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Appraisal of viable optimization techniques for efficient design and control planning of renewable energy-based microgrid systems ☆

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ABSTRACT

Due to the rapid increase in energy demand and technological improvements, a noteworthy shift has been witnessed in the energy sector through the implementation of the distributed energy systems concept. At the hub of these changes are renewable energy sources, which have risen to be the substitute solution for meeting the proliferating energy demand while mitigating the effects of climate change and contributing to socioeconomic growth. Contrary to the conventional approach, these distributed energy systems are integrated using microgrid systems, and this sophisticated technological solution necessitates the management of information exchange and power scheduling between the dispersed generating sources, customer loads, and the primary grid infrastructure. Thus, there is a need for improvement in the optimal planning and control of microgrid operation regarding computational efficiency, reliability of the obtained solution, and algorithm robustness. In addition to comparing various MG optimization problem formulations and solution approaches using multiple optimization algorithms, this paper reviews various optimization techniques used in renewable energy-based microgrid systems design and control planning. The paper evaluates particle swam optimization and mixed integer linear programming capacity for microgrid planning, considering computational efficiency, solution dependability, and algorithm resilience while providing credible information on the capabilities of parallel computing for robust optimal of high renewable microgrid design considering uncertainties and energy market dynamics.

1. Introduction: An overview of microgrids and optimization challenges

Microgrids are recently gaining increasing attention to modernize and decentralize the power grid towards improving energy security and achieving sustainable energy transition objectives. Through adequately designed microgrids, communities of electricity users can augment energy reliability and resiliency by reducing the impact of power outages and grid disruptions towards achieving energy cost savings, improved grid efficiency, energy independence, and community empowerment [1]. The generation sources in MG can either be renewable or clean-burning non-renewable energy resources depending on the location and the goal of MG design [2]. However, prominent components of any sustainable and environmentally compliant MGs are the clean-burning renewable energy sources, such as wind and solar, which produce intermittent distributed power outputs. Thus, in line with the urgent need to meet sustainable energy and environmental objectives while ensuring the quality of supply, different microgrid (MG) architectures have been studied. The proliferation of interests in microgrid design optimization and intelligent control results

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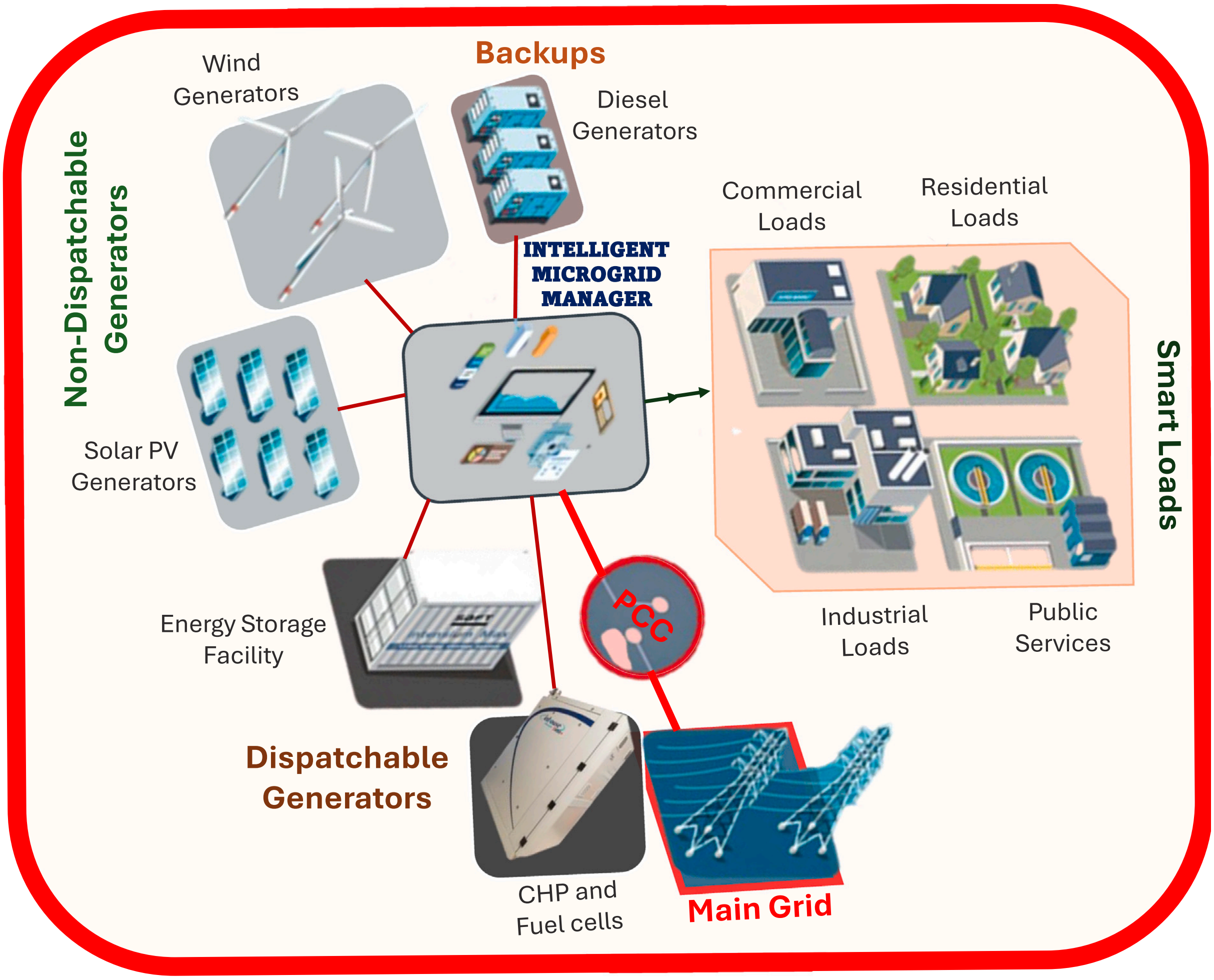

Fig. 1. Functional components of an intelligent microgrid management system.

from the need to increase the supply capacity of existing power systems and extend electricity supply to unconnected, remotely located communities of people without compromising the technical, socioeconomic, environmental, and legal requirements for capital project implementations [3]. Fundamentally, a functional MG consists of distributed energy generators, innovative load resources, energy storage facilities, and the intelligent energy control mechanism (microgrid manager), as illustrated in Fig. 1 [4] :

A microgrid can be designed as a localized and self-autonomous energy management system that can be operated in isolation or synchronized with the central grid infrastructure. Thus, when planning a microgrid project, specific attention must be devoted to socio-environmental factors such as energy resource potential as well as legal and ethical issues in the project location and the project's technical and economic/financial feasibility. Thus, the functions and scope of the microgrid must be predetermined before starting the design because of the enormous economic and technological investment requirements [5,6]. The heartbeat of any microgrid system is the intelligent control achieved through the operations of the microgrid manager. The microgrid manager controls the active communication of all the incorporated components of the microgrid and the interaction of the microgrid with the main grid infrastructure [7,8]. The intelligent capacity of the microgrid manages the involvement of the energy storage facilities for storing excess energy when there is a shortfall in demand compared to the available renewable energy production and releasing the stored energy to meet the load demand when there is a generation shortage. Another prominent function of the microgrid manager is the optimal coordination of controllable loads towards achieving improved energy consumption and economic load models in a process technically referred to as demand-side management [9]. Ultimately, the microgrid manager is the intelligent system that supervises and organizes the microgrid's performance to maintain instantaneous load-generation balance towards ensuring a stable and reliable electricity supply. This chapter discusses general approaches to handling optimization and intelligent microgrid control for diverse operational applications.

This study critically reviews microgrid design and operation optimization approaches and applies numerical analysis to the operational design of hybrid renewable energy systems. The paper compares particle swarm optimization and mixed integer linear programming for microgrid planning based on computer efficiency, solution dependability, and algorithm adaptability. It also

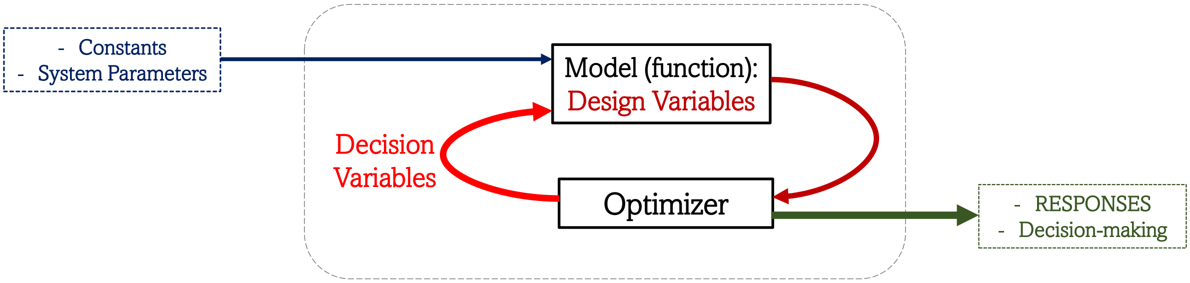

Fig. 2. Features of optimization problems and solution approach.

provides credible information on parallel computing's resilient optimal high-renewable microgrid design capabilities, including uncertainties and energy market dynamics, such as peer-to-peer trading. The remainder of the paper is organized as follows: Section Two provides insight into the different categories of optimization algorithms used in microgrid design and planning. Section Three considers selected optimization algorithms to solve various problems in microgrid planning and scheduling. Section Four reports on new trends in optimization using parallel computing for microgrid planning and implementation, and Section Five concludes the paper.

2. Optimization algorithms in microgrid design and control operation

As illustrated in Fig. 2, the general features of any optimization process are the optimization model and the optimization solver (optimizer) to be deployed. The model constitutes the interrelationship between the specific variables that govern the structure of a functional system of interest, such as the microgrid system being considered in this study and its performance responses based on specific intelligent control actions under a constrained environment. The optimizer described the solution procedure to establish the relationship between the system's variables and create a pathway for inference and informed decision-making for specific planning and operation interests. Every optimization model comprises the problem statements expressed as mathematical expressions known as the objective functions and some complimentary sets of mathematical functions that serve as the guiding principles for the viability of the result based on the requirements of the solution environment, and these are known as the constraints. The expressions for the objective functions and constraints have both constant and variable parameters; however, the desired solution points determining the optimization approach's suitability for a particular design interest are the results of the decision/design variables. Solving optimization problems may take different solutions; however, all optimization model formulations involve similar procedural steps as defined - (i.) determining the design variables and their limits; (ii). formulating the objective functions (iii.) and establishing systems restrictions/constraints.

Optimization and intelligent control are vital components of microgrid planning and implementation for efficient operation and optimal utilization of available energy resources. Microgrid optimization involves finding the best configurations and the most effective operation and control strategies. Through the appropriate design of optimization problems, microgrid planners can make informed decisions on the proper size, location, and combinations of components for achieving design goals such as system economy, supply reliability, economic load modeling, energy resource conservation, and eco-friendliness [7]. Moreover, deploying the appropriate optimization models for grid-connected configurations can help control the power interaction and establish applicable grid operating conditions concerning stability and grid compliance *i.e.* , minimizing grid losses, limiting voltage deviations, and improving power delivery quality. Moreover, the electricity market dynamics are controlled by the performance of RER-based microgrids; thus, the participation of microgrids in energy markets is also an essential aspect of microgrid optimal design and intelligent operational management. At both the grid and sub-grid (microgrid) levels, contemporary power systems infrastructures are provided with adequate information and communication technology capacity for real-time monitoring and time-based control [10]. The intelligent control in microgrids is influenced by some complex optimization algorithms and artificial intelligence (AI) concepts that aim to achieve better performance.

Microgrids are designed with the inherent functionalities to be operationally efficient when it involves load re-shaping based on demand-side management, future generation predictions based on weather conditions, concerns about the volatility of the energy markets, prompt detection of faults, building resilience against natural disasters and cyber-attacks, enacting a rapid self-healing capacity against technical and non-technical disturbances, etc. For specific design goals and interests of microgrid planning and control optimizations, the design variables that are commonly considered include the numbers and sizes of generators and energy storages for lifecycle assessment and cost optimization, electricity tariffs based on different load types and system configurations for optimal implementation of demand-side management, amount of energy sold to the grid and purchased from the grid for grid-connected configurations, grid operation parameters for power quality and stability requirements, selection and arrangement of communication protocols for system protection and control, flexibility needs procurement for system reliability and supply fidelity, amount of greenhouse gas contributions and energy conservation practices for carbon footprint analysis and environmental impact assessments, and more. Contemporary microgrid design processes often consider more than one objective and performance criteria and thus introduce specific tradeoff mechanisms for optimal decision-making as illustrated in Fig. 3.

Some of the different optimization approaches that have been deployed for microgrid operational planning and control for some of the above functionalities are illustrated in Fig. 4:

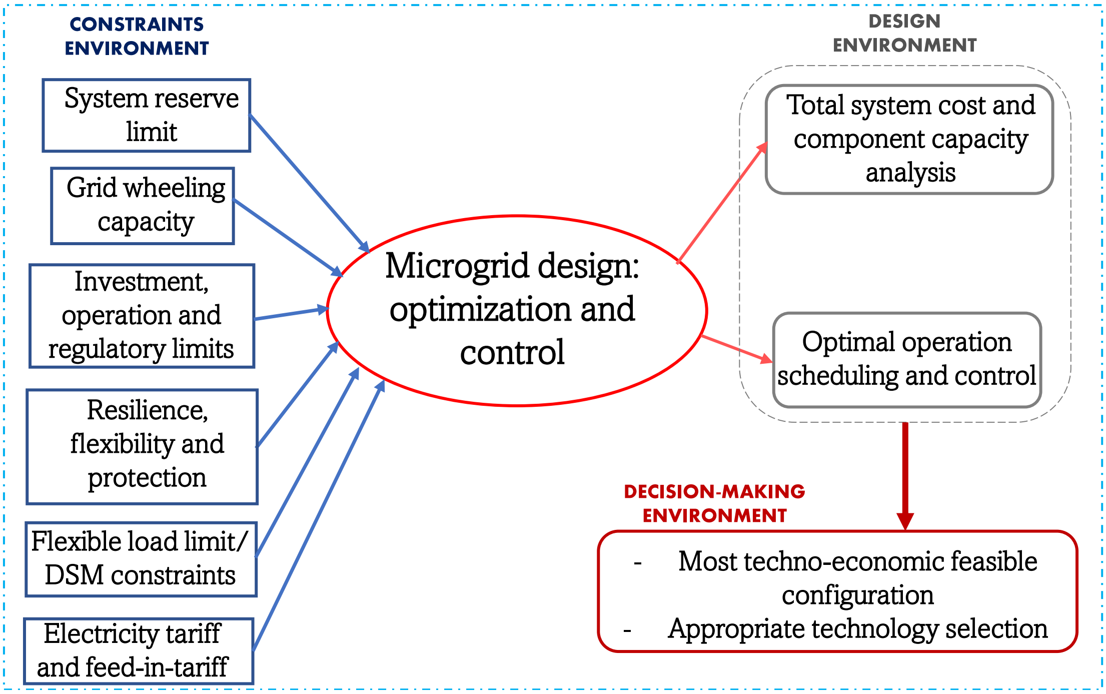

Fig. 3. Microgrid optimization and control planning environments.

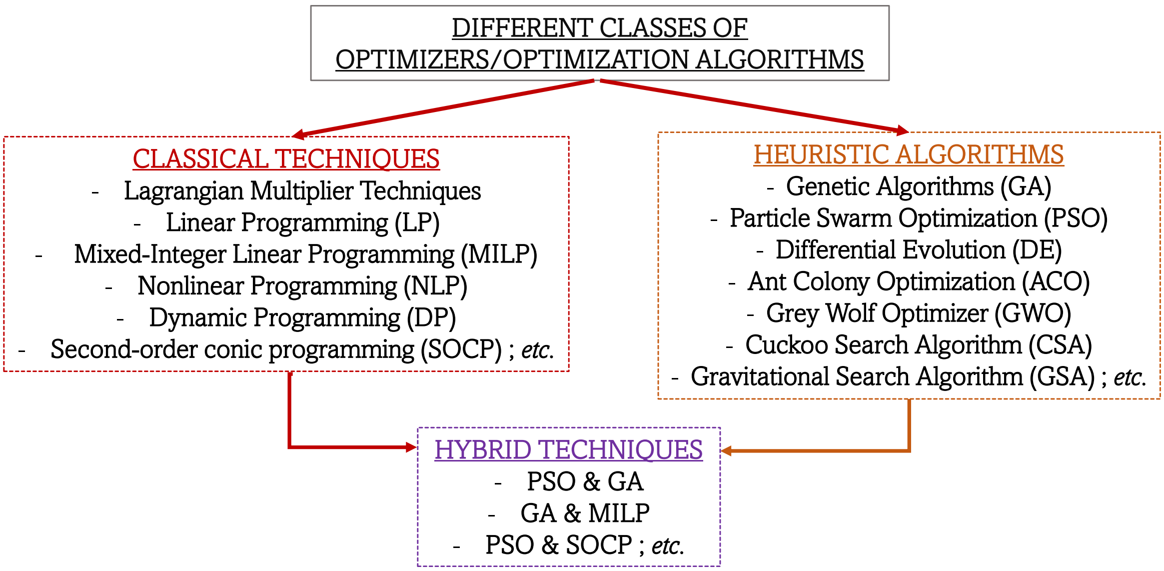

Fig. 4. Classification of microgrid optimization and control techniques.

2.1. Classical optimization techniques

Classical optimization techniques are deployed when the objective and constraint functions are continuous and differentiable with the possibility of obtaining partial derivatives. The optimal solution to such problems can be obtained using appropriate algebraic and iterative numerical analysis. This involves finding the inflection points (maximum and minimum points) for the objective functions, which must be continuous and may either be with or without constraints [11]; thus, classical optimization algorithms are numerical, analytical, or mathematical techniques. At the basic level, the common classical approaches for solving constrained optimization problems are Lagrange's multiplier method and the Karush–Kuhn–Tucker (KKT) conditions [12]. The significant merits of classical optimization problems are the effectiveness of exploring precise global solution options within constrained environments based on proven and well-established mathematical theories; this guarantees deterministic convergence and consistency of results for multiple runs of solution procedures. However, classical optimization techniques cannot be adopted for problems whose functions are non-differentiable (i.e., not continuous), and several engineering problems do not involve differentiable functions. To overcome these challenges, some non-differentiable parts are re-formulated to assume specific problem characteristics by linearization or convexity, which can lead to suboptimal results. Moreover, the larger the size/scale and the intricacy of the optimization problems, the higher the computational requirements and complexity/rigors involved in achieving convergence for finding the problem solution [13].

From the surveyed literature, two main classical optimization algorithms have been widely deployed in microgrid optimal planning; these are mixed Integer Linear Programming (MILP) and Mixed Integer nonlinear programming (MINLP) [14]. MILP algorithm is widely used for microgrid planning in off-grid configurations and with DC power flow for grid-connected designs. As the name implies, MINLP allows the formulation of nonlinear problem objectives and constraint functions; thus, it is used chiefly for microgrid planning that involves the grid's nonlinear AC power flow conditions [15]. An approach for linearization of the nonlinear network parameters and relaxation of the non-convexity around the feasible points of the power flow solution for optimal microgrid design is second-order cone programming (SOCP). Bender's Decomposition, Branch and Bound (B&B), and Gomory cuts are the standard solution approaches for implementing mixed integer programming. Several advanced techniques have been researched for modeling the optimal scheduling of microgrids with capabilities for intelligent control and uncertainty handling. The model predictive control (MPC) approach is the most prominent method deployed for MG control optimization [16]. MPC can handle complex dynamic systems, and it is a comprehensive control algorithm that can handle complex multivariate information within a concise duration with a remarkably high predictive potential [17].

2.2. Heuristic optimization techniques

Converse to the classical approach, where mathematical analysis involving well-defined algebraic functions is necessary, heuristic optimization requires an iterative solution procedure based on specified heuristic rules influenced by natural occurrences and social behaviors. They are applicable for approximate estimations of optimization problems with large dimensionality wherein the objective function and the numerous constraint functions do not obey linearity, continuity, and differentiability rules [18]. Heuristics optimization can handle multiple objectives, and its constraints handling ability is relatively more uncomplicated due to its flexible implementation. Heuristic optimal solution approaches are often adopted for complex problems where conventional analytical techniques become a computational burden and are grossly intractable. Most aspects of the procedures for most heuristic optimizations, especially for initialization of solution procedure, are based on dynamic population and randomization of the elements of the decision variables. Furthermore, heuristic techniques and their improved version, meta-heuristic techniques, are based on the intuitive reasoning of the problem solver. They can find both optimal and close-optimal solutions in large search spaces with minimum computational cost but at a tradeoff to the precision and fidelity of the obtained result (i.e., global optimal solutions are not always guaranteed) [19].

A significant category of heuristic programming that has found wide applications in energy and power systems design and planning is the evolutionary optimization technique, such as the genetic algorithms (GA), grey wolf optimizer (GWO), particle swarm optimization (PSO), ant colony optimization (ACO), and more. Other examples of heuristics optimization techniques are differential programming, artificial bee colony (ABC), simulated annealing (SA), tabu search (TS), and other artificial intelligence optimization techniques. As expected, judging by its flexible implementation and merits, heuristic optimization has been widely adopted in microgrid planning for component sizing, unit commitment problem solutions, and techno-economic feasibility studies for different system configurations and complexities. Some common objectives are total system cost minimization, based on specific criteria such as reliability, carbon footprint, ecological footprint, and economic viability [20]. For real-time and near real-time implementation for intelligent control and system scheduling, artificial intelligence and machine learning capabilities of heuristic optimization techniques are being explored by researchers for more sustainable, reliable, robust, and resilient future-proven microgrid systems [21,22].

2.3. Hybrid optimization techniques

As earlier posited, the heuristics optimization approach depends on some well-defined 'trial and error' or 'hit and miss' rules for approximate estimations of optimization problems [23,24]. Thus, as powerful as the heuristics approach is, especially for problems with high dimensionality, it suffers from some vital implementation challenges, among which are the sub-optimality of obtained solutions due to inaccurate convergence to a local optimum. In such situations, the obtained solution point may be suitable for most scenarios or problem configurations but not enough for all conditions, especially for susceptible configurations. Moreover, depending on the dimensionality, convergence may be challenging to achieve at a definite time even as the solution gets stuck, unable to find the global optimal point [25,26].

To improve on these notable drawbacks, most heuristic algorithms' initialization and implementation procedures are often controlled using supplementary mathematical algorithms in a process known as hybridization. Hybrid optimization algorithms implementation procedures are more accessible to recognize, and fine-tuning the implementation parameters to achieve optimal performance becomes relatively easy [27–29]. With hybridization, the heuristic rules can be adjusted appropriately, and this might bring about significant improvement in the optimization outcomes in terms of solution space exploration and improved speed of convergence, robustness for more reliable solutions, practical implementation for real-world applications, versatility for handling the specificity of individual solution criteria, i.e., problem description and constraints and more [30–32]. In general, hybridization

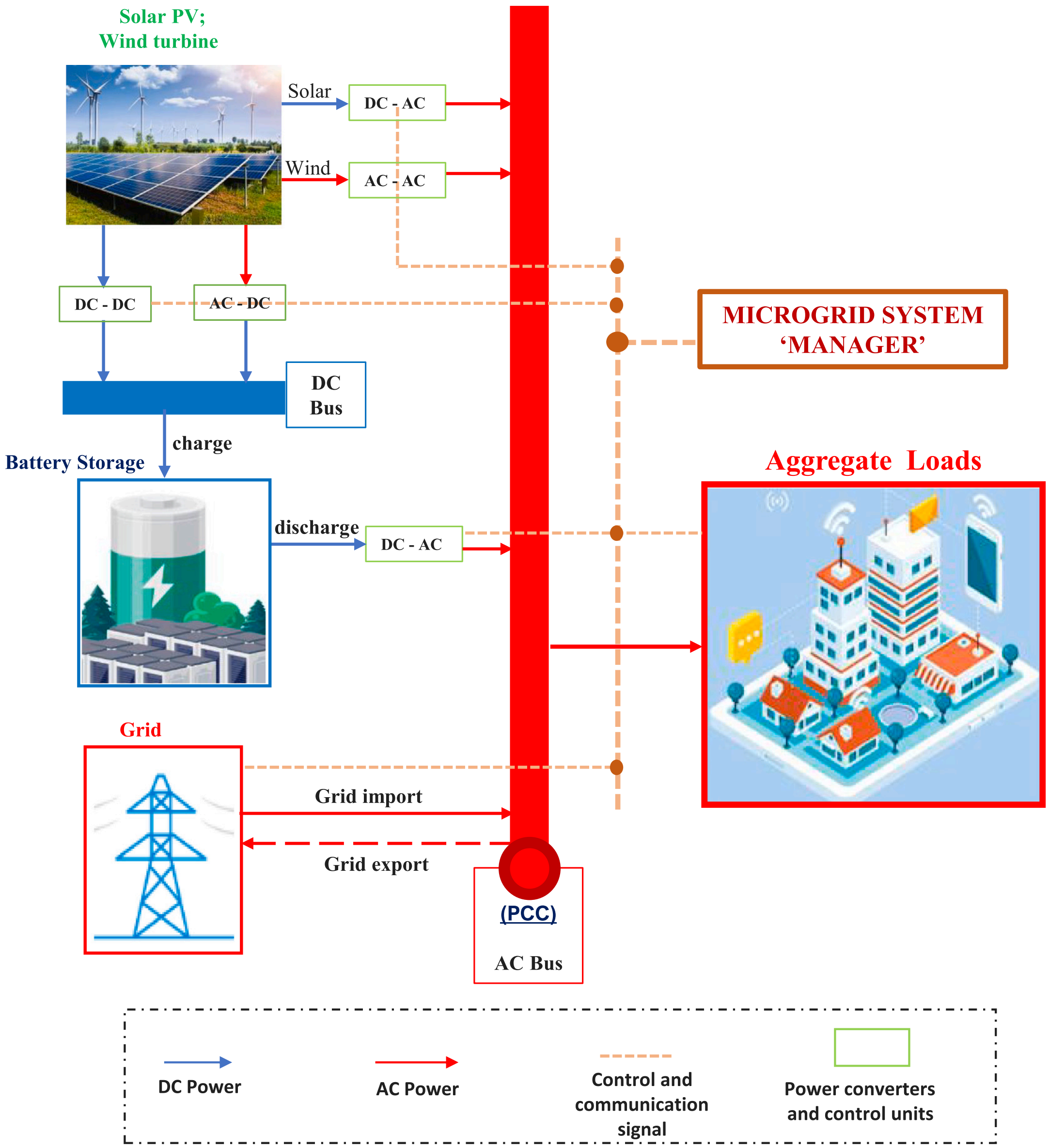

Fig. 5. Microgrid configuration for case study analysis.

in optimization algorithms is a solid strategy for tackling complicated problems effectively and efficiently by fusing the advantages of many approaches to handle contrasting aspects of the optimization problem to be solved.

Specific examples of microgrid planning and control optimization problems formulations and solution approaches are presented in Table 1.

3. Case study problem: PSO and MILP techniques

The optimal planning and scheduling procedure for a simple microgrid configuration is presented in this section for illustration and performance appraisal of the heuristic optimization algorithm using PSO and the classical optimization approach, MILP. The literature shows these two techniques have been widely deployed in several microgrid design and implementation problems. The planned microgrid system consists of solar PV, wind turbine, battery storage, and capacity of grid retrofitting as illustrated in Fig. 5. Firstly, a quick description of the two optimization techniques is given, followed by the modeling of microgrid components, optimization problem descriptions, and solution process.

Table 1
Summary of some applications of optimization algorithms for microgrid planning and control.

Ref.	Problem statement	MG components	MG type	Objective functions	Constraints	Design variables	Solver
[33]	Optimal management and control of demand, storage, electricity, and heat generation using RES	Wind turbine (WT); Combined heat and power (CHP); thermal storage (TS); flexible and inflexible loads	Grid-connected	Linear (minimization of operational cost)	Linear (power balance and system components operational limits)	System power scheduling; energy and heat generation levels; energy purchased from and sold to the grid; TS output and state of energy (SoE)	MILP (classical)
[34]	Optimal operation with hierarchical control (in three-phase)	Wind turbine (WT); solar PV; energy storage (ES); dispatchable distributed generation (DDG); loads	Grid-connected and standalone (islanding)	Nonlinear linearized by approximation (minimization of total operation cost over the planning horizon)	Linear (power balance/power exchange; system components operational limits) and nonlinear (Voltage and load curtailment; AC Power flow parameters)	System power scheduling; RES output; power purchased from and sold to the grid; energy storage output power and state of charge (SoC)	MILP; MINLP (classical)
[35]	optimal techno-economic scheduling of a multi-carrier (electricity and natural gas) microgrid system	Combined heat and power (CHP); energy storage system (ESS); heat storage; WT-based distributed energy resources (DERs); loads	Standalone (islanding)	Linear (minimization of total day-ahead operation cost)	Linear (power balance/power exchange; system components operational limits) and nonlinear linear linearized by approximation (AC Power flow parameters; CHP operational limits; gas and electricity linking constraints)	System power scheduling; WT-DERs power output; ESS power and SoC; TS power and SoE.	MILP (with CPLEX) (classical)
[36]	Optimal control of a hybrid renewable system (HRS) with demand-side management (DSM)	Solar PV; wind turbine (WT); battery energy storage (BESS); fuel cell (FC); flexible and inflexible loads	Grid-connected	Linear (minimization of system operating costs and environmental emissions; maximization of components durability)	Linear (power balance/power exchange; system components operational limits)	System power scheduling; RES output power; BESS power and SoC; FC output power and SoE; energy purchased from and sold to the grid; flexible load coordination	MPC; MILP (classical)
[37]	Optimal capacity sizing considering system reliability	Solar PV; battery energy storage (BESS); diesel generator; loads	Standalone (islanding)	Linear (minimization of total system cost and load curtailment cost) and Nonlinear linearized by approximation (minimization fuel cost; minimization of reliability indices: the expected energy not supplied, EENS and loss of load expectation, LOLE)	Linear (power balance; system components operational limits; time coupling; system reliability)	PV output power; BESS power and SoC; reserved power; curtailed power	MILP (with CPLEX); Monte Carlo analysis (classical)
[38]	Coordination/control of multiple microgrids and the utility grid based on adjusted price signals	Multiple microgrids, each with non-dispatchable (RES-based) DGs and dispatchable DGs (microturbines), ESSs, and loads	Grid-connected and islanding	Linear (minimization of total operating cost of the networked microgrids); Nonlinear linearized by piecewise linearization technique (minimization of generation–load mismatch)	Linear (power balance; system components operational limits; load shedding; power limits at the point of common coupling (PCC)	Output power of DGs; ESS power and SoC; PCC and substation power; net demand and optimal electricity	MILP; alternating direction method of multipliers (ADMM) algorithm (classical)

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Table 1 (*continued*).

[39]	Chance-constrained energy management model considering RESs uncertainties	Non-dispatchable (RES-based) DGs and dispatchable DGs, ESSs, and loads	Islanding	Nonlinear linearized by convex relaxation and approximation (minimization of cost function considering load and generation uncertainties)	Linear (power balance; system components operational limits; islanding conditions; chance constraints)	System power scheduling and control	MISOCP; Optimized Bonferroni Approximation (classical)
[40]	A two-stage chance-constrained optimization framework for multi-sites networked microgrids investment and operational planning (NMP)	Multiple microgrids each with RES-based DGs and dispatchable fuel generators (DFGs), ESSs, and loads	Grid-connected and islanding	Nonlinear linearized by convex relaxation and decomposition (First stage: minimization of the annualized cost of the investment; Second stage: minimization of operational cost)	Linear and nonlinear (power balance; system components operational limits; islanding conditions; grid compliances at PCC; chance constraints; line real and reactive power flow limits; bus voltage magnitude limits)	System power scheduling and control	Stochastic SOCP; bilinear benders decomposition (classical)
[41]	Integrated energy (load and generation) management considering DSM and uncertainties	RES-based DGs; controllable generators (CGs), ESS, fuel cell, diesel generators and smart loads (curtailable, critical, and shiftable loads)	Grid-connected	Nonlinear linearized by convex relaxation and decomposition (minimization of operation cost over the control horizon)	Linear and nonlinear (power balance; power interaction constraints; system components operational limits; islanding conditions; DSM restraints; spinning reserve)	System power scheduling; RES output power; DSM variables BESS power and SoC; FC output power and SoE; energy purchased from and sold to the grid; curtailable and shiftable loads coordination	MIQP; Stochastic MPC (classical)
[42]	optimal operation and coordination/scheduling of multiple MGs considering system resilience and uncertainties	Multiple microgrids each with RES-based DGs, ESSs, and critical loads	Grid-connected	Nonlinear linearized by convex relaxation (maximization of load restoration, *i.e.*, resilience enhancement and minimization of generation curtailment)	Linear and nonlinear (power balance; power interaction constraints; system components operational limits; power flow constraints	System power scheduling; structure of MGs; RES-DGs output power; ESS power and SoC; total power of restored critical loads	Robust MPC (with CPLEX); strong duality theory (classical)
[43]	Optimal planning of remotely located microgrids with hybrid energy sources	Solar; wind turbine; biogas generator; diesel generator; BESS; loads	Standalone (islanding)	Linearized (minimization of total system cost)	Linear (power balance and reliability factor)	System power scheduling; HRES components' power contributions; system sensitivities	PSO-GWO (hybrid)
[44]	Enhancement of microgrid performance considering economic scheduling and system stability based on optimal droop control strategy	Solar; wind turbine; diesel generator; BESS; loads	Standalone (islanding)	Linearized (minimization of total system cost including battery degradation cost)	Linear (energy balance; system components operational limits)	System power scheduling; HRES components' power contributions; BESS power and SoC; microgrid output voltage; DC link power	Sine-cosine based monarch butterfly optimization (SCMBO) (heuristic)
[45]	Two-stage optimal planning framework for multi-energy supply for micro energy grid (MEG) considering RES uncertainty and forecast, and DSM	Solar; wind; conventional gas turbine; grid; BESS; various types of loads and energy conversion systems	Grid-connected	Linearized (maximization of total system revenues – 'upper level' and minimization of load-generation mismatch – 'lower level')	Linear (energy balance; heating and cooling constraints; grid compliance at PCC; system components operational limits)	System power scheduling and power contribution from each component	Artificial bee colony (ABC) (heuristic)

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Table 1 (*continued*).

[46]	Optimal scheduling of diesel generator for efficient utilization of energy storage system (ESS) facility considering inverter efficiency	Solar PV; energy storage system (ESS); diesel generator; pump station (controllable loads)	Standalone (islanding)	Nonlinear linearized by piecewise linear approximation (minimization of diesel engine fuel consump-tion/operating cost)	Linear (power balance/power exchange; system components operational limits, ESS SOC constraints)	System components' output power; ESS power and SoC; controllable load operation dynamics	MILP-PSO (hybrid)
[47]	Optimal control model for flexibility planning considering generation-load balance for frequency regulation following the occurrence of serious disturbances, uncertainties, and load changes (system stability and resilience)	Solar PV; wind turbine; BESS; fuel cells (FC); flywheel energy storage system (FESS); diesel engine generator; loads	Standalone (islanding)	Nonlinear: 'frequency regulation and droop control' (minimization of frequency deviation)	Linear (power balance; system components operational limits; time coupling; system reliability)	System frequency and RES output power	PSO tuned with fuzzy logic and PI controller (hybrid)
[48]	Optimal dispatch scheduling and control from the grid operator's point of view considering time-of-use demand response strategy	Non-dispatchable sources (Solar; wind turbine); dispatchable sources (Fuel cells; micro-turbine; BESS; grid supply); loads (flexible and non-flexible)	Grid-connected	Linear (minimization of social cost function while limiting grid interactions)	Linear (power balance; system components operational limits)	Output power of DGs; BESS power and SoC; energy purchased from and sold to the grid; grid losses	PSO (heuristic)
[49]	Intentional islanding for system reliability enhancement during faults and disturbances considering customers' load priority	Generic DG and load models	Grid-connected with Islanding capability	Nonlinear linearized by approximation using tree knapsack problem (TKP) formulation (maximization of weight (priority for intentional islanding) for selected DG injection nodes)	Nonlinear linearized by approximation (power balance; system components operational limits; grid operation/power flow constraints – voltage magnitude, voltage stability, and line flow)	Candidate nodes for intentional islanding; the amount of restored load; power loss; node voltage deviations; the amount of reactive power support	Binary PSO (heuristic)
[50]	Optimal schedul-ing/dispatching/ coordinating strategies for grid flexibility and reconfigurability using a novel hierarchical model of Colored Petri Net (CPN)	Wind turbine; solar PV; BESS; electric vehicles (EVs); loads	Standalone (islanding) with capacity for grid retrofitting	Linear (Minimization of total system cost minus grid electricity sales profit)	Linear (power balance; system components operational limits)	System power scheduling and control; EV and BESS optimal power dynamics and SOC	Quantum-PSO (QPSO) (heuristic)
[51]	Two-level stochastic planning and coordinated scheduling for DG technologies siting and sizing considering the influence on energy storage, transmission lines capacity expansion and uncertainties	RES-based DGs (solar and wind); ESS and smart loads	Grid-connected	Nonlinear (minimization of the total cost for microgrid expansion planning for long-term and minimization of operational cost over 24-hours for short-term)	Linear and nonlinear (power balance; reserve margin; system reliability; investment budget constraints	RES capacity ratings, components hourly power scheduling; RES output power; ESS power and SoC	culture PSO, co-evolutionary (CPCE) algorithm (heuristic)

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Table 1 (*continued*).

[52]	Coordinated sectional droop charging control (CSDCC) strategy considering EV aggregator for enhancing frequency stability by developing interactive charge management system based on virtual inertial damping	wind turbine; solar PV; EVs; diesel generator and loads	Standalone (islanding)	Nonlinear (minimization of frequency deviation - frequency regulation)	Linear and nonlinear (energy balance; power interaction constraints; system components operational limits; EV aggregators frequency regulation limit	System power scheduling; EVs charging and discharging power and SoC; frequency deviations	inertial damping controller (numerical approach)
[53]	Stochastic programming approach for reactive power scheduling considering the uncertainty of wind output and voltage stability margin	Fixed-speed wind generators (FSWGs) and grid infrastructure	Grid-connected	Nonlinear (Minimization of energy loss; minimization of expected reactive power reserve; minimization of worst expected voltage security index)	Nonlinear (power balance; generator output power limit; voltage magnitude limit)	Optimal DG sites and sizes, reactive power reserve, voltage stability margin	PSO (heuristic)
[54]	Coordinated hierarchical frequency control ancillary service provision based on virtual inertia concept approach for management of demand response and distributed generation resources	VSI-based DGs; RES-based DGs (solar and wind); Electrical loads with demand response resources	Grid-connected with capability for islanding	Non-linear (minimization of Rate of Change of Frequency index; minimization of total operation cost; minimization of worst expected voltage security index)	Nonlinear (hourly power balance; generator output power limit; voltage magnitude limit; frequency dependent; power reserve)	Total frequency excursion index (TFE); rate of Change of frequency index (RCF); total operation cost index (TOC); expected load not supplied (ELNS); total operation emission index (TOE); scheduled control energy reserves; frequency stability	MILP; Monte Carlo simulation; Roulette wheel mechanism (classical)

3.1. Particle swarm optimization algorithm

PSO is a population-based approach for solving optimization problems with linear and nonlinear objective and constraint functions that may involve discrete and continuous variables [55]. PSO, like every other population-based evolutionary algorithm, was developed based on the navigation behavior of insects, birds, and mammals in groups , *i.e.*, the swarm of bees, the flock of birds, and the school of fishes [56]. PSO is, however, found to be more robust, very flexible, and easy to adapt to complex problems with significant decision-making intricacies and more expansive solution space (dimension of the search space which depends on the number of the decision variables); this is due to its less complicated randomized initialization and more tractable implementation procedure which allows for it to be more reliable in exploring the solution space and guarantees a relatively better probability to converge at the global solution point [57].

The spatial location of individual members (particles) within the group is considered their personal best at a particular time, and the interactivity and spatial relationship of a specific particle with other members within the group determines the global best for that individual particle [58]. Thus, the optimal result for a particle will be determined by the quest of the particle to influence the movement direction of all particles in the group towards reinforcing the strength of the whole group while consolidating its position within the group. By that procedure, the orientation of each particle is dynamically coordinated to give a value relating to (or called) the particle's velocity about its nearest neighbors; these continuously changing values are updated to yield the personal best at different iterative steps [59].

Given the current position and velocity vectors (randomly generated based on the problem specifications) of the ith particle within the search space with d-dimension, as $X_i = [x_{i1}, x_{i2}, \dots, x_{id}]$ and $V_i = [v_{i1}, v_{i2}, \dots, v_{id}]$, respectively, the initial value of the fitness function will be evaluated and the best position of the particle at each step (known as the local best) is obtained and reposited as $Pbest_i = (p_{i1}, p_{i2}, \dots, p_{id})$. This process is repeated for increasing iteration steps, and the best position at an iteration step is compared with that of the previous step, and the best is stored separately as the global best, such that $Pbest_g = gbest = (p_{g1}, p_{g2}, \dots, p_{gd})$. This procedure is repeated, and the best out of the local best in the repository is selected and compared with the existing global best. Thus, if the local best at any stage has better value than the existing global best, it replaces the global best, and if not, the current global best is kept [60].

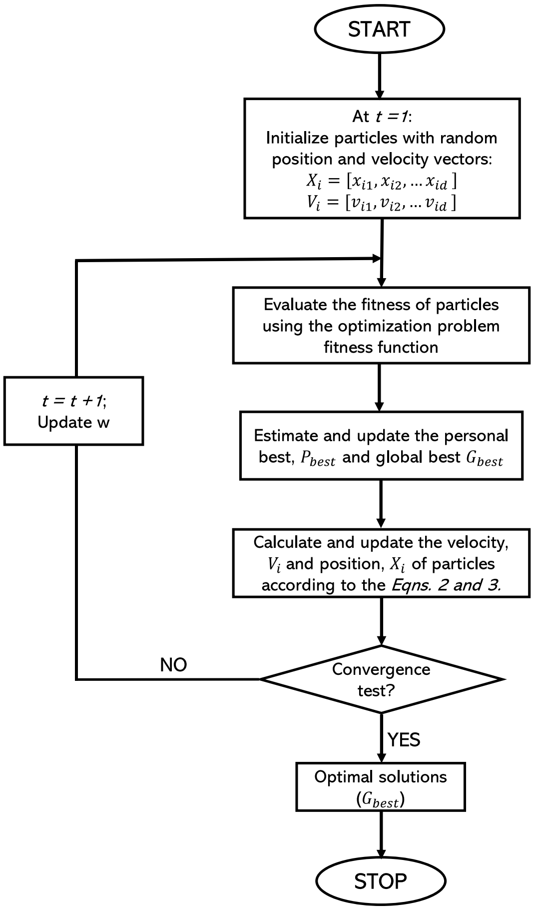

Fig. 6. Simplified flowchart for PSO approach for heuristic solution [61].

The velocity and position update dynamics for the fitness function evaluation for a classical PSO are described by Eqs. (1) and (2):

$$V_{id}^{t+1} = w \cdot v_{id}^{t} + c_1 \cdot rand_1 \cdot (Pbest_{id} - X_{id}) + c_2 \cdot rand_2 \cdot (gbest_d - X_{id}) \tag{1}$$

$$X_{id}^{t+1} = X_{id}^{t} + V_{id}^{t+1} \tag{2}$$

w is the inertia weight that linearly varies over the iteration steps, as given:

$$w = (w_f - w_i) \cdot \frac{t_{max} - t}{t_{max}} + w_i \tag{3}$$

t is the current iteration count, t_{max} is the maximum number of iterations. w_i and w_f are the inertia weight's lower and upper boundary values, respectively. c_1 and c_2 are the cognitive (personal) and social (global) factors for the swarm interactions, respectively; the flowchart for implementing PSO is shown in Fig. 6.

3.2. Mixed integer linear programming, MILP

The generic problem formulation for using the MILP optimization technique involves strictly defining a linear (or linearized by *approximation* or *relaxation* nonlinear) objective function and set of linear (or linearized by *approximation* or *relaxation* nonlinear constraints. The decision/design variables consist of real (continuous) numbers, p, and binary (discrete) variables, q, as described below [62,63]:

$$\min_{p,q}: \; f(p,q) = M^T p + N^T q; \qquad \text{subject to} \begin{cases} A \cdot (p,q) \le b \\ Aeq \cdot (p,q) = beq \\ L_b \le (p,q) \le U_b \end{cases} \tag{4}$$

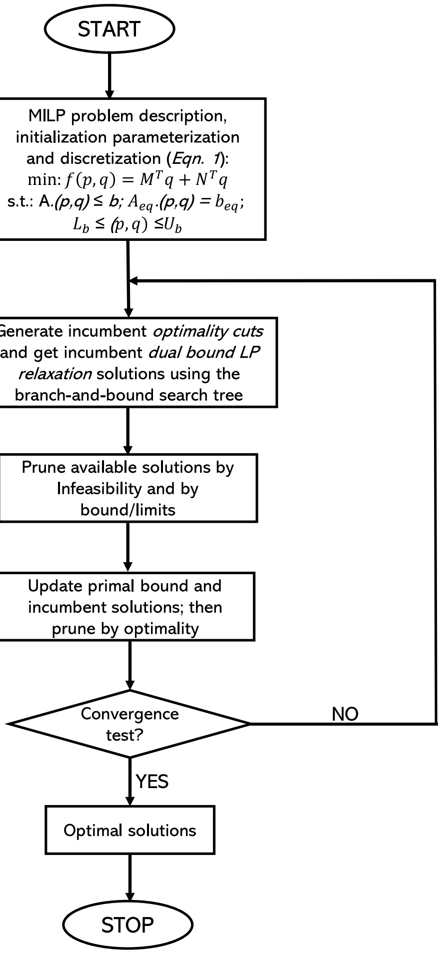

Fig. 7. Simplified flowchart for *Branch and Bound* approach for classical MILP solver [64].

The coefficient terms for the objective functions are defined by the vectors M and N for the continuous and the discrete parts, respectively. More so, the coefficient terms for the inequality and equality constraint sets are defined as A and Aeq matrices, respectively, with their corresponding values expressed as beq and b column vectors, respectively. L_b and U_b are the extreme boundary values (lower and upper limits) of the decision variables. The abridged implementation procedure for the MILP solver using the *Branch and Bound* approach is shown in Fig. 7.

3.3. Microgrid component output power modeling

The microgrid energy supply components' mathematical modeling and scheduling operation at specific time instances are described below.

3.3.1. Solar PV system

For an optimal capacity $\tilde{P}_{pv}$, the output power, $P_{pv}(t)$ (in kW) at any time t, depends on the sun's intensity determined by the incident solar irradiance [65]:

$$P_{pv}(t) = \tilde{P}_{pv} \times \begin{cases} \frac{(Id(t))^2}{Id_{st} \cdot Id_r}; & 0 \le Id(t) \le Id_{st} \\ \frac{Id(t)}{Id_{st}}; & Id(t) > Id_r \end{cases} \tag{5}$$

$Id(t)$ is the instantaneous irradiance, Id_{st} is the standard irradiance (1000 $\mathrm{Wm^{-2}}$) and Id_r is the threshold irradiance (180 $\mathrm{Wm^{-2}}$).

Table 2
Microgrid components model parameters [65,66].

Parameter	Meaning	Value	Unit
Id_r	Threshold irradiance	180.00	W/m^2
Id_{st}	Standard irradiance	1000.00	W/m^2
ws_{ci}	Cut-in wind speed	3.00	m/s
ws_{co}	Cut-out wind speed	25.00	m/s
ws_r	Rated wind speed	12.50	m/s
$\tilde{P}_m^{limit}$	PV and Wind capacity limit	1000.00	kW
$\tilde{C}_{BESS}$	BESS capacity limit	2500.00	kWh
P_{BESS}^{max}	BESS power limit	250.00	kW
η_f	BESS operational efficiency	0.90	–
σ	BESS self-discharge factor	0.05	–

3.3.2. Wind turbine system

Similarly, for a wind system with an optimal rated capacity $\tilde{P}_w$, the hourly power output of the wind system, $P_w(t)$ (in kW), is decided by the strength of the wind speed [66]:

$$P_w(t) = \tilde{P}_w \times \begin{cases} \frac{(ws(t))^3 - ws_{ci}^3}{ws_{rtd}^3 - ws_{co}^3}; & ws_{ci} \le ws(t) \le ws_{rtd} \\ 1; & ws_{rtd} < ws(t) \le ws_{co} \\ 0; & ws(t) < ws_{ci} \text{ and } ws(t) > ws_{co} \end{cases} \tag{6}$$

$ws(t)$ is the instantaneous wind speed, ws_{rtd} is the rated turbine wind speed (12.5 ms^{-1}), ws_{ci} and ws_{co} are the cut-in and cut-out wind speed at 3.0 ms^{-1} and 25.0 ms^{-1}, respectively.

3.3.3. Battery energy storage

The BESS is modeled to store the excess generated energy when the total power from the renewable energy technologies, P_{RES} exceeds the load, P_{LOAD}, and it is modeled to supply stored energy to the microgrid when there is a generation deficit [65,66]. Thus, the ESS power at any time t is expressed as:

$$P_{RES}(t) = P_{pv}(t) + P_w(t) \tag{7}$$

$$P_{BESS}^{charging}(t) = \min\left[P_{BESS}^{max}, \max\left\{(P_{RES}(t) - P_{LOAD}(t)), 0\right\}\right] \tag{8}$$

$$P_{BESS}^{discharging}(t) = \min\left[P_{BESS}^{max}, \max\left\{(P_{LOAD}(t) - P_{RES}(t)), 0\right\}\right] \tag{9}$$

P_{BESS}^{max} is the BESS power transfer limit, and the BESS state of charge, SOC, at any time t is constrained within specified lower and upper limits, SOC_{min} and SOC_{max}, as expressed below:

$$SOC(t) = \begin{cases} (1-\sigma) \times SOC(t-1) - \eta_f \times P_{ESS}^{dch.,ch.}(t); \\ \text{for } \; SOC_{min} \le SOC(t) \le SOC_{max} \end{cases} \tag{10}$$

where, $SOC(t)$ and $SOC(t-1)$ are state of charge of the battery in time t and $t-1$, respectively. σ is the hourly self-discharge rate, and η_f is the ESS charging/discharging factor, which depends on whether the BESS is charging ($P_{BESS}^{charging}$) or discharging ($P_{BESS}^{discharging}$).

3.3.4. Grid retrofitting

Whenever the BESS capacity and SOC limits are reached, excess generation from the microgrid can be exported to the grid (P_{grid}^{export}), and the supply deficit can be imported (P_{grid}^{import}).

$$P_{grid}^{export}(t) = \max\left\{(P_{RES}(t) - P_{LOAD}(t) - P_{BESS}^{charging}(t)), 0\right\} \tag{11}$$

$$P_{grid}^{import}(t) = \max\left\{(P_{LOAD}(t) - P_{RES}(t) - P_{BESS}^{discharging}(t)), 0\right\} \tag{12}$$

In the planned microgrid case study, no limit is placed on how much power can be imported from or exported to the grid. The modeling parameters for the various components of the planned microgrid are presented in Table 2.

3.4. Microgrid optimization problem formulations

This study solves two optimization problems for microgrid optimal design planning and operational control. One is long-term investment planning which involves determining the optimal capacity of all the microgrid components *i.e.* solar PV system, wind turbine system, and battery energy storage over the total planning horizon (project lifetime), and the other involves short-term scheduling of the microgrid for minimum operational cost *i.e.* hourly contribution from all the energy generation sources and the backup grid.

Table 3
PSO implementation parameters.

Parameter	Values
Population size	20
Repository Particles	20
Number of Iterations	150
Cognitive factor, C_1	2.00
Social factor, C_2	2.00
Inertia weight, w	0.9 – 0.4

3.4.1. Microgrid investment and capacity planning with PSO

The decision variables for this problem are strictly continuous and thus can be solved appropriately using the heuristic approach such as PSO. The optimization problem formulation over the project lifetime (taken to be 25 years in this study) is described below:

$$OF_{PSO} = \textbf{minimize} \sum_{m=1}^{N_{MG}} \left(COST_m^{cap} + COST_m^{o\&m} - COST_m^{sal} + COST_{BESS} + COST_{GRID}\right) \quad ;\textbf{MG Capacity planning} \tag{13}$$

$$\bar{x} = \left[\tilde{P}_m, \tilde{C}_{BESS}\right] \quad ;\textbf{decision variables} \tag{14}$$

$$0 \le (\tilde{P}_m; \tilde{C}_{BESS}) \le (\tilde{P}_m^{limit}; \tilde{C}_{BESS}),\ (m \in PV) \quad ;\text{Limit on MG component capacity/rating} \tag{15}$$

$$SOC_{min} \le SOC(t) \le SOC_{max} \quad ;\text{BESS capacity limit} \tag{16}$$

(i.) Capital cost for solar and wind systems:

$$COST_m^{cap} = \tilde{P}_m \times COST_m^{cap-unit} \tag{17}$$

(ii.) Operation and maintenance cost for solar and wind systems:

$$COST_m^{o\&m} = \tilde{P}_m \times COST_m^{o\&m-unit} \times \sum_{n=1}^{N_{year}} \left(\frac{1+\epsilon}{1+\mu}\right)^n \tag{18}$$

(iii.) Resale cost of salvageable parts of solar and wind systems (after project lifetime):

$$COST_m^{sal} = \tilde{P}_m \times COST_m^{sal-unit} \times \left(\frac{1+\epsilon}{1+\mu}\right)^{N_{year}} \tag{19}$$

(iv.) Capital and replacement cost of BESS at the end of every five years:

$$COST_{BESS} = \sum_{n=(0,5,10,15)} \left(\tilde{C}_{BESS} \times COST_{BESS}^{unit} \times \left(\frac{1+\epsilon}{1+\mu}\right)^n\right) \tag{20}$$

(v.) Approximate cost of grid retrofitting for the project lifetime:

$$COST_{GRID} = \sum_{t=1}^{24} \left([P_{grid}^{export}(t) + P_{grid}^{import}(t)] \times \gamma_{loss} \times N_{day} \times N_{year} \times COST_{grid-loss}\right) \tag{21}$$

The decision variables are the ratings of the PV and wind system, $\tilde{P}_m$ in kW and the optimal capacity of BESS, $\tilde{C}_{BESS}$ in kWh. ϵ is the inflation rate, μ is the interest rate, N_{day} is the number of days in a year, N_{year} is the project lifetime, $COST_m^{cap-unit}$ is the unit capital cost for PV and wind systems in \$/kW, $COST_m^{o\&m-unit}$ is the unit operation and maintenance cost for PV and wind systems in \$/kW, $COST_m^{sal-unit}$ is the unit cost of the salvageable components of PV and wind systems after the project lifetime in \$/kW and $COST_{BESS}^{unit}$ is the unit cost of battery energy storage in \$/kWh. γ_{loss} is the assumed percentage losses along the grid, and $COST_{grid-loss}$ is the cost of power losses per kW. The PSO implementation parameters for solving the above problem are presented in Table 3, and the techno-economic parameters are defined in Table 4.

3.4.2. Microgrid scheduling operation with MILP

The decision variables for this problem consist of discrete binary (when the battery charges or discharges; when the microgrid exports to or imports power from the grid) and continuous (amount of energy produced by PV and wind, amount of BESS power charged or discharged and amount of power imported from or exported to the grid). Thus, this problem assumes a unit commitment structure and can be efficiently solved using the classical approach *i.e* MILP. The objective is to minimize the total daily operational cost over a 24-hour scheduling horizon using the levelized cost of electricity, $LCOE$ in \$/kWh, as described below:

$$OF_{MILP} = \textbf{minimize} \sum_{t=1}^{24} \left(\sum_{m=1}^{MG} LCOE_m \cdot P_m(t) + Cost_{grid}^{buy} \cdot P_{grid}^{import}(t) - Cost_{grid}^{sell} \cdot P_{grid}^{export}(t)\right); \quad \textbf{MG scheduling} \tag{22}$$

$$\bar{x} = \left[P_m(t), P_{BESS}^{charging}(t), P_{BESS}^{discharging}(t), P_{grid}^{import}(t), P_{grid}^{import}(t)\right]; \quad \textbf{decision variables} \tag{23}$$

Table 4
Techno-economic parameters for microgrid capacity planning [66–68].

Parameter	Meaning	Value	Unit
ϵ	Inflation rate	4	%
μ	Interest rate	10	%
γ_{loss}	Percentage grid loss	5	%
N_{year}	Project lifetime	25	years
N_{day}	standard days in a year	365	days
$COST_m^{cap-unit}$	Unit capital cost	[1327 - PV; 1718 - wind]	\$/kW
$COST_m^{o\&m-unit}$	Unit operation and maintenance cost	[15.97 - PV; 27.57 - wind]	\$/kW/year
$COST_m^{sal-unit}$	Unit salvage cost	$0.30 \times COST_m^{cap-unit}$	\$/kW
$COST_{BESS}^{unit}$	Unit cost of BESS	138	\$/kWh
$COST_{grid-loss}$	Cost per kW grid loss	0.2	\$

Table 5
Optimal microgrid scheduling implementation parameters [69,70].

Parameter	Value	Unit
$LCOE_{pv}$	4.10	US cent/kWh
$LCOE_{wind}$	4.90	US cent/kWh
$Cost_{grid}^{buy}$	16.30	US cent/kWh
$Cost_{grid}^{sell}$	18.80	US cent/kWh
$[SOC_{min}; SOC_{max}]$	[10; 90]	%
N_t	24	hours

Table 6
RES resource and load data for MG capacity planning and operational scheduling.

Hour (1 – 12)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Irradiance [W/m2]	0.0	0.0	0.0	0.0	1.0	24.6	97.5	224.8	369.7	496.5	578.1	612.8
Wind Speed [m2]	6.6	6.5	6.4	6.6	6.5	6.5	6.3	6.2	6.3	6.3	6.3	6.5
Load demand [kW]	370.0	350.0	345.0	345.0	350.0	355.0	385.0	420.0	460.0	490.0	495.0	495.0
Hour (13 – 24)	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Irradiance [W/m2]	596.1	531.6	419.0	278.1	137.0	43.5	4.3	0.0	0.0	0.0	0.0	0.0
Wind Speed [m2]	6.7	7.0	7.2	7.4	7.6	7.6	7.6	7.6	7.4	7.2	6.7	6.6
Load demand [kW]	475.0	485.0	485.0	480.0	490.0	495.0	500.0	490.0	470.0	450.0	430.0	400.0

$$0 \leq (P_{BESS}^{discharging}; P_{BESS}^{charging}(t)) \leq P_{BESS}^{max}; \qquad \text{BESS power transfer limit} \tag{24}$$

$$SOC_{min} \leq SOC(t) \leq SOC_{max}; \qquad \text{BESS capacity limit} \tag{25}$$

$$\sum_{m=1}^{MG} P_m(t) + P_{grid}^{import}(t) - P_{grid}^{import}(t) + P_{BESS}^{discharging} - P_{BESS}^{charging}(t) = P_{LOAD}(t); \qquad \text{Power balance} \tag{26}$$

The decision variables are the hourly power contribution from the PV and wind system, $P_m(t)$ in kW, the hourly power contributions from the BESS, $P_{BESS}^{charging}(t)$; $P_{BESS}^{discharging}(t)$ and the hourly power contributions from the grid, $P_{grid}^{import}(t)$; $P_{grid}^{import}(t)$. $LCOE_m$ is the levelized cost of electricity for PV and wind systems in \$/kWh; $Cost_{grid}^{buy}$ and $Cost_{grid}^{sell}$ are the per hour unit cost of electricity purchased from and sold to the grid by the microgrid operator in \$/kWh. The implementation parameters for the MILP procedure for microgrid scheduling are presented in Table 5, and the weather and load resource data adopted for the MG design are presented in Table 6.

3.5. Simulation results and discussion: MG optimal design and configuration

The solution to the MG optimal design and configuration problems using PSO for component capacity sizing and MILP for operation scheduling is implemented by simulation on Matlab version R2022b using an HP Elitebook PC with 64-bit data configuration and Intel(R) Core(TM), i7-8650U processor at an average speed of 1.90 GHz. Specifically, the robustness of the CPLEX solver implemented on the YALMIP toolkit is explored to implement the *Branch and Bound* algorithm for the MILP solver [71,72].

3.5.1. MG capacity planning using PSO

Considering multiple simulation runs, the capacity planning results using the PSO algorithm implemented with random population and the influence of hybridization on the solution robustness and speed of convergence by adopting a supplementary deterministic optimizer are illustrated using Fig. 8 and Table 7. Fig. 8 shows the faster convergence of the optimization solution using PSO hybridized with "FMINCON". The specific function of the "FMINCON" implemented in Matlab is to determine the initial feasible solution point for the optimization problem described in the section "*3.4.1*". The solution of the "FMINCON" stage is the initial solution point $\bar{x}_0$ and this accounts for the fast convergence of the hybrid PSO variants at an average of around 15 iteration-point for the recorded five optimization runs compared to the basic PSO solver with solution converging at about 40 iteration-point for the five runs recorded.

The effect on the solution consistency is shown clearly in Table 7. The variation in the optimal values (capacities of PV, wind, and BESS) and the final optimal point are relatively reduced with the modified PSO compared to the fundamental PSO. Apart from

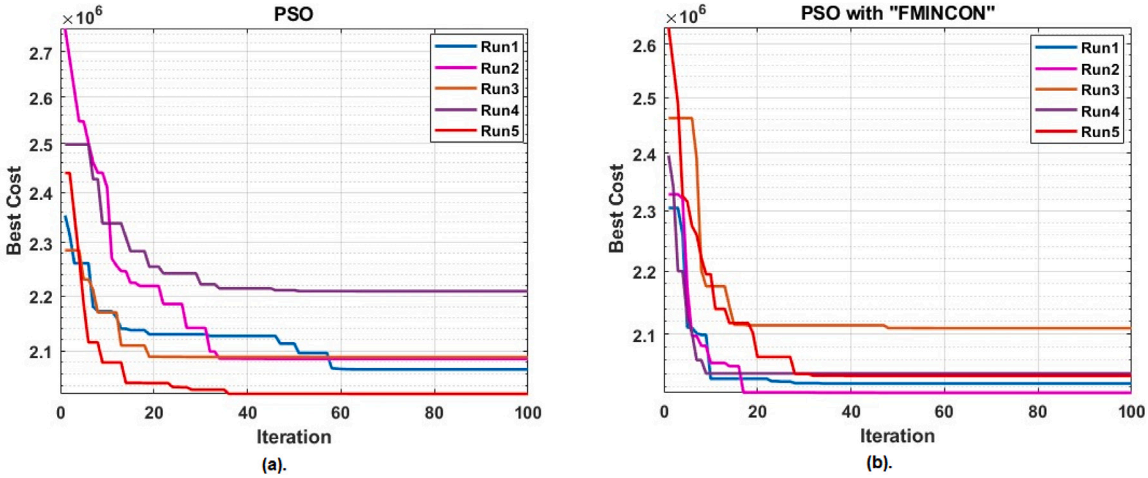

Fig. 8. Convergence characteristics for MG components capacity sizing using PSO and PSO hybrid with 'FMINCON'.

Table 7
Optimal MG component capacity planning results using PSO variants.

Algorithm	Runs	COST (USD)	PV (kW)	WIND (kW)	BESS (kWh)
PSO	1	2068054.38	512.59	538.13	1504.15
	2	2086336.09	542.72	500.00	1613.90
	3	2089442.17	500.00	500.00	1760.40
	4	2208346.74	548.10	500.00	1917.11
	5	2026004.60	500.00	522.43	1500.00
	Average	**2095636.80**	**520.68**	**512.11**	**1659.11**
PSO with "FMINCON"	1	2025162.97	528.25	500.00	1500.00
	2	2011476.06	500.00	500.00	1555.50
	3	2109589.68	500.00	575.01	1500.00
	4	2040263.04	500.00	531.40	1500.00
	5	2036720.11	537.63	500.00	1500.00
	Average	**2044642.37**	**513.18**	**521.28**	**1511.10**

Table 8
Considered cases for MG operational scheduling.

CASES	PV capacity (kW)	Wind Capacity (kW)	BESS Capacity (kW)
CASE 1	750.00	750.00	2000.00
CASE 2	500.00	1000.00	2000.00
CASE 3	1000.00	500.00	2000.00

the consistency of the solution points for the five runs recorded, the average optimal cost (minimization) using PSO and the modified PSO is USD 2095636.80 and USD 2044642.37, respectively.

3.5.2. MG operational scheduling using MILP

To illustrate the impacts of optimal configuration on the operational performances of MG, three cases of MG configurations are considered for a total renewable energy capacity limit of 1500 kW as presented in Table 8.

The 24-hour resource scheduling, which is a mixed-integer linear optimization problem, is achieved for each case using the MILP solver in CPLEX, and the numerical simulation results are presented in Figs. 9, 10, 11 and Table 9. The first part "(a)." of Figs. 9, 10, 11 and Table 9 shows the optimal hourly power output from all the considered RES sources based on the power output models earlier described under the section "*3.3*" against the hourly load demand profile. The second part, "(b)." shows the performance of the BESS in terms of the charging and discharging power and the SOC dynamics, and the third part, "(b)." gives the optimal contribution of all the MG components to meeting the set load demand at each hour.

The information in Figs. 9–11 are effectively summarized in Table 9. Considering the total cost of operation over a 24-hour scheduling plan, Case 3, with a PV capacity of 1000 kW and wind capacity of 500 kW, outperformed Case 1, with equal PV and wind capacities of 750 kW each, and Case 2, with higher wind capacity of 1000 kW against PV capacity of 500 kW. The minimum cost of daily operation for Case 3 is USD 95,658.37 compared to Case 1, with a total cost of operation of USD 97,659.61, and Case 2, with a total cost of USD 99,877.13.

The technical performances of the three MG configurations over a 24-hour schedule plan are compared using criteria such as the amount of grid energy exchange, energy contributed by the RES in percent of the total energy of loads, and the BESS utilization

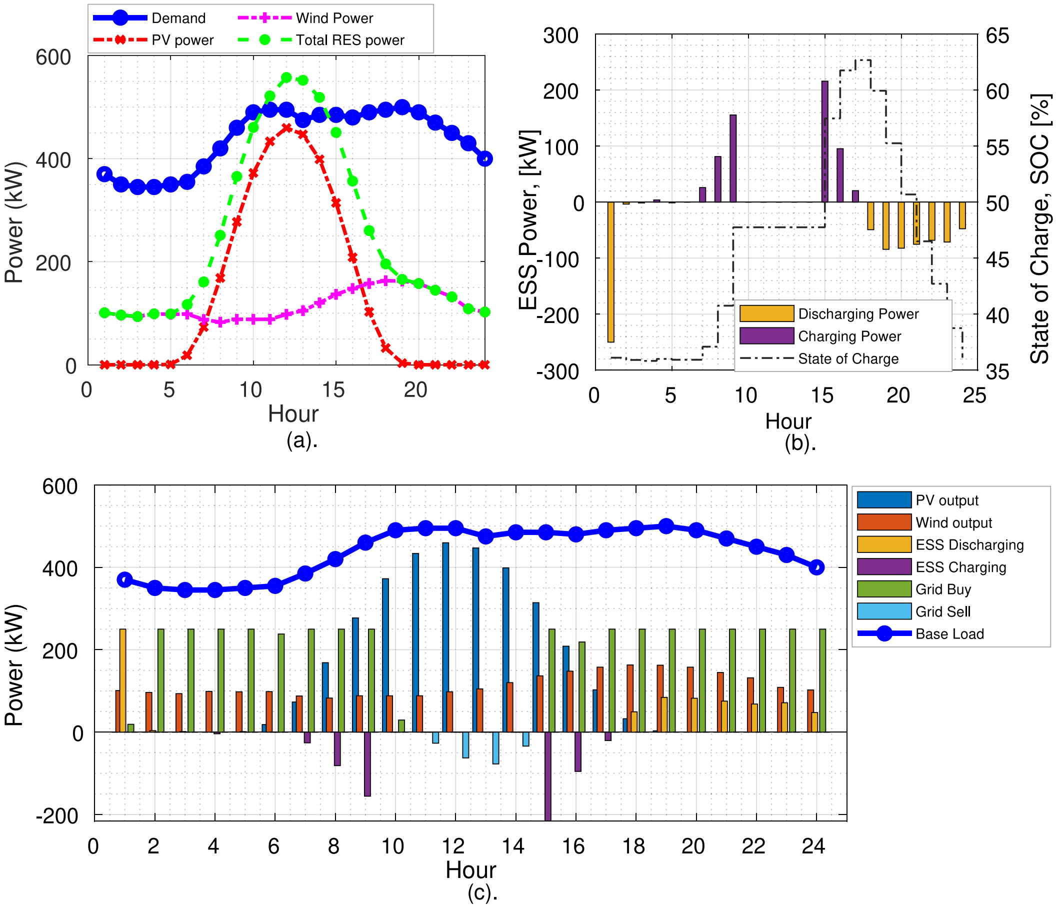

Fig. 9. Optimal MG operational scheduling results for **Case 1** (a). Optimal RES power outputs; (b). Optimal BESS dynamics; (c). Optimal HRES scheduling.

Table 9
Optimal MG operational scheduling using MILP considering three optimal cases.

MG SCHEDULING PARAMETERS	UNITS	CASE 1	CASE 2	CASE 3
Total energy consumed	[kWh]		**10510.00**	
Total energy from PV	[kWh]	3310.88	2207.25	4414.50
Total energy from wind	[kWh]	2757.77	3677.03	1838.52
Total energy import from grid	[kWh]	4505.42	4429.32	4292.70
Total energy export to grid	[kWh]	200.40	14.57	516.19
Total BESS discharged energy	[kWh]	734.59	416.42	1185.87
Total BESS charge energy	[kWh]	598.26	205.45	1155.40
Percentage ESS Utilization	[%]	**36.73**	**20.82**	**59.29**
Percentage RES contribution	[%]	**57.74**	**55.99**	**59.50**
TOTAL DAILY OPERATION COST	[$]	**97659.61**	**99877.13**	**95658.37**

factor in percent as a ratio of the total energy discharged from the BESS over the capacity of the BESS. Thus, technically, Case 3 MG performed better regarding RES energy uptake and BESS exertion as presented in Table 9. Less energy is imported from the grid, and more energy is available for export to the grid in Case 3. This resulted in more energy utilization from the RES supply in Case 3, *i.e.* (57.74% - "Case 1" and 55.99% - "Case 2"). Moreover, the result for the BESS utilization indicated that for the uniform capacity of 2000 kWh across the three cases, Case 3 MG configuration gives a more efficient utilization of the BESS facility with 59.29% compared to 36.73% for Case 1 and 20.82% for Case 2. The extensive benefits and capabilities of the classical MILP optimization algorithm implemented using CPLEX solver on Matlab are verified by the guaranteed solution point obtained for any simulation run for the three cases as long as the simulation condition remains the same.

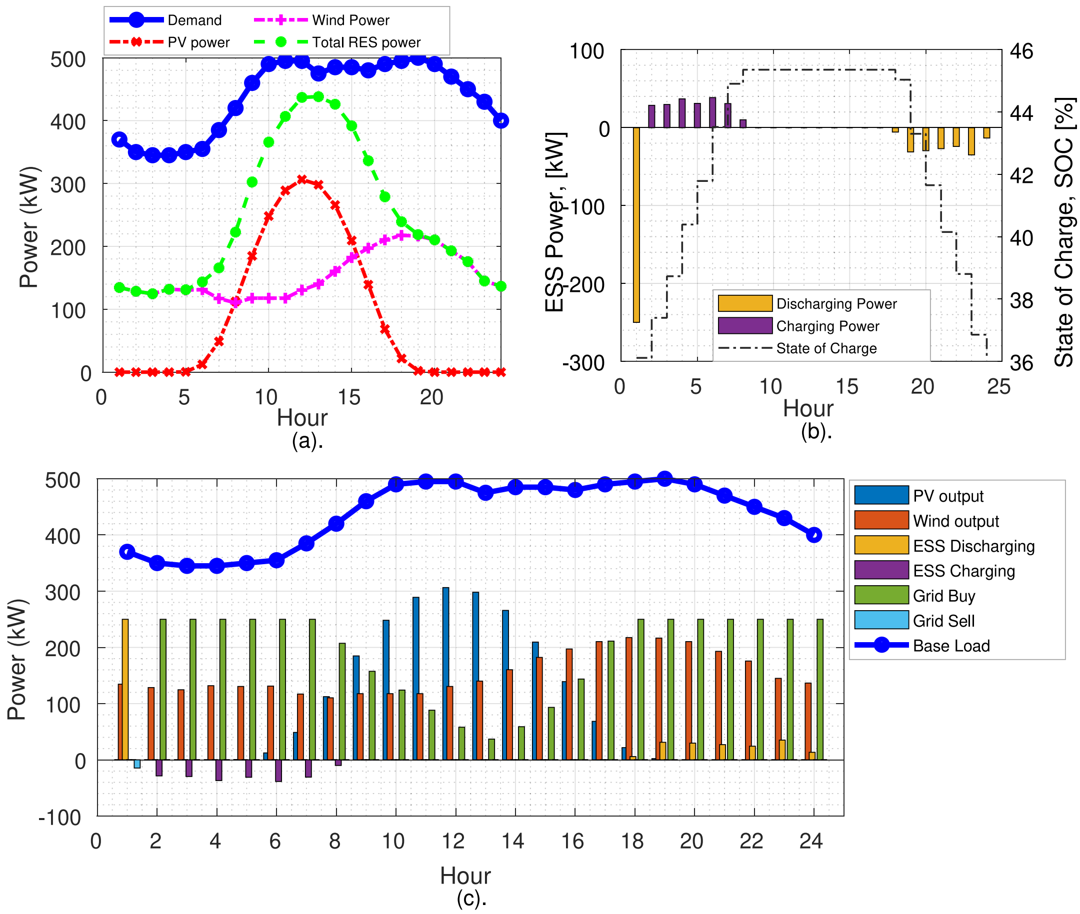

Fig. 10. Optimal MG operational scheduling results for **Case 2** (a). Optimal RES power outputs; (b). Optimal BESS dynamics; (c). Optimal HRES scheduling.

4. Emerging trends: parallel/distributed computing for MG optimization and control planning

As earlier posited, the optimization problem's complexity level determines the computational and memory requirements of the solution tool for achieving a feasible solution that is time-efficient, affecting the computational time and the precision of the solution [73]. Thus, parallel computing (PC) has been enabled by technological advancements in both software and hardware development and has helped to improve the computational proficiency for energy and power system optimization procedures in recent times [74,75]. The concept of parallel computing involves synchronizing multiple computer resources controlled by a master device known as the scheduler to solve a particular computational task [76]. In parallel computing architectural design, several processors work together to carry out several smaller tasks that are each part of a bigger, more complex problem. Thus, for effective implementation of parallel computing, there is a need for a master computer that serves as the information processing and control hub for the exchange of signal data between all the synchronized computers using an adequate communication network in a predefined topology [77]. There are four stages towards the effective implementation of parallel computing: initialization of instruction, execution of the bit-level procedure, task ordering, and data parallelism [78]. Furthermore, depending on the PC's hardware architecture, data streams, and the number of instructions initialized synchronously, parallel computing can be categorized as single instruction single data (SISD), single instruction multiple data (SIMD), multiple instruction single data (MISD), and multiple instructions multiple data (MIMD) [79]. Fig. 12 illustrates the computational architecture for basic parallel computing configuration [80].

Several research activities are ongoing to improve the concept of parallel computing, especially around multi-objective evolutionary algorithms and stochastic optimization problems for electric power systems and energy system planning towards achieving better, faster, and feasible solutions for different system configurations and complexities. The authors in [81] proposed an expected-cost realization-probability (ECRP) optimization approach for microgrids' dynamic energy management (DEM). Decomposing the problem into smaller subproblems to be solved by PC using stochastic mixed-integer nonlinear programming (MINLP) and an approximate dynamic programming algorithm based on ECRP achieves near-optimal results on a real microgrid simulation example, outperforming two other comparison algorithms in terms of computational efficiency. Utilizing the alternating direction multiplier

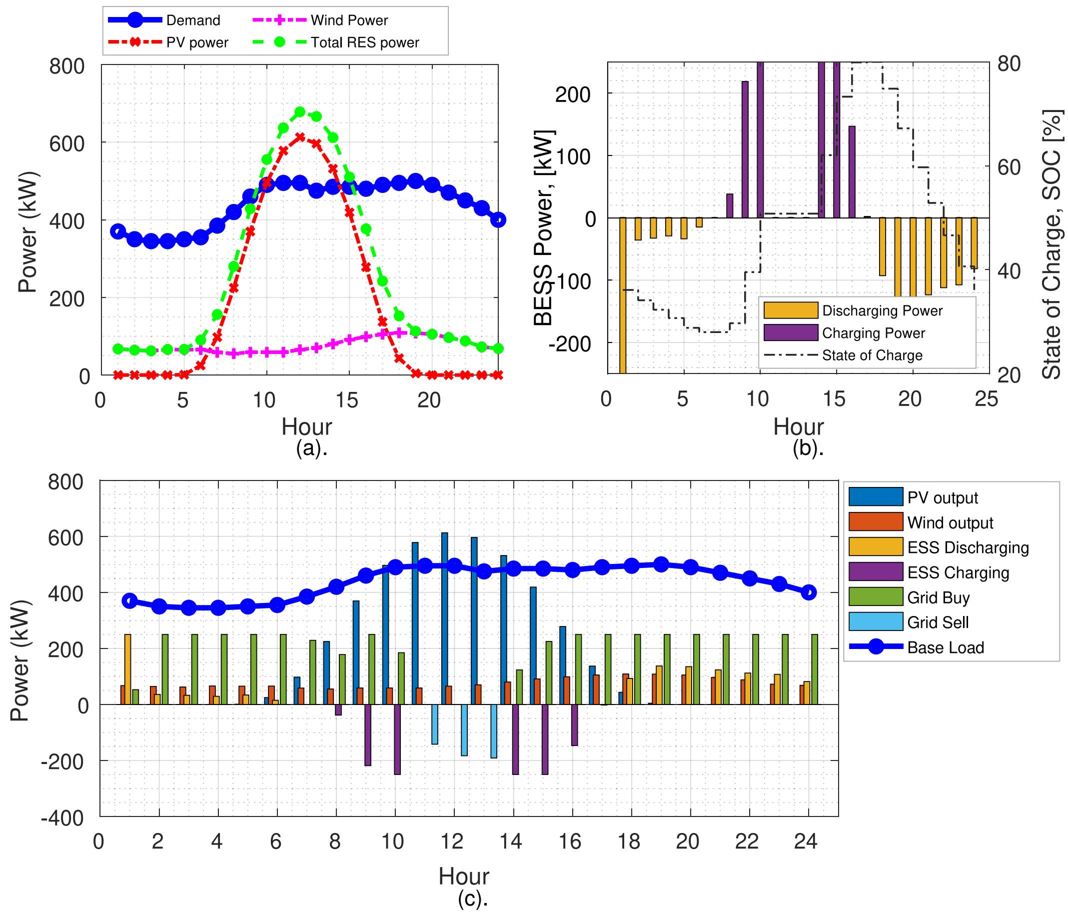

Fig. 11. Optimal MG operational scheduling results for **Case 3** (a). Optimal RES power outputs; (b). Optimal BESS dynamics; (c). Optimal HRES scheduling.

method, a distributed and real-time economic dispatch strategy for islanded microgrids that considers occupant comfort and fair utilization while coordinating thermostatically controlled loads (TCLs) with distributed generation is presented in [82]. This strategy combines a semi-online parameter identification method for TCLs, a virtual battery model with heterogeneous parameters, and a fast distributed consensus algorithm using parallel computing for time-efficient computation. An energy trading framework incorporating independent market operators (IMOs) for multi-stakeholder multiple microgrids is presented in [83]. To ensure consistency, the framework uses an analytical target cascading (ATC) algorithm with Lagrangian penalty terms, and it formulates energy trading and production in individual microgrids as a two-stage adaptive robust optimization model to account for renewable energy sources and loads uncertainties using parallel computing. Simulations demonstrate the advantages of the computational approach, including improved robustness in distributed decision-making and greater computational efficiency.

Moreover, an ADMM-based hierarchical control scheme for interconnected DC microgrids using parallel computing is proposed in [84]. The scheme incorporates three coordinated levels of control through two-level distributed communication networks and effectively decouples the constraints of the economic dispatch problem. Simulations on an off-grid microgrid cluster confirm the effectiveness of the computational approach in restoring voltage, distributing power, and overcoming technical and financial challenges while ensuring information independence and data privacy. The authors in [85] proposed a multi-energy microgrid (MEMG) design using a two-level game theoretic Stackelberg optimization model with adaptive stochastic optimization using distributed/parallel programming. The computing approach allows optimization of the energy planning and pricing strategies for the MEMG operator at the upper level, and the industrial, commercial, and residential agents can optimize their energy trading strategies at the lower level, resulting in a time-efficient and effective solution by simulations. A model for optimizing the operation of microgrids with renewable energy sources and energy storage systems is formulated as a mixed-integer nonlinear programming (MINLP) problem with intertemporal constraints handled using distributed computation in [86]. To find the optimal solution efficiently, the authors propose the parallel computing method based on the generalized Bender decomposition and the decomposition of the optimality constraints. This method shows promise for full-scale parallel computation capability and real-time operation of microgrids in simulations using the CIGRE medium voltage microgrid benchmark system.

The study reported in [87] focuses on optimizing battery operation in standalone and grid-connected DC microgrids with photovoltaic generators using distributed computing to enhance technical, economic, and environmental conditions. The authors

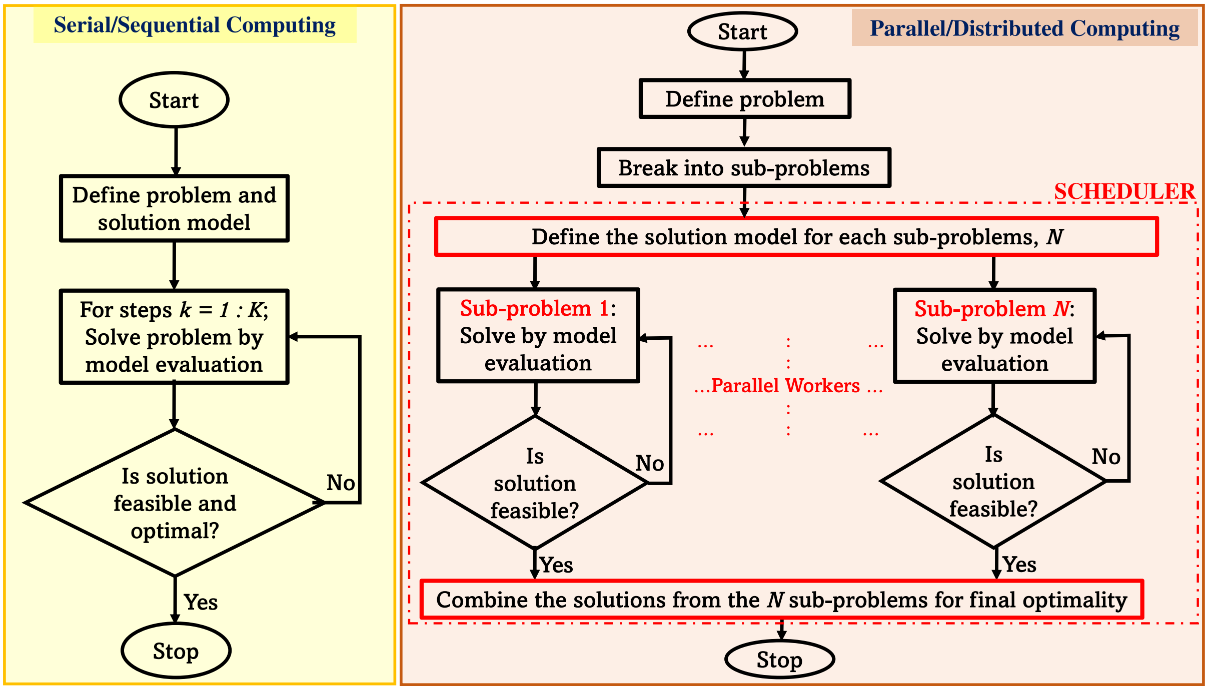

Fig. 12. Functional configuration for parallel computing solution implementation.

proposed three parallel metaheuristic algorithms to solve the optimal power dispatch problem for batteries in DC grids. The study includes the adaptation of two DC microgrids, considering various factors like energy cost, emissions, power demand, and PV generation, and evaluates the performance of different strategies using average results and standard deviation values. In a similar context, an effective method for optimizing various energy infrastructures in a multi-energy microgrid considering uncertainties and network constraints using parallel metaheuristic algorithms is proposed in [88]. The approach involved the design of a coordinated two-stage programming approach using a competitive swarm optimization algorithm, specifically cumulative search optimization (CSO) with chaos theory, to improve computational performance. The proposed method was adopted for solving energy planning optimizations that involve power-to-gas conversion to maximize revenue through price-based demand reduction, and it shows better performance compared to reference methods.

Other areas where parallel computing has been widely applied in microgrid planning and control are contemporary energy market design (such as peer-to-peer trading) and cyber–physical system planning. The authors in [89] proposed a two-stage optimization framework for co-optimization of peer-to-peer (P2P) energy trading among multiple microgrids (MMGs) under uncertainty and optimal topology planning of distribution networks (DNs). The approach uses stochastic programming with a conditional value-at-risk technique and a fully distributed method via parallel computing. The results of the approach showed improved robustness of P2P trading strategies, reduced network losses, and high performance compared to other distributed algorithms. Moreover, the authors in [90] proposed a two-stage distributed optimization framework for grid-connected peer-to-peer (P2P) energy trading among multiple microgrids (MGs) under uncertainty. The approach includes a conditional optimal power flow model at the upper level to minimize power losses and ensure the operational reliability of local distribution networks and a stochastic programming-based P2P trading model at the lower level for flexible energy transactions using parallel computing. The designed model nested a two-level distributed algorithm combining parallel analytical target cascade and alternating direction multiplier methods. The results of the numerical simulation show improved computational performance using parallel configuration compared to the conventional sequential algorithms using the modified IEEE distribution network with 33 nodes and four MGs.

Similarly, in [91], a grid-connected peer-to-peer (P2P) energy trading method for multiple microgrids (MMGs) in an active distribution network considering differentiated zone prices is proposed. The technique uses a leader–follower energy trading framework based on Stackelberg game theory with utility functions for the distribution system operator (DNO) and prosumers within microgrids to optimize operating costs, power flow, and voltage regulation while maximizing profits through demand response strategies. The numerical results in a three MMGs system modified from the IEEE 33-bus distribution network and modeled on Matlab demonstrated the effectiveness of the proposed parallel computing approach in terms of computational requirements and time. The authors in [92] proposed a day-ahead scheduling model using a cyber–physical–social system (CPSS) for the tripartite coordination of communication networks, multi-energy microgrids (MEMGs), and distribution networks. The approach also considered demand-side response for MEMGs, power consumption, and bandwidth allocation in the cyber system while optimizing power flow distribution in the distribution network using a coordinated distributed computing technique with experimentation on the IEEE 33-bus distribution network. The results confirm the effectiveness and economic efficiency of the proposed method, which employs a parallel, improved, self-adaptive algorithm of the alternating direction method of multipliers (ESA-ADMM) for distributed optimization.

5. Conclusions

Mathematical optimization is central to the practical design of a microgrid system for operational reliability and economic efficiency. This paper reviews different optimization methods for the configuration and design planning of renewable energy-based microgrid systems, starting from the basic principles of optimization. This study explored some of the heuristic and classical optimization approaches widely deployed in MG optimal planning and the vital concept of hybridization of algorithms for better performance. Specifically, the performance of the population-based particle swam optimizer and the classical mixed integer linear programming solver for specific MG design and planning problems is investigated using simple numerical simulation. Due to their unique strengths and pertinence, these optimizations have different applications in MG capacity planning and energy resource scheduling. Conclusively, the opportunities for parallel computing for robust solutions and computational effectiveness are discussed for MG design and planning problems.

This study provides specific information for academics and researchers interested in microgrid systems planning and mathematical optimization. However, intelligent planning of renewable energy-based microgrid systems for real-time implementation should be considered, considering the capabilities of artificial intelligence and other intelligent communication protocols with the Internet of Things for the smart grid. This stage of the study provides an appraisal and qualitative survey of viable microgrid design and operation optimization techniques, and the reported numerical analysis shows the concept of microgrid optimization as it relates to hybrid renewable energy system operational design. Considering computational efficiency, solution dependability, and algorithm adaptability, this paper assesses particle swarm optimizations and mixed integer linear programming for microgrid planning. It also provides credible information on the capabilities of parallel computing for robust optimal high-renewable microgrid design, taking uncertainties and energy market dynamics into account. In the subsequent study, adequate optimization models (single or multi-objective) for the intelligent operation of highly renewable energy-based microgrids will be developed and modeled.

CRediT authorship contribution statement

Oludamilare Bode Adewuyi: Resource, Modelling, Investigation, Writing – original draft. **Senthil Krishnamurthy:** Conceptualization, Resource, Validation, Writing – editing.

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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