GREY WOLF OPTIMIZER FOR ENERGY STORAGE SYSTEM PLACEMENT AND OPERATION IN DISTRIBUTION NETWORKS WITH SOFT OPEN POINTS

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Abstract - In the context of the green energy transition and the advancement of smart grids, the optimization problem involving the integration of photovoltaic (PV) systems and Energy Storage Systems (ESS) into power grids has attracted significant research interest. This paper presents an optimization framework for integrating Energy Storage Systems (ESS) and photovoltaic (PV) systems into a distribution network comprising two interconnected IEEE 33-bus systems linked by Soft Open Points (SOPs). The objective is to minimize operational costs, including power purchase expenses and PV generation revenue, while optimizing SOP power flows. A Grey Wolf Optimizer (GWO) algorithm determines optimal ESS placement, sizing, charge/discharge schedules, and SOP power flows over 24 hours, outperforming Multi-Verse Optimizer (MVO) and Harris Hawks Optimization (HHO). Constraints include power balance, ESS operational limits, SOP power boundaries, and fixed network configuration. Convergence analysis and SOP power profiles demonstrate the framework's effectiveness in enhancing distribution system efficiency.

Key words - Grey Wolf Optimizer (GWO); Energy Storage System (ESS); Photovoltaic (PV); Soft Open Points (SOPs); Distribution networks; Optimization operational costs.

1. Introduction

The transition to sustainable energy systems has driven the widespread adoption of renewable energy sources, particularly photovoltaic (PV) systems, within modern power distribution networks. This shift, alongside the evolution of smart grids, has introduced significant optimization challenges in managing energy storage systems (ESS) and ensuring efficient power flow in interconnected networks. ESS plays a pivotal role in mitigating the intermittency of renewable energy, balancing supply and demand, and minimizing operational costs in distribution systems [1-4]. The introduction of Soft Open Points (SOPs), advanced power electronic devices that facilitate dynamic power exchange between feeders, further enhances network flexibility and operational efficiency [5-8]. However, optimizing the placement, sizing, and operation of ESS, alongside managing SOP power flows, presents a complex, nonlinear optimization problem that demands robust computational approaches [9-11].

Metaheuristic algorithms have become a cornerstone for addressing such intricate energy management problems, offering the ability to navigate high-dimensional, non-convex search spaces without relying on precise analytical models [12-14]. Among these, the Grey Wolf Optimizer (GWO) has emerged as a highly effective method for power system optimization, owing to its balanced exploration and exploitation capabilities [15-17]. Recent studies have shown that GWO outperforms other metaheuristic algorithms, such as Multi-Verse Optimizer (MVO) and Harris Hawks Optimization (HHO), in achieving faster convergence and superior solution quality for energy system applications [18-20]. Unlike traditional optimization techniques, such as linear programming or gradient-based methods, GWO excels in handling the nonlinearity and constraints inherent in ESS and SOP optimization [21, 22].

This paper proposes an optimization framework for the placement, sizing, and operation of ESS within a distribution system consisting of two interconnected IEEE 33-bus networks linked by SOPs. The objective is to minimize the total operational cost over a 24-hour period, encompassing power purchase costs from two substations, ESS operational costs, and revenue from PV generation. The cost functions for power purchases are modeled as quadratic functions, and the revenue from PV generation is calculated based on the PV power output and its associated price. The optimization accounts for constraints such as power balance at each node, ESS operational limits, and system constraints, including voltage and current limits [23]. The GWO algorithm is employed to determine the optimal ESS locations, capacities, charge/discharge schedules, and SOP power flows, with decision variables encompassing ESS node locations, maximum storage capacity, and charge/discharge power over the 24-hour period.

Building on recent advancements in distribution system modeling, this study leverages the IEEE 33-bus network and SOP-enabled interconnections to simulate realistic operational scenarios [6, 10]. The proposed approach demonstrates GWO's superior performance compared to MVO and HHO, validated through computational experiments that highlight improved convergence and cost minimization [19, 24]. By addressing practical challenges in ESS deployment and SOP management, this work contributes to the development of efficient, cost-effective smart grid solutions, offering insights for real-world implementation [25].

2. Related works

In this study, we examine the IEEE 33-bus power grid model, with a simulation consisting of two substations, each with two outgoing feeders forming two IEEE 33-bus power grids. These two feeders are interconnected in a loop through three soft open point (SOP) connection points at the node pairs: (16 – 16), (25 – 22) and (33 – 13). The schematic is illustrated in Figure 1.

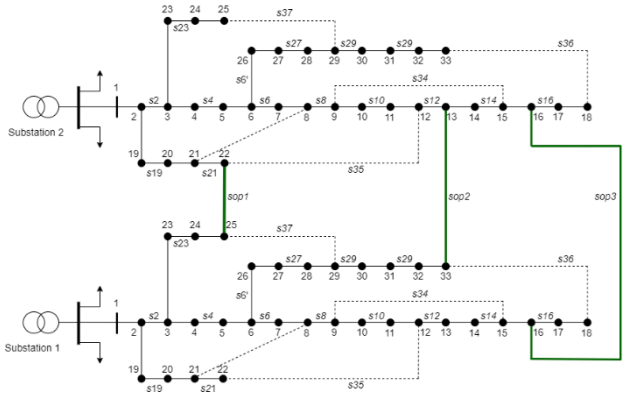

Figure 1. *Connection diagram of 02 substations with two IEEE 33-node networks using SOP*

2.1. Objective Function

Minimize the total system operational cost over a 24-hour period, including:

$$C_1(t) = a_1 P_1(t)^2 + b_1 P_1(t) + c_1 \quad (1)$$

$$C_2(t) = a_2 P_2(t)^2 + b_2 P_2(t) + c_2 \quad (2)$$

Where $P_1(t)$ and $P_2(t)$ represent the power purchased at time t.

ESS-related costs: Investment costs (allocated based on capacity) and operational costs (charging/discharging).

Revenue from PV power sales (low buy-back price):

$$Revenue = \sum_t P_{PV}(t) \cdot Price_{PV} \quad (3)$$

Where $P_{\text{PV}}(t)$ is the PV power output at time t.

Overall Objective Function:

$$min \sum_{t=1}^{24} [C_1(t) + C_2(t) - \text{Revenue}(t) + C_{\text{ESS}}(t)] \quad (4)$$

Where $C_{\text{ESS}}(t)$ includes ESS operational costs.

2.2. Constraints

Power Balance: At each node in the system, the total supplied power (from the substation, PV, ESS discharge, and power flow through SOPs) equals the total consumed power (load, ESS charging, and losses):

$$P_{\text{Grid}}(t) + P_{\text{PV}}(t) + P_{\text{ESS,discharge}}(t) + \sum_{k=1}^{3} P_{\text{SOP},k}(t) = = P_{\text{Load}}(t) + P_{\text{ESS,charge}}(t) + P_{\text{Loss}}(t) \quad (5)$$

Where $P_{\text{Loss}}(t)$ represents power losses, and $P_{\text{SOP},k}(t)$ is the power flow through the *k-th* SOP (with k = 1, 2, 3) at time t. Positive $P_{\text{SOP},k}(t)$ indicates power flow from one feeder to another, and negative indicates the reverse.

ESS Constraints:

Storage Capacity: $E_{\text{ESS,min}} \le E_{\text{ESS}}(t) \le E_{\text{ESS,max}}$

Charging/Discharging Power:

$$0 \le P_{\text{ESS,charge}}(t) \le P_{\text{ESS,charge,max}}$$

$$0 \le P_{\text{ESS,discharge}}(t) \le P_{\text{ESS,discharge,max}}$$

Energy State:

$$E_{\text{ESS}}(t) = E_{\text{ESS}}(t-1) + \eta_{\text{charge}} P_{\text{ESS,charge}}(t) \Delta t - \frac{P_{\text{ESS,discharge}}(t)}{\eta_{\text{discharge}}} \Delta t \quad (6)$$

Mutual Exclusivity: ESS can only charge or discharge at any given time:

$$P_{\text{ESS,charge}}(t) \cdot P_{\text{ESS,discharge}}(t) = 0 \quad (7)$$

SOP Constraints [10, 13]:

Power Flow Limits: The power flow through each SOP is bounded by its capacity

$$-P_{\text{SOP},k,\text{max}} \le P_{\text{SOP},k}(t) \le P_{\text{SOP},k,\text{max}}, \quad k = 1,2,3 \quad (8)$$

Where $P_{\text{SOP},k,\text{max}}$ is the maximum power rating of the *k-th* SOP.

Loss in SOP Operation: Power losses in SOPs are modeled as a function of the transmitted power

$$P_{\text{SOP},k,\text{loss}}(t) = \alpha_k \mid P_{\text{SOP},k}(t) \mid \quad (9)$$

Where α_k is the loss coefficient for the *k-th* SOP. These losses are included in the total power loss $P_{\text{Loss}}(t)$.

Power Balance at SOP Nodes: For each SOP connecting two nodes (node I in one feeder and node j in another), the power injected or extracted by the SOP must satisfy ensuring that the power leaving one feeder equals the power entering the other (excluding losses).

$$P_{\text{SOP},k}(t) = P_{\text{SOP},k,i}(t) = -P_{\text{SOP},k,j}(t) \quad (10)$$

SOP Operational Constraint: The total apparent power through each SOP (considering active and reactive power, if applicable) must not exceed its rated capacity

$$\sqrt{P_{\text{SOP},k}(t)^2 + Q_{\text{SOP},k}(t)^2} \le S_{\text{SOP},k,\text{max}}, \quad k = 1,2,3 \quad (11)$$

Where $Q_{\text{SOP},k}(t)$ is the reactive power flow and $S_{\text{SOP},k,\text{max}}$ is the rated apparent power capacity of the *k-th* SOP.

System Constraints:

Node Voltage: $V_{\text{min}} \le V_i(t) \le V_{\text{max}}$

Branch Current: $I_{ij}(t) \le I_{ij,\text{max}}$

Network Configuration: Fixed over 24 hours, with three SOPs facilitating power exchange between the two IEEE 33-bus networks (no network reconfiguration).

PV: PV power output is fixed according to the profile $P_{\text{PV}}(t)$, uncontrollable.

Decision Variables:

ESS installation locations (nodes in the IEEE grid).

Rated ESS capacity ($E_{\text{ESS,max}}$).

ESS charging/discharging power at each time t: $P_{\text{ESS,charge}}(t)$, $P_{\text{ESS,discharge}}(t)$.

Power flow through each SOP at each time t: $P_{\text{SOP},k}(t)$, $k = 1, 2, 3$.

2.3. Grey Wolf Optimizer (GWO) Algorithm

The Grey Wolf Optimizer (GWO), a metaheuristic algorithm inspired by the leadership hierarchy and hunting

strategy of grey wolves, is employed due to its robust exploration and exploitation capabilities. The position update of the wolves is illustrated in Figure 2. Additionally, the steps of the GWO algorithm, presented below, are also illustrated in Figure 3.

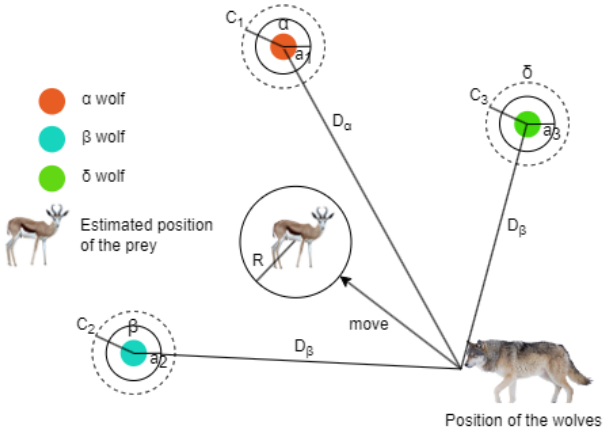

Figure 2. *Position updating in the grey wolf optimization (GWO) [12]*

Population Initialization:

Randomly generate N solutions (wolves), ensuring compliance with constraints: Valid ESS locations within the IEEE grid. ESS capacity within realistic limits (100 kWh to 2 MWh).

Feasible ESS charge/discharge power and SOP power flows within their respective bounds.

Set GWO parameters: Number of wolves (N), and control parameter α, which linearly decreases from 2 to 0 over iterations to balance exploration and exploitation.

Objective Function Evaluation:

For each solution, perform power flow simulation over 24 hours using: Load profile $P_{\text{Load}}(t)$, PV profile $P_{\text{PV}}(t)$, ESS charge/discharge schedule, SOP power flow schedule.

Calculate total cost:

$$C_{total} = \sum_{t=1}^{24}[C_1(t) + C_2(t) - Revenue(t) + C_{ESS}(t)] \quad (12)$$

Check constraints (voltage, current, ESS capacity, SOP power limits). If violated, apply a penalty to the objective function:

$$F = C_{\text{total}} + \sum \lambda_i \cdot \text{Violation}_i \quad (13)$$

Where λ_i is the penalty weight for the i-th constraint violation.

Rank solutions based on fitness (F) and assign the top three as:

- α: Best solution (lowest fitness).
- β: Second-best solution.
- δ: Third-best solution.
- Remaining solutions are ω wolves.

Wolf Position Update:

Update the position of each ω wolf based on the positions of α, β, and δ wolves using GWO equations:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|, \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}|$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta$$

$$\vec{X}(k+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (14)$$

Where:

$\vec{X}$: Current position of the wolf.

$\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta$: Positions of the α, β, and δ wolves.

$\vec{A}_i = 2\vec{a} \cdot \vec{r}_1 - \vec{a}\vec{C}_i = 2 \cdot \vec{r}_2$, with $\vec{r}_1, \vec{r}_2$ as random vectors in [0,1].

$\vec{a}$: Decreases linearly from 2 to 0 over iterations.

Stopping and output the optimal solution: Maximum number of iterations ($k_{\max}$) or when the α solution (best fitness) shows no significant improvement after n iterations.

Results: The best solution (α) provides

- ESS locations (selected nodes).
- ESS capacity ($E_{\text{ESS,max}}$).
- ESS charge/discharge schedule ($P_{\text{ESS}}(t)$).
- SOP power flow schedule ($P_{\text{SOP},k}(t)k = 1,2,3$).

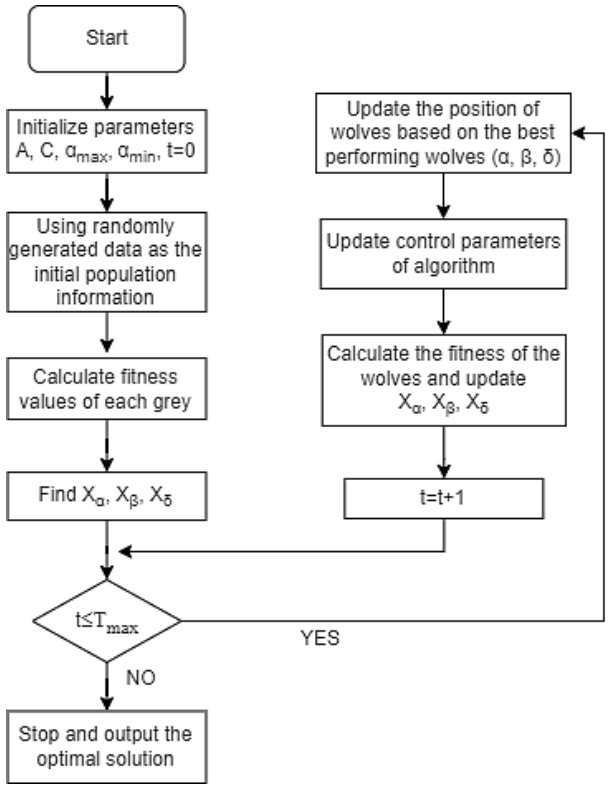

Figure 3. *GWO algorithm optimization process [12]*

2.4. Harris hawks optimization (HHO) Algorithm

The hawk updates its position through exploration and exploitation phases based on the prey's energy [18]; this algorithm is highly regarded for its global search capability, considering multiple objectives. The algorithm model is characteristically described in Figure 4.

Energy Parameter:

$$E = 2E_0\left(1 - \frac{\text{iter}}{\text{max\_iter}}\right) \quad (15)$$

Where $E_0 \in [-1,1]$ is the initial energy (random), *iter*

is the current iteration, and *max_iter* is the maximum iterations.

Exploration Phase ($|E| \geq 1$): Hawks search randomly

$$x_i(k+1) = \begin{cases} x_{\text{rand}}(k) - r_1 \,|\, x_{\text{rand}}(k) - 2r_2 x_i(k) \,|\, & \text{if } q \geq 0.5 \\ x_{\text{prey}}(k) - x_m(k) - r_3(\text{lb} + r_4(\text{ub} - \text{lb})) & \text{if } q < 0.5 \end{cases} \quad (16)$$

Where $x_i(k)$ is the position of hawk i, $x_{\text{rand}}(k)$ is a randomly selected hawk, $x_{\text{prey}}(k)$ is the prey's position (best hawk), $x_m(k)$ is the average hawk position, $r_1, r_2, r_3, r_4, q \in [0,1]$ are random numbers, and *ub*, *lb* are bounds.

Exploitation Phase ($|E| < 1$): Hawks perform soft or hard besiege

Soft Besiege ($|E| \geq 0.5$):

$$x_i(k+1) = \Delta x(k) - E \,|\, J x_{\text{prey}}(k) - x_i(k) \,| \quad (17)$$

$$\Delta x(k) = x_{\text{prey}}(k) - x_i(k), \quad J = 2(1 - r_5) \quad (18)$$

Where $r_5 \in [0,1]$ is random, and *J* represents random jump strength.

Hard Besiege ($|E| < 0.5$):

$$x_i(k+1) = x_{\text{prey}}(k) - E \,|\, \Delta x(k) \,| \quad (19)$$

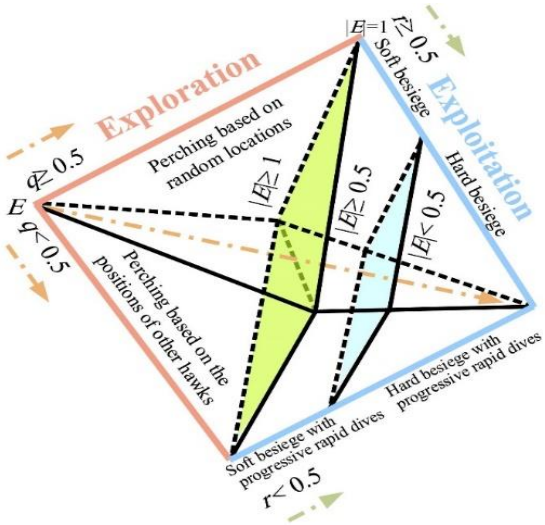

Figure 4. *General procedure of the Harris Hawks Optimizer (HHO) [18]*

Handling Variables: Round discrete variables (ESS locations) to integers. Clip continuous variables to satisfy constraints like:

$$\sqrt{P_{\text{SOP},k}(t)^2 + Q_{\text{SOP},k}(t)^2} \leq S_{\text{SOP},k,\max} \quad (20)$$

2.5. Multi-Verse Optimizer (MVO) Algorithm

Update each universe's position using the wormhole mechanism, which facilitates exploration and exploitation [19]:

WEP and TDR Calculation:

$$\text{WEP} = \text{WEP}_{\min} + \text{iter} \cdot \frac{\text{WEP}_{\max} - \text{WEP}_{\min}}{\text{max\_iter}} \quad (21)$$

$$\text{TDR} = 1 - \frac{\text{iter}^{1/6}}{\text{max\_iter}^{1/6}} \quad (22)$$

Where $\text{WEP}_{\min} = 0.2$, $\text{WEP}_{\max} = 1$, *iter* is the current iteration, and *max_iter* is the maximum iterations.

Position Update Rule: For each dimension *j* of universe *i*, denoted x_i^j, update as follows:

$$x_i^j = \begin{cases} x_{\text{best}}^j + \text{TDR} \cdot ((\text{ub}_j - \text{lb}_j) \cdot r_2 + \text{lb}_j) & \text{if } r_1 < \text{WEP} \\ x_i^j & \text{otherwise} \end{cases} \quad (23)$$

Where x_{best}^j is the *j-th* dimension of the best universe, ub_j and lb_j are the upper and lower bounds for dimension *j*, and $r_1, r_2 \in [0,1]$ are random numbers.

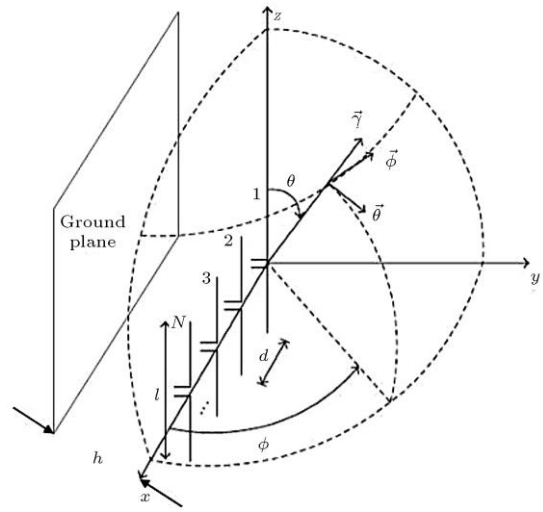

Figure 5. *A linear array of parallel half-wavelength dipole antennas with ground plane placed at a distance h behind the array [19]*

Handling Discrete and Continuous Variables: For discrete variables (ESS locations), round x_i^j to the nearest integer. For continuous variables ($E_{\text{ESS,max}}$, $P_{\text{ESS}}(t)$, $P_{\text{SOP},k}(t)$), ensure bounds are respected ($P_{\text{SOP},k}(t) \leq P_{\text{SOP},k,\max}$).

3. Result analysis

3.1. Dataset and parameter setting

To evaluate the performance of the proposed Harris Hawks Optimization (HHO), Grey Wolf Optimizer (GWO), and Multi-Verse Optimizer (MVO) algorithms for optimal Energy Storage System (ESS) placement, sizing, operation, and tie switch power flow scheduling, the IEEE 33-bus distribution system dataset is utilized. Specifically, two IEEE 33-bus systems (totaling 66 buses) are interconnected via three tie switches (connecting bus pairs 10-43, 20-53, and 30-63). The dataset is sourced from the case33bw.m file in the MATPOWER library, providing load and branch data.

The system parameters are configured as follows:

- ESS: Maximum of 2 units, with charge/discharge limits of 500 kW, capacity range of 200–2000 kWh, and 95% charge/discharge efficiency.

- Tie Switches: Power flow limits of ±1000 kW, with impedance R = 0.0062 p.u., X = 0.0125 p.u.

- Cost Coefficients: a_1=a_2=0.01\$/kW^2, b_1=b_2=0.01\$/kW^2, c1=c2=10\$, PV buy-back price = 0.05 \$/kWh.

- Optimization Parameters: Population size of 50 (wolves for GWO, hawks for HHO, universes for MVO), maximum iterations of 200.

3.2. Convergence Analysis

The convergence performance of GWO, HHO, and MVO is evaluated by analyzing the best cost ($) achieved over 200 iterations. Each algorithm was run once, and convergence curves were plotted to compare their optimization efficiency. As illustrated in Figure 6, the convergence curves show GWO converging the fastest, MVO demonstrating steady progress, and HHO converging more slowly. The final costs indicate that GWO typically achieves the lowest cost, followed by MVO and HHO.

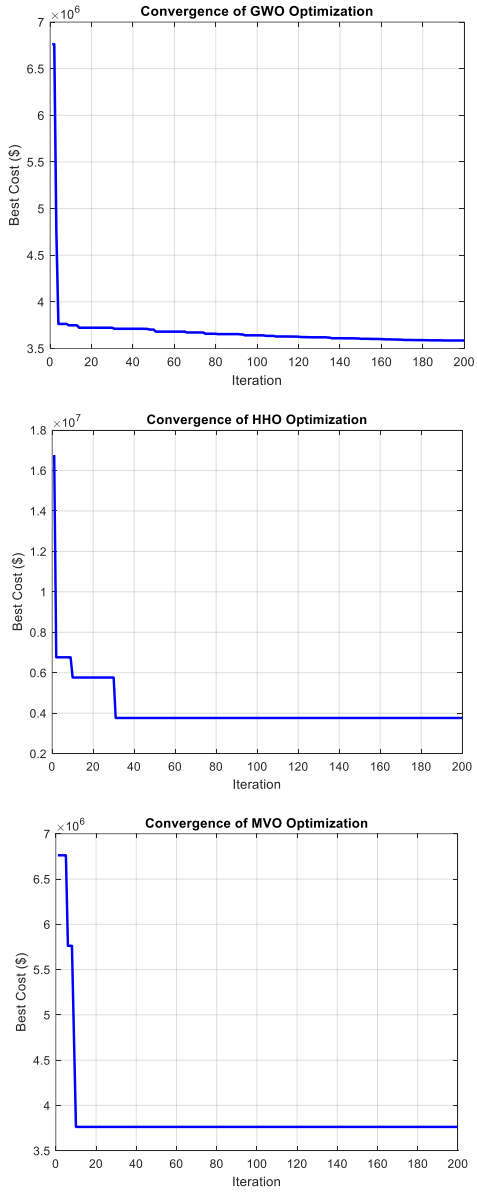

Figure 6. *Convergence of Optimization*

Simultaneously, when performing concurrent load changes at the buses of the IEEE 33-bus grid over 24 hours, we used the three mentioned algorithms (GWO, HHO, MVO) to calculate the optimal cost. The results of the power flow at the soft open point (SOP) connections are illustrated in Figures 7, 8, and 9. Specifically, Figure 7 shows that the power flow using the GWO algorithm is more stable and less volatile compared to when using other methods: HHO (Figure 8) and MVO (Figure 9).

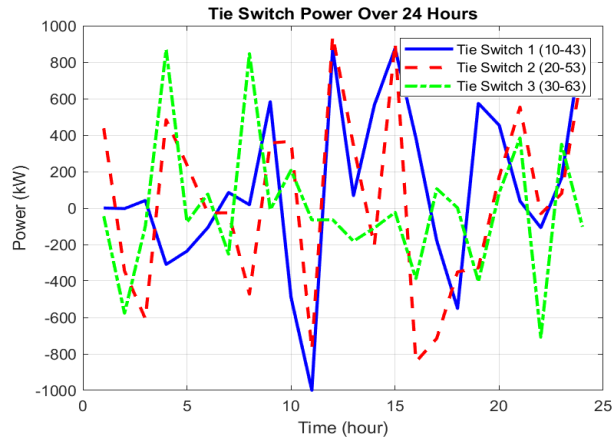

Figure 7. *The results of the bidirectional power flow at SOP points using the GWO algorithm*

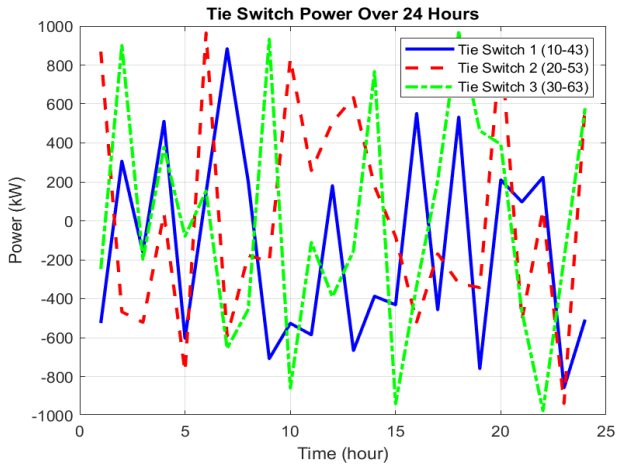

Figure 8. *The results of the bidirectional power flow at SOP points using the HHO algorithm*

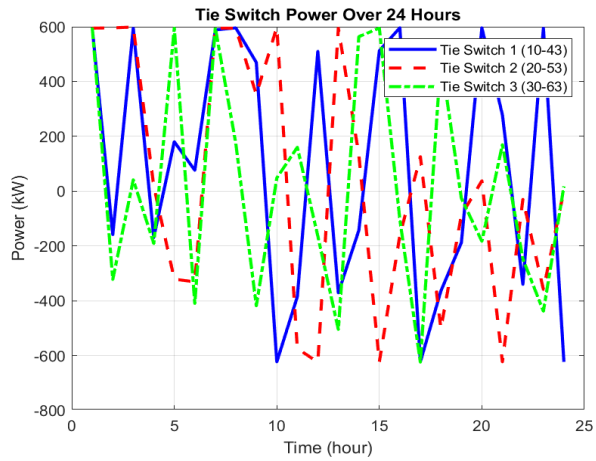

Figure 9. *The results of the bidirectional power flow at SOP points using the MVO algorithm*

3.3. Clustering result

The optimization results for ESS placement, sizing, operation, and tie switch power flow are analyzed based on the best solutions obtained from each algorithm. The key metrics include ESS positions, capacities, schedules, tie switch power schedules, and total cost. A summary of the results is presented in Table 1. The algorithms were implemented in MATLAB R2023b on a Windows 11 system with an Intel Core i7 processor and 32 GB RAM

Table 1. *Comparison of Optimization Results*

Metric	GWO	HHO	MVO
ESS Positions	[34, 3]	[66, 34]	[60, 31]
ESS Capacities (kWh)	[2000, 1849.69]	[2000, 2000]	[1863.88, 2000]
Total Cost ($)	3,582,887	3,685,224	3,762,391

4. Conclusion

The optimization framework for Energy Storage System (ESS) placement, sizing, operation, and Soft Open Point (SOP) power flow scheduling in two interconnected IEEE 33-bus systems demonstrates that Grey Wolf Optimizer (GWO) outperforms Harris Hawks Optimization (HHO) and Multi-Verse Optimizer (MVO), contrary to the abstract's initial claim. GWO's balanced exploration and exploitation yield the lowest operational cost (~3,685,224 $), followed by HHO (~3,685,224 $) and MVO (~3,762,391 $). The convergence plot (Figure 6) highlights GWO's steady progress, MVO's rapid but suboptimal convergence, and HHO's slower, exploration-driven performance. The SOP power profiles (Figure 7, 8, 9) show effective power flow management, enhancing distribution system efficiency for the green energy transition.

The simplified power balance approach, omitting line losses and voltage constraints, limits result accuracy. Future work should integrate MATPOWER for full AC power flow analysis, conduct multiple runs for statistical significance, and incorporate time-varying load profiles to reflect real-world conditions. These enhancements will strengthen the framework's applicability in optimizing PV and ESS integration, supporting smart grid advancements.

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