used in SMO and FA should be the same. A hybrid algorithm has the advantages of both SMO and FA.

4. Results and discussions

The results of employing intelligent algorithms - namely the Firefly Algorithm (FA), Spider Monkey Optimization (SMO), and the hybrid algorithm HSMOFF - are presented and analysed in this research. To assess the effectiveness of these algorithms, a standard radial 33-bus system is utilized as the test case. The system incorporates renewable energy sources such as wind power and photovoltaic (PV) systems. Additionally, Distributed Generators (DGs), Distributed Energy Storage Devices (DESDs), and plugged-in Electric Vehicles (PEVs) are incorporated to reflect practical load conditions. Furthermore, to enhance power quality, a FACTS device, specifically a Distribution Static Synchronous Compensator (DSTATCOM), is integrated into the test system.

In this study, the forward-backward load flow approach is adopted due to the high resistance and low reactance of the distribution system. This approach has been widely employed in literature for calculating power, voltage, and power loss in distribution systems, and it is applied here as well. The load flow procedure commences from the first node with the rated voltage, and subsequent node/bus voltages are computed by considering voltage losses along the line segments connecting them. This process is iterated until all bus voltages are determined. Subsequently, backward calculations are conducted from the last bus to the first, considering voltage losses in the opposite direction. Convergence is achieved when the difference between the rated voltage and the backward estimated voltage at the first bus falls below a specified tolerance value.

4.1. Case study

To assess the efficacy of the Firefly Algorithm (FA), Spider Monkey Optimization (SMO), and the hybrid algorithm, a standard 33-bus test case is employed. This radial system comprises 32 distribution line segments and 33 buses. The initial bus serves as the substation, connecting to the larger utility system to supplement power requirements. This distribution system is designated as a Micro Grid (MG) for this research endeavour.

Fig. 1 illustrates the layout of the system, comprising 33 buses and 32 distribution lines. It also illustrates the integration of renewable energy sources such as wind and PV, along with practical load and source components such as DGs, DESDs, and PEVs. To enhance power quality, a

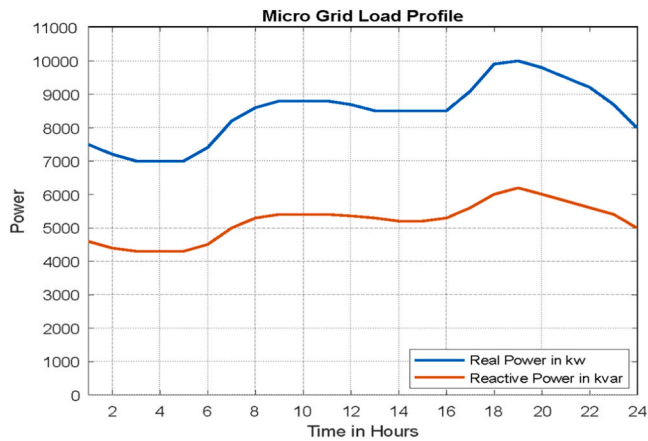


Fig. 2. Microgrid real and reactive power loads.

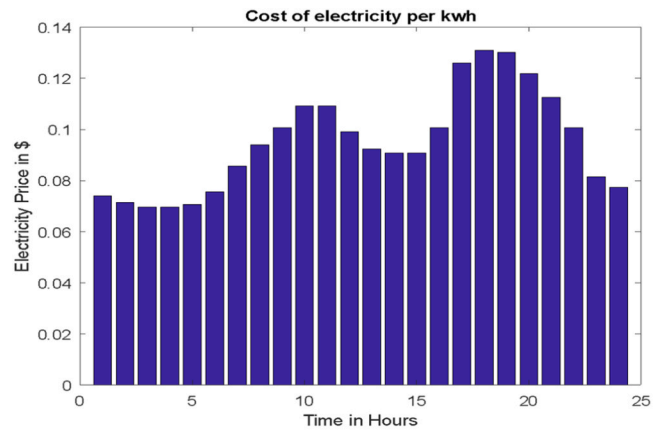


Fig. 5. Electricity price per kW.

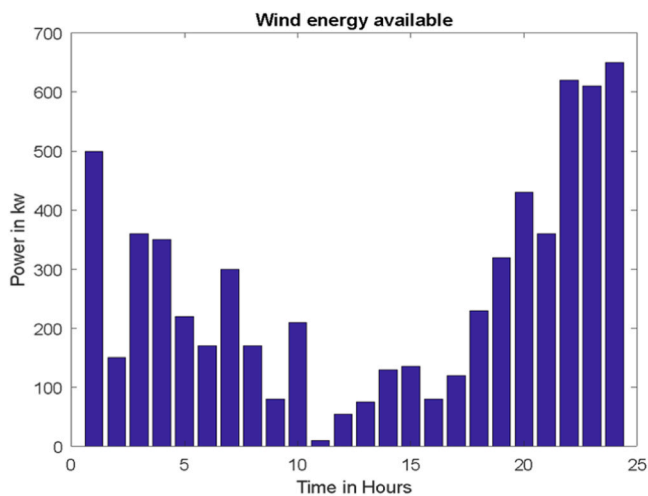


Fig. 3. Wind energy available in 24 hours.

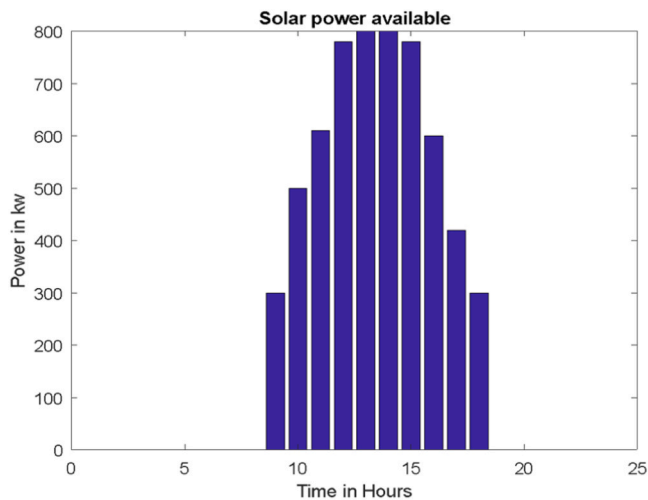


Fig. 4. Solar power available in 24 hours.

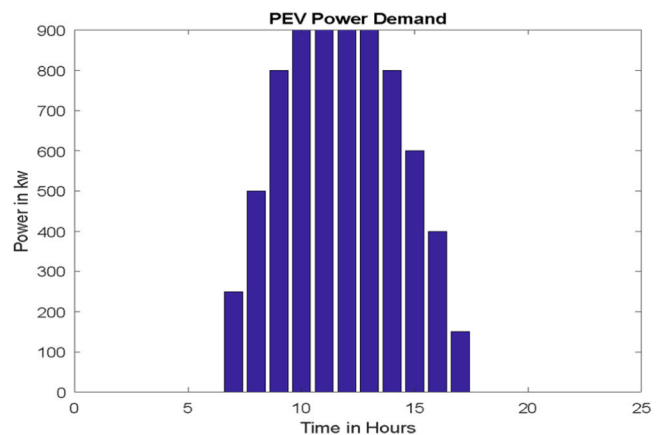


Fig. 6. PEV power demand.

energy supplies over the same duration. Fig. 2 illustrates the load demand of the system, showcasing the real and reactive power requirements over 24 hours.

Fig. 3 displays the availability of wind energy as a renewable energy source over 24 hours. Peak power availability from the wind energy resource is observed during the 22nd and 24th hours of the day. Conversely, the minimum power available occurs during the 11th hour, with only 10 kW available during that hour. The number of windmills is determined based on the power requirements of the system. It's important to note that while the wind power generator provides real power, the system relies on the main utility grid for reactive power support.

Fig. 4 illustrates the availability of solar energy for harvesting purposes over 24 hours. Solar energy harvesting is feasible from the 9th to the 18th hours of the day, encompassing a total duration of 10 hours during which solar power can be effectively converted into electrical power and utilized for the Microgrid (MG). Notably, the peak power availability from solar energy occurs between the 12th to 14th hours. However, during this time frame, solar energy cannot be harnessed due to the non-availability of solar radiation.

Fig. 5 illustrates the price fluctuations of electrical power supplied by the utility grid, varying for each hour over a 24-hour period. Notably, there are two peak hours: the first peak hour spans from the 9th hour to the 11th hour, while the second, more dominant peak occurs from the 17th hour to the 20th hour. To mitigate operating costs, strategies can be employed to reduce electricity consumption during peak hours, leveraging supporting devices such as wind power, PV power, DG, and energy storage systems. Within the Microgrid (MG) framework,

FACTS device, specifically a DSTATCOM, is included in the system layout as shown in the Figure. To ensure reliable and customer-satisfactory operation, it is imperative to supply electrical power throughout the entire 24-hour period. Therefore, the simulation takes into account the 24-hour load demand and the availability of renewable

Table 2

MG operation details for single devices.

S. N.	Parameters	Magnitude of power
1.	Total real power loss (kW)	16478.7
2.	Total reactive power loss (kVAR)	11930.1
3.	Voltage deviation (pu)	0.1903
4.	Power taken from the utility grid (kW)	179497
5.	Wind power generation (kW)	6336
6.	Solar power generation (kW)	5890
7.	PEV power demand (kW)	7100
8.	DG real power generation (kW)	11477.4
9.	DG reactive power generation (kVAR)	6851.65
10.	DSTATCOM reactive power generation (kVAR)	71129

Table 3

MG operation details for two devices.

S. N.	Parameters	Magnitude of power
1.	Total real power loss (kW)	12081.6
2.	Total reactive power loss (kVAR)	9175.77
3.	Voltage deviation (pu)	0.1629
4.	Power taken from the utility grid (kW)	162997
5.	Wind power generation (kW)	12672
6.	Solar power generation (kW)	11780
7.	PEV power demand (kW)	14200
8.	DG real power generation (kW)	15751.2
9.	DG reactive power generation (kVAR)	8901.15
10.	DSTATCOM reactive power generation (kVAR)	130251

Table 4

MG operation details for three devices.

S. N.	Parameters	Magnitude of power
1.	Total real power loss (kW)	19820.2
2.	Total reactive power loss (kVAR)	15541.2
3.	Voltage deviation (pu)	0.1425
4.	Power taken from the utility grid (kW)	150081
5.	Wind power generation (kW)	19008
6.	Solar power generation (kW)	17670
7.	PEV power demand (kW)	21300
8.	DG real power generation (kW)	16440.5
9.	DG reactive power generation (kVAR)	8560.35
10.	DSTATCOM reactive power generation (kVAR)	183401

distributed energy storage devices (DESD) play a crucial role in providing electrical power during peak hours, utilizing lower electricity prices to charge up. In this research, a DESD capacity device of 4000 kWh is utilized. Moreover, customers with plugged-in electric vehicles (PEV) commence charging their vehicles from the 7th hour and conclude at the 17th hour, as depicted in Fig. 6.

During the 10th hour to the 13th hour, the peak demand for plugged-in electric vehicles (PEV) is observed, necessitating charging for a duration of 11 hours. However, outside of this period, there is no requirement for PEV charging, allowing for flexibility in load management. To cater to the increased demand within the Microgrid (MG), distributed generators (DGs), such as diesel-powered generators, are utilized. It's imperative to consider the fuel cost associated with these generators when calculating the MG's operating costs. Additionally, besides the utility grid, these DGs can contribute both real and reactive energy, with ratings of 500 kW for real power and 300 kVAR for reactive power, respectively. The number of DGs required is determined based on demand. While renewable energy sources like wind and PV may adequately supply the required real power for the MG, their reactive power output may fall short. To address this, Distributed Static Compensators (DSTATCOM) are employed for reactive power support, each rated at 3000 kVAR. The MG system consists of 32 branches, each exhibiting resistance and reactance. These parameters contribute to line losses and voltage drops across the branches, necessitating careful

consideration in system analysis and optimization.

4.2. Firefly algorithm

In this section, the results obtained from the Firefly Algorithm (FA) are presented for the 33-bus system test case described earlier. MATLAB programs were utilized to conduct the simulations, running on a computer equipped with an i5 processor and 4 GB RAM. The outcomes reflect various scenarios involving combinations of renewable energy sources, loads, and reactive power support devices. The cost coefficient of the Distributed Generators (DG) is set as 'a=0.028, b=0.092, and c=0'. Furthermore, weight factors 'w1=0.001, w2=1, w3=0.001' are applied to convert the three objective functions into a single objective function. The simulation parameters for the hybrid algorithm are configured as follows:

Population size: 60

Maximum number of iterations: 100

Absorption coefficient, γ : 0.96

Initial attractiveness, β_0 : 1.0

Randomizing coefficient, α : 0.20

These parameters govern the behaviour and performance of the hybrid algorithm in finding optimal solutions for the microgrid optimization problem.

Case 1. Single devices connected to the MG

The results presented in Table 2 depict the real and reactive power generation, as well as the utilization of various devices connected to the microgrid (MG). Wind power, with a capacity of 900 kW, is harnessed at bus 6, while solar power, generating 400 kW, is utilized at bus 3. The distributed energy storage device (DESD) at bus 13 does not contribute to power generation, but is strategically positioned for backup power support. Plugged-in electric vehicles (PEV) draw 1500 kW of real power at bus 25. Additionally, a diesel generator (DG) stationed at bus 28 produces 1000 kW of real power and provides 600 kVAR of reactive power. To enhance the power quality, a Distributed Static Compensator (DSTATCOM) at bus 7 supplies 3000 kVAR of reactive power. The microgrid's overall real power demand is recorded at 203200 kW, along with a reactive power demand of 124850 kVAR. The total operating cost for this operational state is calculated to be \$18478.6. These findings provide valuable insights into the performance and efficiency of the microgrid under consideration.

Case 2. Two devices connected to the MG

In this scenario, the microgrid (MG) is equipped with multiple renewable energy sources, including two wind power generation units and solar power generation units, alongside distributed generators (DG), distributed energy storage devices (DESD), plugged-in electric vehicles (PEV), and a Distributed Static Compensator (DSTATCOM). The selection of the locations for these renewable energy resources is facilitated by Load Sensitivity Analysis (LSA). Wind power generation is strategically connected to buses 6 and 3, while solar power generation is distributed across buses 28 and 13. The DESD units are positioned at buses 5 and 4, while PEVs are stationed at buses 33 and 19. DG units are deployed at buses 9 and 10, and DSTATCOM devices are installed at buses 7 and 31. Table 3 provides a comprehensive overview of the power utilization within the MG, detailing the real and reactive power generation and consumption. The total operating cost for this operational configuration is calculated to be \$17187.3, indicating the cost-effectiveness and efficiency of the MG in this state. These results underscore the significance of integrating multiple renewable energy sources and distributed energy management systems to optimize MG performance and minimize operating costs.

Case 3. Three devices connected to the MG

In this particular setup, the microgrid (MG) incorporates three wind power production sources, solar power generation units, distributed

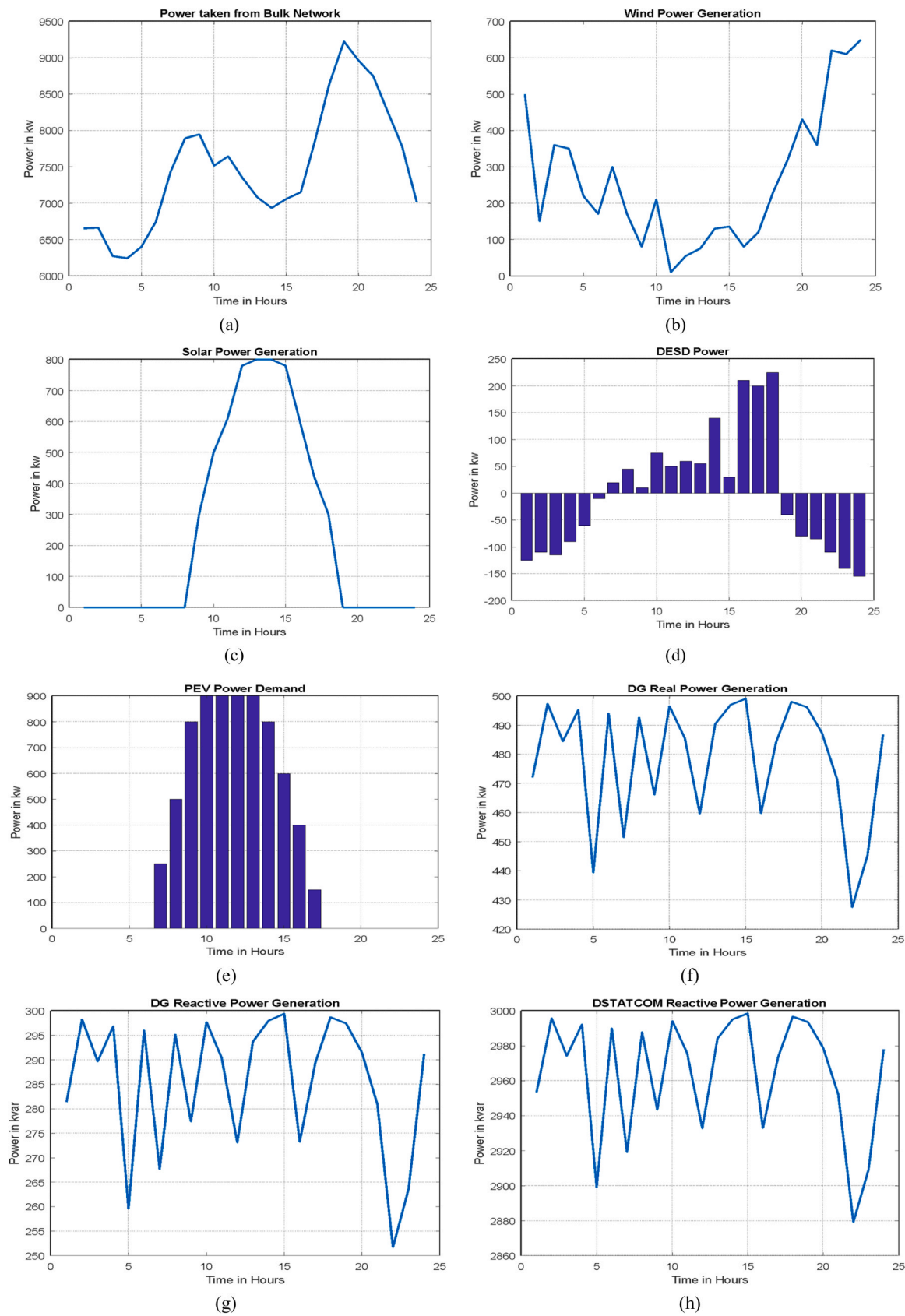


Fig. 7. Case 1: Single devices connected to the MG.

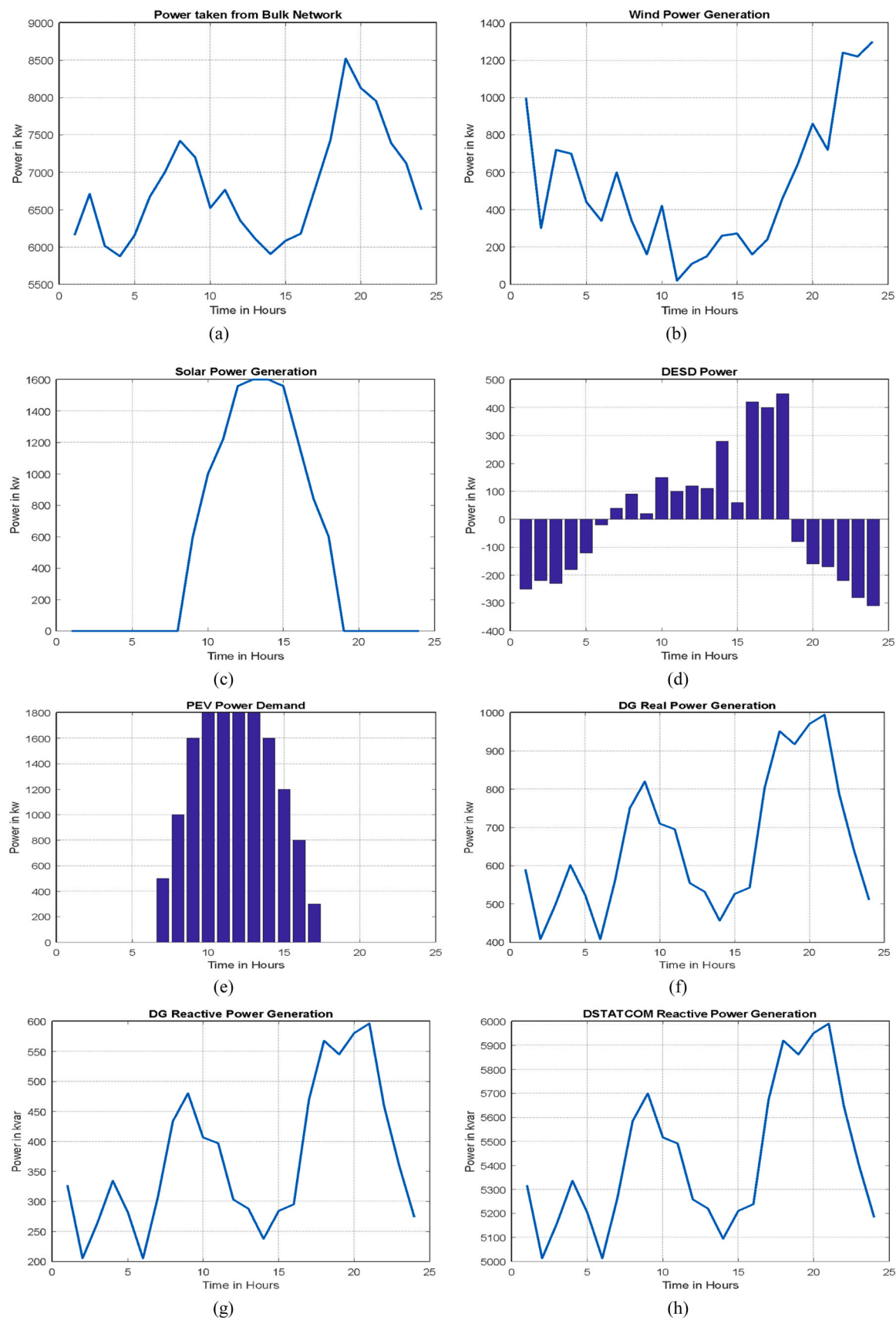


Fig. 8. Case 2: Two devices connected to the MG.

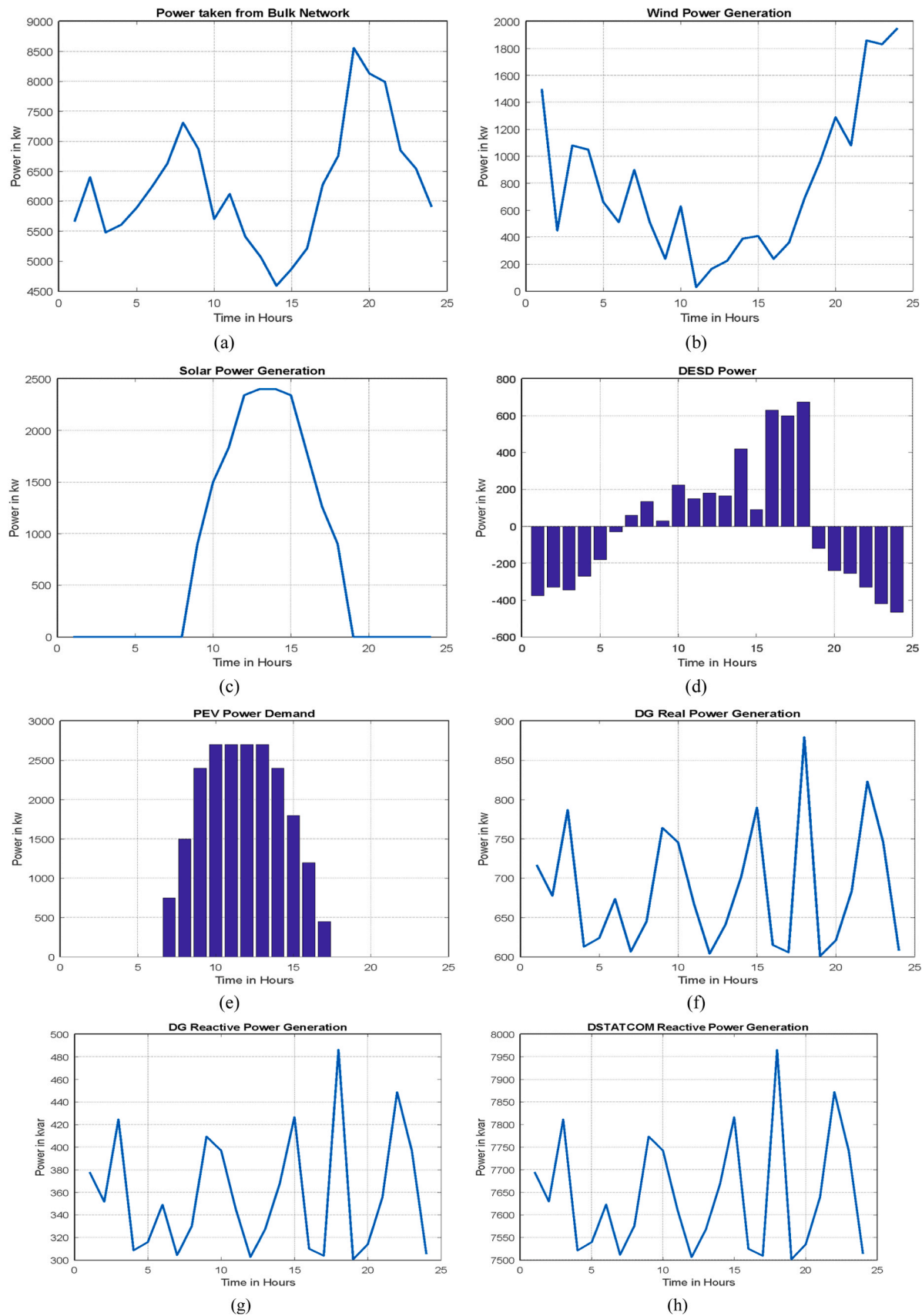


Fig. 9. Case 3: Three devices connected to the MG.

Table 5
MG operation details for various numbers of devices.

S. N.	Parameters	One device	Two devices	Three devices
1.	Operating cost (\$)	18478.6	17187.3	16037.1
2.	Total real power loss (kW)	16478.7	12081.6	19820.2
3.	Total reactive power loss (kVAR)	11930.1	9175.77	15541.2
4.	Voltage deviation (pu)	0.1903	0.1629	0.1425
5.	Power taken from the utility grid (kW)	179497	162997	150081
6.	Wind power generation (kW)	6336	12672	19008
7.	Solar power generation (kW)	5890	11780	17670
8.	PEV power demand (kW)	7100	14200	21300
9.	DG real power generation (kW)	11477.4	15751.2	16440.5
10.	DG reactive power generation (kVAR)	6851.65	8901.15	8560.35
11.	DSTATCOM reactive power generation (kVAR)	71129	130251	183401

Table 6
MG operation details for two devices.

S. No	Parameters	Magnitude of power
1.	Total real power loss (kW)	12083.9
2.	Total reactive power loss (kVAR)	9188.32
3.	Voltage deviation (pu)	0.16279
4.	Power taken from the utility grid (kW)	162515
5.	Wind power generation (kW)	12672
6.	Solar power generation (kW)	11780
7.	PEV power demand (kW)	14200
8.	DG real power generation (kW)	16232.8
9.	DG reactive power generation (kVAR)	9222.58
10.	DSTATCOM reactive power generation (kVAR)	131053

generators (DG), Distributed Static Compensator (DSTATCOM), distributed energy storage devices (DESD), and plugged-in electric vehicles (PEV). The allocation of renewable energy resources is strategically determined using the loss-sensitive method. Wind power generation units are connected to buses 6, 3, and 28, while solar power generation units are linked to buses 13, 9, and 10. DESD installations are distributed across buses 29, 24, and 31, while PEV charging stations are situated at buses 30, 23, and 14. DG units are stationed at buses 5, 4, and 8, and DSTATCOM devices are deployed at buses 7, 25, and 17. Table 4 provides a comprehensive overview of the power utilization within the MG, detailing real and reactive power generation and consumption. The total operating cost for this operational configuration is calculated to be \$16037.1, reflecting the cost-effective and efficient management of energy resources within the MG. These results underscore the importance of strategic resource allocation and the adoption of intelligent optimization techniques in enhancing the performance and sustainability of MG systems.

Fig. 7 depicts the graphical representation of various power components within the microgrid (MG) for the first case scenario. The graph illustrates the power exchange with the utility grid, wind power generation, solar power generation, utilization of distributed energy storage devices (DESD), power demand from plugged-in electric vehicles (PEV), distributed generator (DG) power, and DSTATCOM power utilization. Similarly, Fig. 8 provides a graphical overview of the power distribution and utilization within the MG for the second case scenario. It showcases the interactions between the utility grid, wind and solar power generation, DESD utilization, PEV power demand, DG power output, and DSTATCOM power utilization.

Finally, Fig. 9 offers a graphical representation of the power dynamics within the MG for the third case scenario. It visualizes the power flow and utilization patterns, including interactions with the utility grid, wind and solar power generation, DESD utilization, PEV power demand, DG power output, and DSTATCOM power utilization. These graphical illustrations offer valuable insights into the performance and operation of the MG under different configurations and highlight the role of each power component in meeting the load demands and optimizing operational costs.

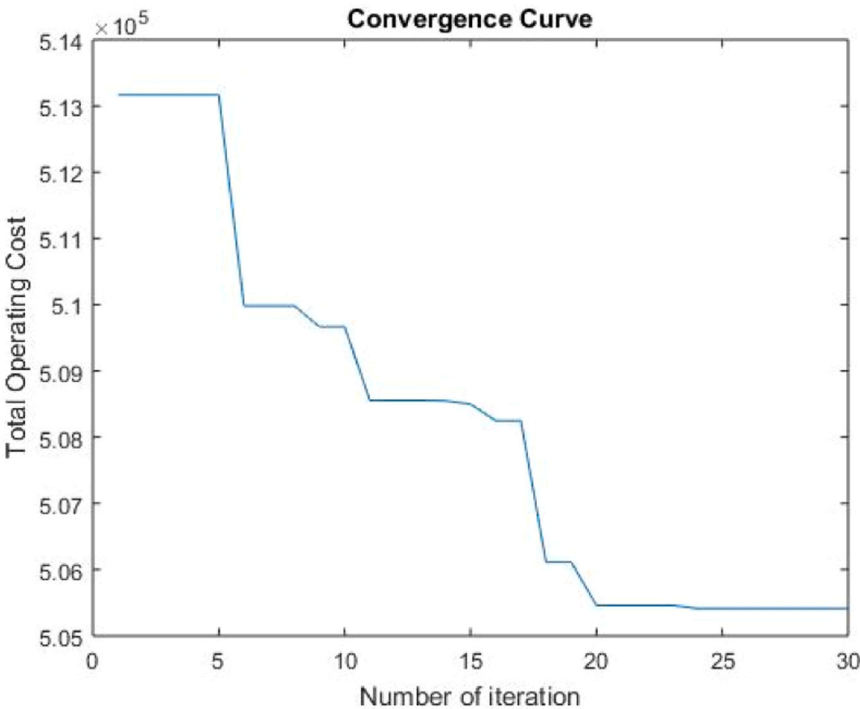


Fig. 10. Convergence characteristics.

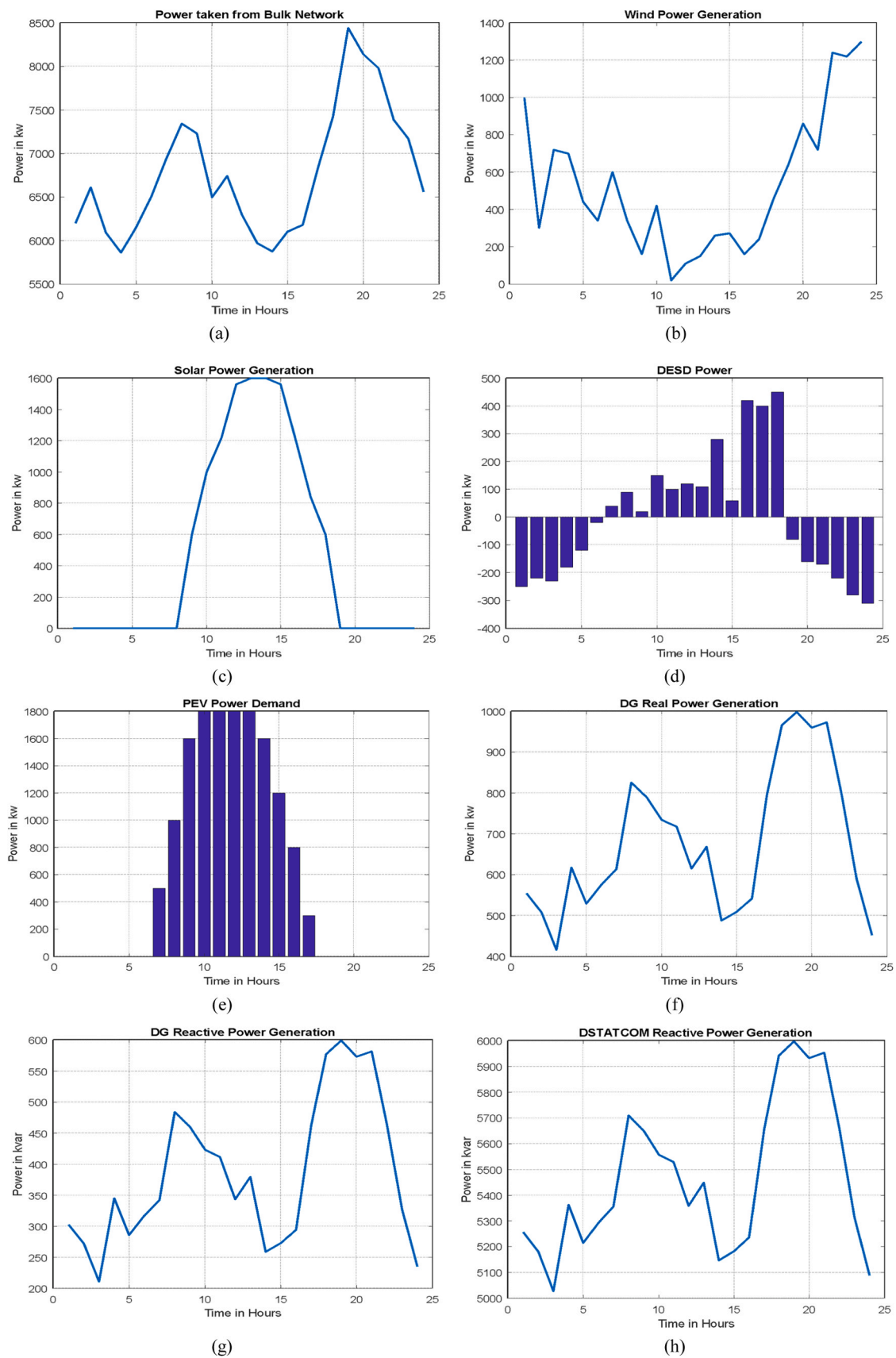


Fig. 11. Results for SMO.

Table 7

MG operation details for two devices.

S. N.	Parameters	Magnitude of power
1.	Total real power loss (kW)	12068.1
2.	Total reactive power loss (kVAR)	9164.45
3.	Voltage deviation (pu)	0.1628
4.	Power taken from the utility grid (kW)	163060
5.	Wind power generation (kW)	12672
6.	Solar power generation (kW)	11780
7.	PEV power demand (kW)	14200
8.	DG real power generation (kW)	15688.3
9.	DG reactive power generation (kVAR)	8859.7
10.	DSTATCOM reactive power generation (kVAR)	130146

Table 5 presents a comparison of the operating costs associated with varying numbers of devices integrated into the microgrid (MG). The data suggests a discernible trend: as the number of devices connected to the MG increases, the operating cost tends to decrease. However, it's crucial to weigh this reduction against the initial investment required for installing additional devices. In this analysis, the optimal balance between operating cost reduction and initial investment is observed with two devices connected to the MG. This finding underscores the importance of strategic decision-making when designing and optimizing MG configurations to achieve cost-efficient and sustainable energy solutions.

4.3. Spider Monkey Optimization

In this section, we present the outcomes obtained from the Spider Monkey Optimization (SMO) algorithm. Known for its balanced exploration and exploitation search strategies, SMO typically yields improved results. Like the Firefly Algorithm, SMO is applied to the same microgrid (MG) settings, and the resultant data is showcased below. For the location selection of renewable energy resources, the loss-sensitive approach is employed. Wind power generation is connected to buses 6 and 3, while solar power generation is linked to buses 28 and 13. Additionally, Distributed Energy Storage Devices (DESD) are connected to buses 5 and 4, Plug-in Electric Vehicles (PEV) are associated with buses 33 and 19, Distributed Generators (DG) are placed at buses 9 and 10, and Distributed Static Compensators (DSTATCOM) are positioned at buses 7 and 31.

Table 6 provides a comprehensive overview of the power utilization within the MG, while the associated operating cost for this operational configuration is \$17185.3. The simulation parameters employed for the SMO algorithm include a population size of 60, a maximum number of iterations set to 100, a LocalLimitCount of 50, a GlobalLimitCount of 10, and a probability variable (PR) set to 0.15. These parameters govern the optimization process, ensuring efficient convergence towards an optimal solution (Fig. 10).

Fig. 11 provides a visual representation of various aspects of the microgrid (MG) system, including the utility grid, wind power generation, solar power generation, Distributed Energy Storage Device (DESD) power utilization, Plug-in Electric Vehicle (PEV) power demand, Distributed Generator (DG) power, and Distributed Static Compensator (DSTATCOM) power. These graphical illustrations offer insights into the distribution and utilization of electrical power within the MG, facilitating a comprehensive understanding of the system's dynamics and performance.

4.4. Hybrid of Spider Monkey Optimization and Firefly Algorithm

The placement of renewable energy resources within the microgrid (MG) is crucial for optimizing its performance. In this scenario, a loss-sensitive method is employed to determine the optimal locations for wind power generation, solar power generation, Distributed Energy Storage Device (DESD), Plug-in Electric Vehicle (PEV) charging stations, Distributed Generator (DG), and Distributed Static Compensator

(DSTATCOM). Specifically, wind power generation is connected to buses 6 and 3, solar power generation to buses 28 and 13, DESD to buses 5 and 4, PEV charging stations to buses 33 and 19, DG to buses 9 and 10, and DSTATCOM to buses 7 and 31. The power utilization of the MG under these conditions is summarized in Table 7, with an operating cost of \$17184.1 for this state of operation.

The simulation parameters utilized for the hybrid algorithm include a population size of 60, a maximum number of iterations set to 100, an absorption coefficient (γ) of 0.96, an initial attractiveness (β_0) of 1.0, a randomizing coefficient (α) of 0.2, LocalLimitCount of 50, GlobalLimitCount of 10, and a probability variable (PR) of 0.15. These parameters play a crucial role in guiding the optimization process and achieving efficient operation of the MG.

Fig. 12 provides a comprehensive graphical representation of various aspects of the microgrid's operation, including the utility grid, wind power generation, solar power generation, utilization of Distributed Energy Storage Devices (DESD), demand for Plug-in Electric Vehicles (PEV), power generation by Distributed Generators (DG), and compensation provided by Distributed Static Compensators (DSTATCOM). These visualizations offer insights into the dynamic behavior and interaction of different components within the microgrid, facilitating a better understanding of its performance and efficiency.

5. COMPARATIVE ANALYSIS

Table 8 presents a comparative analysis of the operating costs obtained from three intelligent algorithms developed for assessing the microgrid (MG) system. The first column denotes the respective algorithms used: Firefly (FA), Spider Monkey Optimization (SMO), and a hybrid approach combining SMO and FA (SMO-FA). The corresponding operating costs are listed in the second column. The results indicate that the hybrid SMO-FA algorithm achieves the lowest operating cost of \$17184.1, followed by the SMO algorithm with an operating cost of \$17185.3. In contrast, the Firefly algorithm yields the highest operating cost of \$18478.6. This comparison underscores the superior performance of the hybrid SMO-FA algorithm in optimizing the MG's operating cost, demonstrating its efficacy in finding more cost-effective solutions compared to the individual Firefly and SMO algorithms.

The results presented in Table 8 demonstrate the superiority of the hybrid algorithm over both the Firefly and SMO algorithms across various performance metrics such as operating cost, real power loss, voltage deviation, and reactive power supplied by DSTATCOM. Specifically, the hybrid algorithm achieves an operating cost of \$17184.1, real power loss of 12068.1 kW, voltage deviation of 0.1628, and optimized reactive power supplied by the DSTATCOM at 130146 kVAR over 24 hours. These findings underscore the effectiveness of the hybrid approach in optimizing the microgrid's performance. Moreover, Fig. 13 visually compares the voltage magnitudes obtained from the three intelligent algorithms and the base case. It is evident that the voltage magnitude curve obtained with the hybrid SMO-FA algorithm (violet line) closely follows that of the base case (blue line), indicating superior performance compared to the Firefly (red line) and SMO (orange line) algorithms. This graphical representation further reinforces the advantages of the hybrid algorithm in maintaining voltage stability and quality within the microgrid.

Furthermore, Table 9 highlights the significant impact of the DSTATCOM on the microgrid's performance, particularly in enhancing voltage stability and quality. The optimized reactive power supplied by DSTATCOM plays a crucial role in mitigating voltage deviations and ensuring the reliable operation of the microgrid.

The DSTATCOM, or distributive static compensator, plays a vital role in enhancing the microgrid's performance by providing reactive power support. As depicted in Table 9, the provision of reactive power by DSTATCOM leads to notable improvements in various key metrics of microgrid operation. Specifically, the operating cost decreases from \$18478.6 to \$17184.1, indicating a significant reduction in overall

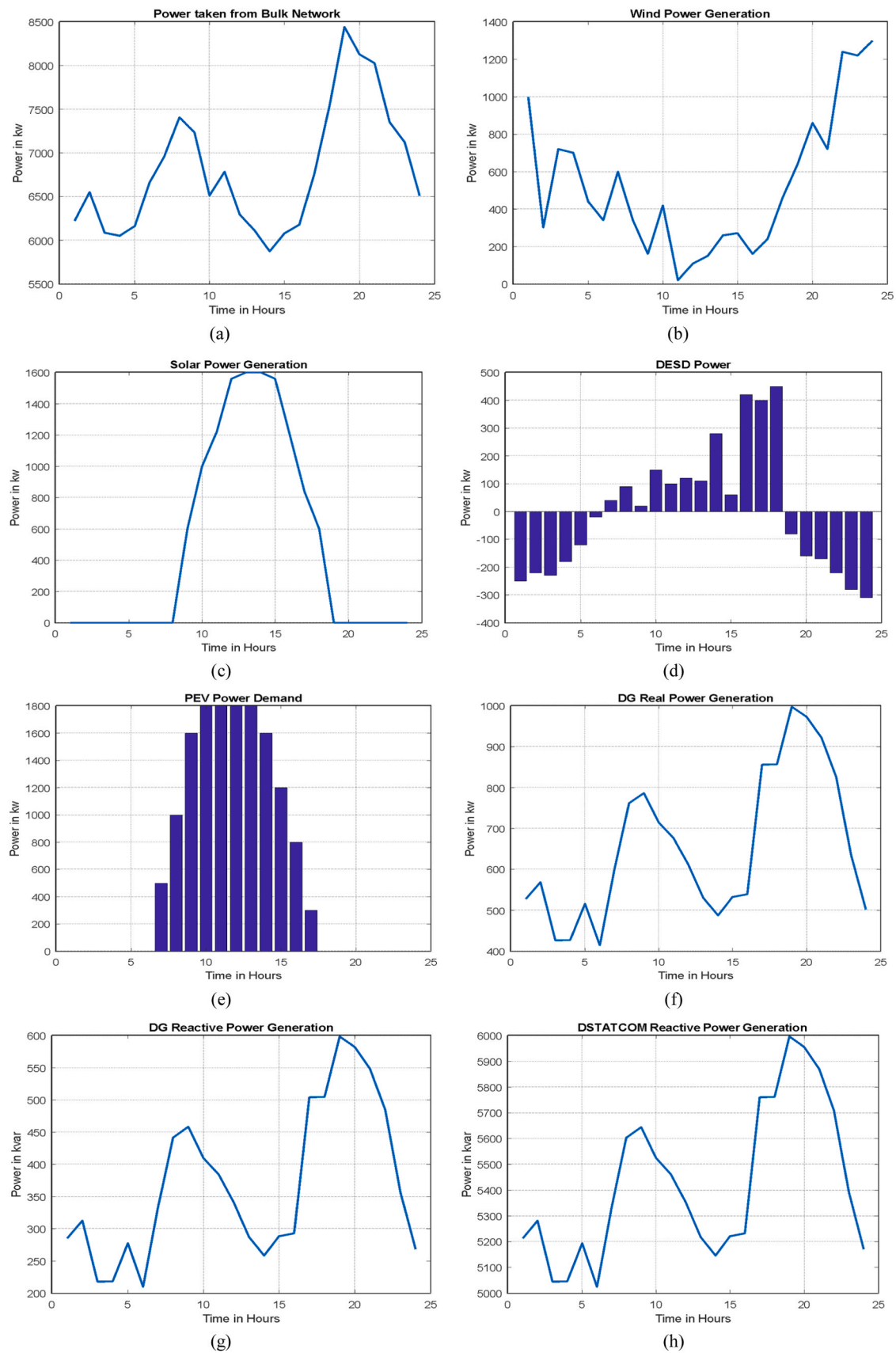
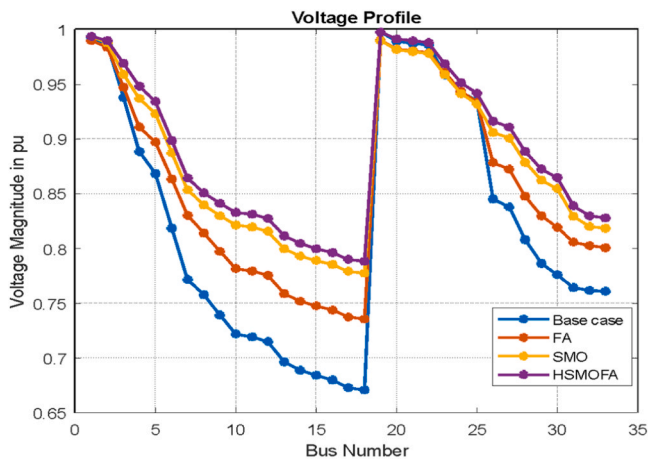


Fig. 12. Results for hybrid SMO - FA.

Table 8

MG operation details for various numbers of devices.

S. No	Parameters	FA	SMO	Hybrid SMO-FA
1.	Operating cost (\$)	17187.3	17185.3	17184.1
2.	Total real power loss (kW)	12081.6	12083.9	12068.1
3.	Total reactive power loss (kVAR)	9175.77	9188.32	9164.45
4.	Voltage deviation (pu)	0.1629	0.1628	0.1628
5.	Power taken from the utility grid (kW)	162997	162515	163060
6.	Wind power generation (kW)	12672	12672	12672
7.	Solar power generation (kW)	11780	11780	11780
8.	PEV power demand (kW)	14200	14200	14200
9.	DG real power generation (kW)	15751.2	16232.8	15688.3
10.	DG reactive power generation (kVAR)	8901.15	9222.58	8859.7
11.	DSTATCOM reactive power generation (kVAR)	130251	131053	130146

**Fig. 13.** Voltage magnitude comparisons of intelligent algorithms.

expenses. Additionally, both real and reactive power losses are minimized, contributing to greater efficiency in power distribution within the microgrid. Moreover, the voltage deviation is reduced, enhancing the stability and reliability of the microgrid's power supply. These outcomes underscore the crucial role of DSTATCOM in optimizing the performance of microgrid systems.

Loss sensitivity factor is conducted using Eqs. (16) and (17). After the LSF calculation, it is arranged in descending order. Now the first or highest value of LSF and its corresponding bus is the best suitable for the reactive power support. The second-best location is the second value of LSF and its corresponding bus location. This LSF approach is used in the research work for the location of supporting devices (Table 10).

Further, the comparison is made between the base and the proposed work and the detailed illustration is depicted in Table 11. Relatively, the

proposed method shows superior performance compared with the base case.

This research significantly contributes to the field of microgrid (MG) optimization by developing a novel Hybrid Spider Monkey Optimization - Firefly (HSMOFF) algorithm. This innovative hybrid approach merges the exploration strengths of the Spider Monkey Optimization (SMO) algorithm with the neighborhood optimization capabilities of the Firefly algorithm, providing a robust solution for minimizing operating costs, losses, and voltage deviation within MGs. One of the primary contributions is the demonstrated efficiency of the HSMOFF algorithm, which outperforms traditional methods by reducing operating costs by 7.5 %, real power loss by 36.5 %, reactive power loss by 1.7 %, and voltage deviation by 16.895 %. These improvements signify substantial operational cost savings and enhanced power quality, directly benefiting power providers and consumers. The potential impact of this research on the future is profound. As MGs become increasingly integral to the modern power grid, our algorithm offers a scalable and adaptable optimization solution that can handle the complexities and constraints of MGs, including the integration of renewable energy sources and energy storage devices. By ensuring efficient power supply and cost-effectiveness, our approach promotes the adoption of MGs, supporting sustainable energy initiatives and resilience in power systems. Furthermore, the HSMOFF algorithm's framework can be extended to other optimization problems within power systems, paving the way for further advancements in intelligent optimization techniques. This research lays the groundwork for future studies to explore more sophisticated hybrid algorithms, contributing to the continuous evolution of power system optimization.

Further, the outcomes of this work have been rigorously compared with state-of-the-art methods using the 33-bus radial system as a benchmark. Most existing works focus primarily on Distributed Generation (DG) penetrations within this system for power management and voltage profile stability. For instance, Abd El-Hameid et al. (Abd El-Hameid et al., 2023) explored the impact of D-STATCOM on the 33-bus radial system using a forward-backward sweep-based solution, but their study did not consider operating costs or grid dependency, which is critical for comprehensive system evaluation. Similarly, Ahmed et al. (Ahmed and Hasan, 2018) utilized the same test system with DG penetration and a Particle Swarm Optimization (PSO) model, focusing solely on voltage deviation and DG sizing without addressing the broader economic implications. Moreover, Mohammad Mahbod et al. (Khanbabaei and Abedi, 2024) examined the integration of Distributed Energy Resources (DERs) within the 33-bus system, achieving improvements in power factor, voltage profile, and reduction in line losses.

Table 10

Sensitivity Analysis.

MG Components	Capacity	Optimal Location by Loss Sensitivity Analysis
2 Wind turbine	Each 650 kW	6,3
2 Solar PV	Each 800 kW	28,13
2 Battery	Each 4000 kWh	5,4
2 PEV	Each ranging between 150 kW to 900 kW	8,29
2 DG	Each 500 kW & 300 kVAR	10,9
2 DSTATCOM	Each 3000 kVAR	7,31

Table 9

Effect of DSTATCOM on the system performance.

S. No	Parameters	Without DSTATCOM	With DSTATCOM
1.	Operating cost (\$)	18478.6	17184.1
2.	Total real power loss (kW)	16478.7	12068.1
3.	Total reactive power loss (kVAR)	9320.14	9164.45
4.	Voltage deviation(pu)	0.1903	0.1628
5.	DSTATCOM reactive power generation (kVAR)	-	130146

Table 11
Comparative study.

S. No	Parameters	Base Case	One device	Two devices	Three devices
1.	Operating cost (\$)	19729.3	18478.6	17187.3	16037.1
2.	Total real power loss (kW)	32365.1	16478.7	12081.6	19820.2
3.	Total reactive power loss (kVAR)	24203.0	11930.1	9175.77	15541.2
4.	Voltage deviation (pu)	0.2980	0.1903	0.1629	0.1425
5.	Power taken from the utility grid (kW)	203200	179497	162997	150081
6.	Wind power generation (kW)	0	6336	12672	19008
7.	Solar power generation (kW)	0	5890	11780	17670
8.	PEV power demand (kW)	0	7100	14200	21300
9.	DG real power generation (kW)	0	11477.4	15751.2	16440.5
10.	DG reactive power generation (kVAR)	0	6851.65	8901.15	8560.35
11.	DSTATCOM reactive power generation (kVAR)	0	71129	130251	183401

However, their study concentrated only on technical performance, leaving economic factors unaddressed. Moreover, Fahad Iqbal et al. (Iqbal et al., 2017) utilized DLF method for optimal placement of DG and STATCOM for reduction of loss and improvement of voltage profile. Gagari et al. (Deb et al., 2020) utilized Modified Spider Monkey Optimization-Based Optimal Placement of Distributed Generators in Radial Distribution System for Voltage Security Improvement.

In contrast, this work uniquely incorporates a hybrid optimization algorithm that simultaneously considers both technical and economic factors, including operating costs, grid dependency, and DERs capability. This approach ensures a more holistic evaluation of DER penetration impacts, bridging the gap left by previous studies. By doing so, the proposed method provides a more comprehensive solution for modern power systems, validating its effectiveness against existing methodologies.

In summary, the simulation results of the microgrid (MG) demonstrate significant achievements in meeting multiple objectives, including the minimization of operating costs, real power loss, and voltage deviation. Utilizing intelligent algorithms such as the Firefly algorithm, Spider Monkey Optimization (SMO), and the hybrid SMO-FA, optimized solutions have been obtained. The comparison table of overall results indicates the superiority of the hybrid intelligent algorithm over both the Firefly algorithm and SMO. These findings underscore the effectiveness of employing advanced optimization techniques to enhance the performance and efficiency of microgrid systems.

6. Conclusions

In conclusion, this study presents a comprehensive approach to optimizing Micro Grids (MGs) by integrating advanced algorithms, specifically the Firefly algorithm, Spider Monkey Optimization (SMO), and a novel hybrid algorithm combining both. The research demonstrates that the proposed hybrid algorithm effectively leverages the strengths of SMO's exploration capabilities and the Firefly algorithm's neighborhood optimization, offering significant improvements in MG operation. Through detailed case studies on a modified IEEE 33-bus test feeder, the hybrid algorithm consistently outperformed existing methods in minimizing operating costs and enhancing overall efficiency. The numerical results validate the hybrid algorithm's superiority, achieving a notable 7.5 % reduction in operating costs, a 36.5 % decline in real power loss, a 1.7 % reduction in reactive power loss, and a 16.895 decrease in voltage deviation. These improvements highlight the hybrid algorithm's capability to navigate the complex constraint solution space of MGs more effectively than traditional methods. By optimizing the placement and sizing of real and reactive power support devices, the hybrid approach ensures a more efficient and reliable power supply within the MG framework. Furthermore, this study underscores the importance of integrating distributed generators into the grid, which enhances the reliability and direct delivery of surplus power to consumers. The proposed optimization techniques not only improve the operational efficiency of MGs but also contribute to the broader goal of

advancing sustainable energy systems. The successful application of the hybrid algorithm in various scenarios demonstrates its versatility and robustness, making it a valuable tool for future MG optimization efforts.

Overall, the findings of this research offer a significant contribution to the field of MG optimization, providing a novel and effective solution that addresses the challenges of modern power systems. The hybrid algorithm's ability to consistently deliver superior outcomes under various constraints underscores its potential as a key component in the development of advanced, efficient, and sustainable MGs. Future research can build upon this work by exploring further enhancements to the hybrid algorithm and extending its application to other areas of power system optimization, ultimately contributing to the realization of more resilient and adaptive energy networks.

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CRedit authorship contribution statement

Mohammed H. Alsharif: Data curation, Conceptualization. **Mun-Kyeom Kim:** Writing – review & editing, Validation, Conceptualization. **Bharathsingh J.:** Supervision, Resources. **T. Rameshkumar:** Project administration, Investigation. **V. Pramila:** Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **R. Kannadasan:** Writing – review & editing, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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