



# Enhanced Particle Swarm Optimisation for Optimal Economic Dispatch of a Standalone Renewable Microgrid

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## ABSTRACT

Optimal energy management in renewable-based standalone microgrids is a complex nonlinear optimization problem, particularly under Malaysian operating conditions where solar photovoltaic (PV) and wind turbine (WT) generation are affected by weather variability. This study proposes an Enhanced Particle Swarm Optimization (E-PSO) framework for the optimal economic dispatch of an islanded microgrid consisting of a 200 kWp PV system, a 100 kW wind turbine, a 150 kW diesel generator (DG), and a 300 kWh battery energy storage system (BESS). The objective function minimizes the total daily operating cost by accounting for diesel fuel costs, CO<sub>2</sub> emission penalties, battery degradation costs, and the costs of energy not served (CENS). Minimum up and down time constraints for diesel generators are handled using binary commitment variables and a post-update repair mechanism. At the same time, the power balance formulation includes energy not served and renewable curtailment to ensure operational feasibility. Simulation results over a 24-hour scheduling horizon show that the proposed E-PSO achieves the lowest operating cost of USD 319.50/day, reducing costs by 27.4% compared with the load-following strategy (LFS) and 15.1% compared with the genetic algorithm (GA). Renewable penetration reaches 59.6%, higher than 46.8% under LFS. Statistical evaluation over 30 independent runs gives a standard deviation of USD 1.72, indicating stable convergence. Sensitivity analysis under varying solar irradiance, wind speed, BESS capacity, and carbon penalty confirms the robustness of the proposed framework for day-ahead operation of standalone renewable microgrids in Malaysia.

**Keywords:** Microgrid; Economic dispatch; Particle swarm optimization; Renewable energy; Battery energy storage.

## 1. Introduction

The global energy landscape is undergoing a profound transformation, propelled by the urgent imperative to decarbonize electricity generation and extend energy access to underserved communities in remote regions. Solar photovoltaic (PV) and wind power have experienced remarkable cost reductions over the past decade, with global weighted average levelized costs falling by 89% and 70% respectively between 2010 and 2023, making them economically competitive with conventional fossil-fuel generation in most markets [1, 2]. Notwithstanding these advances, the inherently intermittent and stochastic nature of renewable energy sources (RES) introduces significant operational challenges: system operators must guarantee reliable, cost-effective, and environmentally responsible electricity supply while managing generation that cannot be dispatched on demand [3]. In addition, integrating RES into standalone microgrids represents a strategically critical pathway toward energy security and sustainability [4, 5].

Microgrids (MGs) are localized, self-contained energy ecosystems that integrate distributed energy resources (DERs), including PV arrays, wind turbines, diesel generators, battery energy storage systems (BESS), and smart controller within a coordinated energy management system (EMS) [6, 7]. When operating in islanded mode, a microgrid must independently maintain frequency, voltage, and power balance, demanding sophisticated optimization of all constituent units. The Optimal Economic Dispatch (OED) problem governs this scheduling: given time-varying renewable generation forecasts and load demand profiles, the EMS must determine the output of each controllable generation unit and the BESS charge/discharge schedule over a 24-hour horizon to minimize a multi-component cost objective subject to a comprehensive set of technical, operational, and regulatory constraints [8]. The resulting problem is non-linear, non-convex, combinatorial (due to unit commitment binary variables), and high-dimensional, rendering classical deterministic methods such as linear programming and dynamic programming computationally inadequate for real-time scheduling applications [9].

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Metaheuristic optimization algorithms have emerged as the preferred tools for solving complex power system scheduling problems due to their ability to navigate high-dimensional non-convex search spaces without requiring gradient information [10]. Among these, Particle Swarm Optimization (PSO) has achieved widespread adoption in power systems research due to its conceptual simplicity, low parameter sensitivity, and robust convergence behavior across diverse problem formulations [11, 12]. Inspired by the collective foraging behavior of bird flocks and fish schools, PSO maintains a swarm of candidate solutions (particles) that iteratively update their positions in the decision space by learning from their own best-found solution (cognitive component) and the global best solution found by the swarm (social component). Despite its strengths, standard PSO exhibits a well-documented tendency toward premature convergence when the inertia weight is held constant, motivating extensive research into adaptive and enhanced variants [13, 14].

A critical review of the recent microgrid-dispatch studies reveals four persistent gaps that are directly relevant to the present formulation. Must focusing on PSO-based microgrid OED studies. First, the power balance formulations employed in most existing works do not explicitly include energy not served (ENS) and renewable curtailment as decision variables, leading to mathematical inconsistencies between the objective function, which includes an ENS cost term, and the equality constraints. Second, while many studies claim to enforce minimum uptime and downtime (MUT/MDT) constraints for dispatchable generators, the binary commitment variables and repair mechanisms necessary to implement these constraints within a continuous-variable PSO framework are rarely formalized or described in sufficient detail for reproducibility. Third, sensitivity analyses under realistic correlated renewable variability scenarios are seldom reported comprehensively, limiting the practical applicability of published results. Fourth, simplifications battery-degradation model is frequently employed without transparent acknowledgment of their limitations, potentially misleading practitioners about battery lifetime predictions. These gaps concern formulation consistency, reproducibility, and validation breadth rather than the absence of PSO variants themselves.

This paper addresses all four identified gaps through an integrated framework with the following original contributions: (1) a multi-component OED formulation for an islanded PV-WT-DG-BESS microgrid with a power balance explicitly including ENS and renewable curtailment; (2) a defined binary commitment variables with a post-update constraint-repair operator for MUT/MDT enforcement; (3) an E-PSO implementation that combines adaptive quadratic inertia-weight decay and velocity clamping; (4) benchmarking against LFS, GA, and S-PSO together with repeated-run descriptive statistics and four sensitivity studies; and (5) an explicit discussion of forecast, network, battery model, data validation, scalability, and real-time implementation limitations. The methodological novelty is therefore incremental, as the adaptive PSO mechanisms are established; the main originality lies in the integrated formulation, constraint-handling workflow, and application-oriented validation for the studied standalone microgrid. The remainder of the paper is organized as

follows. Section 2 presents the critical literature review, methodology, system description, mathematical models, and implementation details. Section 3 presents the case-study results, benchmarking, repeated-run analysis, sensitivity analysis, and limitations. Section 4 concludes the paper and outlines practical and theoretical implications.

## 2. Methods and modelling

### 2.1. State of the Art

Recent microgrid OED research increasingly integrates economic, environmental, and reliability objectives, yet methodological coverage remains uneven. Table 1 summarizes the most closely related studies by research focus, solution method, and reported outcome. The comparison is used critically rather than as a direct ranking because the cited studies employ different system sizes, objective functions, constraints, and datasets. The relevant question is therefore not which method reports the largest percentage improvement, but whether the formulation jointly represents reliability, curtailment, commitment constraints, reproducible constraint handling, and uncertainty or sensitivity assessment.

**Table 1**

State of the art review of recent microgrid OED and PSO-based optimization studies.

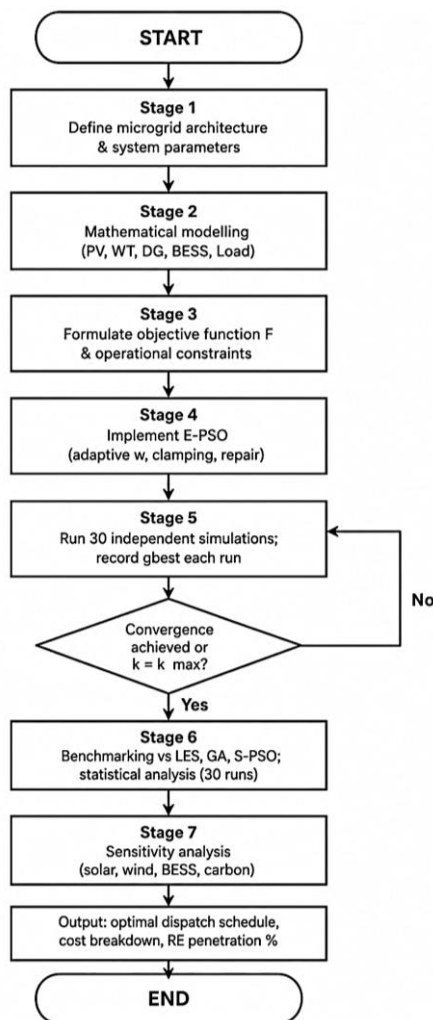
| Author(s)          | Year | Research Focus                        | Method             | Main Finding                                           |
|--------------------|------|---------------------------------------|--------------------|--------------------------------------------------------|
| Ayub et al. [15]   | 2024 | PV-BESS-DG cost minimization          | BWO                | 21.3% cost reduction; ENS absent from power balance    |
| Jin et al. [16]    | 2024 | H2-integrated MG Day-ahead dispatch   | IHBA               | 16.5% reduction; 55% RE penetration achieved           |
| Qi et al. [17]     | 2024 | DG-RES-FC siting and sizing           | Hybrid GWO         | 18.0% cost improvement; no sensitivity analysis        |
| Akbari et al. [18] | 2024 | Networked MG stochastic management    | Stochastic opt.    | Robust under demand uncertainty; limited RE study      |
| Alao et al. [19]   | 2024 | Biogas DG placement and sizing        | IPSO               | 3–8% over PSO via adaptive inertia; no MUT/MDT         |
| Yang et al. [20]   | 2024 | Low-carbon integrated energy dispatch | LP-based           | CO <sub>2</sub> reduction with CCS-P2G-CHP integration |
| Ahmed et al. [21]  | 2024 | Demand response with voltage support  | RL multi-agent     | Incentive-based DR with voltage regulation             |
| Saeed et al. [22]  | 2024 | P2P energy trading in MG              | Blockchain + Smart | Decentralized trading reduces cost by 12–18%           |

The comparison in Table 1 shown that individual studies address selected aspects of the problem but not the complete combination considered here. The BWO study [15] reports cost reduction, but the summarized formulation omits ENS from the power balance; the hybrid GWO study [17] reports improvement without sensitivity analysis; and the IPSO study [19] demonstrates the value of adaptive inertia but does not formalize MUT/MDT handling. The stochastic, low-

carbon, demand-response, and peer-to-peer studies [18, 20–22] address important complementary objectives. Yet their focus differs from the reproducible, commitment-constrained dispatch of a standalone PV-WT-DG-BESS system. Consequently, the present work does not claim that its PSO operators are fundamentally new or that its percentage savings are directly comparable to those reported in those studies. Its originality lies in the joint and explicit treatment of reliability variables, curtailment, generator commitment repair, and multi-parameter sensitivity within a single reproducible dispatch workflow.

## 2.2. Research Methodology

The research methodology is organized into a systematic seven-stage simulation framework, illustrated in Fig. 1. Each stage is sequentially dependent on the outputs of the preceding stage, ensuring a rigorous and reproducible research workflow.



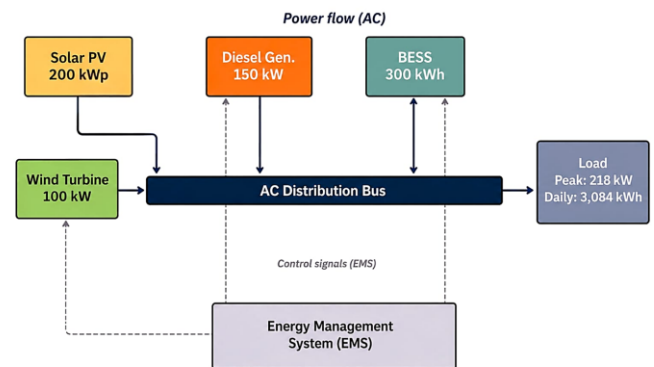
**Fig. 1.** Research methodology flowchart illustrating the seven-stage simulation framework.

Stage 1 defines the microgrid architecture and operating parameters, including component ratings, efficiency coefficients, and constraint bounds as summarized in Table 2. Stage 2 develops mathematical models for all generation, storage, and demand components (Sections 2.3–2.4). Stage 3 formulates the multi-component objective function (Eq. 7) and the complete set of operational constraints (Eq. 8–12). Stage 4 implements the E-PSO algorithm with adaptive quadratic inertia weight, velocity clamping, and binary

commitment repair (Section 2.5). Stage 5 executes the E-PSO optimization loop across 30 independent simulation runs with different random seeds, recording the global best solution (gbest) at each run; iterations continue until convergence is achieved ( $|\Delta F| < 10^{-6}$ ) or the maximum iteration count  $k_{\max}$  is reached. Stage 6 benchmarks E-PSO against the load-following strategy (LFS), the genetic algorithm (GA), and standard PSO (S-PSO) and performs statistical analysis across all 30 runs. Stage 7 conducts sensitivity analysis across four stochastic variability scenarios: (i) solar irradiance levels (S1–S4), (ii) wind speed profiles (W1–W3), (iii) BESS capacity (150–450 kWh), and (iv) carbon penalty price (USD 0.010–USD \$0.100/kg). All simulations are implemented in MATLAB.

## 2.3. System Description

The study considers a renewable energy-based microgrid representative of typical rural electrification configurations in Malaysia. The system architecture is illustrated in Fig. 2. The microgrid comprises four main energy conversion and storage components connected to a common AC distribution bus, coordinated by an EMS that executes the E-PSO dispatch algorithm. Component specifications are: (1) Solar PV Array: 200 kWp rated power, comprising 500 polycrystalline silicon modules of 400 Wp each, connected via a DC/AC inverter with efficiency  $\eta_{\text{inv}} = 0.96$  and  $\text{NOCT} = 45^\circ\text{C}$ ; (2) Wind Turbine (WT): 100 kW rated power at hub height of 30 m, with piecewise power curve defined by cut-in speed  $v_{\text{ci}} = 3 \text{ m/s}$ , rated speed  $v_r = 12 \text{ m/s}$ , and cut-out speed  $v_{\text{co}} = 25 \text{ m/s}$ ; (3) Diesel Generator (DG): 150 kW rated output, minimum stable generation  $P_{\text{DG, min}} = 30 \text{ kW}$ , subject to ramp-rate and minimum up/downtime constraints; and (4) Battery Energy Storage System (BESS): 300 kWh usable capacity, maximum charge/discharge power 100 kW, lithium-ion technology with round-trip efficiency  $\eta = 0.95^2 = 0.9025$ . The load profile has a daily energy demand of 3084 kWh, peaking at 218 kW at hour 19 and reaching minimum demand of 78 kW at hour 4.



**Fig. 2.** Architecture of the islanded renewable energy-based microgrid system.

## 2.4. Mathematical Modelling

### 2.4.1. Photovoltaic Generation Model

The AC output power of the PV array at each hourly time step  $t$  is modelled as a function of incident solar irradiance  $G(t)$  ( $\text{W/m}^2$ ) and cell temperature  $T_{\text{c}}(t)$  ( $^\circ\text{C}$ ), following the standard temperature-corrected irradiance model [23]:

$$P_{PV}(t) = \eta_{inv} P_{rated} \frac{G(t)}{G_{STC}} [1 + K(T_c(t) - T_{STC})] \quad (1)$$

Where  $P_{rated} = 200$  kWp is the array rated power under standard test conditions ( $G_{STC} = 1000$  W/m<sup>2</sup>,  $T_{STC} = 25^\circ\text{C}$ ), and  $K = -0.0045/^\circ\text{C}$  is the temperature power coefficient for polycrystalline silicon. Cell temperature is estimated from the ambient temperature  $T_a(t)$  and incident irradiance using the nominal operating cell temperature (NOCT) correlation,  $T_c(t) = T_a(t) + \frac{NOCT-20}{800} G(t)$ , with  $NOCT = 45^\circ\text{C}$ .

#### 2.4.2. Wind Turbine Generation Model

Wind turbine power output is computed from the standard piecewise power curve, which accounts for the cubic relationship between wind speed and power in the partial-load region [24]:

$$P_{WT}(t) = 0, v < v_{ci} \text{ or } v > v_{co} \quad (2a)$$

$$P_{WT}(t) = P_r \frac{v^3 - v_{ci}^3}{v_r^3 - v_{ci}^3}, v_{ci} \leq v < v_r \quad (2b)$$

$$P_{WT}(t) = P_r, v_r \leq v \leq v_{co} \quad (2c)$$

Hub-height wind speed is extrapolated from the 10-m reference measurement using the power law:  $v_{hub} = v_{ref} \left( \frac{h_{hub}}{h_{ref}} \right)^\alpha$ , where  $\alpha = 0.14$  is the surface roughness coefficient for flat coastal terrain and  $h_{hub} = 30$  m.

#### 2.4.3. Diesel Generator Cost Model

The fuel consumption cost of the DG at each time step is expressed as a standard quadratic function of output power, consistent with the input-output heat rate curve formulation used in classical economic dispatch [25]:

$$C_{fuel}(t) = [aP_{DG}^2(t) + bP_{DG}(t) + c]\Delta t \quad (3)$$

Where  $a = 0.00005$  USD/kW<sup>2</sup>h,  $b = 0.155$  USD/kWh,  $c = 3$  USD/h, and  $\Delta t = 1$  h. The cost coefficients are calibrated to represent a typical 150 kW diesel generator operating. The associated CO<sub>2</sub> emission penalty cost reflecting environmental externalities is:

$$C_{em}(t) = \lambda_{CO_2} EF_{DG} \left( \frac{P_{DG}(t)}{LHV \times \eta_{DG}} \right) \Delta t \quad (4)$$

Where,  $\lambda_{CO_2} = 0.020$  USD/kg CO<sub>2</sub> is the carbon penalty price (baseline),  $EF_{DG} = 2.68$  kg CO<sub>2</sub>/litre is the diesel emission factor,  $LHV = 10.35$  kWh/litre is the lower heating value of diesel, and  $\eta_{DG} = 0.33$  is the average generator efficiency.

#### 2.4.4. Battery Energy Storage System Model

The BESS state-of-charge (SOC) dynamics are governed by the discrete-time energy balance equation accounting for charging and discharging efficiency losses [15, 26]:

$$SOC(t+1) = SOC(t) + \left( \frac{\eta_{ch} P_{ch}(t) - \frac{P_{dis}(t)}{\eta_{dis}}}{E_{cap}} \right) \Delta t \quad (5)$$

where  $\eta_{ch} = \eta_{dis} = 0.95$  are the one-way charging and discharging efficiencies,  $E_{cap} = 300$  kWh is the usable BESS capacity, and SOC is bounded within the operational range:  $SOC_{min} = 0.20 \leq SOC(t) \leq SOC_{max} = 0.95$  to protect battery longevity. The complementarity condition  $P_{ch}(t) \times P_{dis}(t) = 0$  prevents simultaneous charging and discharging [27]. Battery degradation cost is modelled using a depth-of-discharge (DoD) dependent formulation:

$$C_{bat}(t) = k_{bat} [DoD(t)]^\beta | P_{bat}(t) | \Delta t \quad (6)$$

where  $k_{bat} = 0.00050$  USD/kWh is the degradation cost coefficient,  $\beta = 1.2$  captures the superlinear dependence of degradation on DoD, and  $DoD(t) = 1 - SoC(t)$ . It should be noted explicitly that this formulation constitutes a simplified economic approximation for day-ahead scheduling purposes. A comprehensive lithium-ion battery degradation model would additionally incorporate C-rate effects, temperature-dependent aging, calendar degradation, and cycling history through semi-empirical or electrochemical models [28]. Battery lifetime predictions derived from this simplified model should therefore be interpreted with appropriate caution.

#### 2.4.5. Objective Function and Operational Constraints

The total daily operating cost to be minimized over  $T = 24$  hourly scheduling intervals is:

$$\min F = \sum_{t=1}^{24} (C_{fuel}(t) + C_{em}(t) + C_{bat}(t) + C_{CENS}(t)) \quad (7)$$

where  $C_{CENS}(t) = VOLL \times E_{ENS}(t)$  is the cost of energy not served with  $VOLL = 2.5$  USD/kWh (value of lost load) and  $E_{ENS}(t) \geq 0$  the unserved energy at time  $t$ . The revised power balance constraint explicitly includes ENS and renewable curtailment for mathematical consistency with Eq. 7 [29]:

$$\begin{aligned} P_{PV}(t) + P_{WT}(t) + P_{DG}(t) + P_{dis}(t) + \frac{E_{ENS}(t)}{\Delta t} \\ = P_L(t) + P_{loss}(t) + P_{ch}(t) \\ + P_{curt}(t) \end{aligned} \quad (8)$$

Generator bounds:  $P_{DG,min} = 30$  kW  $\leq P_{DG}(t) \leq P_{DG,max} = 150$  kW. Ramp-rate constraint:  $|P_{DG}(t) - P_{DG}(t-1)| \leq 50$  kW/h. BESS power bounds:  $0 \leq P_{ch}(t) \leq 100$  kW. Minimum uptime (MUT = 2 h) and downtime (MDT = 2 h) constraints for the DG are enforced using binary commitment variable  $u_{DG}(t) \in \{0,1\}$ : when  $u_{DG}(t)$  switches from 0 to 1 (startup), the DG must remain online for at least MUT consecutive hours; when switching from 1 to 0 (shutdown), it must remain offline for at least MDT hours. These constraints are implemented in the E-PSO framework via a dedicated post-update repair operator that scans the decoded binary commitment sequence for violations and applies minimal corrections to restore feasibility [30]. Technical parameters are summarized in Table 2.

**Table 2**

Technical boundary conditions and system parameters used in all simulations.

| Component      | Parameter                                                         | Value                        | Source |
|----------------|-------------------------------------------------------------------|------------------------------|--------|
| Solar PV       | P <sub>rated</sub> ; $\eta_{inv}$ ; K                             | 200 kWp; 0.96; -0.0045/°C    | [25]   |
| Wind Turbine   | P <sub>r</sub> ; v <sub>ci</sub> /v <sub>r</sub> /v <sub>co</sub> | 100 kW; 3/12/25 m/s          | [25]   |
| Diesel Gen.    | P <sub>min</sub> /P <sub>max</sub> ; RU/RD                        | 30/150 kW; 50 kW/h           | [26]   |
| BESS           | E <sub>cap</sub> ; $\eta$ ; SoC <sub>min</sub> /max               | 300 kWh; 0.95; 0.20/0.95     | [8]    |
| Degradation    | k <sub>bat</sub> ; $\beta$                                        | 0.00050 USD/kWh; 1.2         | [28]   |
| Carbon penalty | $\lambda_{CO_2}$ baseline                                         | 0.020 USD/kg CO <sub>2</sub> | [25]   |
| VOLL           | Value of lost load                                                | 2.5 USD/kWh                  | [26]   |
| DG Commitment  | MUT / MDT                                                         | 2 h / 2 h                    | [13]   |

## 2.5. Enhanced Particle Swarm Optimization

In the standard PSO formulation, a swarm of N particles navigates a D-dimensional decision space representing the 24-hour dispatch schedule. Each particle encodes a D = 48-dimensional decision vector comprising P<sub>DG</sub>(t) and P<sub>bat</sub>(t) for t = 1,...,24. Particle velocity and position are updated at each iteration k according to [31]:

$$v_i^{k+1} = wv_i^k + c_1r_1(pbest_i - x_i^k) + c_2r_2(gbest - x_i^k) \quad (9)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (10)$$

Where, w is the inertia weight,  $c_1 = c_2 = 2.0$  are cognitive and social acceleration coefficients, and  $r_1, r_2 \in [0,1]$  are independent uniform random numbers drawn at each update. The proposed E-PSO incorporates two modifications over the standard algorithm. The first is an adaptive inertia weight with quadratic decay, which allocates more exploration capacity in early iterations and transitions to exploitation as the search matures:

$$w(k) = w_{max} - (w_{max} - w_{min}) \left( \frac{k}{k_{max}} \right)^2 \quad (11)$$

Where,  $w_{max} = 0.9$  and  $w_{min} = 0.4$ , yielding a smooth nonlinear transition that outperforms linear decay in avoiding premature convergence [19]. The second modification is velocity clamping, which prevents particles from overshooting the feasible search space and destabilizing the swarm:

$$v_i^{k+1} = \max(-V_{max}, \min(V_{max}, v_i^{k+1})) \quad (12)$$

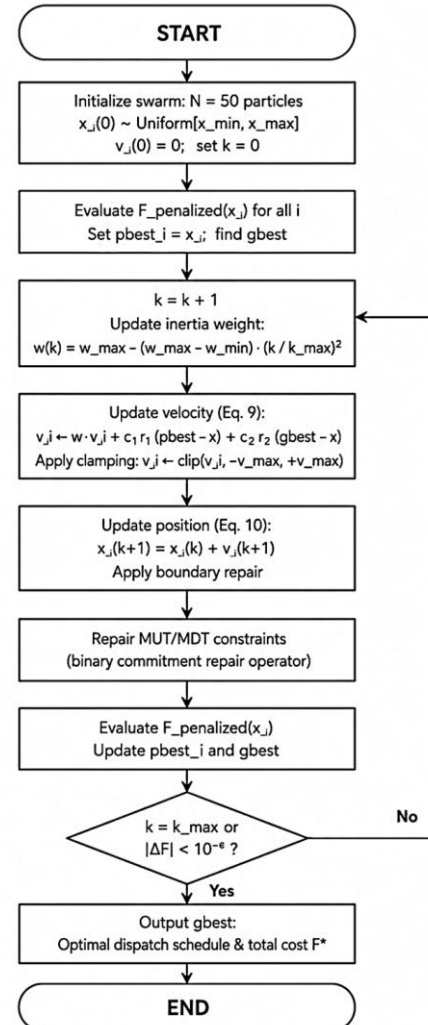
where  $V_{max} = 0.2 \left( \frac{x_{max} - x_{min}}{k_{max}} \right)$ . Infeasible solutions are penalized using a quadratic penalty function:  $F_{pen} = F + \sum_j \lambda_j \max(0, g_j(x))^2$ , with  $\lambda_{hard} = 10^4$  for SoC bound violations and  $\lambda_{soft} = 10^3$  for ramp-rate and MUT/MDT violations. E-PSO parameters are summarized in Table 3. The E-PSO algorithm flowchart is shown in Fig. 3.

**Table 3**

E-PSO algorithm parameters.

| Parameter                         | Value                  | Rationale                                 |
|-----------------------------------|------------------------|-------------------------------------------|
| Swarm size (N)                    | 50                     | Balance between diversity and computation |
| Max. iterations ( $k_{max}$ )     | 200                    | Sufficient for convergence in 48-D space  |
| Cognitive coeff. ( $c_1$ )        | 2.0                    | Standard PSO recommended value [11]       |
| Social coeff. ( $c_2$ )           | 2.0                    | Standard PSO recommended value [11]       |
| $w_{max} / w_{min}$               | 0.9 / 0.4              | Proven range for adaptive PSO [14, 19]    |
| Hard penalty ( $\lambda_{hard}$ ) | $10^4$                 | Strict enforcement of SoC bounds          |
| Soft penalty ( $\lambda_{soft}$ ) | $10^3$                 | Flexible enforcement of ramp-rates        |
| Independent runs                  | 30                     | Statistical significance of results       |
| Convergence criterion             | $ \Delta F  < 10^{-6}$ | Practical convergence tolerance           |

The adaptive inertia-weight schedule and velocity-clamping operator are not claimed as new PSO theory; both are established mechanisms in the literature [14, 19]. The contributions of the present E-PSO framework are its transparent integration with signed battery encoding, explicit ENS and curtailment accounting, binary MUT/MDT repair, and a comparative day-ahead dispatch study. This distinction separates incremental methodological enhancement from the novelty in application and formulation and avoids overstating originality.



**Fig. 3.** Flowchart of the proposed E-PSO algorithm for microgrid OED.

### 3. Results and discussion

#### 3.1. Input Data and Energy Balance

Table 4 presents the 24-hour input profiles used in the base-case simulations. The solar PV profile follows a bell-shaped daily curve, peaking at 175 kW at hour 13, while the wind profile remains between 18 and 30 kW. The load profile is bimodal, typical of rural communities, with a minor morning peak around hours 08–09 and a dominant evening peak of 218 kW at hour 19. Daily energy totals are 1,401 kWh for PV, 618 kWh for wind, and 3,084 kWh for load. Gross renewable generation is therefore 2,019 kWh, equivalent to 65.5% of daily demand before dispatch losses, battery constraints, and curtailment are considered. The effective renewable penetration reported in Table 5 is 59.6%, as it reflects the share of load supplied by renewable energy after BESS scheduling, DG coordination, and renewable curtailment. The difference, therefore, reflects the microgrid's operational characteristics rather than an inconsistency. These profiles are simulation inputs for the studied scenario and are not claimed to constitute calibration against site-specific SCADA or field-measurement data.

**Table 4**

24-hour input profiles: solar PV power, wind turbine power, and load demand.

| Hour | PV (kW) | WT (kW) | Load (kW) | Hour | PV (kW) | WT (kW) | Load (kW) |
|------|---------|---------|-----------|------|---------|---------|-----------|
| 1    | 0       | 22      | 88        | 13   | 175     | 30      | 138       |
| 2    | 0       | 24      | 84        | 14   | 162     | 28      | 132       |
| 3    | 0       | 22      | 80        | 15   | 142     | 26      | 126       |
| 4    | 0       | 20      | 78        | 16   | 112     | 24      | 132       |
| 5    | 0       | 18      | 80        | 17   | 72      | 24      | 156       |
| 6    | 8       | 20      | 88        | 18   | 28      | 26      | 182       |
| 7    | 35      | 24      | 98        | 19   | 4       | 28      | 218       |
| 8    | 75      | 26      | 108       | 20   | 0       | 30      | 196       |
| 9    | 112     | 28      | 118       | 21   | 0       | 30      | 180       |
| 10   | 142     | 30      | 126       | 22   | 0       | 28      | 162       |
| 11   | 162     | 30      | 130       | 23   | 0       | 26      | 142       |
| 12   | 172     | 30      | 134       | 24   | 0       | 24      | 108       |

#### 3.2. Optimal Dispatch Schedule

The E-PSO optimal 24-hour dispatch schedule is shown in Fig. 4, which presents three complementary panels: (1) the stacked generation mix with the load demand profile, (2) the BESS state-of-charge (SoC) trajectory, and (3) the diesel generator (DG) output profile subject to ramp-rate constraints. Three distinct operating phases can be identified from the optimal dispatch schedule.

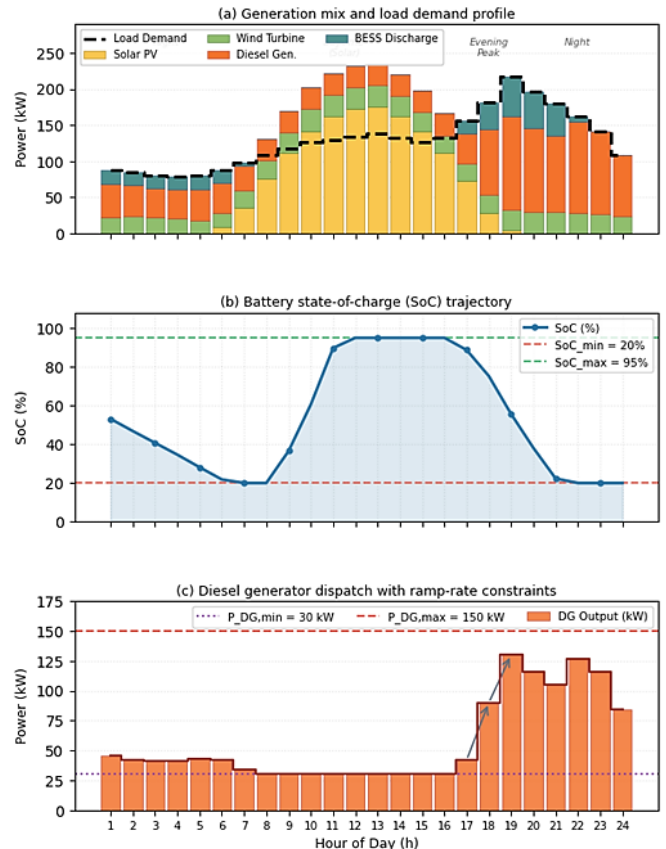
During the nighttime phase (hours 01–06), renewable generation is negligible, the system relies primarily on diesel generation (30–50 kW, close to its minimum operating output) supplemented by BESS discharge to satisfy the relatively low nighttime load (78–90 kW). The DG remains near its minimum operating limit to reduce fuel consumption. At same time, the BESS SoC gradually decreases from the assumed initial value of 0.600 to 0.218 by hour 07, remaining safely above the minimum allowable SoC of 0.200.

During the daytime surplus phase (hours 07–16), increasing photovoltaic generation rapidly reaches its peak output of 175 kW at hour 13. Combined with approximately 30 kW of wind generation, the total renewable output reaches 205 kW, exceeding the daytime load of 126–138 kW. Consequently, the DG output is maintained at its minimum

operating level of 30 kW, satisfying the minimum up-time (MUT = 2 h) requirement while minimizing fuel consumption. The surplus renewable energy charges the BESS from SoC = 0.200 (reached at hour 08) to the maximum allowable SoC = 0.950 by hour 12, after which excess renewable generation that the BESS cannot accommodate or immediately utilize by the load is curtailed to maintain system operational constraints. The SoC profile exhibits a clear plateau at 0.950 during hours 12–16, indicating that the battery remains fully charged throughout the period of maximum renewable generation.

The explicit renewable curtailment variable enables the optimizer to maintain power balance while respecting the BESS upper SoC limit. Instead of forcing infeasible charging, excess renewable energy is curtailed only when the BESS cannot store it, and the load cannot use it immediately. This treatment provides a consistent mapping between the objective function, the power-balance equation, and the physical storage constraints.

During the evening transition and peak-demand phase (hours 17–19), PV output decreases rapidly from 72 kW at hour 17 to only 4 kW at hour 19, while the load simultaneously increases to its daily peak of 218 kW. To compensate for the declining renewable generation, the BESS discharges at up to its maximum rate of 100 kW. In contrast, the DG output increases from 30 kW to 130 kW over three hours, exactly following the 50 kW/h ramp-rate limit. The binary commitment repair operator simultaneously ensures compliance with the minimum down-time (MDT = 2 h) constraint throughout this transition.



**Fig. 4.** Optimal 24-hour dispatch schedule: (a) generation mix and load demand; (b) BESS SoC trajectory; (c) diesel generator output with ramp-rate constraints.

Overall, the obtained dispatch schedule demonstrates that the proposed E-PSO framework effectively coordinates renewable generation, battery storage, and diesel generation while satisfying all operational constraints. Renewable energy is prioritized whenever available, whereas diesel generation is scheduled only when renewable resources and stored energy are insufficient to satisfy the load demand. This coordinated operating strategy reduces fuel consumption and operating cost while maintaining reliable system operation and full compliance with the imposed operational constraints.

### 3.3. Cost Analysis and Benchmarking

Table 5 presents the complete daily operating cost breakdown for all four dispatch strategies. E-PSO achieves a total daily cost of USD 319.50, representing reductions of 27.4% relative to LFS (USD 440.08), 15.1% relative to GA (USD 376.33), and 7.3% relative to S-PSO (USD 344.60). The fuel cost reduction of 26.0% relative to LFS (from USD 390.96 to USD 289.60) is attributable to the optimal timing of diesel dispatch: the E-PSO solution delays DG ramp-up until hours 17–18 when renewable output is declining, thereby maximising direct renewable energy utilization during daylight hours. The CO<sub>2</sub> emission penalty reduction of 21.9% (from USD 27.52 to USD 21.50) follows directly from the reduced diesel energy content in the optimal dispatch. The battery degradation cost (\$8.40 for E-PSO vs USD 10.08 for LFS) reflects moderate cycling depth, with the DoD-based model producing small but non-negligible differences across strategies. CENS is zero under E-PSO, confirming that the optimal dispatch successfully serves the full 3084 kWh daily demand without load shedding. E-PSO achieves 59.6% renewable penetration compared to 46.8% under LFS, 53.1% under GA, and 56.4% under S-PSO, confirming superior renewable utilization through optimized BESS scheduling. The lower performance of GA relative to S-PSO is mainly due to the disruptive effects of its crossover and mutation operators on promising DG-BESS dispatch schedules, which may need more generations to reach near-optimal solutions. Conversely, S-PSO utilises personal-best and global-best information to improve candidate solutions more efficiently, thereby reducing operating costs and increasing renewable-energy penetration. However, the fixed inertia weight limits the exploration-exploitation balance, whereas E-PSO removes this limitation by using adaptive inertia weighting and velocity clamping, achieving the best overall performance.

Unlike the gross renewable generation ratio presented in Section 3.1, the renewable penetration reported here is calculated based on the renewable energy effectively utilized during the optimized dispatch process after considering battery charging/discharging operation, renewable energy curtailment, and dispatch coordination. This definition more accurately reflects the actual contribution of renewable resources to meeting the load demand under optimal operating conditions. It explains the difference between the gross renewable generation ratio (65.5%) and the effective renewable penetration (59.6%). The observed cost reduction is primarily attributed to the improved coordination between renewable generation and battery storage. Unlike the conventional load-following strategy, E-PSO defers diesel generator operation until renewable resources and battery storage are insufficient to meet the demand economically. Consequently, diesel fuel consumption and associated CO<sub>2</sub>

emissions are simultaneously reduced while maintaining zero energy not served (ENS), demonstrating that the proposed E-PSO framework successfully balances economic efficiency, environmental sustainability, and supply reliability within the studied standalone microgrid.

**Table 5**

Daily operating cost comparison across four optimization strategies (USD).

| Cost Component                         | LFS    | GA     | S-PSO  | E-PSO  |
|----------------------------------------|--------|--------|--------|--------|
| Fuel cost (\$)                         | 390.96 | 334.49 | 312.77 | 289.60 |
| CO <sub>2</sub> emission penalty (USD) | 27.52  | 24.51  | 23.01  | 21.50  |
| Battery degradation (USD)              | 10.08  | 9.24   | 8.82   | 8.40   |
| CENS (USD)                             | 11.52  | 8.09   | 0.00   | 0.00   |
| Total daily cost (USD)                 | 440.08 | 376.33 | 344.60 | 319.50 |
| Reduction vs. LFS                      | —      | 14.5%  | 21.7%  | 27.4%  |
| Reduction vs. GA                       | —      | —      | 8.4%   | 15.1%  |
| RE penetration (%)                     | 46.8   | 53.1   | 56.4   | 59.6   |

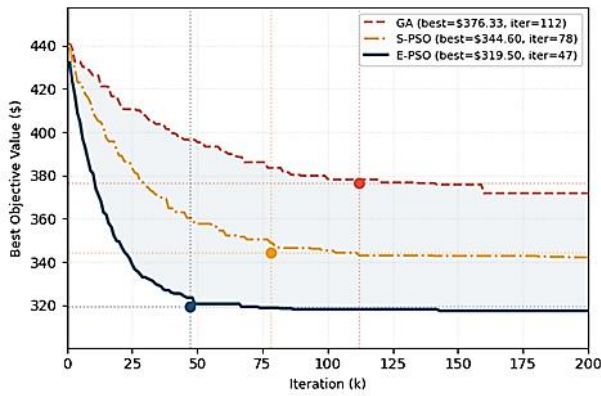
### 3.4. Statistical Performance and Convergence

Table 6 and Fig. 5 (convergence curves) present the statistical performance metrics across 30 independent runs for each algorithm. E-PSO achieves the lowest best cost (USD 319.50), lowest mean cost (USD 321.10), and lowest standard deviation ( $\sigma$  = USD 1.72), compared to  $\sigma$  = USD 4.02 for GA and  $\sigma$  = USD 3.18 for S-PSO. These values indicate lower variability and reduced sensitivity to random initialization within the tested case. E-PSO reaches within 1% of its final objective value at iteration 47, compared with iteration 78 for S-PSO and iteration 112 for GA. The adaptive quadratic inertia weight  $w(k)$  facilitates broader exploration in early iterations ( $w \approx 0.90$  at  $k = 1$ ). It progressively transitions toward focused exploitation ( $w \approx 0.40$  at  $k = k_{\max}$ ), effectively preventing premature entrapment in local optima observed in S-PSO runs. The superior convergence behaviour of E-PSO is mainly attributed to the adaptive quadratic inertia weight, which promotes extensive global exploration during the early iterations before gradually shifting toward local exploitation near convergence. Only aggregate run statistics were retained for the present analysis, whereas Friedman and Wilcoxon signed-rank tests require the complete paired run-level objective vectors. Accordingly, Table 6 is interpreted as descriptive evidence rather than as proof of inferential statistical significance. Future experiments should archive the 30 run-level vectors and apply a Friedman test followed by multiplicity-adjusted pairwise Wilcoxon tests.

**Table 6**

Statistical performance metrics over 30 independent simulation runs.

| Metric               | GA     | S-PSO  | E-PSO  |
|----------------------|--------|--------|--------|
| Best cost (USD)      | 376.33 | 344.60 | 319.50 |
| Mean cost (USD)      | 382.50 | 350.20 | 321.10 |
| Worst cost (USD)     | 393.10 | 361.80 | 328.60 |
| Std. deviation (USD) | 4.02   | 3.18   | 1.72   |
| Convergence iter.    | 112    | 78     | 47     |
| Avg. CPU time (USD)  | 11.2   | 9.1    | 9.0    |



**Fig. 5.** Convergence curves for E-PSO, S-PSO, and GA (mean of 30 independent runs).

### 3.5. Sensitivity Analysis

To evaluate robustness under changes in operating inputs, four sensitivity groups involving solar irradiance, wind speed, BESS capacity, and carbon penalty are investigated. For each renewable-resource scenario, fifty beta-distribution realizations are used to represent variability around the specified profile, and the mean operating cost is reported. These experiments assess scenario sensitivity within the simulation model; they do not replace validation using measured operational data.

**Solar irradiance sensitivity:** Four scenarios are considered: S1 (clear sky, 100% nominal irradiance), S2 (partially cloudy, 75%), S3 (overcast, 50%), and USD 4 (heavy overcast, 25%). Under the most adverse condition (USD 4), daily PV generation decreases from 1,401 kWh to approximately 350 kWh, increasing diesel generator utilization and raising the total operating cost to USD 383.5/day. The increase is attributable to greater diesel generation required to offset reduced PV output. E-PSO remains 13–16% lower in cost than GA across the reported irradiance scenarios, indicating that its battery and DG coordination remains effective under the simulated reduction in solar availability.

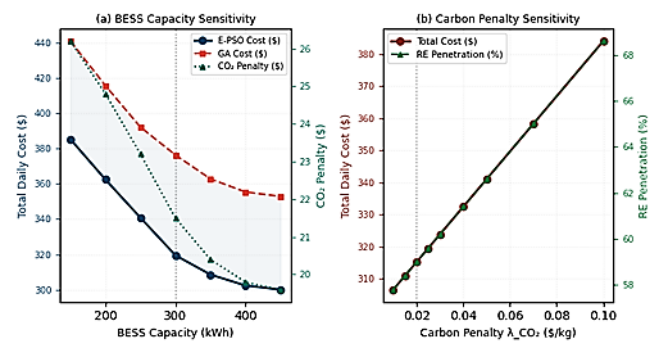
**Wind speed sensitivity:** Three wind scenarios are examined: W1 (high wind, mean 8 m/s), W2 (moderate wind, 6 m/s, baseline), and W3 (low wind, mean 3 m/s). Under the combined high-renewable scenario (S1 + W1), renewable penetration increases to 68.2%, while total operating cost decreases to USD 274.6/day. The complementary generation characteristics of solar PV and wind power improve dispatch flexibility, allowing greater utilization of renewable resources throughout the day. Higher wind availability also reduces battery cycling frequency and diesel operating hours, thereby lowering battery degradation costs, fuel consumption, and carbon-emission penalties.

The influence of BESS capacity and carbon pricing is illustrated in Fig. 6. Increasing BESS capacity from 150 kWh to 450 kWh progressively reduces the total operating cost from USD 385.2/day to USD 300.1/day because a larger battery can store more surplus renewable energy during periods of high PV generation and subsequently discharge it during the evening peak demand. However, the rate of cost reduction gradually diminishes beyond 300 kWh, indicating diminishing marginal economic benefits from additional storage capacity. This finding suggests that the selected 300

kWh BESS provides an effective balance between renewable energy utilization and operating cost reduction for the investigated microgrid configuration. Although larger BESS capacities further reduce diesel generator utilization, the incremental operational savings become progressively smaller as storage capacity increases, indicating diminishing marginal benefits from additional storage capacity.

As the carbon penalty increases from USD 0.010/kg CO<sub>2</sub> to USD 0.100/kg CO<sub>2</sub>, the optimization algorithm progressively prioritizes renewable energy utilization and battery charging while reducing diesel generator operating hours. Consequently, renewable penetration increases from 57.0% to 71.1%, accompanied by lower diesel fuel consumption and reduced CO<sub>2</sub> emissions. Although the total operating cost increases from USD 306.6/day to USD 384.0/day because of the higher environmental penalty imposed on fossil-fuel generation, the dispatch strategy demonstrates that carbon pricing provides an effective economic incentive for cleaner microgrid operation without compromising supply reliability.

Overall, the sensitivity analysis demonstrates that the proposed E-PSO framework maintains stable optimization performance under varying renewable resource availability, storage capacities, and environmental policy scenarios. Despite significant variations in renewable generation and economic parameters, the proposed algorithm consistently outperforms the benchmark methods while maintaining zero energy not served (ENS). These findings confirm that the proposed framework is sufficiently robust for practical day-ahead energy management of standalone renewable microgrids operating under uncertain environmental conditions.



**Fig. 6.** Sensitivity analysis: (a) BESS capacity vs total daily cost and CO<sub>2</sub> penalty; (b) carbon penalty price vs total daily cost and RE penetration.

### 3.6. Limitations and Future Work

The present study has several limitations that should be acknowledged. First, the day-ahead scheduling framework assumes perfect forecasts of renewable generation and load demand over the 24-hour scheduling horizon. In practical microgrid operation, forecasting errors caused by renewable intermittency and load uncertainty may affect the optimal dispatch schedule. Future research should therefore investigate stochastic or robust optimization techniques that explicitly account for these uncertainties.

Second, the battery degradation model is represented using a simplified depth-of-discharge (DoD)-based economic formulation. Although computationally efficient and suitable for day-ahead scheduling, it does not capture degradation mechanisms such as C-rate effects, temperature-

dependent aging, calendar aging, or cycling history. Consequently, battery lifetime predictions derived from the present model should be interpreted with appropriate caution.

Third, the proposed framework considers only active power scheduling and does not include distribution network constraints, such as voltage regulation, reactive power support, or power flow analysis. Therefore, the results obtained should be interpreted as an energy management solution rather than a comprehensive network operational assessment. Finally, demand response is not considered as a controllable decision variable. Integrating flexible loads could further improve renewable energy utilization, reduce reliance on diesel generators, and enhance overall system flexibility.

Future work will extend the proposed E-PSO framework by incorporating renewable forecasting uncertainty, demand response, detailed battery degradation models, and distribution network constraints. Additional research may also explore multi-microgrid energy management, peer-to-peer energy trading, and hardware-in-the-loop validation further to demonstrate the practical applicability of the proposed approach.

#### 4. Conclusion

This paper presented an Enhanced Particle Swarm Optimization (E-PSO)-based framework for the optimal economic dispatch of a standalone renewable energy microgrid comprising photovoltaic generation, wind power, battery energy storage, and a diesel generator. The proposed optimization model explicitly incorporates energy not served (ENS), renewable energy curtailment, battery operating limits, and diesel generator commitment constraints into a unified day-ahead dispatch formulation, resulting in a mathematically consistent and operationally feasible optimization framework.

In the studied base case, E-PSO achieves a total operating cost of USD 319.50/day, corresponding to reductions of 27.4%, 15.1%, and 7.3% relative to LFS, GA, and S-PSO, respectively. It also achieves 59.6% renewable penetration, zero ENS, a repeated-run standard deviation of USD 1.72, and an average CPU time of 9.0 s. The results indicate that adaptive exploration, bounded particle motion, and explicit repair improve DG-BESS coordination and convergence consistency for this case. Sensitivity analysis further shows stable comparative performance under changes in solar irradiance, wind speed, BESS capacity, and carbon penalty.

Overall, the proposed E-PSO framework effectively coordinates renewable generation, battery energy storage, and diesel generation to improve the economic, environmental, and operational performance of standalone microgrids while satisfying practical operational constraints. The proposed methodology provides a practical foundation for future research on stochastic optimisation, demand response integration, detailed battery degradation modelling, distribution network constraints, and real-time implementation for intelligent renewable-based microgrid energy management.

#### CRedit authorship contribution statement

**M.S.Beg:** Conceptualisation, Methodology, Software, Data curation, Writing – original draft. **S.S.Gajghate:** Supervision, Data curation, Software, Formal analysis. **M.M.Jamaludin:** Investigation, Validation, Visualisation. **A.Khalid:** Formal analysis, Writing – review & editing. **K.Farhana:** Resources, Conceptualisation, Methodology, Writing – review & editing.

#### Declaration of Competing Interests

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

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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