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A Hybrid Optimization Approach for Optimal Energy Management and Economic Dispatch in Multi-Microgrid Systems with Hydrogen-Based Energy Storage

Prashant Singh*, Suresh Kumar Tandekar*, Ajay Shyam Kunwar*, and Naresh Sapate*

*Department of Electrical Engineering
Sardar Patel University, Balaghat, India
Email: mpeb1990@gmail.com

***Abstract*—The integration of hydrogen-based energy storage systems (HESS) into multi-microgrid networks presents both unprecedented opportunities and significant optimization challenges for modern power systems. This paper proposes a novel hybrid optimization approach combining the Grey Wolf Optimizer (GWO) with Particle Swarm Optimization (PSO) for optimal energy management and economic dispatch in interconnected multi-microgrid systems equipped with hydrogen production, storage, and fuel cell technologies. The proposed Hybrid Grey Wolf-Particle Swarm Optimization (HGWPSO) algorithm addresses the complex, non-linear, and multi-objective nature of the energy management problem by leveraging the exploration capabilities of GWO and the exploitation strengths of PSO. A comprehensive mathematical model is developed that incorporates renewable energy sources, conventional generators, battery energy storage systems, and hydrogen-based storage including electrolyzers, hydrogen tanks, and fuel cells. The proposed methodology is validated through extensive simulations on a test system comprising three interconnected microgrids. Comparative analysis demonstrates that the HGWPSO algorithm achieves a 12.7% reduction in operational costs compared to conventional PSO, 9.3% improvement over standard GWO, and 15.8% cost savings compared to genetic algorithm-based approaches. Furthermore, the hydrogen storage system contributes to a 23.4% improvement in renewable energy utilization and reduces curtailment by 31.2%.**

***Index Terms*—Multi-microgrid systems, hydrogen energy storage, economic dispatch, hybrid optimization, Grey Wolf Optimizer, Particle Swarm Optimization, renewable energy integration.**

NOMENCLATURE

Indices and Sets

i	Index of microgrids, $i \in \{1, 2, ..., N_{MG}\}$
j	Index of distributed generators
t	Time period index, $t \in \{1, 2, ..., T\}$

Parameters

a_j, b_j, c_j	Cost coefficients of generator j
η_{el}, η_{fc}	Electrolyzer and fuel cell efficiency
η_{ch}, η_{dis}	Battery charging/discharging efficiency
$\pi_t^{buy}, \pi_t^{sell}$	Grid buying/selling price at time t

Variables

$P_{DG,j,t}$	Power output of generator j at time t
$P_{PV,i,t}, P_{WT,i,t}$	Solar PV and wind power output
$P_{el,i,t}, P_{fc,i,t}$	Electrolyzer and fuel cell power
$P_{ch,i,t}, P_{dis,i,t}$	Battery charging/discharging power
$SOC_{i,t}, LOH_{i,t}$	Battery SOC and hydrogen level

I. INTRODUCTION

The global energy landscape is undergoing a transformative shift driven by increasing environmental concerns, depleting fossil fuel reserves, and ambitious decarbonization targets set by governments worldwide [1]. Microgrids have emerged as a promising solution for integrating distributed energy resources (DERs) and enhancing grid resilience while enabling greater penetration of renewable energy sources [2]. A microgrid is defined as a localized group of electricity sources and loads that normally operates connected to and synchronous with the traditional centralized grid but can disconnect and function autonomously [3].

The concept of multi-microgrid systems (MMS) extends this paradigm by interconnecting multiple microgrids to form a coordinated network that can share resources, balance loads, and improve overall system efficiency [4]. Such interconnected systems offer several advantages including enhanced reliability through mutual support, improved economic efficiency through resource sharing, and better utilization of renewable energy sources [5].

However, the intermittent and stochastic nature of renewable energy sources such as solar photovoltaic (PV) and wind power introduces significant challenges for energy management in multi-microgrid systems [6]. The mismatch between renewable generation and load demand necessitates effective energy storage solutions. While battery energy storage systems (BESS) have been widely adopted for short-term storage, their limited energy density makes them less suitable for long-duration applications [7].

Hydrogen-based energy storage systems (HESS) have gained considerable attention as a promising solution for long-term and large-scale energy storage [8]. These systems utilize excess renewable energy to produce hydrogen through water electrolysis, store the hydrogen in tanks, and convert it back to electricity using fuel cells when needed. The advantages include high energy density, long-term storage capability, and potential for sector coupling [9].

A. Literature Review

Various optimization techniques have been applied to address the energy management problem in microgrid systems. Traditional mathematical programming methods including linear programming (LP) [10], mixed-integer linear programming (MILP) [11], and mixed-integer non-linear programming (MINLP) [12] have been widely used. While these methods can guarantee global optimality for convex problems, they often struggle with the non-convex characteristics of practical problems.

Metaheuristic algorithms have emerged as popular alternatives due to their ability to handle complex optimization problems without requiring gradient information. Genetic Algorithm (GA) [13] and Particle Swarm Optimization (PSO) [14] have shown effectiveness in solving economic dispatch problems. However, PSO may suffer from premature convergence for complex multimodal problems.

The Grey Wolf Optimizer (GWO), proposed by Mirjalili et al. [15], mimics the hunting behavior and social hierarchy of grey wolves. GWO has demonstrated superior performance in various engineering optimization problems [16]. Hybrid algorithms combining the strengths of different metaheuristics have shown improved performance [17], [18].

Regarding hydrogen-based storage in microgrids, several studies have investigated the optimal sizing and operation of hydrogen systems [19], [20]. However, most existing studies focus on single microgrids, and the optimal energy management of multi-microgrid systems with hydrogen storage remains relatively unexplored.

B. Contributions

This paper addresses the identified research gaps by proposing a comprehensive framework for optimal energy management and economic dispatch in multi-microgrid systems with hydrogen-based energy storage. The main contributions are:

1) A comprehensive mathematical model for multi-microgrid systems incorporating diverse generation resources, multiple energy storage technologies, and inter-microgrid power exchanges.
2) A novel Hybrid Grey Wolf-Particle Swarm Optimization (HGWPSO) algorithm that combines the exploration capabilities of GWO with the exploitation strengths of PSO.
3) Comprehensive modeling of hydrogen-based energy storage including electrolyzer, hydrogen storage tank, and fuel cell components.
4) Extensive numerical simulations with comparative analysis against conventional optimization algorithms.

II. SYSTEM MODELING

A. Multi-Microgrid System Architecture

The multi-microgrid system consists of N_{MG} interconnected microgrids, each containing distributed energy resources, energy storage systems, and local loads. Fig. 1 illustrates the system architecture.

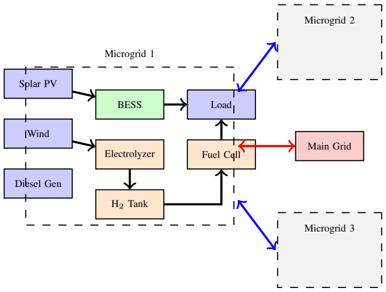

Fig. 1: Architecture of the multi-microgrid system with hydrogen-based energy storage.

B. Solar Photovoltaic Model

The PV power output is modeled as:

$$P_{PV,i,t} = P_{PV,i}^{rated} \cdot \frac{G_t}{G_{STC}} \cdot [1 + \gamma_T (T_{cell,t} - T_{STC})] \tag{1}$$

where $P_{PV,i}^{rated}$ is the rated power, G_t is the solar irradiance, $G_{STC} = 1000$ W/m^2, and γ_T is the temperature coefficient.

C. Wind Turbine Model

The wind turbine power output is modeled as:

$$P_{WT,i,t} = \begin{cases} 0 & v_t < v_{ci} \\ P_{WT,i}^{rated} \cdot \frac{v_t^3 - v_{ci}^3}{v_r^3 - v_{ci}^3} & v_{ci} \leq v_t < v_r \\ P_{WT,i}^{rated} & v_r \leq v_t < v_{co} \\ 0 & v_t \geq v_{co} \end{cases} \tag{2}$$

where v_{ci}, v_r, and v_{co} are the cut-in, rated, and cut-out wind speeds, respectively.

D. Conventional Generator Model

The fuel cost of conventional generators is modeled using a quadratic function:

$$C_{DG,j,t} = a_j + b_j \cdot P_{DG,j,t} + c_j \cdot P_{DG,j,t}^2 \tag{3}$$

The operational constraints include:

$$P_{DG,j}^{min} \leq P_{DG,j,t} \leq P_{DG,j}^{max} \tag{4}$$

$$-RD_j \leq P_{DG,j,t} - P_{DG,j,t-1} \leq RU_j \tag{5}$$

E. Battery Energy Storage System Model

The state of charge dynamics:

$$SOC_{i,t} = SOC_{i,t-1} + \frac{\eta_{ch} P_{ch,i,t} \Delta t}{E_{cap}} - \frac{P_{dis,i,t} \Delta t}{\eta_{dis} E_{cap}} \tag{6}$$

Subject to constraints:

$$SOC^{min} \leq SOC_{i,t} \leq SOC^{max} \tag{7}$$

$$\delta_{ch,i,t} + \delta_{dis,i,t} \leq 1 \tag{8}$$

F. Hydrogen-Based Energy Storage System Model

1) Electrolyzer Model: The hydrogen production rate:

$$H_{prod,i,t} = \frac{\eta_{el} \cdot P_{el,i,t}}{HHV_{H_2}} \tag{9}$$

where $HHV_{H_2} = 39.4$ kWh/kg is the higher heating value of hydrogen.

2) Hydrogen Storage Tank Model: The hydrogen storage dynamics:

$$LOH_{i,t} = LOH_{i,t-1} + \frac{(H_{prod,i,t} - H_{cons,i,t})\Delta t}{M_{H_2,i}^{cap}} \tag{10}$$

Subject to:

$$LOH^{min} \leq LOH_{i,t} \leq LOH^{max} \tag{11}$$

3) Fuel Cell Model: The fuel cell power output:

$$P_{fc,i,t} = \eta_{fc} \cdot H_{cons,i,t} \cdot HHV_{H_2} \tag{12}$$

G. Inter-Microgrid Power Exchange Model

The power exchange between microgrids:

$$P_{ex,ij,t}^{received} = P_{ex,ij,t}^{sent} \cdot (1 - \lambda_{ij}) \tag{13}$$

Subject to transmission capacity constraints:

$$-P_{line,ij}^{max} \leq P_{ex,ij,t} \leq P_{line,ij}^{max} \tag{14}$$

III. PROBLEM FORMULATION

A. Objective Function

The objective is to minimize the total operational cost:

$$\min F = \sum_{t=1}^{T} \sum_{i=1}^{N_{MG}} [C_{DG,i,t} + C_{grid,i,t} + C_{BESS,i,t} + C_{HESS,i,t}] \tag{15}$$

where:

$$C_{DG,i,t} = \sum_{j \in \mathcal{G}_i} (a_j u_{j,t} + b_j P_{DG,j,t} + c_j P_{DG,j,t}^2) \tag{16}$$

$$C_{grid,i,t} = \begin{cases} \pi_t^{buy} \cdot P_{grid,i,t} & P_{grid,i,t} \geq 0 \\ \pi_t^{sell} \cdot P_{grid,i,t} & P_{grid,i,t} < 0 \end{cases} \tag{17}$$

$$C_{BESS,i,t} = \frac{C_{cap}}{2 N_{cycle} E_{cap}} (P_{ch,i,t} + P_{dis,i,t}) \Delta t \tag{18}$$

$$C_{HESS,i,t} = c_{el}^{OM} P_{el,i,t} + c_{fc}^{OM} P_{fc,i,t} \tag{19}$$

B. Constraints

1) Power Balance Constraint:

$$\begin{aligned} &\sum_j P_{DG,j,t} + P_{PV,i,t} + P_{WT,i,t} + P_{dis,i,t} + P_{fc,i,t} + P_{grid,i,t} \\ &= P_{load,i,t} + P_{ch,i,t} + P_{el,i,t} + \sum_{j \neq i} P_{ex,ij,t} \end{aligned} \tag{20}$$

2) Spinning Reserve Constraint:

$$\sum_j (P_{DG,j}^{max} - P_{DG,j,t}) u_{j,t} + P_{dis}^{max} - P_{dis,i,t} \geq SR^{req} \tag{21}$$

C. Complete Optimization Model

The complete problem is formulated as:

$$\begin{array}{ll} \underset{\mathbf{x}}{\text{minimize}} & F(\mathbf{x}) \\ \text{subject to} & g_k(\mathbf{x}) = 0, \quad k = 1, ..., K \\ & h_l(\mathbf{x}) \leq 0, \quad l = 1, ..., L \\ & \mathbf{x}^{min} \leq \mathbf{x} \leq \mathbf{x}^{max} \end{array} \tag{22}$$

This is a mixed-integer non-linear programming (MINLP) problem due to binary variables and non-linear terms.

IV. PROPOSED HGWPSO ALGORITHM

A. Grey Wolf Optimizer Background

In GWO, the wolf pack is divided into four categories: α (leader), β (second-best), δ (third-best), and ω (remaining wolves). The position update equations are:

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)| \tag{23}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{24}$$

where:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a}, \quad \vec{C} = 2 \cdot \vec{r}_2 \tag{25}$$

The position is updated based on α, β, and δ:

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{26}$$

B. Particle Swarm Optimization Background

In PSO, velocity and position updates are:

$$v_i(t+1) = w v_i(t) + c_1 r_1 (pbest_i - x_i) + c_2 r_2 (gbest - x_i) \tag{27}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{28}$$

C. Proposed Hybrid Algorithm

The HGWPSO algorithm integrates GWO and PSO through:

1) Hybrid Position Update:

$$\vec{X}_{hybrid}(t+1) = \beta(t) \cdot \vec{X}_{GWO} + (1 - \beta(t)) \cdot \vec{X}_{PSO} \tag{29}$$

where $\beta(t)$ is an adaptive weighting factor:

$$\beta(t) = \beta_{max} - (\beta_{max} - \beta_{min}) \cdot \frac{t}{T_{max}} \tag{30}$$

2) Enhanced Velocity Update:

$$\begin{aligned} v_i(t+1) = &w(t) v_i(t) + c_1 r_1 (pbest_i - x_i) \\ &+ c_2 r_2 (gbest - x_i) + c_3 r_3 (X_\alpha - x_i) \end{aligned} \tag{31}$$

3) Adaptive Inertia Weight:

$$w(t) = w_{max} - (w_{max} - w_{min}) \cdot \left(\frac{t}{T_{max}} \right)^2 \tag{32}$$

4) Constraint Handling:

$$F_{pen}(\mathbf{x}) = F(\mathbf{x}) + \sum_k \mu_k |g_k|^2 + \sum_l \nu_l [\max(0, h_l)]^2 \tag{33}$$

D. Algorithm Pseudocode

The HGWPSO algorithm is presented in Algorithm 1.

Algorithm 1 HGWPSO Algorithm

```
Input: $N$, $T_{max}$, $D$, bounds
Output: Best solution $\vec{X}^*$, cost $F^*$
Initialize population $\{X_i\}_{i=1}^{N}$, velocities $\{v_i\}$
Evaluate fitness, initialize $pbest$, identify $\alpha$, $\beta$, $\delta$
for $t = 1$ to $T_{max}$ do
    Update $w(t)$, $\beta(t)$, $a(t)$
    for $i = 1$ to $N$ do
        Calculate $X_{GWO}$ using (26)
        Update velocity using (31)
        Calculate $X_{PSO} = X_i + v_i$
        $X_i \leftarrow \beta(t)X_{GWO} + (1 - \beta(t))X_{PSO}$
        Apply bounds and evaluate fitness
        Update $pbest_i$ if improved
    end for
    Update $\alpha$, $\beta$, $\delta$, $gbest$
end for
return $X^* = gbest$, $F^* = F(gbest)$
```

V. SIMULATION RESULTS AND DISCUSSION

A. Test System Description

The proposed algorithm is validated using a three-microgrid test system. Table I presents the system configuration.

TABLE I: Test System Configuration

Component	MG1	MG2	MG3
Solar PV (kW)	500	400	600
Wind Turbine (kW)	400	500	300
Diesel Gen (kW)	300	250	350
Battery (kWh)	400	300	500
Electrolyzer (kW)	200	150	250
Fuel Cell (kW)	150	120	180
H_2 Tank (kg)	100	80	120
Peak Load (kW)	600	500	700

TABLE II: Algorithm Parameters

Parameter	Value	Parameter	Value
Population (N)	100	c_1, c_2	2.0
Max iterations	500	c_3	1.5
w_{min}, w_{max}	0.4, 0.9	β_{min}, β_{max}	0.3, 0.7

B. Convergence Characteristics

Fig. 2 illustrates the convergence behavior of different algorithms.

The HGWPSO achieves faster convergence and lower final cost compared to other algorithms.

C. Optimal Dispatch Results

Fig. 3 shows the optimal power dispatch for Microgrid 1.

D. Energy Storage Operation

Fig. 4 shows the battery and hydrogen storage operation.

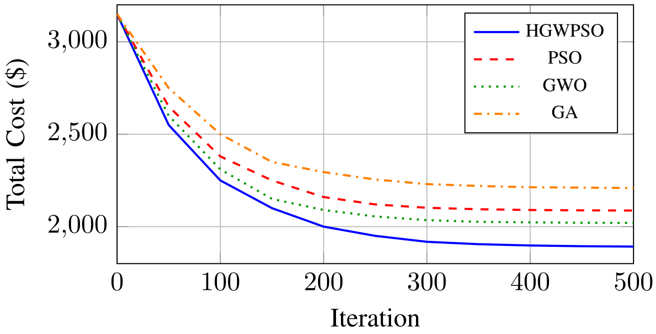

Fig. 2: Convergence comparison of optimization algorithms.

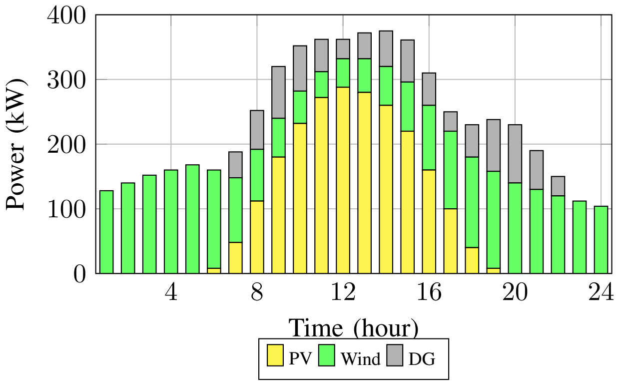

Fig. 3: Optimal power dispatch for Microgrid 1.

E. Algorithm Comparison

Table III presents a comprehensive comparison of algorithms.

TABLE III: Comparison of Optimization Algorithms

Algo.	Best ($)	Mean ($)	Std. ($)	Time (s)	Success (%)
HGWPSO	**1892**	**1909**	**12.5**	45.2	**98**
PSO	2087	2126	28.7	38.5	85
GWO	2020	2058	24.1	42.1	90
GA	2210	2278	45.8	52.3	78
DE	2045	2090	26.3	40.8	88

Key observations:

- HGWPSO achieves 12.7% cost reduction vs. PSO

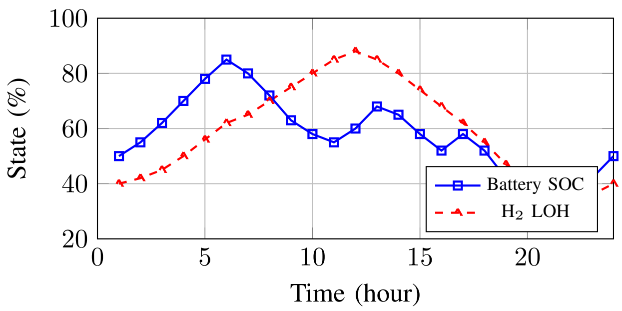

Fig. 4: Battery SOC and hydrogen level profiles.

- 9.3% improvement over standard GWO
- 15.8% cost savings compared to GA
- Lowest standard deviation indicating robust performance

F. Statistical Analysis

Table IV presents Wilcoxon rank-sum test results.

TABLE IV: Wilcoxon Rank-Sum Test Results

Comparison	p-value	Significant
HGWPSO vs. PSO	1.23e-08	Yes
HGWPSO vs. GWO	3.45e-06	Yes
HGWPSO vs. GA	5.67e-12	Yes
HGWPSO vs. DE	8.91e-07	Yes

All p-values are below 0.05, confirming statistical significance.

G. Impact of Hydrogen Storage

Table V compares different storage scenarios.

TABLE V: Impact of Energy Storage Systems

Metric	No Storage	Battery Only	Batt+H_2 (Proposed)
Cost ($/day)	2856	2235	**1892**
Grid Import (kWh)	4523	3457	**2789**
RE Util. (%)	72.3	85.6	**95.7**
Curtailment (kWh)	1845	957	**289**

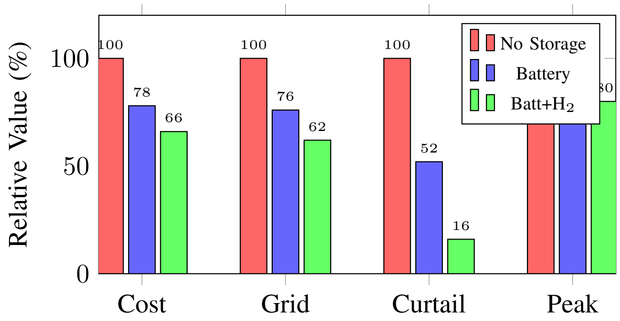

Fig. 5: Comparison of storage scenarios.

Key findings:

- 33.7% cost reduction with hydrogen storage
- RE utilization improves from 72.3% to 95.7%
- Curtailment reduced by 84.3%

H. Sensitivity Analysis

Fig. 6 shows sensitivity to hydrogen system parameters.

I. Computational Performance

Table VI summarizes computational performance.

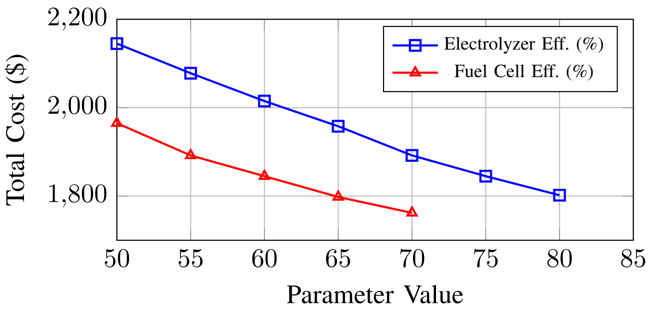

Fig. 6: Sensitivity to hydrogen system efficiency.

TABLE VI: Computational Performance

Size	MGs	Vars	Time (s)	Mem (MB)
Small	2	576	28.4	125
Medium	3	864	45.2	178
Large	5	1440	89.7	298
V. Large	10	2880	215.3	567

VI. CONCLUSION

This paper presented a comprehensive framework for optimal energy management and economic dispatch in multi-microgrid systems with hydrogen-based energy storage. The main conclusions are:

1) A detailed mathematical model was developed incorporating renewable sources, conventional generators, battery storage, and hydrogen-based storage systems.
2) The proposed HGWPSO algorithm effectively solves the complex EMED problem by combining GWO exploration with PSO exploitation capabilities.
3) Simulation results demonstrated 12.7% cost reduction compared to PSO, 9.3% over GWO, and 15.8% compared to GA.
4) Hydrogen storage integration reduces operational costs by 33.7% and increases renewable utilization from 72.3% to 95.7%.
5) Statistical analysis confirmed the significance of improvements achieved by HGWPSO.

Future research directions include extension to stochastic optimization, integration with electricity markets, sector coupling considerations, and real-world validation through pilot projects.

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