CHAPTER 6

Hybrid Optimized Controller for HESS

6.1 Hybrid Optimization Techniques

Optimization is a fundamental concept in various domains, including engineering, artificial intelligence, finance, and logistics. Traditional optimization techniques, whether mathematical or metaheuristic often struggle with issues such as slow convergence, local optima entrapment, or inefficient handling of constraints. To overcome these limitations, hybrid optimization techniques have emerged as a powerful approach that combines the strengths of multiple algorithms while mitigating their weaknesses.

Hybrid optimization methods integrate different optimization strategies to enhance solution quality, improve computational efficiency, and ensure robustness across various problem types. Unlike individual optimization techniques that may either explore too broadly (global search) or exploit too narrowly (local search), hybrid approaches strike a balance between exploration and exploitation, leading to faster convergence, higher accuracy, and better adaptability in complex optimization problems.

The advantages of hybrid optimization over individual techniques, demonstrate their effectiveness in multi-objective, constrained, and large-scale optimization problems. By leveraging hybridization, optimization models become more adaptive, efficient, and capable of solving real-world challenges than single-method approaches.

Here, represents two powerful hybrid optimization techniques: Hybrid Particle Swarm Optimization–Artificial Bee Colony (PSO-ABC) and Artificial Bee Colony–Grey Wolf Optimization (ABC-GWO). These hybrid models integrate complementary characteristics of different metaheuristic algorithms to achieve better performance in terms of accuracy, convergence speed, and robustness.

6.1.1 Hybrid PSO-ABC Approach: Formulation

The optimization algorithm is designed as a hybrid approach combining the PSO and the ABC, referred to as PSO-ABC. The hybrid PSO-ABC algorithm optimizes the power flows in island DC MGs to minimize losses and enhance battery efficiency. Table 6.1 shows parameters for hybrid PSO-ABC algorithms.

6.1.1.1 Control parameters for hybrid PSO-ABC algorithms.

Table 6. 1 Parameters for hybrid PSO-ABC

Parameters	Values
***ABC Parameters**:*	
Bee Size (Nb)	50
Scout Bee Limit	10
PSO Parameters	
Particles Size (Np)	50
Inertia Weight (ω)	0.9 to 0.4
Cognitive Coefficient (c1)	2
Social Coefficient (c2)	2
Iterations (T)	100

6.1.1.2 Flowchart and Procedure of Hybrid PSO-ABC Algorithm

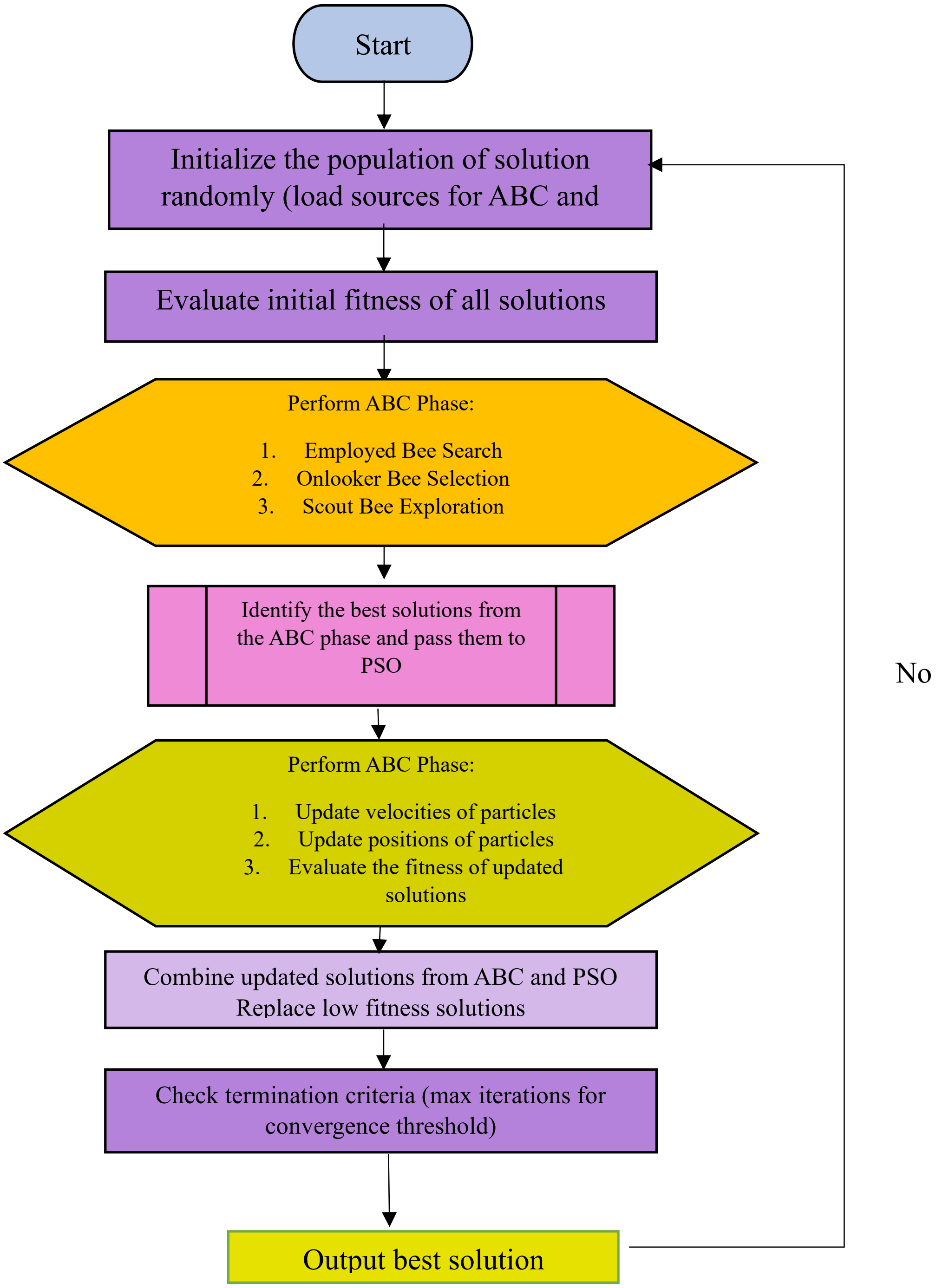

Figure 6. 1 Flowchart of Hybrid ABC-PSO

Figure 6.1 shows a flowchart designed for the proposed hybrid PSO-ABC algorithm. This flowchart represents the modified steps and the integration of the ABC technique within the PSO framework.

The main procedure of the proposed hybrid algorithm includes:

Step 1: Initialization

- **Objective Function**: Define the fitness function (minimize power loss, and maximize the battery efficiency).
- **Constraints**: Include limits for power (Pb, SOCb, SOCsc).
- **Bounds**: Define the range of each variable.
- **Initialize population:**
  Generate a random population of solutions (bees for ABC and particles for PSO). Assign initial velocities for particles in PSO.
- **Set algorithm parameters:**

  For ABC: Number of bees, limit for scout activity.

  For PSO: Inertia weight (ω), cognitive and social coefficients (c1, c2).

Step 2: Combine ABC and PSO

Phase 1: Exploration using ABC

1. **Employed Bees:**
   For each bee, generate a new candidate solution:

$$\text{new\_bee} = \text{bees}(i, :) + \phi \times (\text{bees}(i, :) - \text{bees}(j, :)) \tag{4.11}$$

where $j \neq i$ and $\phi \in [-1,1]$.

Apply boundary constraints.

Evaluate the objective function for new_bee.

Update the bee's position if new_bee has better fitness.

2. **Onlooker Bees:**
   Calculate fitness-based probabilities:

$$\text{probability}(i) = \frac{\text{fitness}(i)}{\sum_{j=1}^{N} \text{fitness}(j)}$$

Use roulette-wheel selection to choose food sources.

Generate new positions for selected bees using the employed bee update rule.

Update positions if fitness improves.

3. **Scout Bees:**
   Replace stagnated solutions (not improved after a set limit) with random solutions.

4. **Store ABC Best:**
   Identify and store the best solution found by the ABC phase.

Phase 2: Exploitation using PSO

1. **Initialization**:
   Use ABC's best solutions as the initial particles for PSO.
2. **Update Velocities and Positions**:
   Update velocities for each particle
   Update positions:
   Apply boundary constraints.
3. **Evaluate Fitness**:
   Compute the fitness for updated particle positions.
   Update personal best (pbest) and global best (gbest).

Step 3: Evaluation

- **Hybrid Evaluation**:
  Combine ABC and PSO solutions.
  Replace low-fitness solutions in ABC with high-fitness solutions from PSO.
- **Update Global Best**:
  Compare the global best solutions from ABC and PSO.
  Retain the best solution overall.

Step 4: Termination Criteria

- **Check for convergence**
  Stop if the maximum number of iterations is reached or if the fitness value converges within a threshold.

6.1.2 Hybrid ABC-GWO Approach: Formulation

The ABC-GWO hybrid optimization in DC microgrids combines the Artificial Bee Colony (ABC) and Grey Wolf Optimizer (GWO) algorithms to enhance system performance, minimize power losses, improve battery efficiency by optimizing charging and discharging cycles, and reduce peak overshoot and settling time for better system response. Table 6.2 represents the Parameters of the Hybrid ABC-GWO algorithm.

6.1.2.1 Control parameters for hybrid ABC-GWO algorithms

Table 6. 2 Parameters of Hybrid ABC-GWO algorithm

Parameters	Values
***ABC Parameters**:*	
No. of Bee (Nb)	50
Scout Bee Limit	10
GWO Parameters	
No. of wolves	100
Iterations (T)	50

6.1.2.2 Flowchart and Procedure of Hybrid ABC-GWO Algorithm

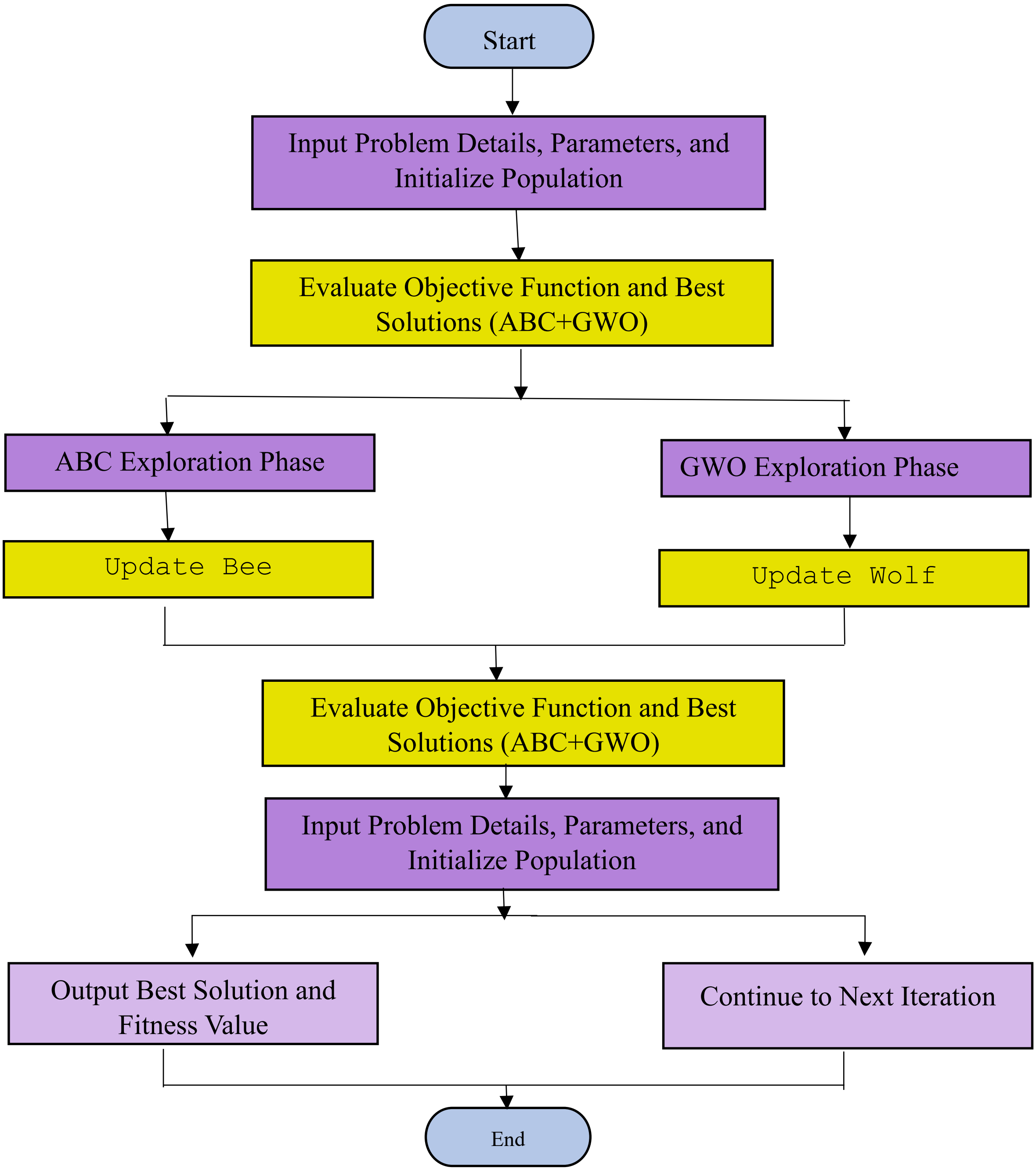

Figure 6. 2 Flowchart of ABC-GWO

Figure 6.2 shows a flowchart designed for the proposed hybrid ABC-GWO algorithms. This flowchart represents the modified steps and the integration of the ABC technique within the GWO framework.

The main procedure of the proposed hybrid algorithm includes:

Step 1: Initialization

Objective Function: Define the fitness function (minimize power loss, and maximize the battery efficiency).

Constraints: Include limits for power (Pb, SOCb, SOCsc).

Initialize population:

ABC (Artificial Bee Colony): Randomly generate a population of solutions (bees), where each bee represents a potential solution for power, and state of charge (SOC).

GWO (Grey Wolf Optimizer): Initialize the positions of wolves in the solution space. Each wolf represents a candidate solution, and they are distributed randomly within the bounds.

Set algorithm parameters:

ABC: Number of bees, limit for scout activity (number of iterations before new random solutions are generated).

GWO: Number of wolves, alpha, beta, and delta wolves (representing best, second-best, and third-best positions), and the number of iterations for optimization.

Step 2: Combine ABC and GWO

Phase 1: Exploration using ABC

Employed Bees:

For each bee, generate a new candidate solution:

$$\text{new\_bee} = \text{bees}(i, :) + \phi \times (\text{bees}(i, :) - \text{bees}(j, :))$$

where $j \neq i$ and $\phi \in [-1,1]$.

Apply boundary constraints.

Evaluate the objective function for new_bee.

Update the bee's position if new_bee has better fitness.

Onlooker Bees:

Calculate fitness-based probabilities:

$$\text{probability(i)}= \frac{\text{fitness(i)}}{\sum_{j=1}^{N}\text{fitness(j)}}$$

Use roulette-wheel selection to choose food sources.

Generate new positions for selected bees using the employed bee update rule.

Update positions if fitness improves.

Scout Bees:

Replace stagnated solutions (not improved after a set limit) with random solutions.

Store ABC Best:

Identify and store the best solution found by the ABC phase.

Phase 2: Exploitation with GWO

Initialization:

Use the best solution found by ABC as the initial positions for the wolves in GWO.

Update Positions of Wolves:

For each wolf, update its position according to the GWO formula:

$$D\alpha = C1\cdot\alpha\text{position\_wolf (i)}$$

$$D\beta = C2\cdot\beta\text{position\_wolf (i)}$$

$$D\delta = C3\cdot\delta\text{position\_wolf (i)}$$

C1, C2, and C3 are random coefficients, and αposition, βposition, and δposition are the positions of the alpha, beta, and delta wolves.

The new positions are computed as: $X_{new} = \frac{(X\alpha+X\beta+X\delta)}{3}$

Evaluate Fitness for GWO:

For each updated wolf position, evaluate the fitness using the objective function.

Update the alpha, beta, and delta positions based on the fitness values.

Store Best Solution from GWO:

After completing the iterations, store the best solution found by GWO.

Step 3: Evaluation

Hybrid Evaluation:

Combine ABC and GWO solutions.

If the GWO solution has better fitness, replace the ABC solution with it.

Update Global Best:

Compare the global best solutions found by both ABC and GWO.

Keep the solution that minimizes energy loss and maximizes battery efficiency.

Step 4: Termination Criteria

Check for convergence

The algorithm terminates when the maximum number of iterations is reached or when the fitness value converges within a specified threshold.

6.1.3 Hybrid Optimization Results

Novel Hybrid optimization techniques approaches were implemented in a DC microgrid to achieve two primary objectives: maximizing battery efficiency and minimizing the battery's charge-discharge period.

Table 6. 3 Output Results of Hybrid Optimization Algorithms

Algorithms	Best score(W)	Iteration	t_s	$\%M_p$	Best Efficiency (%)
PSO-ABC	5984.16	11	0.05 sec	7.04%	78%
ABC-GWO	4314.63	17	0.016 sec	4.72%	85.58%

Table 6.3 shows the PSO-ABC algorithm achieved a best score of 5984.16W in 11 iterations, with a settling time of 0.05 seconds, an overshoot of 7.04%, and a battery efficiency of 78%. In comparison, the ABC-GWO hybrid approach achieved the best score of 4314.63W over 17 iterations, with a settling time of 0.016 seconds, a reduced overshoot of 4.72%, and a superior battery efficiency of 85.58%. Among the two, the hybrid ABC-GWO technique successfully satisfied both objectives, making it the more effective optimization approach for the DC microgrid.

6.2 Comparative Analysis with Existing Techniques

The performance of the proposed optimization techniques is evaluated against existing methodologies based on key parameters such as settling time (t_s), peak overshoot ($\%M_p$), and battery efficiency (%). A lower settling time indicates a faster system response, while reduced peak overshoot ensures better stability. Additionally, higher battery efficiency signifies improved energy utilization, which is crucial for power management systems. The following comparison highlights the advantages of the proposed techniques over traditional methods, demonstrating superior transient response, enhanced system stability, and optimized battery efficiency.

Table 6. 4 Existing Methodology with Results

Specifications	Ref.No.	Methodology	Settling time (t_s)	Peak Overshoot ($\%M_p$)	Battery Efficiency (%)
PV, Battery, SC (400Vdc)	[166]	Double Loop Control	0.04 sec	17%	62%
PV, Battery	[167]	Derivative Control Technique	0.3 sec	N/A	67.3%
PV, Battery (300V)	[168]	Distributed Predictive Control, Model predictive control	0.012 sec	4.8%	75%
DC Motor	[169]	GA-PSO	0.02 sec	5.29%	N/A
PV, Battery	[170]	PSO, PI techniques	0.18 sec	11.1%	N/A
PV, Battery (Grid connected mode)	[171]	PSO, ABC, H-Infinity Controller with Artificial Bee Colony	0.041sec, 0.072sec, 0.07sec	15.8%, 7.41%, 1.26%	N/A
PV, Battery, EDLC supercapacitor (325Vdc)	[172]	Harries hawks and particle swarm optimization (HHO-PSO), HHO, GWO, PSO	0.03 sec, 0.11 sec, 0.16 sec, 0.23 sec	8%, 13%, 12%, 14%	N/A
PV, Battery, Fuel cell	[173]	voltage-frequency (VF) control, PSO-GA	0.02 sec	5.15%	N/A
PV, Battery	[174]	Fractional-order proportional-integral-derivative	0.8 sec	13%	N/A
		GWO	0.4 sec	10%	N/A
Li-ion battery and, SC, Fuel cell, RESs: PV, WTG, (55V)	[175]	GWO (55Vdc)	0.32 sec	15.6%	71%
		PSO-GWO algorithms (55Vdc)	0.17 sec	10.8%	79%

Table 6.4 presents a comparative analysis of various methodologies applied to different power system configurations, highlighting their settling time, peak overshoot, and battery efficiency.

Table 6. 5 Results of the Proposed Techniques

Proposed Techniques					
Algorithm	**Best score(W)**	**Iteration**	**Settling time (t_s)**	**Peak Overshoot ($\%M_p$)**	**Best Battery Efficiency (%)**
PSO	9851.56	38	0.23 sec	6.2%	76%
ABC	10522.6	27	0.4 sec	5.95%	69%
GWO	5327.19	25	0.1 sec	0%	81%
PSO-ABC	5984.16	11	0.05 sec	7.04%	78%
ABC-GWO	4314.63	17	0.016 sec	4.72%	85.58%

Table 6.5 shows the results of the proposed optimization techniques applied to the system. Among the standalone algorithms, GWO delivered notable results with the best score of 5327.19 W achieved in 25 iterations, a settling time of 0.1 seconds, zero overshoot, and the highest efficiency among standalone methods at 81%.

The hybrid techniques further enhanced performance. Among them, the ABC-GWO hybrid emerged as the most effective, achieving the best score of 4314.63 W in 17 iterations, a settling time of 0.016 seconds, a low overshoot of 4.72%, and the highest overall efficiency of 85.58%. These results emphasize the superior optimization capabilities of hybrid techniques, particularly ABC-GWO, in balancing performance metrics and achieving high battery efficiency.

The proposed ABC-GWO, PSO-ABC, and GWO techniques significantly reduce settling time, eliminate or lower peak overshoot, and improve battery efficiency compared to traditional methods. ABC-GWO stands out as the best overall performer, making it a superior choice for power management applications.

Summary

Hybrid metaheuristic optimization techniques, particularly PSO-ABC and ABC-GWO, enhance optimization performance with faster convergence, reduced overshoot, and higher battery efficiency. However, ABC-GWO achieves superior results, offering higher accuracy, faster convergence, and better dynamic response by integrating ABC's adaptive search with GWO's exploitation strategy.