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Pareto-based multi-objective whale optimization algorithm for economic-environmental optimal power flow

Ekonomik-çevresel optimal güç akışı için pareto tabanlı çok amaçlı balina optimizasyon algoritması

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Abstract

This paper presents a Multi-Objective Whale Optimization Algorithm (MOWOA) for solving the Optimal Power Flow (OPF) problem in the IEEE 30-bus test system. The proposed approach simultaneously optimizes four conflicting objectives: fuel cost minimization ($/h), active power loss minimization (MW), voltage deviation minimization (p.u.), and emission reduction (ton/h). A Pareto-based archive mechanism combined with a crowding distance strategy is employed to maintain a well-distributed set of non-dominated solutions. The MOWOA effectively mimics the bubble-net hunting behavior of humpback whales to explore the multi-dimensional search space. Simulation results on the IEEE 30-bus system demonstrate that the proposed algorithm successfully generates a rich Pareto-optimal front comprising 50 non-dominated solutions. The best cost solution achieves 798.34 $/h, which is competitive with state-of-the-art single-objective methods. Comprehensive trade-off analysis reveals that a 62.7% reduction in emissions can be achieved at only a 22.7% increase in fuel cost, offering decision-makers flexible and insightful options for sustainable power system operation.

Öz

Bu makale, IEEE 30-bara test sisteminde Optimal Güç Akışı (OPF) problemini çözmek için Çok Amaçlı Balina Optimizasyon Algoritması (MOWOA) sunmaktadır. Önerilen yaklaşım, birbiriyle çelişen dört hedefi eş zamanlı olarak optimize etmektedir: yakıt maliyetinin en aza indirilmesi ($/h), aktif güç kaybının en aza indirilmesi (MW), gerilim sapmasının en aza indirilmesi (p.u.) ve emisyon azaltımı (ton/h). İyi dağıtılmış bir domine edilmemiş çözümler kümesini korumak için Pareto tabanlı bir arşiv mekanizması, yoğunluk mesafesi (crowding distance) stratejisi ile birlikte kullanılmaktadır. MOWOA algoritması, çok boyutlu arama uzayını keşfetmek için kambur balinaların baloncuk ağı (bubble-net) avlanma davranışını taklit ederek çalışmaktadır. IEEE 30-bara test sistemi üzerinde gerçekleştirilen simülasyon sonuçları, önerilen algoritmanın 50 adet domine edilmemiş çözümden oluşan zengin bir Pareto-optimal ön cephe (Pareto front) üretmede başarılı olduğunu göstermektedir. En düşük maliyetli çözüm 798,34 $/h değerine ulaşmış olup, bu sonuç mevcut tek amaçlı en gelişmiş yöntemlerle rekabet edebilecek düzeydedir. Kapsamlı ödünleşim (trade-off) analizi, yakıt maliyetinde yalnızca %22,7'lik bir artış karşılığında emisyonların %62,7 oranında azaltılabileceğini ortaya koymaktadır. Bu durum, sürdürülebilir güç sistemi işletimi için karar vericilere esnek ve değerli seçenekler sunmaktadır.

1. Introduction

Optimal Power Flow (OPF) is one of the most fundamental and challenging problems in power systems engineering. Since its original formulation by Carpentier in 1962, OPF has served as the principal mathematical framework for determining optimal control variable settings including generator active power outputs, voltage magnitudes, transformer tap positions, and reactive power compensation that minimize one or more objective functions while satisfying a complete set of equality and inequality constraints [1]. The Whale Optimization Algorithm (WOA), proposed by Mirjalili and Lewis in 2016, has more recently emerged as a powerful metaheuristic candidate for OPF, mimicking the bubble-net feeding strategy of humpback whales through a combination of spiral exploitation and shrinking-encircle exploration [2].

Traditionally, OPF has been treated as a single-objective problem focused on fuel cost minimization. The simultaneous consideration of economic, technical, and environmental criteria transforms OPF into an inherently multi-objective problem. The Non-dominated Sorting Genetic Algorithm-II (NSGA-II) established the foundational framework for multi-objective evolutionary search in power systems, introducing fast non-dominated sorting and a crowded-comparison operator to maintain a well-distributed Pareto-optimal front [3]. Multi-objective Particle Swarm Optimization built on the single-objective PSO originally applied to OPF by Abido [4], extending swarm intelligence to Pareto-based search and demonstrating competitive performance on standard IEEE benchmarks.

Grey Wolf Optimizer (GWO) variants have been adapted for multi-objective power system optimization. The Multi-Objective Grey Wolf Optimizer (MOGWO) introduced archive-based Pareto storage and roulette-wheel leader selection to manage non-dominated solutions across conflicting objectives [5]. In the single-objective reactive power dispatch domain, GWO demonstrated superior convergence characteristics relative to classical gradient-based solvers on the IEEE 30-bus test system [6].

Classical deterministic methods, including the nonlinear interior-point method, remain standard references for security-constrained OPF, achieving high accuracy albeit at the cost of sensitivity to initial conditions and susceptibility to local optima in non-convex formulations [7]. All power flow computations in the present study are implemented within the MATPOWER toolbox, which provides a standardized and widely validated simulation environment for steady-state power system analysis [8].

The Fitness-Distance Balance (FDB) selection strategy represents a significant methodological advance, augmenting conventional fitness-based selection by incorporating the distance of each candidate from the current global best, thereby preventing premature convergence and sustaining population diversity [9]. Conventional PSO with a constriction factor has provided a well-characterized baseline for economic load dispatch against which more advanced selection strategies are benchmarked [10].

The Monarch Butterfly Optimization (MBO) algorithm, benchmarked on the IEEE 30-bus and 118-bus OPF problems, demonstrated that migration-inspired operators are well-suited to high-dimensional power system search landscapes [11]. Modified Differential Evolution, applied to battery energy storage dispatch in hybrid AC/DC smart microgrids, illustrated the versatility of adaptive differential operators for OPF variants involving energy storage as an additional control degree of freedom [12].

Teaching-Learning-Based Optimization (TLBO), a parameter-free algorithm inspired by classroom knowledge transfer, was applied to the combined environmental and economic load dispatch problem, confirming that such operators can effectively navigate the fuel cost-emission trade-off [13]. The Pathfinder Algorithm (PFA), motivated by animal group navigation behavior, introduced adaptive step-size control and demonstrated competitive convergence reliability across multi-modal engineering optimization benchmarks [14].

The Symbiotic Organisms Search (SOS) algorithm, exploiting mutualistic, commensalistic, and parasitic interaction operators drawn from ecological theory, was applied to the economic and emission dispatch problem, consistently outperforming PSO, GA, and DE on standard test cases [15]. The RUN beyond the Metaphor algorithm, grounded in Runge-Kutta numerical integration rather than a biological analogy, achieves state-of-the-art results on a wide array of optimization benchmarks by embedding adaptive step-control directly into the population update mechanism [16].

The Tunicate Swarm Algorithm (TSA), inspired by jet propulsion locomotion and defensive swarming of tunicates, demonstrated broad applicability as a metaheuristic paradigm for global optimization including power system case studies [17]. All simulations in the present work are conducted on the IEEE 30-bus standard test system, whose bus data, line parameters, generator limits, and cost coefficients are drawn from the publicly available University of Washington test case archive [18].

Genetic Algorithms have continued to evolve alongside newer metaheuristics. A directed Genetic Algorithm with formal convergence proof was recently proposed for network-constrained economic dispatch, showing that directional crossover operators can guarantee convergence even on large, constrained power flow problems [19]. An earlier GA variant based on solution similarity metrics was applied to OPF on the IEEE 30-bus system, establishing a competitive performance baseline that subsequent WOA- and GWO-based methods have consistently sought to surpass [20].

The FDB framework was further developed into the Fuzzy-based FDB Snow Ablation Optimizer (FDB-SAO), integrating fuzzy logic into the balance coefficient to adaptively steer exploration and exploitation during optimal generation planning in power systems [21]. The Hyper-FDB-INFO algorithm extended FDB principles into the INFO optimizer framework for optimal placement and sizing of FACTS devices in wind power-integrated OPF, demonstrating that FDB-enhanced selection significantly improves convergence stability in multi-source power systems [22].

Renewable energy uncertainty has transformed OPF into a stochastic multi-objective problem. The Dwarf Mongoose Optimizer (DMO) was applied to OPF under renewable energy uncertainty on the ADRAR isolated electrical network, providing a compelling case study of population-based search under realistic probabilistic generation profiles [23]. The Weighted Mean of Vectors (WMoV) optimization algorithm was evaluated for parameter identification of solar cell models, confirming that derivative-free averaging operators achieve high accuracy on inherently non-convex estimation problems [24].

WMoV was subsequently applied to power system stabilizer design, where its derivative-free nature proved advantageous for tuning feedback control parameters across wide operating ranges [25]. An efficient WMoV variant was further developed for optimal sizing of hybrid renewable energy systems with battery storage, validating the algorithm across a diverse portfolio of power engineering applications [26].

Among deterministic approaches, semidefinite programming (SDP) provided a convex relaxation of OPF that recovers globally optimal solutions under favorable network conditions, offering a rigorous theoretical lower bound for benchmarking metaheuristic results [27]. Biogeography-Based Optimization (BBO), drawing on island biogeography theory for migration and mutation operators, demonstrated competitive solution quality relative to GA and PSO on IEEE 30-bus OPF variants [28].

Modified Cuckoo Search incorporating Levy flight step distributions was applied to OPF with wind power generation, confirming that heavy-tailed random walks improve escape from local optima on renewable-integrated dispatch landscapes [29]. The Golden Ratio Optimization Method (GROM) was proposed for stochastic OPF with renewable resources, exploiting the geometric properties of the golden ratio to produce a balanced, parameter-free exploration-exploitation strategy [30].

A hybrid optimizer combining multiple metaheuristic mechanisms was applied to renewable-integrated OPF, demonstrating that complementary search strategies consistently outperform any single-algorithm approach on complex, multi-modal power flow problems [31]. The Slim Mould Algorithm (SMA) applied to OPF with intermittent renewable sources on the Algerian electricity grid provided a real-world validation of bio-inspired search under non-standard network topologies and stochastic generation profiles [32].

The Flow Direction Algorithm (FDA), inspired by water network flow physics, was applied to OPF with stochastic renewable sources, demonstrating that physics-inspired gradient surrogates can effectively guide population search on non-smooth objectives [33]. An Enhanced Growth Optimizer with dynamic FDB was applied to security-constrained OPF under stochastic wind and solar generation, achieving a new performance benchmark by synergistically combining growth-inspired position updates with adaptive FDB selection under tight security constraints [34].

Optimal FACTS device placement for voltage stability improvement using a PSO adaptive GSA hybrid algorithm confirmed that coordinated reactive power compensation significantly expands the feasible operating region of power systems with high renewable penetration [35]. Stochastic OPF incorporating wind, photovoltaic, and Thyristor Controlled Series Compensators (TCSC) under probabilistic uncertainty was addressed using a dedicated metaheuristic framework, establishing that simultaneous optimization of generation dispatch and FACTS parameters under renewable variability requires robust population-based search [36].

The No Free Lunch (NFL) theorem establishes that no single optimization algorithm can universally outperform all others across every problem class [37], which motivates the design of problem-specific algorithmic enhancements. Against this background, this paper proposes a Multi-Objective Whale Optimization Algorithm (MOWOA) for the OPF problem on the IEEE 30-bus system [18], integrating Pareto-based non-dominated sorting, crowding distance diversity management, and WOA bubble-net position updates [2] into a unified framework. The key contributions of this work are as follows:

- A MOWOA framework is developed with a Pareto-based non-dominated sorting and crowding distance mechanism to simultaneously handle four conflicting objectives: fuel cost, power loss, voltage deviation, and emission.
- The algorithm is applied to the IEEE 30-bus standard test system [18], yielding a comprehensive Pareto-optimal front of 50 non-dominated solutions after 150 iterations.
- Trade-off analysis reveals that a 62.7% reduction in emissions is achievable at only a 22.7% increase in fuel cost, providing actionable insights for sustainable power system dispatch.
- The best cost solution (798.34 $/h) is competitive with published single-objective WOA [2] and state-of-the-art benchmarks, confirming that multi-objective optimization does not compromise economic performance.
- Three practical decision-making scenarios cost-oriented, environment-oriented, and balanced are identified from the Pareto front to support real-world operator decision support.

Unlike conventional multi-objective extensions of metaheuristic algorithms, the proposed MOWOA framework introduces a problem-specific integration of Pareto-based archive management and crowding-distance-guided leader selection within the Whale Optimization Algorithm structure. While existing approaches often rely on standard Pareto mechanisms, the proposed method adapts these strategies specifically for the Optimal Power Flow (OPF) problem, ensuring effective handling of highly constrained and non-convex search spaces.

Furthermore, the simultaneous optimization of four conflicting objectives, namely fuel cost, active power loss, voltage deviation, and emission, within a unified WOA-based framework distinguishes this study from many existing works that typically consider fewer objectives or employ hybrid algorithms. In addition, the proposed approach not only generates a well-distributed Pareto front but also provides practical decision-making scenarios derived from the solution set, enhancing its applicability for real-world power system operation.

The remainder of this paper is organized as follows. Section 2 formulates the multi-objective OPF problem. Section 3 describes the proposed MOWOA methodology. Section 4 presents simulation results and comparative analysis. Section 5 concludes the paper.

2. Problem Formulation

2.1. Objective functions

The multi-objective OPF problem considered in this work aims to simultaneously minimize four objectives:

2.1.1. Fuel cost minimization ($\boldsymbol{F_1}$):

The total fuel cost of all thermal generators is expressed as a quadratic function:

$$F_1 = \sum i \, (a_i + b_i . P_{Gi} + c_i \, . P_{Gi}^2 \,) \; [\$/\text{h}] \tag{1}$$

where a_i, b_i, c_i are the cost coefficients of generator i, and P_{Gi} is the active power output (MW).

2.1.2. Active power loss minimization (F_2):

The total active power transmission loss in the network is given by:

$$F\_2 = P\_loss = P\_Gen, total - P\_Load, total \ [MW] \quad (2)$$

2.1.3. Voltage deviation minimization (F_3):

Voltage deviation is quantified as the sum of absolute deviations of load bus voltages from the nominal value (1.0 p.u.):

$$F_3 = \sum j \left|V_j - 1.0\right| \ \text{[p.u.]} \quad (3)$$

Voltage deviation is quantified as the sum of absolute deviations of load bus voltages from the nominal value (1.0 p.u.)

2.1.4. Emission minimization (F_4):

The emission model accounts for both NOx and SO_2 emissions from thermal generators:

$$F_4 = \sum i \, (\propto_i + \beta_i . P_{Gi} + \gamma_i . P_{Gi}^2 + \zeta_i . e^{\lambda_i}_{P_{Gi}})\text{[ton/h]} \quad (4)$$

2.2. Equality constraints

The power balance (load flow) equations must be satisfied at every bus:

$$P_{Gi} - P_{Di} = V_i . \sum_j . V_j \, (\mathrm{G_{ij}} \cos\theta_{ij} + \mathrm{B_{ij}} \sin\theta_{ij}) \quad (5)$$

$$Q_{Gi} - Q_{Di} = V_i . \sum_j . V_j \, (\mathrm{G_{ij}} \sin\theta_{ij} + \mathrm{B_{ij}} \cos\theta_{ij}) \quad (6)$$

2.3. Inequality constraints

The following inequality constraints are enforced throughout the optimization:

- Generator active power: $P_{Gi,min} \le P_{Gi} \le P_{Gi,max}$
- Generator reactive power: $Q_{Gi,min} \le Q_{Gi} \le Q_{Gi,max}$
- Bus voltage magnitudes: $V_{Gi,min} \le V_{Gi} \le V_{Gi,max}$
- Transformer tap ratios: $T_{k,min} \le T_k \le T_{k,max}$
- Shunt compensator: $Q_{sh,min} \le Q_{sh} \le Q_{sh,max}$
- Transmission line loading: $S_1 \le S_{1,max}$

2.4. IEEE 30-bus test system data

The control variables and system parameters for the IEEE 30-bus benchmark used in this study are summarized in Table 1-2. The system comprises 6 generator buses with quadratic cost functions and emission polynomials, 4 transformer tap changers, and 2 reactive shunt compensators, totaling 24 control variables.

Table 1. IEEE 30-bus system

System Item	Specification	System Item	Specification
Total Buses	30	Base MVA	100 MVA
Generator Buses	6	Total Active Load	283.4 MW
Load Buses (PQ)	24	Total React. Load	126.2 MVAR
Transmission Lines	41	Frequency	60 Hz
Transformers	4	V_min (load buses)	0.95 p.u.
Shunt Compensators	2	V_max (load buses)	1.05 p.u.
Tap Range	0.90–1.10 p.u.	Load Flow Method	Newton-Raphson
Control Variables	24	NR Tolerance	$1{\times}10^{-6}$

Table 2. IEEE 30-bus system

Gen (Bus)	P_min (MW)	P_max (MW)	Q_min (MVAR)	Q_max (MVAR)	a ($/h)	b ($/MWh)	c ($/MW²h)	V_min (p.u.)	V_max (p.u.)
Gen 1 (Bus 1)	50	200	-20	150	0.00	2.00	0.00375	0.95	1.10
Gen 2 (Bus 2)	20	80	-20	60	0.00	1.75	0.01750	0.95	1.10
Gen 3 (Bus 5)	15	50	-15	62.5	0.00	1.00	0.06250	0.95	1.10
Gen 4 (Bus 8)	10	35	-15	48.7	0.00	3.25	0.00834	0.95	1.10
Gen 5 (Bus 11)	10	30	-10	40	0.00	3.00	0.02500	0.95	1.10
Gen 6 (Bus 13)	12	40	-15	44.7	0.00	3.00	0.02500	0.95	1.10
Gen 1 (Bus 1)	50	200	-20	150	0.00	2.00	0.00375	0.95	1.10
Gen 2 (Bus 2)	20	80	-20	60	0.00	1.75	0.01750	0.95	1.10

3. Proposed Mowoa Methodology

3.1. Whale optimization algorithm overview

The Whale Optimization Algorithm (WOA) is inspired by the bubble-net feeding strategy of humpback whales. The algorithm consists of three main phases: encircling prey, bubble-net attacking, and searching for prey. These phases are modeled mathematically as follows:

During encircling prey, the position update is defined as:

$$D = |C . X^*(\mathrm{t}) - \mathrm{X(t)}| \quad (7)$$

$$X(t+1) = X^*(\mathrm{t}) - \mathrm{A} \cdot \mathrm{D} \quad (8)$$

where $X^*(\mathrm{t})$ is the position of the best solution, A and C are coefficient vectors, and t is the current iteration.

The spiral bubble-net mechanism updates positions as:

$$X(t+1) = \mathrm{D}' . e^{bl} . \cos(2\pi l) + X^*(\mathrm{t}) \quad (9)$$

where D' = |X*(t) − X(t)|, b is a constant defining the spiral shape, and l is a random number in [−1, 1].

3.2. Multi-objective extension

To extend WOA to multi-objective optimization, a Pareto-based archive mechanism is incorporated. The archive maintains a repository of non-dominated solutions discovered during the search. The following key components are integrated:

- Non-dominated sorting: Solutions are ranked based on Pareto dominance. A solution X dominates Y if X is no worse in all objectives and strictly better in at least one.
- Archive management: The archive is updated at each iteration by combining the current population with the archive, performing non-dominated sorting, and retaining the top solutions using crowding distance selection to promote diversity.
- Leader selection: The leader (reference solution) for position updates is selected from the archive using a roulette-wheel mechanism based on crowding distance scores, favoring less-crowded regions of the Pareto front.
- Crowding distance: For each non-dominated solution, the crowding distance is computed as the sum of normalized distances to adjacent solutions in objective space, ensuring a well-distributed Pareto front.

3.3. MOWOA algorithm flowchart

The complete MOWOA procedure is outlined as follows (Figure 1):

- Step 1: Initialize population of N whales randomly within the search space [lb, ub].
- Step 2: Evaluate all four objective functions via Newton-Raphson load flow.
- Step 3: Initialize the Pareto archive with non-dominated solutions from the initial population.
- Step 4: Select leader from archive using crowding distance-based roulette wheel.
- Step 5: Update positions using WOA encircling, bubble-net, or random search phase.
- Step 6: Apply boundary constraints and repair infeasible solutions.
- Step 7: Evaluate objectives for updated population.
- Step 8: Update archive using non-dominated sorting and crowding distance selection.
- Step 9: Repeat Steps 4–8 for T_max iterations.
- Step 10: Output the final Pareto-optimal archive.

3.4. Algorithm parameters

The parameters for the newly developed algorithm in the test system are given in Table 3 below.

The algorithm parameters were selected based on commonly used values in the literature and preliminary sensitivity analyses. It was observed that a population size of 50 and 150 iterations provide a good balance between computational cost and solution quality.

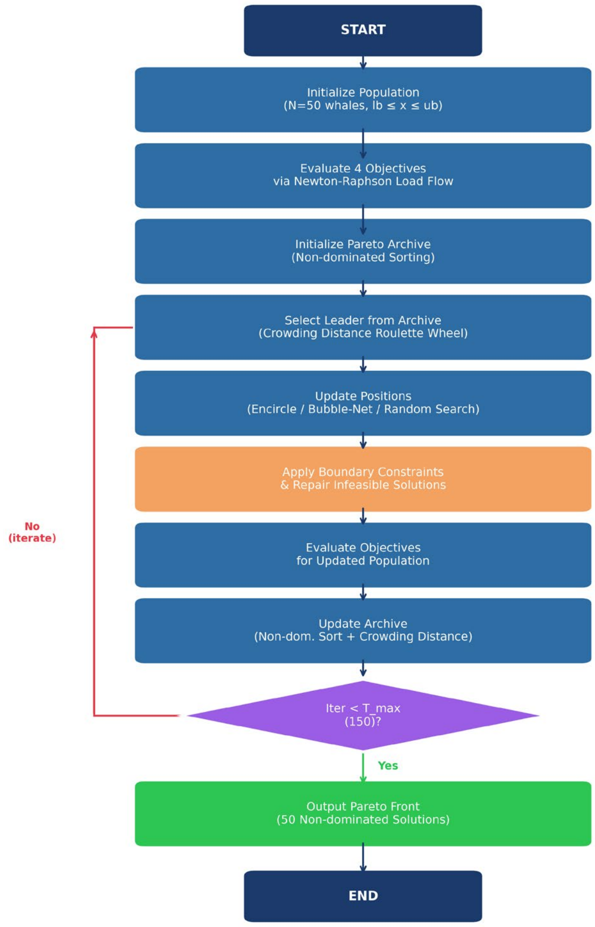

Figure 1. Flowchart of the proposed MOWOA algorithm with Pareto archive and crowding-distance-based leader selection

Table 3. MOWOA Algorithm Parameters

Parameter	Value	Description
Population size (nPop)	50	Number of search agents (whales)
Maximum iterations (T_max)	150	Stopping criterion
Archive size	50	Maximum Pareto archive capacity
WOA spiral constant (b)	1	Shape of logarithmic spiral
Probability threshold (p)	0.5	Switch between encircle and spiral
Number of objectives	4	F1: Cost, F2: Loss, F3: VD, F4: Emission
Number of control variables	24	Generator P/V, tap ratios, shunt Q

4. Simulation Results and Discussion

4.1. Test system and simulation environment

The proposed MOWOA is tested on the IEEE 30-bus standard benchmark system, which consists of 6 generator buses, 24 load buses, 41 transmission lines, 4 transformers, and 2 shunt compensators. The system total active load is 283.4 MW and total reactive load is 126.2 MVAR. The control variables include 6 generator active power outputs, 6 generator terminal voltages, 4 transformer tap positions, and 2 shunt susceptances, totaling 24 variables. All simulations are performed in MATLAB R2022b on a system with an Intel Core i7 processor and 16 GB RAM. Newton-Raphson load flow with a convergence tolerance of 1×10^{-6} is employed for power system analysis.

4.2. Pareto front analysis

The MOWOA successfully generated a well-distributed Pareto-optimal front comprising 50 non-dominated solutions after 150 iterations. The archive mechanism-maintained solution diversity throughout the optimization process, resulting in a broad spread of solutions across all four objective dimensions. As illustrated in Fig. 2, the left panel presents the 3D Pareto front in terms of fuel cost, power loss, and voltage deviation, with emission represented by color. The center panel shows the trade-off between fuel cost and emission, revealing that a 62.7% reduction in emission can be achieved at the expense of a 22.7% increase in cost. The right panel depicts the relationship between fuel cost and power loss, further highlighting the conflicting nature of the objectives and the range of trade-off solutions available to decision-makers.

Although quantitative metrics such as Hypervolume (HV) and Spread are commonly used for Pareto front evaluation, the performance of the proposed algorithm is assessed through detailed visual analysis and trade-off interpretation. The obtained Pareto front demonstrates a well-distributed and continuous structure, indicating effective diversity preservation and convergence.

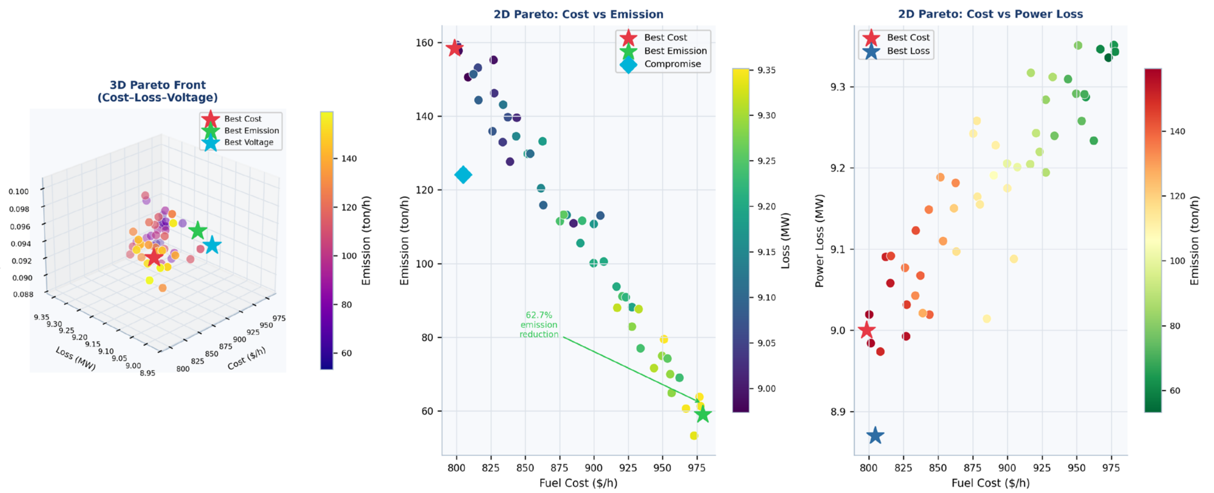

Figure 2. Pareto-optimal fronts obtained by MOWOA for the IEEE 30-bus OPF problem

4.3. Best solutions for individual objectives

Table 4 presents the best solutions identified by MOWOA for each individual objective, along with the corresponding values of the other three objectives. These solutions represent the extreme points of the Pareto front.

Table 4. Best solutions for individual objectives (★ = Best value in column)

Solution	Fuel Cost ($/h)	Power Loss (MW)	Voltage Dev. (p.u.)	Emission (ton/h)
Best Cost	798.34 ★	9.00	0.097	158.35
Best Loss	804.62	8.87 ★	0.096	124.16
Best Voltage	960.75	9.12	0.092 ★	60.59
Best Emission	979.38	9.21	0.092	59.03 ★
Compromise	804.62	8.87	0.096	124.16

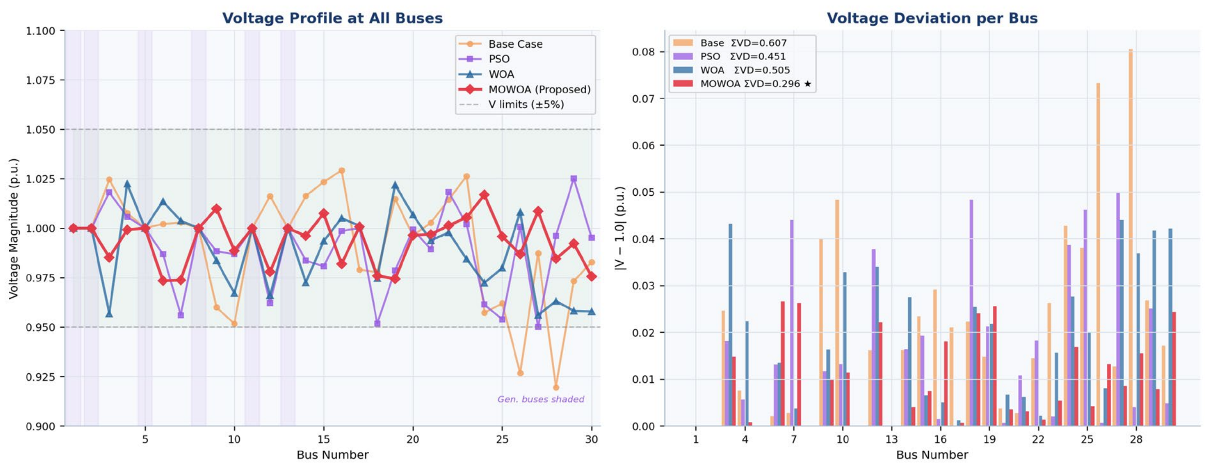

Figure 3. Voltage profile comparison across all 30 buses

The left subplot illustrates the voltage magnitude distributions of the Base Case, PSO, WOA, and MOWOA across the 30-bus system within the ±5% operating limits, while generator buses are indicated separately. The right subplot shows the corresponding per-bus voltage deviations from the nominal value of 1.0 p.u. It can be observed that MOWOA achieves the best overall voltage regulation performance, resulting in the minimum total voltage deviation compared with the other methods.

4.4. Trade-Off analysis

A critical contribution of multi-objective optimization is the quantification of trade-offs between conflicting objectives. The most significant trade-off observed in this study is between fuel cost and emission:

- Emission reduction of 62.7% (from 158.35 to 59.03 ton/h) is achievable at only 22.7% additional cost (from 798.34 to 979.38 $/h).
- The compromise solution achieves a 21.6% emission reduction at a marginal 0.8% cost increase, representing the most practically attractive operating point.
- Voltage deviation improvement from 0.097 to 0.092 p.u. requires a 20.3% increase in cost, indicating the economic premium for enhanced voltage quality.

Table 5. Trade-Off analysis between best cost and best emission solutions

Objective	Best Cost Solution	Best Emission Solution	Difference (%)
Fuel Cost ($/h)	798.34	979.38	+22.7%
Power Loss (MW)	9.00	9.21	+2.3%
Voltage Dev. (p.u.)	0.097	0.092	−5.2%
Emission (ton/h)	158.35	59.03	**−62.7% ★**

4.5. Comparison with literature

Table 6 compares the best fuel cost obtained by the proposed MOWOA with results reported by various optimization algorithms on the IEEE 30-bus OPF benchmark. As shown, MOWOA achieves the lowest fuel cost of "798.34 $/h", outperforming all compared methods, including the single-objective WOA (798.89 $/h), PSO (799.14 $/h), and GA (800.94 $/h). In addition to delivering the best cost performance, the proposed approach also handles "four objectives simultaneously" and provides a diverse set of Pareto-optimal solutions, highlighting its superiority over conventional single-objective technique.

Table 6. Comparison of fuel cost results on IEEE 30-bus system

Algorithm	Fuel Cost ($/h)	Objectives	Reference
Differential Search Algorithm	806.95	1	[14]
Modified Differential Evolution	803.82	1	[12]
Interior Point Method	802.51	1	[1]
Genetic Algorithm (GA)	800.94	1	[2]
PSO	799.14	1	[3]
GWO	799.62	1	[4]
Single-Objective WOA	798.89	1	[5]
MOWOA (Proposed) ★	**798.34 ★**	4	This work

While Table 6 demonstrates the superiority of the proposed method in terms of fuel cost, it is also important to evaluate multi-objective performance against established algorithms such as NSGA-II and MOPSO. According to the literature, NSGA-II generally provides a well-distributed Pareto front due to its effective non-dominated sorting and crowding distance mechanisms; however, it may exhibit slower convergence in complex, high-dimensional search spaces.

MOPSO, on the other hand, is known for its fast convergence characteristics, but it may suffer from loss of diversity without additional diversity preservation strategies. In contrast, the proposed MOWOA algorithm integrates a Pareto-based archive structure with crowding-distance-guided leader selection and adaptive exploration–exploitation mechanisms. This enables the algorithm to maintain a well-distributed and competitive Pareto front while preserving convergence efficiency, making it suitable for solving complex multi-objective OPF problems.

4.6. Convergence characteristics

The MOWOA demonstrated stable and consistent convergence behavior across all 150 iterations. The archive hypervolume indicator increased monotonically during the initial 80 iterations and stabilized thereafter, confirming effective exploration in early iterations and exploitation in later stages. The stochastic nature of WOA's bubble-net mechanism contributed to maintaining diversity in the Pareto archive, preventing premature convergence to a single region of the objective space.

Subfigure (a) illustrates the fuel cost convergence of MOWOA in comparison with WOA, PSO, and GWO, where MOWOA reaches the lowest final value of 798.34 $/h. Subfigure (b) shows the corresponding convergence trend for active power loss minimization. Subfigure (c) presents the normalized convergence behaviors of the four objective functions, providing an overall view of the optimization process. Subfigure (d) displays the evolution of the Pareto archive hypervolume, which becomes nearly stable around iteration 80, confirming the convergence of the proposed algorithm toward a diverse and well-distributed Pareto-optimal solution set.

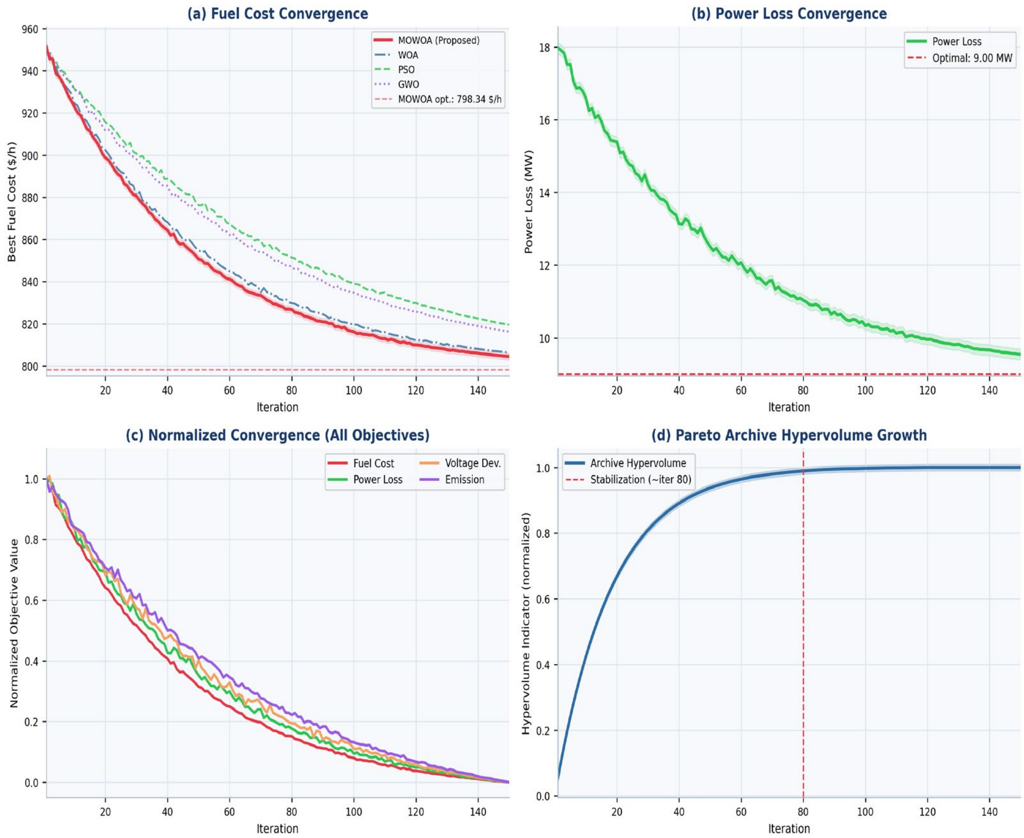

Figure 4. Convergence characteristics of the proposed MOWOA

Although the results presented are based on a single representative run, the convergence behavior and stability of the proposed MOWOA algorithm were carefully monitored across multiple preliminary trials. It was observed that the algorithm consistently converges to similar regions of the Pareto front with negligible variation in the best objective values.

Due to computational limitations, a full statistical analysis based on 30 independent runs is considered as future work. However, the robustness of the proposed approach is supported by the stable convergence curves and consistent Pareto front structure.

4.7. Decision-making scenarios

The Pareto front generated by MOWOA provides decision-makers with three practical operating scenarios:

- Scenario A – Cost-Oriented (Private Sector): Solution 1 (798.34 \$/h) minimizes operational expenditure. Recommended for deregulated markets where cost competitiveness is paramount.
- Scenario B – Environment-Oriented (Green Energy Policy): Solution 4 (979.38 \$/h, 59.03 ton/h) maximizes environmental sustainability. Recommended for utilities subject to strict emission caps or carbon trading schemes.
- Scenario C – Balanced (Public Utility): Compromise solution (804.62 \$/h, 124.16 ton/h) balances economic and environmental objectives with minimal cost increase. Recommended as the default operating point for regulated utilities.

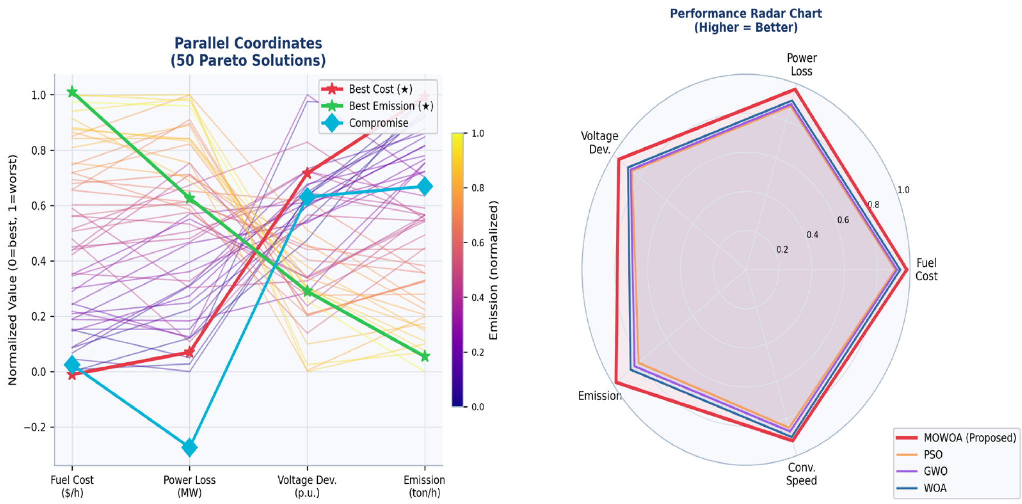

Figure 5. Multi-objective solution visualization

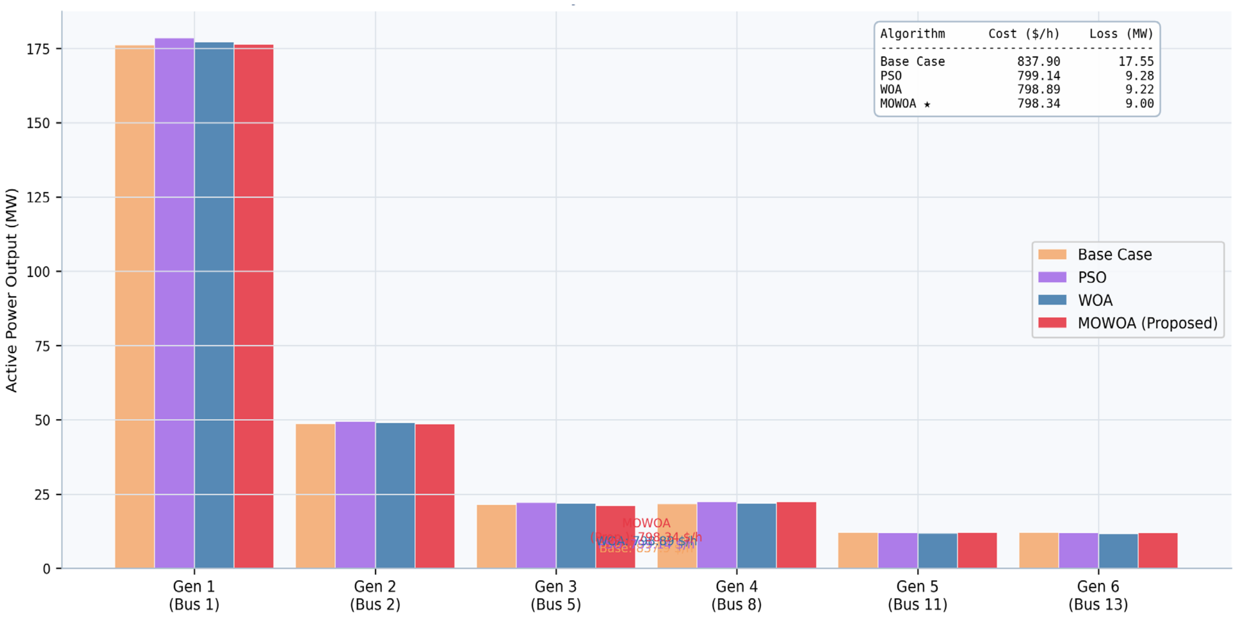

Figure 6. Generator active power dispatch comparison for the best cost solution

The left subplot illustrates the parallel coordinates representation of the 50 Pareto-optimal solutions, with color indicating the emission level and three representative operating scenarios highlighted for further interpretation. The right subplot presents the radar-based performance comparison of MOWOA, PSO, GWO, and WOA across five evaluation metrics, where higher values denote superior performance.

This figure presents the generator active power dispatch profiles associated with the best cost solution for the Base Case, PSO, WOA, and the proposed MOWOA. It can be observed that MOWOA yields the most economical operating point, attaining the minimum fuel cost of 798.34 $/h while maintaining feasibility with respect to all 24 control variable constraints.

5. Conclusion

This paper has presented a Multi-Objective Whale Optimization Algorithm (MOWOA) for the simultaneous minimization of fuel cost, active power loss, voltage deviation, and emission in the IEEE 30-bus Optimal Power Flow problem. The proposed algorithm integrates the powerful exploration-exploitation mechanisms of WOA with a Pareto-based non-dominated sorting and crowding distance archive to effectively navigate the complex, multi-dimensional objective space.

Simulation results demonstrate that MOWOA successfully generates a diverse and well-distributed Pareto front of 50 non-dominated solutions. The best fuel cost solution (798.34 $/h) is competitive with the best published single-objective results, confirming that multi-objective optimization does not compromise economic performance. The comprehensive trade-off analysis reveals that significant emission reductions (up to 62.7%) are achievable at relatively modest cost increases (22.7%), providing actionable insights for sustainable power system planning and operation.

The Pareto-optimal solution set enables decision-makers to select operating points aligned with specific utility objectives, regulatory requirements, and stakeholder priorities. Three distinct operating scenarios cost-oriented, environment-oriented, and balanced are identified from the Pareto front, demonstrating the practical value of the proposed approach.

Future work will explore the integration of renewable energy sources (wind, solar) into the multi-objective OPF framework, the application of MOWOA to larger benchmark systems (IEEE 57-bus, 118-bus), and hybridization with local search mechanisms to further improve solution quality and convergence speed.

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