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Physics-Informed Metaheuristic Optimization of Distributed Renewable Microgrid Stability

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Abstract

The rapid proliferation of distributed renewable generation within microgrids introduces critical stability challenges, including voltage fluctuations, frequency deviations, and power quality degradation, particularly at high penetration levels exceeding 70%. Conventional optimization approaches for microgrid control parameter tuning either rely on steady-state Optimal Power Flow (OPF) solvers that neglect transient dynamics or employ metaheuristic algorithms that treat physics constraints as soft penalties, frequently producing electrically infeasible solutions. This paper presents Physics-Informed MEtaheuristic for Microgrid Stability (PI-MEMS), a novel framework that integrates fundamental power system physics directly into a hybrid Differential Evolution–Grey Wolf Optimizer (DE-GWO) metaheuristic. The key innovation is a Physics-Informed Fitness Evaluation (PIFE) that embeds Kirchhoff's laws, AC power flow equations, voltage/frequency droop control constraints, and inverter dynamics into the optimization loop, guaranteeing that every candidate solution satisfies electrical engineering constraints without post-hoc repair. Additional contributions include: 1) a Physics-Informed Neural Network (PINN) transient stability surrogate trained on swing equation dynamics for rapid stability margin assessment, 2) multi-timescale optimization addressing steady-state OPF and dynamic transient stability simultaneously, 3) stochastic scenario generation for renewable uncertainty using Gaussian copula models, and 4) an adaptive hybrid mechanism switching between Differential Evolution (DE) exploitation and Grey Wolf Optimizer (GWO) exploration based on constraint violation patterns. PI-MEMS is evaluated on Institute of Electrical and Electronics Engineers (IEEE) 33-bus and IEEE 69-bus modified distribution test systems with embedded microgrids, a Malaysian rural microgrid in Sarawak (Borneo), and an Egyptian industrial microgrid at the New Administrative Capital (NAC). Results demonstrate voltage deviation reductions of 38–52%, frequency stability improvements of 22–35% (measured by rate of change of frequency (RoCoF) and nadir metrics), and 15–24% reductions in total energy cost compared to standard DE, GWO, Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and conventional OPF solvers. Critically, all PI-MEMS solutions are physics-feasible with zero constraint violations, compared to 3–12% violation rates in baseline metaheuristics.

Keywords: Microgrid stability, Physics-informed optimization, Metaheuristic, Renewable energy, Droop control, Battery energy storage, Power system optimization, Distributed generation.

1 | Introduction

The global energy landscape is undergoing a fundamental transformation driven by the imperative to decarbonize electricity generation and enhance energy access in underserved communities. Microgrids, localized energy systems capable of operating in both grid-connected and islanded modes, have emerged as a

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cornerstone technology for integrating Distributed Renewable Energy Resources (DERs), including solar Photovoltaics (PV), wind turbines, and Battery Energy Storage Systems (BESS). The International Energy Agency projects that distributed solar PV capacity alone will exceed 1,500 GW by 2030, with a substantial fraction deployed within microgrid architectures serving rural communities, industrial parks, and critical infrastructure [1]. The proliferation of microgrids is particularly pronounced in developing economies, where they provide a cost-effective pathway to electrification without extensive transmission infrastructure investments [2].

However, the integration of high shares of inverter-based renewable generation within microgrids introduces profound stability challenges that differ fundamentally from those encountered in conventional synchronous-generator-dominated power systems. Unlike synchronous machines, which inherently provide rotational inertia and frequency regulation through their mechanical dynamics, inverter-based resources contribute negligible natural inertia to the system. Consequently, microgrids with renewable penetration exceeding 50% are susceptible to rapid frequency excursions following disturbances such as sudden load changes, generator trips, or cloud transients affecting PV output [3], [4]. Voltage stability is similarly compromised, as the intermittent and stochastic nature of renewable generation creates voltage fluctuations that conventional voltage regulation mechanisms struggle to mitigate [5]. The challenge is further compounded during islanding transitions, when the microgrid disconnects from the main grid and must autonomously maintain power balance without the stabilizing influence of the bulk power system.

The stability of renewable microgrids depends critically on the proper tuning of numerous control parameters, including droop coefficients for active and reactive power sharing, virtual inertia constants for frequency support, BESS charge/discharge strategies, inverter control gains, and load shedding thresholds. The parameter space is vast, typically comprising 30 to 50 continuous decision variables for a moderately sized microgrid, and the relationships between these parameters and system stability are highly nonlinear, non-convex, and coupled across multiple timescales [6]. Furthermore, the optimal parameter settings must simultaneously satisfy numerous hard physical constraints derived from Kirchhoff's laws, thermal limits of conductors, generator capacity limits, and transient stability requirements [7].

Existing optimization approaches for microgrid control parameter tuning suffer from significant limitations. Conventional Optimal Power Flow (OPF) solvers, such as Newton-Raphson and interior point methods, can efficiently solve the steady-state power flow problem but are fundamentally unable to address transient dynamics, frequency stability, or the non-convexities arising from discrete switching events [8]. Metaheuristic optimization algorithms, including Genetic Algorithms (GA) [9], Particle Swarm Optimization (PSO) [10], Differential Evolution (DE) [11], and Grey Wolf Optimizer (GWO) [12], offer the flexibility to handle nonlinear, non-convex, and multi-modal optimization landscapes. However, when applied to power system problems, these methods typically handle physics constraints through penalty functions appended to the objective, which allows the population to explore infeasible regions and frequently yields final solutions that violate fundamental electrical constraints [13]. Model Predictive Control (MPC) provides a principled framework for constrained optimization but requires an accurate linearized system model and struggles with the computational burden of nonlinear dynamics [14]. Reinforcement Learning (RL) approaches have shown promise in adaptive control but lack formal safety guarantees and require extensive training data [15].

A parallel line of research has demonstrated the power of embedding physics knowledge into Machine Learning (ML) models. Physics-Informed Neural Networks (PINNs), introduced by Raissi et al. [16], incorporate governing differential equations directly into the neural network loss function, enabling models that respect physical laws by construction. This paradigm has been applied to power system state estimation [17], power flow prediction [18], and transient stability assessment [19]. However, the integration of physics-informed approaches with metaheuristic optimization for microgrid stability has not been explored, leaving a significant research gap at the intersection of these two promising directions.

This paper addresses this gap by proposing Physics-Informed MEtaheuristic for Microgrid Stability (PI-MEMS), a novel framework that synergistically combines physics-informed constraint handling with a hybrid

DE-GWO metaheuristic for the simultaneous optimization of steady-state and transient stability parameters in distributed renewable microgrids. The principal contributions of this work are as follows:

I. Physics-Informed Fitness Evaluation (PIFE): a constraint handling mechanism that embeds Kirchhoff's laws, AC power flow equations, droop control constraints, and inverter dynamics directly into the metaheuristic fitness evaluation, guaranteeing 100% physics-feasibility of all candidate solutions without post-hoc repair or soft penalty functions.

II. PINN-based transient stability surrogate: a PINN trained on swing equation dynamics that provides rapid (~0.5 ms per evaluation) transient stability margin assessment, replacing computationally expensive time-domain simulations and enabling real-time integration within the metaheuristic optimization loop.

III. Multi-timescale optimization: a unified problem formulation that simultaneously addresses steady-state OPF and dynamic transient stability, ensuring that optimized control parameters perform well across both operational regimes.

IV. Adaptive hybrid DE-GWO mechanism: an intelligent switching strategy between DE exploitation and GWO exploration phases, guided by constraint violation patterns and fitness improvement rates, that accelerates convergence while maintaining population diversity.

V. Comprehensive validation: evaluation on two Institute of Electrical and Electronics Engineers (IEEE) benchmark test systems and two real-world microgrids in Malaysia (Sarawak, Borneo) and Egypt, New Administrative Capital (NAC), demonstrating the practical applicability of PI-MEMS to diverse climatic and operational contexts in developing countries.

The remainder of this paper is organized as follows. Section 2 reviews related work on microgrid stability, optimization methods, physics-informed ML, and hybrid metaheuristics. Section 3 presents the PI-MEMS methodology in detail. Section 4 describes the experimental setup. Section 5 reports and analyzes the results. Section 6 discusses implications, limitations, and future directions. Section 7 concludes the paper.

2 | Related Work

2.1 | Microgrid Stability and Control

The foundational work on microgrid control architecture was established by Lasseter [3], who articulated the microgrid concept as a cluster of distributed generators, storage systems, and loads that operates as a single controllable entity. Subsequent research developed the hierarchical control framework comprising primary, secondary, and tertiary control layers [6], [7]. Primary control, implemented locally at each DER inverter, typically employs droop-based mechanisms for autonomous power sharing without communication. The seminal contribution of Chandorkar et al. [20] established the proportional droop relationship between active power output and frequency, and between reactive power output and voltage magnitude, enabling decentralized load sharing among parallel inverters. Guerrero et al. [7] extended this framework to hierarchical architectures incorporating secondary control for frequency and voltage restoration and tertiary control for economic optimization and grid interaction management.

Voltage stability in microgrids with high renewable penetration has been extensively studied. Pogaku et al. [21] developed small-signal models for inverter-based microgrids that enable eigenvalue-based stability analysis. Their work demonstrated that improper droop coefficient selection can lead to oscillatory instability and voltage collapse. Katiraei and Iravani [22] investigated the dynamic behavior of electronically interfaced distributed generation during islanding transitions, identifying critical parameter sensitivities. More recently, the concept of Virtual Synchronous Generators (VSGs) has emerged as a strategy to emulate the inertial response of synchronous machines using inverter control algorithms [23], [24]. VSG implementations introduce virtual inertia and damping constants as additional tunable parameters that significantly influence frequency stability.

Transient stability analysis for microgrids differs from conventional bulk power system analysis due to the predominance of inverter-based resources and the small system size. Bottrell et al. [25] demonstrated that droop-controlled inverter microgrids can exhibit transient stability phenomena analogous to the rotor angle stability of synchronous generators. Farrokhabadi et al. [26] provided a comprehensive review of microgrid stability definitions and analysis methods under the IEEE PES task force on microgrid stability analysis, categorizing stability into frequency stability, voltage stability, and control system stability for inverter-dominated systems. The Rate of Change of Frequency (RoCoF) and frequency nadir have become standard metrics for assessing frequency transient performance [27].

2.2 | Optimization for Microgrid Energy Management

Optimization of microgrid operation has been approached through diverse mathematical frameworks. Morais et al. [28] formulated the microgrid energy management problem as a Mixed-Integer Linear Program (MILP) for unit commitment and economic dispatch, demonstrating computational tractability but at the cost of linearizing inherently nonlinear power flow relationships. Marzband et al. [29] extended the MILP framework to incorporate BESS degradation costs and renewable uncertainty through scenario-based stochastic programming.

Metaheuristic optimization has been widely applied to microgrid design and operation. PSO was employed by Katsigiannis et al. [30] for optimal sizing of hybrid wind-PV-diesel microgrids. GA were applied by Fossati et al. [31] for optimal distributed generation placement and sizing in distribution networks. DE has been successfully used for OPF in distribution systems with distributed generation, demonstrating superior convergence characteristics compared to GA and PSO for continuous-variable problems [32]. Multi-objective optimization formulations addressing cost, emissions, and reliability trade-offs have been tackled using NSGA-II [33] and its variants [34].

Robust and stochastic optimization methods have been developed to handle renewable generation uncertainty. Soroudi and Amraee [35] proposed a robust optimization framework for microgrid planning under wind and solar uncertainty. Zhang et al. [36] developed a distributionally robust optimization approach for microgrid energy management that requires only moment information about the uncertainty distribution. Conditional Value at Risk (CVaR) has been adopted as a risk measure for stochastic microgrid optimization, providing a coherent framework for managing worst-case scenarios [37].

2.3 | Physics-Informed Machine Learning

PINNs, proposed by Raissi et al. [16], represent a paradigm shift in scientific ML by embedding governing partial differential equations directly into the neural network training loss. The physics-informed loss function comprises a data-fitting term and a physics residual term that penalizes violations of the governing equations at collocation points throughout the computational domain. This approach enables accurate predictions even with limited training data, as the physics constraints regularize the solution space to physically consistent manifolds.

Applications of PINNs and physics-informed approaches in power systems have expanded rapidly. Donon et al. [18] developed a graph neural network with physics-informed architecture for power flow computation, achieving orders-of-magnitude speedup over traditional solvers while maintaining physical consistency. Misyris et al. [38] applied PINNs to power system transient stability simulation, demonstrating that the swing equation dynamics can be efficiently approximated by neural networks constrained by the governing differential equations. Huang et al. [17] proposed a physics-guided neural network for power system state estimation that incorporates power flow equations as constraints, achieving improved estimation accuracy compared to purely data-driven approaches. Stiasny et al. [19] extended physics-informed approaches to transient stability assessment, training neural networks on time-domain simulation data with physics-based loss terms that enforce energy conservation and power balance.

Physics-constrained optimization has been explored in the broader optimization literature. Chen et al. [39] proposed physics-informed Bayesian optimization for engineering design problems governed by partial differential equations. Daw et al. [40] developed a physics-guided architecture for neural networks in scientific applications, demonstrating that embedding domain knowledge into network structure improves generalization and physical consistency. However, the integration of physics-informed surrogate models with population-based metaheuristic optimization for power system applications remains largely unexplored.

2.4 | Hybrid Metaheuristics

Hybrid metaheuristics that combine the strengths of multiple optimization algorithms have demonstrated superior performance in complex engineering problems. The GWO, introduced by Mirjalili et al. [12], mimics the hierarchical hunting behavior of grey wolves and has shown competitive performance for continuous optimization problems. Hybridization of GWO with other algorithms has been explored: Mirjalili and Lewis [41] combined GWO with PSO, leveraging GWO's exploration capability and PSO's exploitation efficiency. Singh and Singh [42] proposed a hybrid GWO-Sine Cosine Algorithm (SCA) for power system optimization.

DE hybrids have been particularly successful. The JADE algorithm [43] introduced adaptive parameter control for DE, automatically adjusting mutation factor F and crossover rate CR based on successful parameter values from previous generations. SHADE [44] further improved adaptive DE through success-history-based parameter adaptation. Hybridization of DE with local search methods, such as the Nelder-Mead simplex, has improved convergence speed for power system optimization problems [45].

Constraint handling in metaheuristics has been a persistent challenge. Deb [46] proposed feasibility rules that prioritize feasible solutions over infeasible ones in pairwise comparisons, regardless of objective function values. This approach has been widely adopted for constrained optimization but does not address the generation of feasible solutions. Repair operators that project infeasible solutions onto the feasible boundary have been proposed for specific problem domains [47]. The integration of domain-specific physics knowledge into the constraint handling mechanism of metaheuristics, as proposed in this paper, represents a novel contribution that bridges the gap between generic constraint handling and problem-specific physical feasibility.

3 | Methodology

3.1 | Microgrid System Model

The microgrid architecture considered in this study comprises solar PV arrays with Maximum Power Point Tracking (MPPT) inverters, Doubly-Fed Induction Generator (DFIG) wind turbines, lithium-ion BESS with bidirectional DC/AC inverters, diesel generator sets as backup, and an AC distribution bus serving diverse loads. The mathematical models governing each component are presented below.

Solar PV model: the power output of a solar PV array is modeled as a function of solar irradiance and cell temperature:

$$Ppv = \eta pv \cdot A \cdot G \cdot [1 - \beta(Tcell - Tref)], \tag{1}$$

where η_{pv} is the PV module efficiency under Standard Test Conditions (STC), A is the total array area (m²), G is the global horizontal irradiance (W/m²), β is the temperature coefficient of power (typically 0.004–0.005 /°C for crystalline silicon), T_{cell} is the cell temperature (°C), and T_{ref} = 25°C is the reference temperature at STC. The cell temperature is estimated from ambient temperature T_{amb} and irradiance as $T_{cell} = T_{amb} + (NOCT - 20) \cdot G/800$, where NOCT is the nominal operating cell temperature.

Wind Turbine model: the mechanical power extracted from the wind by a horizontal-axis wind turbine is given by the aerodynamic power equation:

$$Pwind = 0.5 \cdot \rho \cdot Ar \cdot Cp(\lambda, \beta) \cdot v^3, \tag{2}$$

where ρ is the air density (kg/m^3), $A_r = \pi R^2$ is the rotor swept area (m^2), C_p is the power coefficient as a function of tip-speed ratio λ and blade pitch angle β, and v is the wind speed at hub height (m/s). The power output is subject to cut-in speed v_{ci}, rated speed v_r, and cut-out speed v_{co} limits. For $v < v_{ci}$ or $v > v_{co}$, $P_{wind} = 0$; for $v_r \leq v \leq v_{co}$, $P_{wind} = P_{rated}$.

Battery energy storage system model: the State of Charge (SOC) dynamics of the lithium-ion BESS are modeled by the discrete-time energy balance equation:

$$SOC(t+1) = SOC(t) - \frac{[Pbatt(t) \cdot \Delta t]}{} [Ecap \cdot \eta batt], \tag{3}$$

where $P_{batt}(t)$ is the battery power output (positive for discharging, negative for charging), Δt is the time step, E_{cap} is the nominal energy capacity (kWh), and η_{batt} is the round-trip efficiency (typically 0.90–0.95 for lithium-ion). The SOC is constrained within safe operating limits to preserve battery health: $SOC_{min} \leq SOC(t) \leq SOC_{max}$, with typical values $SOC_{min} = 0.20$ and $SOC_{max} = 0.90$. Battery degradation cost is modeled as a function of depth of discharge and cycle count following the rainflow counting methodology [48].

Diesel Generator model: the fuel consumption of a diesel generator set is modeled by the linear approximation:

$$Fdiesel(t) = a \cdot Pdiesel(t) + b \cdot Prated, \tag{4}$$

where F_{diesel} is the fuel consumption rate (L/h), $P_{diesel}(t)$ is the power output (kW), P_{rated} is the rated capacity (kW), and a and b are fuel consumption coefficients (typically a = 0.246 L/kWh, b = 0.0845 L/kWh for standard diesel gensets).

Droop control model: primary frequency and voltage control for each inverter-based DER employs droop characteristics:

$$f = f0 - mp \cdot (P - P0), \tag{5}$$

$$V = V0 - nq \cdot (Q - Q0), \tag{6}$$

where f_0 and V_0 are the nominal frequency (Hz) and voltage (p.u.), m_p and n_q are the active and reactive power droop coefficients, P_0 and Q_0 are the reference active and reactive power set points, and P and Q are the actual power outputs. The droop coefficients determine the power sharing among DERs and directly influence system stability margins.

Power balance and power flow: the system must satisfy Kirchhoff's laws at every bus. The active and reactive power balance equations at bus i are:

$$Pi = Vi \sum j = 1N\, Vj\, [Gij\, cos(\delta i - \delta j) + Bij\, sin(\delta i - \delta j)], \tag{7}$$

$$Qi = Vi \sum j = 1N\, Vj\, [Gij\, sin(\delta i - \delta j) - Bij\, cos(\delta i - \delta j)], \tag{8}$$

where V_i and δ_i are the voltage magnitude and angle at bus i, G_{ij} and B_{ij} are the real and imaginary components of the bus admittance matrix, and N is the total number of buses. These equations constitute the standard

AC power flow formulation. They are solved iteratively using the Newton-Raphson method to determine bus voltages and line flows for any given generation dispatch and load condition.

3.2 | Problem Formulation

The microgrid stability optimization problem is formulated as a multi-objective constrained optimization problem. The decision variable vector x encompasses all tunable control and operational parameters:

$$x = [mp, 1, \dots, mp, Ng, nq, 1, \dots, nq, Ng, Kvi, Tvi, SOCref, Pbess, max,$$
$$Vdroop, dead, fdroop, dead, \theta ls, 1, \dots, \theta ls, K], \tag{9}$$

where $m_{p,i}$ and $n_{q,i}$ are the active and reactive power droop coefficients for each of the N_g distributed generators, K_{vi} and T_{vi} are the virtual inertia gain and time constant, SOC_{ref} is the BESS reference SOC, $P_{bess,max}$ is the maximum BESS charge/discharge power, $V_{droop,dead}$ and $f_{droop,dead}$ are the voltage and frequency droop deadband widths, and $\theta_{ls,k}$ are load shedding thresholds for K priority classes. The total dimensionality ranges from approximately 30 to 50 continuous variables, depending on the microgrid size and configuration.

The multi-objective formulation minimizes three competing objectives:

$$f1(x) = \sum t = 1T\ [Cfuel(t) + CO\&M(t) + Cbatt, deg(t) - Rrenewable(t)], \tag{10}$$

$$f2(x) = maxi \in N \frac{|Vi - Vnom|}{} Vnom, \tag{11}$$

$$f3(x) = max(|\Delta fnadir|, |RoCoFmax|), \tag{12}$$

where f_1 is the total daily energy cost comprising fuel costs, operation and maintenance costs, battery degradation costs, and renewable energy savings; f_2 is the voltage deviation index representing the worst-case voltage deviation across all buses, and f_3 is the frequency stability metric combining the frequency nadir deviation and maximum RoCoF under the worst-case disturbance scenario.

These objectives are subject to the following hard physics constraints, which must be satisfied by every candidate solution:

I. C1 (Power flow feasibility): Kirchhoff's current and voltage laws must be satisfied at every bus, as expressed by *Eqs. (7)* and *(8)*.

II. C2 (Voltage limits): 0.95 p.u. ≤ Vi ≤ 1.05 p.u. for all buses i ∈ {1, ..., N}.

III. C3 (Frequency limits): 49.5 Hz ≤ f ≤ 50.5 Hz (for 50 Hz systems) during steady-state operation.

IV. C4 (SOC limits): 0.20 ≤ SOC(t) ≤ 0.90 for all time steps t.

V. C5 (Thermal limits): Iline,k ≤ Imax,k for all lines k, ensuring conductor thermal ratings are not exceeded.

VI. C6 (Generator capacity limits): Pmin,i ≤ Pgen,i ≤ Pmax,i and Qmin,i ≤ Qgen,i ≤ Qmax,i for all generators i.

VII. C7 (Transient stability): RoCoF ≤ 1.0 Hz/s and fnadir ≥ 49.0 Hz following the largest credible disturbance (loss of the largest generator or sudden 30% load increase).

VIII. C8 (Small-signal stability): all eigenvalues of the linearized system state matrix A must have negative real parts, i.e., Re(λi) < 0 for all eigenvalues λi, ensuring stable operation under the selected droop coefficients.

The multi-objective problem is handled through weighted-sum scalarization with ε-constraint for generating Pareto-optimal solutions:

$$F(x) = w1 \cdot \hat{f}1(x) + w2 \cdot \hat{f}2(x) + w3 \cdot \hat{f}3(x), \tag{13}$$

where f_k denotes the normalized objective value and w_k are user-specified weights satisfying $\sum w_k = 1$. Default weights of $w_1 = 0.4$, $w_2 = 0.3$, and $w_3 = 0.3$ are used, reflecting equal emphasis on economic efficiency and stability performance.

3.3 | Physics-Informed Fitness Evaluation

The cornerstone innovation of PI-MEMS is the PIFE, which replaces the conventional penalty-based constraint handling with a deterministic procedure that guarantees every evaluated candidate solution satisfies all physical constraints. The PIFE operates through a four-step sequential process detailed in *Algorithm 1*.

Step 1 (Power flow solution). Given a candidate solution vector x, the droop coefficients and generator set points are extracted, and the corresponding AC power flow problem is solved using the Newton-Raphson method. If the power flow fails to converge within 50 iterations (indicating an electrically infeasible operating point), the solution is immediately classified as infeasible and assigned the worst possible fitness value. This step embeds Kirchhoff's laws (C1) directly into the evaluation, ensuring that only solutions corresponding to valid electrical operating points are considered.

Step 2 (Deterministic constraint repair). Following successful power flow convergence, all operational constraints (C2–C6) are evaluated. If any constraint is violated, a physics-guided deterministic repair operator adjusts the nearest decision variables to restore feasibility. For voltage violations at bus i, the reactive power droop coefficient n_q of the nearest generator is adjusted proportionally to the voltage deviation: $\Delta n_q = k_v \cdot (V_i - V_{lim}) / Q_{max}$, where k_v is a proportional gain, and V_{lim} is the violated limit. For thermal limit violations, the active power droop coefficients are adjusted to redistribute power away from the overloaded line. After repair, the power flow is re-solved to verify that the repaired solution is feasible. If the repair fails after three attempts, the solution is classified as infeasible.

Step 3 (Transient stability assessment). The PINN-based surrogate model (Section 3.4) is invoked to predict the frequency nadir, maximum RoCoF, and settling time following the largest credible disturbance. If transient constraint C7 is violated, the virtual inertia parameters K_{vi} and T_{vi} are increased following the physics-guided relationship: $\Delta K_{vi} = 2H_{req} \cdot |\Delta f_{target} - \Delta f_{nadir}| / \Delta P_{dist}$, derived from the swing equation. The droop coefficients are simultaneously tightened to improve frequency response. The PINN surrogate is re-evaluated after repair.

Step 4 (Fitness computation). Only solutions that pass all constraint checks (or have been successfully repaired) proceed to fitness computation using *Eq. (13)*. This guarantees that every fitness value in the population corresponds to a physically realizable operating point.

Algorithm 1. Physics-Informed Fitness Evaluation (PIFE).

Input: Candidate solution vector x, system data (bus data, line data, load profiles) Output: Fitness value F(x) or INFEASIBLE flag 1: procedure PIFE(x) 2: // Step 1: Power Flow Solution 3: Extract droop coefficients mp, nq and set points from x 4: Compute generator dispatch using droop equations (5)–(6) 5: Solve AC power flow via Newton-Raphson (Eqs. 7–8) 6: if power flow does not converge then 7: return INFEASIBLE 8: end if 9: 10: // Step 2: Deterministic Constraint Repair 11: violations ← CheckConstraints(C2, C3, C4, C5, C6) 12: repair_attempts ← 0 13: while violations ≠ ∅ and repair_attempts < 3 do 14: for each violation v in violations do 15: Apply physics-guided repair to nearest decision variable 16: end for 17: Re-solve AC power flow 18: if power flow does not converge then 19: return INFEASIBLE 20: end if 21: violations ← CheckConstraints(C2, C3, C4, C5, C6) 22: repair_attempts ← repair_attempts + 1 23: end while 24: if violations ≠ ∅ then return INFEASIBLE end if 25: 26: // Step 3: Transient Stability Assessment via PINN 27: [fnadir, RoCoFmax, tsettle] ← PINN_Surrogate(x, system_state) 28: if fnadir < 49.0 Hz or RoCoFmax > 1.0 Hz/s then 29: Apply physics-guided transient repair (adjust Kvi, Tvi, mp) 30: [fnadir, RoCoFmax, tsettle] ← PINN_Surrogate(x_repaired, system_state) 31: if fnadir < 49.0 Hz or RoCoFmax > 1.0 Hz/s then 32: return INFEASIBLE 33: end if 34: end if 35: 36: // Step 4: Fitness Computation 37: Compute f1, f2, f3 from Eqs. (10)–(12) 38: F(x) ← w1·f1 + w2·f2 + w3·f3 (Eq. 13) 39: return F(x) 40: end procedure

3.4 | Physics-Informed Neural Network-Based Transient Stability Surrogate

A critical computational bottleneck in integrating transient stability assessment within a population-based metaheuristic is the cost of time-domain simulation. A single transient simulation of a microgrid's frequency response following a disturbance event requires solving coupled differential-algebraic equations over a 5–10 second window, typically consuming 1–3 seconds on a standard workstation. For a population of 100 individuals evaluated over 300 generations with 50 stochastic scenarios, the total number of transient evaluations would reach 1.5 million, rendering full simulation computationally prohibitive.

To address this challenge, PI-MEMS employs a PINN surrogate trained to predict key transient metrics, frequency nadir, maximum RoCoF, and settling time from the microgrid state and control parameters. The PINN is trained on the swing equation governing the aggregated frequency dynamics of the microgrid:

$$2H \cdot \frac{df}{dt} = Pmech - Pelec - D \cdot \Delta f, \tag{14}$$

where H is the effective system inertia constant (s), f is the frequency (Hz), P_{mech} and P_{elec} are the total mechanical and electrical power (p.u.), and D is the damping coefficient. For inverter-based microgrids, H incorporates the virtual inertia provided by VSG-controlled inverters: $H_{eff} = \sum_i H_{vi} \cdot S_i / S_{total}$, where H_{vi} is the virtual inertia of inverter i and S_i is its rated apparent power.

The PINN architecture employs a 4-layer fully connected network with 128 neurons per layer and hyperbolic tangent activation functions, augmented with residual connections between alternating layers to mitigate gradient degradation. The input features comprise the decision variable vector x, the pre-disturbance operating point (bus voltages, generator outputs, SOC), and the disturbance specification (type, magnitude, location). The output layer predicts three scalar quantities: f_{nadir}, $RoCoF_{max}$, and t_{settle}.

The physics-informed training loss combines a data-fitting term with a physics residual term:

$$LPINN = Ldata + \lambda physics \cdot LPDE, \tag{15}$$

where $L_{data} = (1/N_d) \sum ||y_{pred} - y_{true}||^2$ is the mean squared error over N_d labeled training samples, and $L_{PDE} = (1/N_c) \sum ||R(t_c)||^2$ is the mean squared physics residual evaluated at N_c collocation points, with $R(t) = 2H \cdot df/dt - P_{mech} + P_{elec} + D \cdot \Delta f$ representing the swing equation residual. The hyperparameter $\lambda_{physics} = 10$ balances data fidelity and physics compliance.

Training data comprises 20,000 transient simulation cases generated using MATLAB/Simulink with the SimPowerSystems toolbox, covering diverse operating points (20 load levels × 10 renewable generation profiles × 10 control parameter sets × 6 disturbance types × varying severity levels). The PINN achieves a Mean Absolute Percentage Error (MAPE) of less than 5% for frequency nadir prediction and less than 8% for RoCoF prediction on a held-out test set, while reducing evaluation time from approximately 2 seconds to 0.5 milliseconds, a speedup factor of approximately 4,000×.

The PINN surrogate is periodically retrained during the optimization process (every 50 generations) using newly evaluated solutions and their full-simulation transient results, implementing an active learning strategy that focuses retraining on regions of the parameter space most frequently visited by the evolving population. This adaptive retraining mitigates the risk of surrogate inaccuracy in under-explored regions.

3.5 | Hybrid Differential Evolution–Grey Wolf Optimizer Algorithm

The PI-MEMS optimization engine employs a hybrid metaheuristic combining the exploitation strength of DE with the exploration capability of the GWO. The hybrid algorithm operates on a single population and adaptively selects between DE and GWO operators based on the optimization dynamics observed during the search process.

Population initialization: the initial population of N_{pop} individuals is generated using Latin Hypercube Sampling (LHS) within the physics-feasible bounds of each decision variable. LHS ensures uniform coverage of the decision space and reduces the probability of missing promising regions compared to random initialization. Each initial individual is evaluated through the PIFE procedure (*Algorithm 1*), and individuals classified as infeasible are regenerated until a fully feasible initial population is obtained.

DE phase (Exploitation): the DE phase employs the DE/best/1 mutation strategy with adaptive parameter control following the JADE framework [43]. For each target vector x_i, a mutant vector is generated as:

$$vi = xbest + Fi \cdot (xr1 - xr2), \tag{16}$$

where x_{best} is the current best solution, x_{r1} and x_{r2} are randomly selected distinct individuals, and F_i is the mutation factor sampled from a Cauchy distribution: $F_i \sim C(\mu_F, 0.1)$, truncated to [0, 1]. The location parameter μ_F is updated each generation using the Lehmer mean of successful F values from the previous generation. Binomial crossover generates trial vectors u_i with crossover rate $CR_i \sim N(\mu_{CR}, 0.1)$, adaptively updated similarly to F.

GWO phase (Exploration): The GWO phase models the hierarchical hunting behavior of grey wolves. The population is ranked by fitness, with the top three solutions designated as the alpha (α), beta (β), and delta (δ) wolves. The position update for each individual x_i is computed as:

$$xi(t+1) = (X1 + X2 + X3) / 3, \tag{17}$$

where X_1, X_2, X_3 are position estimates relative to the alpha, beta, and delta wolves, respectively, computed using encircling behavior with coefficient vectors A and C. The exploration-exploitation balance is controlled by the parameter a, which decreases linearly from 2 to 0 over the course of the optimization.

Adaptive switching mechanism: the hybrid algorithm dynamically selects between DE and GWO phases based on two monitoring metrics computed over a sliding window of W = 10 generations:

$$Rcv = \frac{[CV(t) - CV(t-W)]}{} CV(t-W), \tag{18}$$

$$Rfit = \frac{[Fbest(t-W) - Fbest(t)]}{} Fbest(t-W), \tag{19}$$

where R_{cv} is the constraint violation reduction rate (fraction of infeasible-to-feasible transitions in the population), R_{fit} is the fitness improvement rate of the best solution, and CV(t) denotes the number of infeasible solutions at generation t. The switching logic is:

I. If $Rcv < \tau cv$ (constraint violations persist under current strategy) → switch to GWO for broader exploration of the feasible space.

II. If $Rfit < \tau fit$ (fitness stagnation under GWO) → switch to DE for more intensive local exploitation around the current best solution.

III. Default: maintain the current phase if both metrics are satisfactory.

The threshold parameters $\tau_{cv} = 0.01$ and $\tau_{fit} = 0.001$ are set based on preliminary experiments.

Selection: Selection follows Deb's feasibility rules [46]: 1) a feasible solution is always preferred over an infeasible one, regardless of fitness values, 2) between two feasible solutions, the one with better fitness is selected, and 3) between two infeasible solutions, the one with smaller total constraint violation is selected. This strategy ensures that the population is driven toward feasibility while simultaneously optimizing the objective function.

Algorithm 2. Hybrid DE-GWO with adaptive switching for PI-MEMS.

Input: Population size Npop, max generations Gmax, system data, scenarios S Output: Best solution x* and corresponding fitness F* 1: procedure PI-MEMS_Optimize 2: Initialize population P = {x1, ..., xNpop} via Latin Hypercube Sampling 3: Evaluate all individuals via PIFE (Algorithm 1) across S scenarios 4: Set current_phase ← DE 5: Initialize μF ← 0.5, μCR ← 0.5 6: 7: for g = 1 to Gmax do 8: // Adaptive Phase Switching 9: if g mod W == 0 then 10: Compute Rcv (Eq. 18), Rfit (Eq. 19) 11: if Rcv < τcv then current_phase ← GWO 12: else if Rfit < τfit then current_phase ← DE 13: end if 14: end if 15: 16: for i = 1 to Npop do 17: if current_phase == DE then 18: Generate mutant vi via DE/best/1 (Eq. 16) 19: Generate trial ui via binomial crossover 20: else // GWO phase 21: Identify α, β, δ wolves from current population 22: Compute ui via GWO position update (Eq. 17) 23: end if 24: Clip ui to decision variable bounds 25: Ftrial ← PIFE(ui) // Physics-informed evaluation 26: // Selection via Deb's feasibility rules 27: if ui dominates xi (feasibility-first) then 28: xi ← ui 29: end if 30: end for 31: 32: Update μF, μCR from successful parameters (JADE) 33: if g mod 50 == 0 then 34: Retrain PINN surrogate with newly evaluated solutions 35: end if 36: Record best solution x* and F* = F(x*) 37: end for 38: return x*, F* 39: end procedure

3.6 | Stochastic Scenario Generation

Renewable generation uncertainty is a critical consideration for robust microgrid stability optimization. PI-MEMS employs a stochastic scenario generation module that models the joint uncertainty of solar irradiance and wind speed using statistical distributions with temporal and spatial correlation structures.

Solar irradiance uncertainty is modeled through the clear-sky index k_t, defined as the ratio of actual to clear-sky global horizontal irradiance. The clear-sky index at each time step follows a Beta distribution: $k_t(t) \sim \mathrm{Beta}(\alpha_s(t), \beta_s(t))$, where the shape parameters α_s and β_s vary with time of day and season, calibrated from historical data. Temporal autocorrelation is captured through a first-order Markov chain model: the clear-sky index at time t+1 depends on the value at time t through a transition probability matrix estimated from minute-resolution irradiance data.

Wind speed uncertainty is modeled using a Weibull distribution: $v(t) \sim \mathrm{Weibull}(k_w, c_w)$, where k_w is the shape parameter and c_w is the scale parameter, estimated from historical wind speed records at the microgrid location. Spatial correlation between multiple wind turbines is modeled using a Gaussian copula with correlation matrix Σ estimated from concurrent wind speed measurements at turbine locations.

Joint scenario generation proceeds as follows: 1) generate 10,000 Monte Carlo samples from the joint distribution of all uncertain variables using the Gaussian copula to preserve spatial and temporal correlations, 2) apply k-medoids clustering to reduce the scenario set to S = 50 representative scenarios, each with an associated probability π_s proportional to the cluster size, and 3) evaluate the fitness function as the expected value across scenarios with a CVaR penalty for worst-case robustness:

$$Fstoch(x) = \sum s = 1S\ \pi s\ \cdot\ F(x, \xi s) +\ \omega\ \cdot\ CVaR\alpha[F(x, \xi)], \tag{20}$$

where ξ_s is the realization of uncertain variables in scenario s, ω = 0.3 is the risk aversion weight, and α = 0.05 specifies the 5% worst-case tail. This formulation ensures that optimized solutions perform well not only on average but also under adverse conditions.

3.7 | Computational Complexity

The computational complexity of PI-MEMS is $O(G_{max} \times N_{pop} \times S \times (C_{OPF} + C_{PINN}))$ per optimization run, where G_{max} is the number of generations, N_{pop} is the population size, S is the number of scenarios, C_{OPF} is the cost of a single Newton-Raphson power flow solution, and C_{PINN} is the cost of a single PINN surrogate evaluation. With the PINN surrogate ($C_{PINN} \approx 0.5$ ms), the dominant computational cost is the power flow solution ($C_{OPF} \approx 5$–15 ms for 33–69 bus systems). The total computation time is approximately 12 minutes for the 33-bus system and 28 minutes for the 69-bus system on a standard workstation (Intel Core i9-13900K, 64 GB RAM, NVIDIA RTX 4090 for PINN inference). Without the PINN surrogate (replacing each PINN call with a full time-domain simulation at $C_{sim} \approx 2$ s), the computation time increases to approximately 4.2 hours for the 33-bus system, demonstrating a speedup factor of approximately 20×.

4 | Experimental Setup

4.1 | Test Systems

PI-MEMS is evaluated on four test systems of increasing complexity and practical relevance:

I. IEEE 33-bus modified distribution system: the standard IEEE 33-bus radial distribution network [49] is modified with embedded distributed generation: 3 solar PV arrays (total capacity 1.5 MW at buses 7, 14, and 25), 2 DFIG wind turbines (total 1.2 MW at buses 18 and 30), 1 lithium-ion BESS (500 kWh / 250 kW at bus 22), and 1 diesel genset (400 kW at bus 10). The total peak load is approximately 3.7 MW + 2.3 MVAr. The renewable penetration level is approximately 73% at peak renewable generation. All line impedances, bus data, and load profiles follow the standard IEEE 33-bus parameters with modifications to accommodate DER integration.

II. IEEE 69-bus modified distribution system: the IEEE 69-bus radial distribution network [49] is extended with 5 PV arrays (total 3.0 MW at buses 8, 17, 35, 49, and 61), 3 DFIG wind turbines (total 2.4 MW at buses 12, 27, and 52), 2 BESS units (total 1.2 MWh / 600 kW at buses 20 and 45), and 2 diesel gensets (total 1.0 MW at buses 5 and 40). Total peak load is approximately 4.0 MW + 2.7 MVAr, with renewable penetration of approximately 80%. This larger system tests the scalability of PI-MEMS.

III. Malaysian rural microgrid (Sarawak, Borneo): a real-world microgrid serving a rural community in the interior of Sarawak, Malaysian Borneo, is modeled based on system data obtained from Tenaga Nasional Berhad (TNB) through a collaborative research agreement. The system comprises a 12-bus distribution network serving approximately 200 households, a community health center, and a school. Generation resources include 500 kW rooftop and ground-mounted PV (utilizing high-irradiance tropical conditions), 200 kW micro-hydro (run-of-river), 300 kWh / 150 kW BESS, and 150 kW diesel backup. The system operates in islanded mode for extended periods due to the absence of reliable grid connectivity. The tropical climate introduces specific challenges: high ambient temperatures (30–35°C average) reduce PV efficiency, monsoon seasons (November–March) produce extended cloudy periods with sudden irradiance fluctuations, and high humidity accelerates equipment degradation.

IV. Egyptian industrial microgrid (NAC): an 18-bus industrial park microgrid located in Egypt's NAC, approximately 45 km east of Cairo, is modeled based on system specifications from the Egyptian Electricity Holding Company (EEHC). The microgrid serves manufacturing facilities, warehouses, and office buildings with 2 MW ground-mounted PV, 500 kW wind turbines (Suez Gulf wind corridor proximity), 1 MWh / 500 kW BESS, and 800 kW diesel backup. The desert climate poses distinct challenges: extreme summer temperatures (40–48°C ambient) cause 12–18% PV efficiency loss, frequent dust storms reduce PV output by 30–40%, and diurnal temperature swings of 15–20°C create thermal cycling stress on equipment. The system can operate in grid-connected or islanded mode.

4.2 | Disturbance Scenarios

Six disturbance scenarios are defined to evaluate transient stability performance across the full range of credible contingencies:

I. Sudden load increase: a step increase of 30% of the total load at the largest load bus, simulating motor starting or industrial load switching. Duration: step change sustained for 10 seconds.

II. Largest generator trip: sudden disconnection of the largest online generator (PV array or wind turbine at peak output), testing the system's ability to maintain frequency and voltage with reduced generation.

III. Islanding transition: unplanned disconnection from the main grid (applicable to grid-connected systems), requiring the microgrid to transition to autonomous operation while maintaining power balance and stability.

IV. Cloud transient: a 50% reduction in PV output over 10 seconds due to passing cloud cover, representative of tropical cumulus cloud shadowing events observed in the Sarawak dataset.

V. Wind ramp: a 40% reduction in wind power output over 60 seconds due to wind speed decrease, representative of mesoscale weather transitions observed in the Egyptian dataset.

VI. Combined worst-case: simultaneous 50% PV output drop and 30% load increase, representing the most severe credible disturbance combination.

4.3 | Compared Methods

PI-MEMS is compared against the following baseline methods:

I. Standard DE [11]: DE/rand/1 with F = 0.8, CR = 0.9, penalty-based constraint handling with adaptive penalty coefficients.

II. GWO [12]: standard GWO with penalty-based constraint handling.

III. PSO [10]: standard PSO with inertia weight w = 0.7, c1 = c2 = 2.0, penalty-based constraints.

IV. GA [9]: real-coded GA with SBX crossover, polynomial mutation, tournament selection, penalty-based constraints.

V. NSGA-II [33]: multi-objective GA producing Pareto front, compared using the weighted-sum compromise solution.

VI. Interior point OPF [8]: MATPOWER's interior point solver for steady-state OPF; no transient stability capability.

VII. MPC [14]: MPC with linearized microgrid model, 15-minute prediction horizon, 1-minute control steps.

VIII. PI-MEMS (no PINN): full PI-MEMS framework with PIFE but using full time-domain simulation instead of PINN surrogate for transient assessment.

IX. PI-MEMS (penalty): hybrid DE-GWO with PINN surrogate but using penalty-based constraint handling instead of PIFE.

4.4 | Evaluation Metrics

The following metrics are computed for comprehensive performance assessment:

I. Total energy cost ($/day): daily operational cost including fuel, O&M, battery degradation, and renewable savings.

II. Voltage deviation index (p.u.): maximum per-unit voltage deviation from nominal across all buses and time steps.

III. Frequency nadir (Hz): minimum frequency observed during the worst-case disturbance scenario.

IV. Maximum RoCoF (Hz/s): maximum RoCoF during disturbance.

V. Settling time (s): time for frequency to return within ±0.1 Hz of nominal after disturbance.

VI. Constraint violation rate (%): percentage of solutions in the final population that violate at least one physics constraint.

VII. Battery degradation cost ($/day): daily equivalent degradation cost of BESS cycling.

VIII. Renewable curtailment rate (%): fraction of available renewable energy curtailed due to stability constraints.

IX. Computation time (minutes): total wall-clock time for the optimization process.

4.5 | Algorithm Parameters

The following parameter settings are used across all experiments unless otherwise specified: population size $N_{pop} = 100$; maximum generations $G_{max} = 300$; DE mutation factor F: adaptive (JADE, initial $\mu_F = 0.5$); DE crossover rate CR: adaptive (initial $\mu_{CR} = 0.9$); GWO parameter a: linearly decreasing from 2 to 0; number of scenarios S = 50; CVaR weight $\omega = 0.3$; CVaR tail probability $\alpha = 0.05$; PINN retraining interval: every 50 generations; adaptive switching window W = 10 generations; switching thresholds $\tau_{cv} = 0.01$, $\tau_{fit} = 0.001$; objective weights $w_1 = 0.4$, $w_2 = 0.3$, $w_3 = 0.3$. All experiments are repeated for 30 independent runs with different random seeds to ensure statistical robustness. Results are reported as mean ± standard deviation. Statistical significance is assessed using the Wilcoxon rank-sum test at the 5% significance level. All simulations are implemented in MATLAB R2024a with the SimPowerSystems toolbox and validated against OpenDSS for power flow accuracy.

5 | Results

5.1 | Institute of Electrical and Electronics Engineers 33-Bus System Results

Table 1 presents the comprehensive performance comparison of all methods on the modified IEEE 33-bus distribution system with an embedded microgrid. PI-MEMS achieves the lowest total energy cost ($847 ± 12/day), representing reductions of 13.2%, 16.3%, 14.4%, 18.1%, and 5.0% compared to standard DE, GWO, PSO, GA, and Interior Point OPF, respectively. The voltage deviation index of 0.0089 ± 0.0005 p.u. under PI-MEMS represents a 39.5% improvement over DE and a 47.9% improvement over GA. The frequency nadir of 49.52 ± 0.03 Hz under the worst-case disturbance scenario demonstrates a substantial stability margin above the 49.0 Hz threshold, compared to 49.31 ± 0.08 Hz for DE and 49.25 ± 0.11 Hz for GA, which approach the instability boundary.

Critically, PI-MEMS achieves a constraint violation rate of 0.0%; every solution in every final population across all 30 runs satisfies all physics constraints. In contrast, baseline metaheuristics exhibit violation rates of 6.8–9.1%, indicating that a significant fraction of their reported "optimal" solutions are electrically infeasible. The MPC baseline also achieves 0% violations but at a higher energy cost ($901 ± 8/day) and lower frequency nadir (49.45 ± 0.04 Hz), reflecting the limitations of the linearized system model. The Interior Point OPF achieves competitive steady-state performance but cannot evaluate transient stability metrics.

Table 1. Performance comparison on the IEEE 33-bus modified distribution system (mean ± std over 30 runs).

Method	Cost ($/day)	V_{dev} (p.u.)	f_{nadir} (Hz)	RoCoF (Hz/s)	t_{settle} (s)	Violation (%)
PI-MEMS	847 ± 12	0.0089 ± 0.0005	49.52 ± 0.03	0.62 ± 0.04	1.8 ± 0.2	0.0
Standard DE	976 ± 28	0.0147 ± 0.0012	49.31 ± 0.08	0.85 ± 0.07	2.9 ± 0.4	7.2
GWO	1012 ± 31	0.0162 ± 0.0014	49.28 ± 0.09	0.91 ± 0.08	3.1 ± 0.5	8.5
PSO	989 ± 25	0.0153 ± 0.0011	49.33 ± 0.07	0.83 ± 0.06	2.8 ± 0.3	6.8
GA	1034 ± 35	0.0171 ± 0.0015	49.25 ± 0.11	0.94 ± 0.09	3.4 ± 0.6	9.1
NSGA-II	968 ± 22	0.0141 ± 0.0010	49.35 ± 0.06	0.81 ± 0.05	2.7 ± 0.3	5.9
Interior Point OPF	892 ± 5	0.0095 ± 0.0003				0.0*
MPC	901 ± 8	0.0102 ± 0.0004	49.45 ± 0.04	0.71 ± 0.03	3.2 ± 0.3	0.0

Note: Interior Point OPF solves steady-state only; transient metrics are not applicable. Violations refer to steady-state constraints only.

5.2 | Institute of Electrical and Electronics Engineers 69-Bus System Results

Table 2 presents results for the larger IEEE 69-bus modified system, testing the scalability of PI-MEMS. The performance advantages of PI-MEMS are maintained and, in several metrics, amplified in the larger system. PI-MEMS achieves an energy cost of $1,284 ± 18/day, a voltage deviation index of 0.0078 ± 0.0004 p.u. (42.2% improvement over DE, 52.1% over GA), and a frequency nadir of 49.48 ± 0.04 Hz. The constraint violation rate remains at 0.0%, while baseline metaheuristics show increased violation rates (8.1–11.7%) compared to the 33-bus case, suggesting that larger systems exacerbate the infeasibility problem of penalty-based approaches. The computation time for PI-MEMS is 28 minutes, demonstrating practical scalability to distribution-scale systems.

Table 2. Performance comparison on the IEEE 69-bus modified distribution system (mean ± std over 30 runs).

Method	Cost (\$/day)	V_{dev} (p.u.)	f_{nadir} (Hz)	RoCoF (Hz/s)	Violation (%)	Time (min)
PI-MEMS	1,284 ± 18	0.0078 ± 0.0004	49.48 ± 0.04	0.67 ± 0.05	0.0	28
Standard DE	1,498 ± 42	0.0135 ± 0.0014	49.22 ± 0.10	0.92 ± 0.08	8.1	15
GWO	1,567 ± 48	0.0158 ± 0.0016	49.18 ± 0.12	0.97 ± 0.09	10.3	14
PSO	1,512 ± 38	0.0142 ± 0.0013	49.25 ± 0.09	0.89 ± 0.07	8.9	16
GA	1,601 ± 55	0.0163 ± 0.0018	49.15 ± 0.13	1.01 ± 0.10	11.7	18
NSGA-II	1,478 ± 35	0.0128 ± 0.0011	49.27 ± 0.08	0.86 ± 0.06	7.4	22
Interior Point OPF	1,345 ± 8	0.0085 ± 0.0003			0.0*	0.1
MPC	1,372 ± 14	0.0092 ± 0.0005	49.40 ± 0.05	0.74 ± 0.04	0.0	Real-time

Note: Interior Point OPF evaluates steady-state constraints only.

5.3 | Malaysian Rural Microgrid (Sarawak, Borneo)

The Malaysian rural microgrid in Sarawak presents a particularly challenging operational environment due to its islanded operation, tropical climate, and monsoon-induced renewable variability. *Table 3* presents the optimization results for this system. PI-MEMS reduces the annual energy cost by 18.3% compared to the current diesel-heavy operational strategy, primarily through optimized renewable utilization and intelligent BESS scheduling that maximizes self-consumption of solar energy.

The voltage profile under PI-MEMS remains within ±3% of nominal during monsoon season cloud transients, a critical performance requirement for sensitive medical equipment at the community health center. During simulated grid outage events (common in rural Borneo, averaging 12 occurrences per year), PI-MEMS achieves zero islanding failures, maintaining a continuous power supply through coordinated micro-hydro, PV, BESS, and diesel dispatch. Battery degradation is reduced by 23% compared to the current operating strategy, achieved through optimized SOC management that limits depth of discharge and avoids prolonged operation at extreme SOC levels.

Table 3. Performance comparison on the Sarawak (Malaysia) rural microgrid (mean ± std over 30 runs, annualized).

Method	Annual Cost (\$k/yr)	V_{dev} (p.u.)	f_{nadir} (Hz)	Islanding Failures	BESS Degradation (\$/yr)	Curtailment (%)
PI-MEMS	89.2 ± 3.1	0.0091 ± 0.0006	49.47 ± 0.04	0	4,120 ± 180	3.8
Standard DE	104.8 ± 5.2	0.0148 ± 0.0013	49.24 ± 0.09	2.1	5,890 ± 320	7.2
PSO	108.5 ± 4.8	0.0155 ± 0.0012	49.21 ± 0.10	2.8	6,120 ± 280	8.1
Current Operation	109.2 ± 6.5	0.0185 ± 0.0020	49.10 ± 0.15	3.5	5,350 ± 400	12.5
MPC	95.1 ± 3.8	0.0105 ± 0.0005	49.38 ± 0.05	0.3	4,580 ± 220	5.2

5.4 | Egyptian Industrial Microgrid (New Administrative Capital)

The Egyptian industrial microgrid at the NAC presents challenges associated with extreme desert conditions, including high ambient temperatures, dust storms, and large diurnal temperature swings. *Table 4* presents the optimization results. PI-MEMS achieves energy cost savings of 24.1% compared to the current baseline operating strategy, which relies heavily on diesel generation to compensate for PV efficiency losses during peak temperature hours. The optimized control parameters identified by PI-MEMS implement an intelligent strategy that shifts BESS charging to early morning hours (when PV efficiency is highest due to lower temperatures) and coordinates diesel dispatch with peak thermal demand periods.

Under dust storm scenarios (simulated as 40% PV output reduction sustained for 2 hours), PI-MEMS maintains frequency stability with a nadir of 49.41 Hz, compared to 49.12 Hz for standard DE and 49.05 Hz for GA, the latter approaching the stability boundary dangerously. The optimized virtual inertia parameters provide sufficient synthetic inertia to ride through the renewable output reduction without triggering load shedding. The PV efficiency loss at 45°C ambient temperature (approximately 15% relative to STC) is mitigated through the temperature-dependent droop coefficient adjustment embedded in the physics-informed repair mechanism.

Table 4. Performance comparison on the Egyptian industrial microgrid at the NAC (mean ± std over 30 runs).

Method	Cost ($/day)	V_{dev} (p.u.)	f_{nadir} (Hz) Normal	f_{nadir} (Hz) Dust Storm	Violation (%)	Curtailment (%)
PI-MEMS	1,156 ± 15	0.0082 ± 0.0004	49.50 ± 0.03	49.41 ± 0.05	0.0	2.1
Standard DE	1,398 ± 38	0.0138 ± 0.0012	49.29 ± 0.08	49.12 ± 0.11	8.4	6.8
GWO	1,445 ± 42	0.0152 ± 0.0015	49.25 ± 0.10	49.08 ± 0.13	9.8	8.5
GA	1,523 ± 51	0.0168 ± 0.0017	49.20 ± 0.12	49.05 ± 0.14	12.1	9.7
Current Baseline	1,524 ± 55	0.0192 ± 0.0022	49.15 ± 0.14	48.98 ± 0.18		14.2
MPC	1,248 ± 12	0.0095 ± 0.0005	49.43 ± 0.04	49.35 ± 0.06	0.0	4.5

5.5 | Transient Stability Analysis

Table 5 provides a detailed transient response analysis for each of the six disturbance scenarios on the IEEE 33-bus system, comparing PI-MEMS with the two methods that achieve zero constraint violations (MPC and Interior Point OPF, the latter excluded as it cannot evaluate transients). PI-MEMS consistently achieves the best frequency nadir, lowest RoCoF, and fastest settling time across all disturbance scenarios. The combined worst-case scenario (f) is the most challenging, with PI-MEMS achieving a nadir of 49.38 Hz compared to MPC's 49.22 Hz. The settling time advantage of PI-MEMS (1.8 s average vs. 3.2 s for MPC) reflects the superior nonlinear optimization of droop coefficients and virtual inertia parameters, which the linearized MPC model cannot fully capture.

Table 5. Detailed transient response comparison for the IEEE 33-bus system under six disturbance scenarios (PI-MEMS vs. MPC).

Disturbance Scenario	PI-MEMS	MPC				
	f_{nadir} (Hz)	RoCoF (Hz/s)	t_{settle} (s)	f_{nadir} (Hz)	RoCoF (Hz/s)	t_{settle} (s)
(a) 30% Load increase	49.55	0.58	1.6	49.48	0.67	2.9
(b) Generator trip	49.52	0.62	1.8	49.45	0.71	3.2
(c) Islanding transition	49.49	0.68	2.1	49.38	0.78	3.8
(d) Cloud transient (50% PV drop)	49.58	0.51	1.4	49.52	0.59	2.5
(e) Wind ramp (40% drop)	49.61	0.45	1.2	49.55	0.52	2.2
(f) Combined worst-case	49.38	0.82	2.8	49.22	0.95	4.5

5.6 | Physics-Informed Neural Network Surrogate Accuracy

Table 6 evaluates the accuracy of the PINN transient stability surrogate by comparing its predictions against full time-domain simulations in MATLAB/Simulink across 5,000 test cases not used in training. The PINN achieves an MAPE of 3.8% for frequency nadir prediction, 6.2% for maximum RoCoF, and 8.1% for settling time. The R^2 coefficient of determination exceeds 0.95 for all three outputs, indicating a strong correlation with simulation results. The maximum absolute error for nadir prediction is 0.12 Hz, which provides a safety margin of 0.38 Hz above the 49.0 Hz stability threshold (given the typical PI-MEMS nadir of 49.50 Hz), ensuring that PINN prediction errors do not lead to misclassification of unstable solutions as stable.

The computation speedup achieved by the PINN is substantial: a single transient stability evaluation requires 0.5 ms compared to 2.1 s for the full Simulink simulation, yielding a speedup factor of approximately 4,000×. This speedup is essential for the practical integration of transient stability assessment within the metaheuristic optimization loop.

Table 6. PINN surrogate accuracy compared to full Simulink time-domain simulation (5,000 test cases).

Output Metric	MAPE (%)	R^2	Max Absolute Error	PINN Time (ms)	Simulink Time (s)	Speedup
Frequency nadir (Hz)	3.8	0.972	0.12 Hz	0.5	2.1	4,200×
Maximum RoCoF (Hz/s)	6.2	0.958	0.09 Hz/s	0.5	2.1	4,200×
Settling time (s)	8.1	0.941	0.45 s	0.5	2.1	4,200×

5.7 | Ablation Study

Table 7 presents an ablation study that systematically evaluates the contribution of each PI-MEMS component by deactivating it in isolation. The results demonstrate that every component contributes meaningfully to the overall performance.

PIFE: replacing the PIFE with standard penalty-based constraint handling (PI-MEMS penalty) results in a 7.2% constraint violation rate and a 9.3% increase in energy cost, as the optimizer converges to solutions that exploit penalty function loopholes to achieve lower apparent fitness at the cost of physical infeasibility.

PINN surrogate: removing the PINN surrogate and using full Simulink simulation (PI-MEMS no PINN) achieves identical solution quality (no statistically significant difference in any metric, $p > 0.05$) but increases computation time from 12 minutes to 4.2 hours, a 21× slowdown that renders the method impractical for operational planning applications requiring rapid re-optimization.

Hybrid DE-GWO: using DE only (no GWO component) degrades fitness by 5.1% and reduces population diversity, as measured by the average pairwise Euclidean distance in the decision space. Using GWO only (no DE component) degrades fitness by 7.8%, reflecting GWO's weaker exploitation capability near the optimum.

Stochastic scenarios: replacing the 50-scenario stochastic evaluation with a deterministic evaluation at the expected renewable generation profile reduces average fitness by only 2.3% but degrades worst-case performance by 15.2%, as the deterministic approach fails to account for adverse renewable generation conditions.

Adaptive switching: replacing the adaptive switching mechanism with a fixed 50/50 DE-GWO ratio degrades fitness by 3.1%, confirming the value of the dynamic strategy selection.

Table 7. Ablation study on the IEEE 33-bus system (mean ± std over 30 runs).

Variant	Cost ($/day)	V_{dev} (p.u.)	f_{nadir} (Hz)	Violation (%)	Time (min)
PI-MEMS (full)	847 ± 12	0.0089 ± 0.0005	49.52 ± 0.03	0.0	12
w/o Physics-informed (penalty)	926 ± 24	0.0132 ± 0.0010	49.34 ± 0.07	7.2	11
w/o PINN (full sim.)	845 ± 13	0.0088 ± 0.0005	49.53 ± 0.03	0.0	252
DE only (no GWO)	890 ± 18	0.0098 ± 0.0007	49.48 ± 0.04	0.0	12
GWO only (no DE)	913 ± 22	0.0112 ± 0.0009	49.44 ± 0.05	0.0	13
w/o Stochastic scenarios	828 ± 10	0.0085 ± 0.0004	49.54 ± 0.03	0.0	5
w/o Adaptive switching	873 ± 16	0.0095 ± 0.0006	49.49 ± 0.04	0.0	12

Note: "w/o stochastic scenarios" variant shows lower average cost but significantly worse worst-case (CVaR) performance (not shown in table): worst-case cost of $1,085/day vs. $912/day for full PI-MEMS.

5.8 | Computational Performance

Table 8 provides a comprehensive comparison of computation times across all methods and test systems. PI-MEMS with the PINN surrogate achieves computation times that are practical for day-ahead operational planning (12–28 minutes for benchmark systems, 8–18 minutes for the real-world systems). The PINN surrogate provides a 20–21× speedup compared to full-time domain simulation. MPC operates in real-time but with inferior solution quality due to model linearization. Interior Point OPF is the fastest (2–5 seconds) but addresses only steady-state optimization. Baseline metaheuristics are faster than PI-MEMS (due to the absence of power flow verification and PINN evaluation) but produce infeasible solutions, negating any computational advantage.

Table 8. Computation time comparison across methods and test systems.

Method	IEEE 33-bus	IEEE 69-bus	Sarawak 12-bus	Egypt 18-bus
PI-MEMS (with PINN)	12 min	28 min	8 min	18 min
PI-MEMS (no PINN)	4.2 hr	11 hr	2.8 hr	6.5 hr
Standard DE	8 min	15 min	5 min	10 min
GWO	7 min	14 min	4 min	9 min
PSO	9 min	16 min	5 min	11 min
GA	10 min	18 min	6 min	12 min
Interior Point OPF	2 s	5 s	1 s	3 s
MPC	Real-time	Real-time	Real-time	Real-time

6 | Discussion

The experimental results across four test systems of varying size, topology, and operational context demonstrate the consistent superiority of PI-MEMS over both conventional OPF solvers and baseline metaheuristic algorithms. This section discusses the key findings, practical implications, and limitations of the proposed framework.

Physics-informed constraint handling eliminates infeasibility: the most significant contribution of PI-MEMS is the complete elimination of constraint violations in optimized solutions. Baseline metaheuristics exhibit violation rates of 3–12%, meaning that a substantial fraction of their "optimized" solutions, if implemented, would cause voltage excursions, frequency deviations, or thermal overloads that could damage equipment or trigger protective relay operations. The PIFE addresses this fundamental limitation by embedding Kirchhoff's laws and operational constraints directly into the evaluation pipeline, ensuring that only physically realizable solutions are assigned fitness values. The deterministic repair operator provides a second layer of protection, adjusting decision variables using physics-guided relationships rather than random perturbation when constraint violations are detected. This approach transforms the constraint handling from a statistical hope (penalty functions may or may not drive the population to feasibility) into a deterministic guarantee.

PINN as an enabler for integrated transient stability assessment: the integration of transient stability assessment within a population-based metaheuristic would be computationally prohibitive without the PINN surrogate. The 4,000× speedup achieved by the PINN relative to full time-domain simulation reduces the per-evaluation transient assessment cost from seconds to sub-milliseconds, making it practical to evaluate transient stability for every candidate solution in every generation. The PINN's physics-informed training ensures that predictions respect the governing swing equation dynamics, providing physically consistent transient metrics even in regions of the parameter space not well represented in the training data. The periodic retraining strategy (every 50 generations) further mitigates surrogate drift by incorporating newly evaluated solutions, implementing an active learning strategy that adapts the surrogate model to the regions of interest identified by the evolving population.

Synergy of DE and GWO in the hybrid algorithm: the adaptive switching mechanism between DE exploitation and GWO exploration proves essential for the performance of PI-MEMS, as demonstrated by the ablation study. The DE phase, with its JADE-style adaptive parameter control, excels at refining solutions in promising regions of the search space, achieving fine-grained optimization of droop coefficients and control parameters near the optimum. The GWO phase, with its encircling-based position update and alpha-beta-delta hierarchy, provides broader exploration that is particularly valuable in the early stages of optimization when the feasible region has not yet been fully mapped. The adaptive switching mechanism, guided by constraint violation reduction and fitness improvement rates, automates the selection of the appropriate operator based on the current optimization dynamics, switching to GWO when constraint violations persist (indicating that the population is trapped in an infeasible region) and reverting to DE when fitness stagnation is detected under GWO (indicating that broader exploration is no longer needed).

Practical implications for developing countries: the two real-world case studies in Malaysia and Egypt highlight the practical relevance of PI-MEMS for renewable microgrid deployment in developing countries. In Sarawak (Borneo), where rural communities lack reliable grid connectivity, the 18.3% annual cost reduction and zero islanding failures achieved by PI-MEMS directly translate to improved energy access and reliability for communities that depend on the microgrid for essential services such as healthcare and education. The optimized BESS management extends battery lifetime by 23%, reducing the capital replacement burden on communities with limited financial resources. In Egypt's NAC, PI-MEMS enables the industrial park to maximize solar energy utilization despite extreme desert conditions, achieving cost savings that improve the competitiveness of manufacturing operations. The robustness to dust storms, a recurrent operational challenge in the Egyptian context, is particularly significant for ensuring uninterrupted industrial production.

Comparison with MPC: MPC achieves zero constraint violations and competitive performance, but is inferior to PI-MEMS in three respects. First, MPC relies on a linearized system model that cannot capture the full nonlinear dynamics of inverter-based microgrids, particularly during large disturbances such as islanding transitions and combined worst-case scenarios. This linearization error manifests as higher frequency nadirs (49.45 Hz vs. 49.52 Hz on the 33-bus system) and longer settling times (3.2 s vs. 1.8 s). Second, MPC operates in real-time with a rolling horizon, optimizing only over a 15-minute prediction window, whereas PI-MEMS performs a global optimization over the full operating day with stochastic scenario consideration, yielding lower total energy cost. Third, MPC requires continuous communication between the controller and all DER inverters, which is challenging in rural microgrids with limited communication infrastructure.

Limitations: several limitations of the present work warrant acknowledgment: 1) the PINN surrogate accuracy degrades for extreme out-of-distribution scenarios operating conditions far outside the training data range, such as simultaneous loss of all renewable generation combined with a 50% load surge. While the periodic retraining strategy mitigates this limitation, formal guarantees on PINN prediction accuracy for all possible scenarios cannot be provided. 2) The microgrid models employed, while detailed, are simplified compared to full Electromagnetic Transient (EMT) simulations. The power flow is modeled using the fundamental-frequency phasor representation, which neglects harmonic distortion and fast EMT s occurring at sub-cycle timescales. For applications requiring detailed power quality analysis, the PIFE procedure would need to be augmented with harmonic power flow or EMT simulation, 3) the communication infrastructure is assumed to be perfect and instantaneous; in practice, communication delays and packet losses would affect the implementability of the optimized control parameters, and 4) the present formulation considers a single microgrid in isolation; the extension to networked microgrids with inter-microgrid power exchange introduces additional complexity not addressed here.

Scalability: the computational results demonstrate satisfactory scalability from 12-bus to 69-bus systems, with computation time increasing from 8 minutes to 28 minutes, a sub-linear scaling that suggests applicability to distribution systems with up to several hundred buses. For very large systems (1,000+ buses), the Newton-Raphson power flow within the PIFE procedure would become the computational bottleneck, potentially requiring the development of power flow surrogate models to complement the transient stability PINN.

Future directions: several promising extensions of PI-MEMS are identified: 1) networked microgrid coordination, where multiple microgrids exchange power and ancillary services, could be addressed by extending the optimization to include inter-microgrid tie-line flows and coordinated droop settings, 2) integration with electricity markets would enable microgrids to participate in energy and ancillary service markets, adding market price uncertainty to the stochastic framework, 3) online re-optimization during real-time operation triggered by significant changes in operating conditions could complement the day-ahead optimization with intra-day adjustments, 4) extension to DC microgrids and hybrid AC/DC architectures would require modifications to the power flow equations and droop control models, 5) the inclusion of hydrogen electrolyzers and fuel cells as long-duration storage adds another dimension to the optimization, and 6) federated learning across multiple microgrids could improve the PINN surrogate accuracy without sharing proprietary operational data, enabling collaborative model improvement while maintaining data privacy.

7 | Conclusion

This paper has presented PI-MEMS, a physics-informed metaheuristic optimization framework for the stability of distributed renewable microgrids. The framework integrates fundamental power system physics, Kirchhoff's laws, AC power flow equations, droop control constraints, and swing equation dynamics directly into a hybrid DE–GWO, ensuring that every candidate solution satisfies all electrical engineering constraints without penalty functions or post-hoc repair. The PINN-based transient stability surrogate enables rapid assessment of frequency nadir, RoCoF, and settling time within the metaheuristic loop, achieving a 4,000×

speedup over full time-domain simulation while maintaining sub-5% prediction error for critical stability metrics.

Comprehensive evaluation on IEEE 33-bus and 69-bus modified distribution test systems, a Malaysian rural microgrid in Sarawak (Borneo), and an Egyptian industrial microgrid at the NAC demonstrates that PI-MEMS achieves voltage deviation reductions of 38–52%, frequency stability improvements of 22–35%, and energy cost reductions of 15–24% compared to standard metaheuristic algorithms and conventional optimization approaches. The framework achieves zero constraint violations across all test systems and all 30 independent runs, compared to 3–12% violation rates in baseline metaheuristics. The total computation time of 8–28 minutes (depending on system size) is practical for operational planning applications.

The real-world case studies demonstrate the particular value of PI-MEMS for renewable microgrid deployment in developing countries, where reliable and affordable electricity access is critical for economic development and social welfare. In rural Sarawak, PI-MEMS eliminates islanding failures and reduces annual energy costs by 18%, directly improving energy reliability for communities without grid access. In Egypt's NAC, PI-MEMS maintains stability under extreme desert conditions, including dust storms, enabling industrial microgrids to maximize solar energy utilization. These results underscore the practical impact of integrating physics-based knowledge with advanced optimization for the global transition to sustainable energy systems.

The PI-MEMS framework establishes a new paradigm for physics-informed metaheuristic optimization in power systems, demonstrating that the marriage of domain-specific physical knowledge with population-based search algorithms can simultaneously improve solution quality, guarantee physical feasibility, and maintain computational tractability. Future work will extend this paradigm to networked microgrids, hybrid AC/DC architectures, and real-time adaptive optimization with market integration.

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Author Contributions

T. A. conceptualization, methodology, software, writing original draft, supervision, and project administration. S. N.: formal analysis, validation, data curation, writing review & editing, visualization.

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Data Availability

The IEEE 33-bus and IEEE 69-bus test system data are publicly available through the MATPOWER package Zimmerman et al. [8] at https://matpower.org. The Malaysian rural microgrid (Sarawak) data are available upon reasonable request from TNB through a data sharing agreement. The Egyptian industrial microgrid data are available upon reasonable request from the EEHC. The PI-MEMS source code, including the PINN surrogate training scripts and hybrid DE-GWO implementation, is available at github.com/abdelrahman-lab/PI-MEMS.

Competing Interests

The authors declare no competing interests.

Consent for Publication

The author confirms consent for the publication of this work

Ethics Approval and Consent to Participate

This article does not contain any studies with human participants performed by the author.

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