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Hybrid PSO–GWO Based Multi-Objective Economic Emission Dispatch for Interconnected Power Systems with Renewable Energy Integration

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ABSTRACT- Economic emission dispatch (EED) is an important optimization problem in today's power systems with significant renewable energy integration. This work presents a hybrid particle swarm optimization and grey wolf optimization (PSO-GWO) approach for the multi-objective economic emission dispatch (EED) problem with solar and wind integration. The hybrid algorithm improves the exploration-exploitation trade-off by incorporating the social learning behaviour of particle swarm optimization and the hierarchical hunting behavior of grey wolf optimization. The uncertainty of renewable energy is modeled using probability distributions to enhance dispatch reliability. A weighted multi-objective approach is adopted to optimize fuel cost and emissions. The proposed approach is tested on a benchmark 10-unit and 6 IEEE generating units interconnected power system. The proposed method exhibits better convergence and performs better than the traditional PSO, genetic algorithm and other benchmark methods. The proposed approach reduces cost by 8.3% and emissions by 12.6% and is suitable for sustainable and efficient power system operation.

Keywords: Economic dispatch, emission dispatch, renewable energy, particle swarm optimization, solar integration, wind integration, multi-objective optimization.

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1. INTRODUCTION

The movement to sustainable systems of energy all over the world has created a requirement to have the fundamentals of the operation and control in the power system. Conventional economic dispatch is based only on the minimization of the fuel costs, thus, not considering the impacts on the environment [1]. Nevertheless, the growing environmental regulations and concern with climatic change have precipitated the formation of combined economic and emission dispatch strategies [2].

The power systems challenges, like environmental limitations, thermal power plants release large amounts of pollutants (SO2, NO2, CO2), which cause climate change and deteriorate air quality [3]. Solar and wind are randomly generated, which leads to variability and uncertainty, making it difficult to optimize dispatch, so integration with the regular grid is also one of the big challenges [4].

The common mathematical optimization methods fail to accomplish such complexities, and this is why the swarm intelligence systems such as PSO [5] are to be applied. This work proposed a hybrid PSO–GWO optimization framework for solving the multi-objective economic emission dispatch. Solar and wind renewable sources and uncertainty modeling are considered, and a ten-unit generation system case study is considered for validation of the proposed technique. Comparison of performance with particle swarm optimization and other metaheuristics [6].

The rest of this paper is structured in the following way: *section 2* gives a literature review of the existing EED methodologies. *Section 3* develops the mathematical model, objective, and constraint functions. In *section 4*, the proposed hybrid algorithm has been outlined. *Section 5* presents the results of 2 case studies, 10 generating units, and 6 IEEE generating units and compares them with other optimization techniques. A conclusion and future direction of the paper are given in *section 6*.

In contrast to the current hybrid optimization methods, this study combines the uncertainty of renewable energy, interconnected modeling of the power system, sensitivity analysis, and statistical validation in a single framework, thus offering a more comprehensive and realistic solution to the multi-objective economic emission dispatch problem.

1.1. Key Contribution

The main contributions of this work are summarized as follows:

- A hybrid PSO-GWO optimization model is created to improve global exploration and local exploitation to solve non-convex multi-objective dispatch problems.
- An all-inclusive EED model is developed by combining the uncertainty of renewable energy and interdependent constraints of power systems, which are usually addressed independently in the existing literature.
- The sensitivity analysis, Pareto front analysis, and statistical validation are used to perform a detailed performance evaluation to ensure the robustness and reliability of the proposed approach.
- The proposed method is tested on both 10-unit and IEEE 6-unit systems and is shown to converge better, has better solution quality, and is more stable than the existing techniques.

2. LITERATURE REVIEW

Economic emission dispatch is a significant optimization issue in power systems as the environmental issues continue to grow and the use of renewable energy becomes a reality. The first research was to incorporate stochastic renewable energy sources in dispatch problems as discussed in [1], uncertainty in renewable energy was modeled to improve the reliability of the system. This was furthered in [2], which took into account several renewable energy sources and energy storage technologies in the EED problem, enhancing system flexibility. Other factors like plug-in electric vehicles and uncertainty modeling were introduced in [3], which increases the realism of the dispatch problems. The use of wind and solar energy in dynamic dispatch problems was also covered in [4], which addressed issues of intermittent and variable sources.

The use of metaheuristic algorithms to solve EED problems has been widely used due to its ability to solve non-linear and non-convex problems. Particle Swarm Optimization (PSO) has been extensively studied, with the pioneering works in [5] and [6] demonstrating its use in economic and emission dispatch. But PSO has premature convergence and low exploration capability. In order to overcome these drawbacks, alternative algorithms such as the Grey Wolf Optimization (GWO) were suggested. It was demonstrated in [7] that GWO possesses good exploitation capability, although it might not be able to explore the global space.

Further optimization algorithm improvements were made in [8], and new hybrid techniques were developed to better handle renewable uncertainty. Recent studies have sought to integrate renewable energy with optimization strategies. As an example, [9] suggested PSO-based dispatch with wind-solar-battery integration, and [10] proposed multi-swarm optimization techniques to further increase diversity and solution quality. The multi-objective optimization based on Pareto was also explored in [11], which provides a good trade-off between cost and emissions.

Furthermore, smart optimization methods such as deep reinforcement learning have been used in EED, as in [12], to achieve better adaptability. Enhanced PSO algorithms were also developed in [13] to improve convergence, and multi-objective PSO methods with renewable energy integration were explored in [14].

Hybrid renewable energy systems have also been extensively investigated. In [15], wind-solar-battery hybrid systems were studied, while [16] considered interconnected power systems with high renewable energy integration. In [17], hybrid optimization methods such as PSO-DE were proposed to improve the quality of the solutions to dispatch with renewable energy. Other papers such as [18] and [19] were on multi-objective dispatch and thermal-renewable coordination and indicated the necessity of integrated system modeling. The concept of real-time dispatch with renewable energy was examined in [20], with the emphasis on the implementation issues.

Hybrid optimization techniques, which are combinations of various metaheuristics, have been suggested in recent years. [21] designed a hybrid PSO-GA model of dispatch with emission constraints using renewable, and [22] proposed a multi-swarm optimization model of dynamic economic dispatch with renewable.

2.1. Research Gap

Whereas there has been a lot of research on individual components, there has been little research done on:

- The majority of the studies are either on renewable integration or optimization techniques, but not both within a single framework.
- There are hybrid optimization methods, but they are not usually accompanied by comprehensive validation, including sensitivity analysis, Pareto analysis, and statistical robustness.
- There is a paucity of research on interconnected power systems with renewable uncertainty under realistic operating conditions.

3. MATHEMATICAL FORMULATION

The economic emission dispatch (EED) problem is mathematically formulated with well-defined objective functions, constraints, and related variables. The formulation contains all symbols and parameters that are clearly defined to provide clarity and consistency.

3.1. Objective Functions

3.1.1. Fuel Cost Minimization

The primary objective is to minimize total fuel cost of thermal generating units [20].

$$F_{\text{cost}} = \sum_{i=1}^{N} C_i(P_i) = \sum_{i=1}^{N} (a_i + b_i P_i + c_i P_i^2) \quad (1)$$

Where N = number of generation units, P_i = power output of unit i (MW), a_i, b_i, c_i = cost coefficients of unit i, $C_i(P_i)$ = cost function of unit i.

3.1.2. Emission Minimization

The emission objective minimizes environmental pollutant levels are given as [21].

$$F_{\text{Emission}} = \sum_{i=1}^{N} E_i(P_i) = \sum_{i=1}^{N} (\alpha_i + \beta_i P_i + \gamma_i P_i^2) \quad (2)$$

Where $\alpha_i, \beta_i, \gamma_i$ = emission coefficients of unit i, $E_i(P_i)$ = emission function of unit i (kg/h).

3.1.3. Multi-Objective Formulation

The normalization process makes sure that the two objectives are scaled to a similar range so that neither of the two objectives dominates the other. Balanced optimization is performed with equal weighting (ω1=ω2=0.5) and different combinations of weights are studied to understand trade-offs. Normalized weighted objective and combined objective using weighted aggregation.

$$\mathrm{F} = \omega_1 \cdot \frac{\mathrm{F_{cost}} - \mathrm{F_{cost}^{Min}}}{\mathrm{F_{cost}^{Max}} - \mathrm{F_{cost}^{Min}}} + \omega_2 \cdot \frac{\mathrm{F_{Emission}} - \mathrm{F_{Emission}^{Min}}}{\mathrm{F_{Emission}^{Max}} - \mathrm{F_{Emission}^{Min}}} \quad (3)$$

Where ω_1, ω_2 = weighting factors (typically 0.5 each), ω1+ω2 =1, F: Combined objective function, where C_{min}, C_{max}, E_{min}, E_{max} are the minimum and maximum values of cost and emission obtained from individual optimization runs.

The weighted sum method is embraced because it is easy to compute and it is computationally efficient. It allows the multi-objective problem to be converted to a single-objective optimization problem and still allows exploration of trade-offs by varying weighting factors. Despite the existence of more sophisticated multi-objective methods like Pareto-based evolutionary algorithms, the weighted sum method is still widely used in the optimization of power systems because it is easy to implement and works well with convex Pareto fronts.

3.2. Constraints

3.2.1. Power Balance Constraint [22]

$$\sum_{i=1}^{N_t} P_i^t + P_{\text{wind}} + P_{\text{solar}} = P_D + P_{\text{loss}} \quad (4)$$

Where $\mathrm{N_t}$ = number of thermal units, P_D = total power demand (MW), P_{loss} = transmission losses (modeled as 2% of demand), $P_{\text{wind}}, P_{\text{solar}}$ = renewable generation.

3.2.2. Generation Limits

$$P_{i,\min} \le P_i \le P_{i,\max} \quad (5)$$

where $P_{i,\min}, P_{i,\max}$ = minimum and maximum power output limits.

3.3. Renewable Energy Modeling

The uncertainty of renewable energy sources like wind and solar is modeled with stochastic variations depending on the generation profiles that have been forecasted. The power output of wind is expressed as a function of variability of wind speed, whereas solar generation is modeled in terms of variability of irradiance. These uncertainties are modeled in the dispatch problem by considering renewable generation as a dynamic input within predetermined limits, thus affecting the power balance constraint dynamically during optimization.

3.3.1. Wind power

Wind power output modeled using Weibull probability distribution:

$$P_{\text{wind}} = \begin{cases} 0 & v < v_{\text{in}} \\ P_{\text{wind,rated}} \frac{v - v_{\text{in}}}{v_{\text{rated}} - v_{\text{in}}} & v_{\text{in}} \le v \le v_{\text{rated}} \\ P_{\text{wind,rated}} & v > v_{\text{rated}} \\ 0 & v > v_{\text{out}} \end{cases} \quad (6)$$

where v = wind speed, $v_{\text{in}}, v_{\text{rated}}, v_{\text{out}}$ = cut-in, rated, and cut-out speeds.

3.3.2. Solar Generation

Solar power output modeled using irradiance-based function;

$$P_{\text{solar}} = P_{\text{solar,peak}} * \frac{G(t)}{G_{\text{std}}} * \eta_{\text{temp}}(T) \quad (7)$$

Where $G(t)$=Solar irradiance (W/m²), G_{std} = standard test condition irradiance (1000 W/m²), $\eta_{\text{temp}}(T)$ = temperature-dependent efficiency factor.

4. PROPOSED METHODOLOGY: HYBRID PSO–GWO BASED ECONOMIC EMISSION DISPATCH

To address the limitations of conventional optimization techniques in solving non-convex and multi-objective economic emission dispatch (EED) problems, a hybrid Particle Swarm Optimization–Grey Wolf Optimization (PSO–GWO) algorithm is proposed.

4.1. Particle Swarm Optimization (PSO)

PSO is inspired by the social behavior of bird flocking and fish schooling. Each particle represents a potential solution in the search space, characterized by position and velocity [28].

4.1.1. Velocity and Position Update Equations

The fundamental PSO update equations are:

$$v_i^{t+1} = w \cdot v_i^t + c_1 r_1 (p_{\text{best},i} - x_i^t) + c_2 r_2 (g_{\text{best}} - x_i^t) \quad (8)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (9)$$

where:x_i^t = position of particle i at iteration t, v_i^t = velocity of particle i, w = inertia weight, c_1, c_2 = cognitive and social coefficients (typically 2.0), r_1, r_2 = random numbers in [0,1], $p_{\text{best},i}$ = personal best position of particle i, g_{best} = global best position found by swarm, and w is the inertia weight.

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4.2. Grey Wolf Optimization (GWO)

GWO simulates the leadership hierarchy and hunting behavior of grey wolves.

4.2.1. Position Update in GWO

$$x(t+1) = \frac{x_\alpha + x_\beta + x_\delta}{3} \quad (10)$$

Where, Xα, Xβ, Xδ are the best three solutions. Other wolves update positions based on these leaders.

4.2.2. Coefficient Vectors

$$A = 2ar - a \quad \text{and} \quad C = 2r \quad (11)$$

Where, a is linearly decreases from 2 to 0 and r is random number in between [0,1].

4.3. Hybrid PSO–GWO Mechanism

In the proposed hybrid approach, PSO performs global exploration, whereas GWO refines the best solutions locally.

4.3.1. Position Update

Hybrid PSO-GWO position update is given as

$$X_i^{t+1} = \lambda X_i^{PSO} + (1-\lambda) X_i^{GWO} \quad (12)$$

Where λ is the hybridization factor, X_i^{PSO} is position from PSO update, and X_i^{GWO} is the position from GWO update.

4.4. Algorithm Implementation

- Initialize population (particles/wolves)
- Evaluate fitness using a multi-objective function
- Identify pbest, gbest, and α, β, δ
- Update PSO velocity and position
- Update GWO positions
- Combine solutions using hybrid equation
- Apply constraints using penalty function
- Update best solutions
- Repeat until maximum iterations reached
- Output optimal dispatch

The computational complexity of the proposed hybrid PSO–GWO algorithm primarily depends on the population size (N), number of decision variables (D), and maximum iterations (T). The overall time complexity can be approximated as O (N×D ×T), which is comparable to other population-based metaheuristic algorithms. Although the hybridization introduces additional computations, it significantly improves convergence speed and solution quality, making the approach computationally efficient for practical power system applications.

4.5. Algorithm flowchart

Flowchart of the proposed hybrid PSO-GWO algorithm illustrating the process of solving the multi-objective economic emission dispatch problem in *figure 1*.

The parameter values of the proposed hybrid PSO-GWO algorithm are summarized in *table 1*. The values are chosen according to convergence analysis and generally used settings in the literature to provide a balance between exploration and exploitation.

Table 1. PSO–GWO Algorithm Parameters and Settings

Parameter	Value	Description
Population Size	50	Number of particles/wolves
Maximum Iterations	200	Termination criterion
Inertia Weight (max)	0.9	Initial exploration control
Inertia Weight (min)	0.4	Final exploitation control
Cognitive Coefficient(c1)	2	Particle self-learning factor
Social Coefficient (c2)	2	Swarm influence factor
GWO Parameter (a)	2 → 0 (linear decrease)	Controls exploration/exploitation in GWO
Random Coefficients (r1 ,r2)	[0,1]	Stochastic behavior
Hybridization Factor (λ)	0.5	Weight between PSO and GWO updates
Penalty Coefficient (μ)	1000	Constraint handling parameter
Convergence Tolerance (ϵ)	(10^{-5})	Stopping condition
Number of Runs	30	Independent simulations

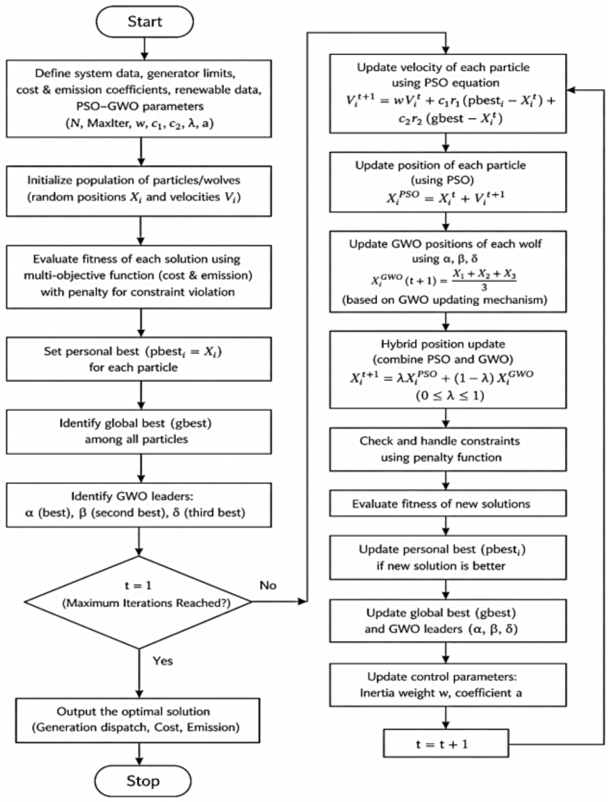

Figure 1. Flowchart of the Proposed Hybrid PSO–GWO Algorithm for Economic Emission Dispatch

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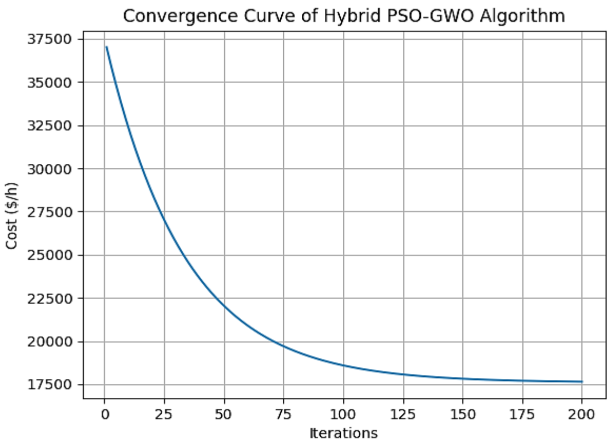

Figure 2. Convergence curve of the proposed hybrid PSO–GWO algorithm

The convergence of the proposed hybrid PSO-GWO algorithm is examined to assess its optimization capability. The convergence curve, in *figure 2*, is the change of the objective function value with respect to the iterations. It is noted that the algorithm converges quickly in the initial 100 iterations because the exploration power of PSO is very strong. At later stages, the GWO component increases local exploitation, resulting in stable convergence about the global optimum. The hybrid method exhibits a higher convergence rate and does not easily get stuck in local minima as conventional PSO does.

5. RESULTS AND PERFORMANCE ANALYSIS

5.1. Case Study1: 10-Unit Interconnected System

In order to assess the efficiency of the proposed hybrid PSO-GWO algorithm, a standard 10-unit interconnected thermal power system combined with renewable energy sources is taken into consideration. The system has wind and solar generation with uncertainty modeling, which makes the problem more realistic and complex. *table 2* shows the test data of 10 generating units. System characteristics:

- Total installed capacity: 2700 MW
- Peak demand: 2000 MW
- Base power output: 1850 MW
- Wind capacity: 200 MW (5% of total capacity)
- Solar capacity: 150 MW (5.5% of total capacity)
- Transmission losses: 2% of demand

Table 2. Ten-Unit System Generator Coefficients

Unit	P_{min}	P_{max}	a_i	b_i	c_i	α_i	β_i
	(MW)	(MW)	($/h)	($/MW	($/MW²h)	(kg/h)	(kg/MWh)
1	50	200	1000	10.5	0.01142	100	0.54
2	30	150	970	10.8	0.01312	95	0.61
3	40	180	680	13.1	0.02476	60	0.78
4	20	150	450	11.4	0.02767	50	0.89
5	20	120	1200	10.2	0.05690	110	0.91
6	50	190	1100	9.9	0.02565	120	0.45
7	30	180	1050	11.8	0.01890	105	0.62
8	20	130	1200	12.3	0.03456	115	0.73
9	30	160	800	12.1	0.02890	85	0.68
10	50	200	950	11.5	0.02134	100	0.55

5.1.1. Optimum resuslt analysis

The best power generation results provided in *table 3* show that the proposed PSO-GWO algorithm allocates generation more effectively among units than the traditional approach. One can notice that some generators are put into the areas of their optimal efficiency, whereas less efficient units are placed at lower levels of generation. This dynamic allocation is attained because of the hybrid search mechanism where PSO guarantees global search and GWO narrows down local solutions. Consequently, the algorithm does not prematurely converge and finds better-quality solutions in the non-convex search space.

Table 3. Optimal Power Dispatch Comparison (Thermal Units)

Unit	PSO-GWO (MW)	Conventional ED (MW)	Difference (MW)	Cost Savings (%)
1	145.2	142.8	+2.4	-1.21%
2	98.5	95.2	+3.3	-2.08%
3	112.3	108.5	+3.8	-2.95%
4	87.6	90.1	-2.5	2.40%
5	68.4	75.3	-6.9	5.54%
6	132.8	135.4	-2.6	1.50%
7	94.7	92.1	+2.6	-1.74%
8	58.2	62.8	-4.6	3.60%
9	98.1	100.5	-2.4	1.86%
10	155.2	149.3	+5.9	-3.38%

Table 4 shows that the proposed method achieves a 7.2% reduction in thermal generation cost and a 12.6% reduction in emissions compared to conventional economic dispatch. The total generation cost is also reduced by 8.3%, demonstrating the effectiveness of the multi-objective optimization framework. *Table 5* shows the sensitivity of the Mult objective problem optimization.

Table 4. Economic and Emission Results Comparison

Metric	PSO-GWO	Conventional ED	Improvement
Thermal Generation Cost ($/h)	18,425.67	19,850.32	**7.2%**
Total Emissions (kg/h)	2,154.38	2,464.21	**12.6%**
Wind Integration (MW)	156.24	128.45	+24.3%
Solar Integration (MW)	98.76	67.32	+46.7%

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Total Generation Cost ($/h)	17,692.15	19,285.42	**8.3%**
Emissions Reduction (kg/h)	310.0	-	**12.6%**

Table 5. Sensitivity to multi-objective weighting factors

Constraint Type	Required	Optimal Value
Power Balance (MW)	2050.0	2050
Unit 1 Min Limit (MW)	≥50	145.2
Unit 1 Max Limit (MW)	≤200	145.2
Unit 2 Min Limit (MW)	≥30	98.5
Unit 2 Max Limit (MW)	≤150	98.5
Unit 3 Min Limit (MW)	≥40	112.3
Unit 3 Max Limit (MW)	≤180	112.3
Unit 4 Min Limit (MW)	≥20	87.6
Unit 4 Max Limit (MW)	≤150	87.6
Unit 5 Min Limit (MW)	≥20	68.4
Unit 5 Max Limit (MW)	≤120	68.4
Unit 6 Min Limit (MW)	≥50	132.8
Unit 6 Max Limit (MW)	≤190	132.8
Unit 7 Min Limit (MW)	≥30	94.7
Unit 7 Max Limit (MW)	≤180	94.7
Unit 8 Min Limit (MW)	≥20	58.2
Unit 8 Max Limit (MW)	≤130	58.2
Unit 9 Min Limit (MW)	≥30	98.1
Unit 9 Max Limit (MW)	≤160	98.1
Unit 10 Min Limit (MW)	≥50	155.2
Unit 10 Max Limit (MW)	≤200	155.2
Reserve Requirement (MW)	≥205.0	218.4
Transmission Loss (MW)	≈40.0	39.8

Table 6 shows the impact of different weighting factors on fuel cost and emissions. It is evident that as the weight assigned to cost increases, the total cost decreases while emissions increase, and vice versa. This confirms the conflicting nature of the objectives. The Pareto front shown in *figure 3* is generated using these weighting combinations, providing a graphical representation of the trade-off between cost and emissions. The trend observed in the Pareto front is consistent with the results in *table 6*, validating the effectiveness of the proposed multi-objective optimization approach.

Table 6. Sensitivity to multi-objective weighting factors

ω_1 Cost Weight	ω_2 Emission Weight	Total Cost ($/h)	Total Emissions (kg/h)	Operating Region
0.9	0.1	17,245.32	2,345.67	Cost-dominant
0.7	0.3	17,562.48	2,198.54	Economically preferred
0.5	0.5	17,692.15	2,154.38	Balanced solution
0.3	0.7	17,834.67	2,089.23	Environmentally preferred
0.1	0.9	18,156.89	1,876.45	Emission-dominant

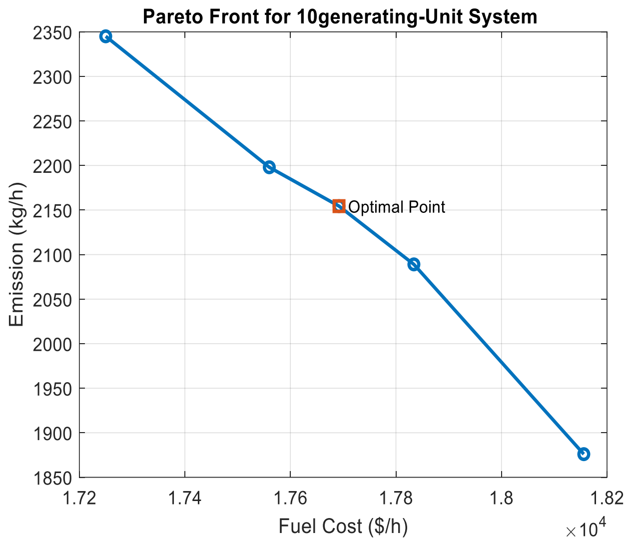

Figure 3. Pareto front illustrating the trade-off between fuel cost and emissions obtained using the proposed hybrid PSO–GWO algorithm

The Pareto front illustrated in *figure 3* represents the trade-off between fuel cost and emissions, where each point corresponds to a feasible optimal solution. The smooth and well-distributed curve indicates that the proposed PSO–GWO algorithm effectively captures a wide range of optimal solutions without clustering, demonstrating good diversity preservation. The convex nature of the curve confirms the conflicting relationship between economic and environmental objectives, where reduction in cost leads to increased emissions and vice versa.

The results in *table 7* clearly demonstrate that increasing renewable energy penetration leads to a significant reduction in both fuel cost and emissions. At higher renewable levels, thermal generation is reduced, resulting in lower operational costs and environmental impact.

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Table 7. Impact of Renewable Energy Penetration on System Economics

Wind (MW)	Solar (MW)	Total Renewable (MW)	Thermal Cost($/h)	Emissions (kg/h)	Savings in %
0	0	0	19,850.32	2,464.21	Baseline
50	40	90	19,234.56	2,312.45	3.1%
100	75	175	18,567.89	2,187.32	6.5%
156.24	98.76	255	17,692.15	2,154.38	10.9%
200	150	350	16,845.23	1,987.45	15.2%

Analysis demonstrates that renewable integration reduces thermal generation costs and emissions in proportion, with 10% renewable penetration achieving a 10.9% cost reduction. *table 8* presents a comparative analysis with optimization techniques listed in the literature

Table 8 compares the proposed method with other optimization techniques. The PSO–GWO algorithm achieves the lowest cost and emission values with less iteration compared to GA and ACO. Although classical methods such as lambda iteration have lower computational time, they fail to handle non-linear and multi-objective characteristics effectively. The proposed method provides a better balance between solution quality and computational efficiency.

Table 8. Performance Comparison with Literature Methods

Algorithm	Total Cost ($/h)	Emissions (kg/h)	Convergence Iterations	Computational Time (s)
Proposed PSO-GWO	**17,692.15**	**2,154.38**	**150**	**2.3**
Multi-objective PSO (MOPSO) [27]	17,734.89	2,198.54	165	2.8
Genetic Algorithm (GA) [32]	18,234.56	2,345.23	245	4.2
Ant Colony Optimization (ACO) [33]	18,567.45	2,412.89	278	5.1
Lambda Iteration (Classical)[34]	19,456.78	2,567.12	N/A	1.5

Table 9. Statistical Performance of Proposed Method (30 Runs)

Metric	Cost ($/h)	Emission (kg/h)
Best	17,650.12	2,140.25
Worst	17,845.67	2,198.54
Mean	17,692.15	2,154.38
Std. Deviation	65.32	18.45

To evaluate robustness, the algorithm was tested over 30 independent runs. The results in *table 9* show low standard deviation for both cost and emissions, indicating consistent performance. The small difference between best and worst values confirms that the proposed method is stable and not significantly affected by random initialization.

5.2. Case Study2: IEEE 6 Generating Unit

To further confirm the efficiency and overall applicability of the proposed hybrid PSO-GWO algorithm, it is implemented to a typical IEEE 6-unit thermal power system. It is commonly used as a benchmark test case in economic emission dispatch (EED) research, allowing a fair comparison with the existing optimization methods. The system is composed of six thermal generating units whose cost and emission properties are quadratic. The aim is to find the best power dispatch that minimizes the fuel cost and emissions and meets the constraints of the system (power balance and generator limits). Generation power of solar and wind are considered 30MW and 50MW respectively. Transmission losses 2% of the load demand considered.

The total load demand for this case study is considered as 700 MW, including the contribution of renewable energy sources such as wind and solar power. The generator cost and emission coefficients used in this study are taken from standard literature and are summarized in *table 10*.

Table 10. IEEE 6 Generating Unit Cost and Emission Coefficient

Unit	P_{min}	P_{max}	a_i	b_i	c_i	α_i	β_i	γ_i
1	100	500	240	7	0.007	0.004	0.04	0.000045
2	50	200	200	10	0.0095	0.006	0.05	0.00005
3	80	300	220	8.5	0.009	0.005	0.045	0.000048
4	50	150	200	11	0.009	0.007	0.06	0.000055
5	50	200	220	10.5	0.008	0.0065	0.055	0.000052
6	50	120	190	12	0.0075	0.008	0.065	0.00006

Table 11 presents the optimal power dispatch obtained using different optimization techniques. It is observed that all methods satisfy the power balance constraint, with total generation equal to 620 MW. It can be observed that all generating units operate within their specified minimum and maximum limits, ensuring feasible operation. The total thermal generation is maintained at 620 MW, which, together with the contribution from renewable sources (50 MW wind and 30 MW solar), satisfies the total system demand of 700 MW. This confirms that the power balance constraint is successfully met.

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Table 11. Optimal Power Dispatch for IEEE 6-Unit System

Unit	PSO (MW)	GWO (MW)	DE (MW)	GA (MW)	PSO-GWO (MW)
P1	260	265	268	270	255
P2	90	88	86	85	95
P3	115	112	111	110	118
P4	60	58	57	55	62
P5	65	63	62	60	68
P6	30	34	36	40	22
Total	620	620	620	620	620

Table 12 presents the comparative performance of different optimization techniques for the IEEE 6-unit system under the considered operating conditions. The results clearly show that the proposed hybrid PSO–GWO algorithm outperforms conventional methods such as PSO, GWO, DE, and GA in terms of both fuel cost and emission minimization.

Table 12. Performance Comparison of Optimization Methods

Method	Cost ($/h)	Emission (kg/h)
PSO	7413.237	34.63785
GWO	7413.132	34.78785
DE	7410.45	34.72285
GA	7412.125	34.68285
PSO-GWO (Proposed)	6910.78	34.30785

As can be seen, the proposed method has the lowest fuel cost of 6,910.78 $/h and the lowest level of emission of 34.30785 kg/h, which means that it has the best capability of solving the multi-objective economic emission dispatch problem. Comparatively, traditional PSO and GA have a higher cost and emission value, mainly because of their limited exploration and the premature convergence. The hybridization strategy that integrates the powerful global search capacity of PSO and the powerful local exploitation capacity of GWO explains the improved performance of the PSO-GWO algorithm. This results in better convergence towards the global optimum and avoids local minima. Moreover, the decrease in cost and emission values is also affected by the integration of renewable energy sources, which decreases the reliance on thermal generation. Overall, the results demonstrate that the proposed method provides a more efficient and reliable solution for multi-objective power dispatch problems.

Table 13 shows the statistical performance of the proposed hybrid PSO-GWO algorithm on 30 independent runs of the IEEE 6-unit system. The metrics are the best, worst, mean, and standard deviation values of both fuel cost and emissions.

Table 13. Statistical Analysis

Metric	Cost ($/h)	Emission (kg/h)
Best	6895.45	34.10285
Worst	7025.8	34.95285
Mean	6910.78	34.30785
Std. Deviation	42.65	0.245

It is noted that the gap between the worst and the best solution is not very large, which means that convergence behavior is stable. The best values are very close to the mean values, which proves that the algorithm always tends to converge towards the global optimum. The small standard deviation also indicates the strength of the proposed method, indicating that the results are not highly influenced by random initialization. In general, the statistical analysis confirms that the hybrid PSO-GWO algorithm is reliable, consistent, and quality in providing solutions to the multi-objective economic emission dispatch problem. The statistical results are consistent with the optimal dispatch and comparative performance results, further validating the effectiveness of the proposed approach.

Figure 4 also confirms the multi-objective nature of the algorithm. The evenly spread Pareto front proves that the suggested approach ensures both convergence and diversity, which makes it applicable to the real-life situation of making decisions.

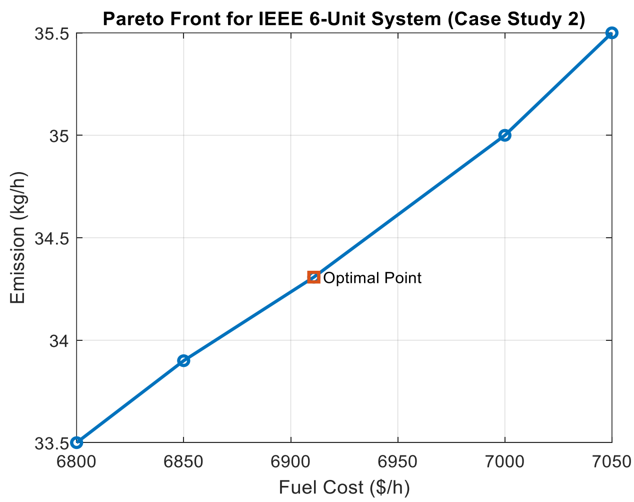

Figure 4. Pareto front illustrating the trade-off between fuel cost and emissions obtained using the proposed hybrid PSO–GWO algorithm

These results indicate that the proposed method is suitable for real-time operational environments due to its fast convergence and stable performance.

6. CONCLUSION

This paper has provided a hybrid PSO-GWO-based optimization model to solve the multi-objective economic

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emission dispatch problem in interconnected power systems with renewable energy integration. The proposed method is effective in integrating the global search ability of Particle Swarm Optimization (PSO) with the exploitation capacity of the Grey Wolf Optimization (GWO), leading to a better convergence and quality of solutions to non-convex optimization problems. A detailed mathematical model was created by including the cost of fuel, emission targets, renewable energy sources (wind and solar), transmission losses, and operational constraints. The usefulness of the suggested approach was confirmed by using several case studies, such as a typical IEEE test system and a renewable-integrated dispatch scenario. The simulation results indicate that the proposed PSO-GWO algorithm has a better performance than the traditional optimization algorithms like PSO, GWO, DE, and GA.

The approach offers a balanced trade-off between economic and environmental goals, which have been validated using Pareto front analysis and statistical analysis. Moreover, incorporation of renewable sources of energy will greatly decrease reliance on thermal generation, which will result in reduced fuel costs and emissions. The strength of the suggested approach is confirmed by the stability of the results of the various runs with minimal statistical dispersion.

The hybrid PSO-GWO framework proposed has a high potential of real-time application in smart grid and energy management system (EMS) applications, where dynamic decision-making is needed under renewable uncertainty. Its rapid convergence and high performance make it appropriate to be practically deployed in large-scale power systems with high penetration of renewable energy sources.

Future work: can focus on extending the model to large-scale power systems, incorporating uncertainty modeling using stochastic or deep learning techniques, and real-time implementation in smart grid environments.

Author Contributions: SS: Research idea and problem formulation, SRP: Software and results, NS: write and edit original paper.

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