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Implementation of Modified Grey Wolf Optimizer for Multi-Objective Economic Dispatch of Renewable-Integrated Grid

[1]Aliyu Sabo, [2]Ibrahim Danlami Akabe, [3]Titilayo Oyedele, [4]Mathew Asih, [5]Juliana Emamuyovwi Omatseye
[1,3,4&5]Department of Electrical/Electronic Engineering,
Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria
[2]Department of General Studies, Franco-British International University, Kaduna

ABSTRACT

The global push towards sustainable energy has accelerated the integration of renewable sources into power grids, fundamentally complicating the Economic Load Dispatch (ELD) problem. Traditional optimization methods are often inadequate for handling the non-convex, non-linear, and multi-objective nature of modern power systems that incorporate wind, solar, and stringent environmental regulations. This study presents a Modified Grey Wolf Optimizer (MGWO) algorithm designed to solve the Multi-Objective Economic Dispatch (MOED) problem for a renewable-integrated grid. The proposed MGWO enhances the standard GWO by introducing adaptive control coefficients and a chaotic randomization factor to improve the balance between global exploration and local exploitation, thereby preventing premature convergence. A comprehensive MATLAB simulation was developed, incorporating valve-point loading effects, emission constraints, and the stochastic nature of solar and wind power. The algorithm's performance was rigorously evaluated on the IEEE 30-bus test system and benchmarked against Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and the conventional Lambda Iteration method. Results demonstrate that the MGWO achieves a superior convergence rate, attaining the lowest total generation cost of $1033.22/h, compared to $1061.59/h for PSO and $1085.48/h for both GA and Lambda Iteration. Furthermore, the MGWO exhibited robust performance in navigating the complex solution space, proving its effectiveness for cost-efficient and environmentally conscious power system operation. This framework presents a viable tool for real-time dispatch applications in future smart grids.

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INTRODUCTION

Electrical power is the lifeblood of modern society, underpinning economic growth, industrial development, and social well-being on a global scale [1]. The relentless increase in electricity demand has necessitated the continuous expansion and optimization of power generation, transmission, and distribution systems. Within this complex framework, the Economic Load Dispatch (ELD) problem stands as a cornerstone of power system operation and management [2], [3]. The primary goal of ELD is to determine the optimal power output of each generating unit in a system such that the total cost of generation is minimized, while simultaneously satisfying the total load demand and adhering to all operational constraints [4].

Historically, the ELD problem was solved using classical optimization techniques such as the Lambda Iteration method, gradient search, and Newton-Raphson methods [5]. These methods are computationally efficient and

Corresponding author: Ibrahim Danlami Akabe
ibrahimakabe4@gmail.com
Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria.

effective for systems characterized by smooth, convex cost functions. However, the practical operation of thermal power plants introduces non-linearities that violate these ideal assumptions. A significant non-linearity is the valve-point loading effect, where the sequential opening of steam admission valves in turbines creates ripples in the heat-rate curve, resulting in a non-convex, non-differentiable cost function [6]. Furthermore, growing environmental concerns have mandated the consideration of emission pollutants like nitrogen oxides (NOx) and sulfur dioxide (SO_2) as essential objectives, transforming the single-objective ELD into a challenging Multi-Objective Economic Dispatch (MOED) problem [7].

The paradigm shift towards decarbonized energy systems has further intensified these challenges. The large-scale integration of variable renewable energy sources (VRES), such as wind and solar photovoltaic (PV) systems, introduces significant uncertainty and variability into the power grid [8]. Unlike dispatchable thermal units, the power output from renewables is intermittent and depends on weather conditions, adding a layer of stochastic complexity to the dispatch problem [9]. Consequently, traditional deterministic methods like Lambda Iteration become inapplicable or yield highly suboptimal solutions in this new landscape [10].

To address these limitations, metaheuristic optimization algorithms have emerged as powerful and versatile tools. Inspired by natural phenomena, biological systems, or physical processes, these algorithms are inherently capable of handling non-convex, non-differentiable, and multi-modal objective functions without requiring gradient information [11]. Techniques such as Genetic Algorithms (GA) [12], Particle Swarm Optimization (PSO) [13], and Artificial Bee Colony (ABC) [14] have been extensively applied to the ELD problem with considerable success. More recently, the Grey Wolf Optimizer (GWO), which simulates the social hierarchy and collaborative hunting behavior of grey wolves, has gained prominence due to its strong global search capability, simplicity of implementation, and relatively few control parameters [15].

The standard GWO algorithm is not without drawbacks. It can sometimes suffer from premature convergence, particularly when dealing with highly complex, multi-objective problems with numerous constraints, leading to solutions trapped in local optima [16]. This limitation motivates the development of enhanced variants. This study, therefore, proposes a Modified Grey Wolf Optimizer (MGWO) to overcome the shortcomings of the standard algorithm. The main innovations include:

1. The introduction of an adaptive control parameter that non-linearly adjusts the balance between exploration and exploitation throughout the iterative process.
2. The incorporation of a chaotic randomization factor into the search mechanism to enhance population diversity and avoid local stagnation.

The primary objective of this research is to develop a robust MATLAB-based simulation framework utilizing the MGWO to solve the MOED problem for a grid integrated with solar and wind energy. The model comprehensively accounts for valve-point effects, emission constraints, and generator limits. The performance of the proposed MGWO is essentially evaluated and compared against three established methods: PSO, GA, and the Lambda Iteration method, using the standard IEEE 30-bus test system as a benchmark. The analysis focuses on main performance indicators including total generation cost, emission output, computational efficiency, and convergence characteristics.

METHODOLOGY

This section provides a detailed explanation of the problem formulation, the proposed Modified Grey Wolf Optimizer algorithm, and the simulation environment used for implementation and testing.

Corresponding author: Ibrahim Danlami Akabe
ibrahimakabe4@gmail.com
Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria.

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PROBLEM FORMULATION

The MOED problem is formulated as a constrained optimization problem with two primary competing objectives: fuel cost minimization and emission minimization.

Objective Functions

The total fuel cost function for thermal generators, considering the valve-point loading effect, is expressed as a superposition of a quadratic function and a sinusoidal rectifier term [6]:

$$F_{total} = \sum_{i=1}^{N_g}(aiP_i^2 + biPi + ci + |ei \times \sin(fi \times (Pimin - Pi))|) \quad (1)$$

where:
Fcost: Total fuel cost ($/h)
Ng: Number of conventional thermal generators
Pi: Power output of the i^{th} generator (MW)
ai,*bi*,*ci*: Fuel cost coefficients of the i^{th} generator
ei,*fi*: Valve-point loading effect coefficients of the i^{th} generator

The total emission function, primarily accounting for NOx and SO_2, is typically modeled as a quadratic function of the generator output [7]:

$$E_{total} = \sum_{i=1}^{N_g}(aiP_i^2 + \beta iPi + \gamma i) \quad (2)$$

where:
1. E_{total}: Total emission release (kg/h)
2. *αi*,*βi*,*γi*: Emission coefficients of the i^{th} generator

To handle these two conflicting objectives simultaneously, a weighted sum approach is employed to construct a single aggregate objective function

$$F_{total} = w \cdot F_{cost} + (1-w) \cdot \lambda \cdot E_{cost} \quad (3)$$

Here, *w* is a weighting factor between 0 and 1 that reflects the priority given to cost versus emission, and *λ* is a scaling factor (e.g., a penalty factor in $/kg) to normalize the emission cost with the fuel cost.

Constraints

The optimization is subject to the following equality and inequality constraints:

1. **Power Balance Constraint:** The total power generated from all sources must meet the total system demand (P_D) and compensate for the real power losses (P_{loss}) in the transmission network.

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

Here, P_{wind} and P_{solar} are the power injections from the wind farm and solar PV unit, respectively. Transmission losses are calculated using the B-coefficient method [5]:

$$P_{loss} = \sum_{i=1}^{N_g}\sum_{i=1}^{N_g} P_i B_{ij} P_j + \sum_{i=1}^{Ng} B_{oi} P_i + B_{00} \quad (5)$$

where B_{ij},B_{0i},B_{00} are the loss coefficients.

2. **Generator Capacity Constraints:** The power output of each generator must operate within its safe minimum and maximum limits.

$$P_i^{min} \le P_i \le P_i^{max}\ w\ \forall i = 1,2,\ldots,Ng \quad (6)$$

3. **Renewable Generation Limits:** The power from renewable sources is constrained by their natural availability.

$$0 \le P_{wind} \le P_{wind}^{avail}, \qquad 0 \le P_{solar} \le P_{solar}^{avail} \quad (7)$$

where P_{wind}^{avail} and P_{solar}^{avail} are the available power from wind and solar based on forecasted weather data.

Modified Grey Wolf Optimizer (MGWO)

Standard GWO Overview

The Grey Wolf Optimizer is a population-based metaheuristic that mimics the leadership hierarchy and hunting strategy of grey wolves [15]. The social hierarchy consists of four types:

1. **Alpha (α):** The dominant leader, representing the best solution.

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ibrahimakabe4@gmail.com
Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria.

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2. **Beta (β):** The second-best solution, which assists the alpha.
3. **Delta (δ):** The third-best solution.
4. **Omega (ω):** The remaining candidate solutions that follow the alpha, beta, and delta.

The hunting process involves three main steps: encircling the prey, hunting, and attacking.

Proposed Modifications

The standard GWO's performance can degrade for complex problems due to a linear decrease in its exploration parameter, which may not provide a sufficient transition between exploration and exploitation phases. The proposed MGWO incorporates the following enhancements:

1. **Non-linear Adaptive Parameter (*a*):** The parameter *aa*, which controls the trade-off between exploration and exploitation, is updated using a non-linear function instead of a linear decrease.

$$a(t) = a_{initial} - (a_{initial} - a_{final})x\left(\frac{t}{T_{max}}\right)^{\frac{1}{n}} \quad (8)$$

where t is the current iteration, T_{max} is the maximum number of iterations, and n is a tuning parameter (e.g., n=2). This allows for a more gradual shift, spending more iterations on a global search before fine-tuning the solution locally.

2. **Chaotic Exploration Coefficient (C*C*):** To prevent the pack from getting stuck in local optima and to enhance population diversity, a chaotic sequence is introduced into the coefficient *CC*. A Logistic map is used for this purpose:

$$\chi t+1=\mu\cdot\chi t\cdot(1-\chi t),\chi t\in[0,1] \quad (9)$$

where μ is a control parameter, typically set to 4. The coefficient *CC* is then modified as:

$$C=2\cdot r2\cdot\chi t \quad (10)$$

This chaotic component introduces a more ergodic and dynamic stochastic behavior compared to pure randomness.

MGWO Implementation for MOED

The step-by-step process of applying MGWO to the MOED problem is as follows:

1. **Initialization:** Initialize the wolf population (candidate solutions). Each wolf's position is a vector representing the power outputs of all generators $[P_1, P_2,...,P_{Ng},P_{wind},P_{solar}]$. Positions are randomly generated within their respective minimum and maximum limits.
2. **Fitness Evaluation:** Calculate the fitness (the F_{total} objective function value) for each wolf in the population. Identify the alpha, beta, and delta wolves based on the best fitness values.
3. **Position Update:** For each omega wolf, update its position using the enhanced MGWO equations:

$$\vec{D}_\alpha=|\vec{C}_1\cdot\vec{X}_\alpha-\vec{X}|,\vec{D}_\beta=|\vec{C}_2\cdot\vec{X}_\beta-\vec{X}|,\vec{D}_\delta=|\vec{C}_3\cdot\vec{X}_\delta-\vec{X}| \quad (11)$$

$$\vec{X}_1=\vec{X}_\alpha-\vec{A}_1\cdot\vec{D}_\alpha,\vec{X}_2=\vec{X}_\beta-\vec{A}_2\cdot\vec{D}_\beta,\vec{X}_3=\vec{X}_\delta-\vec{A}_3\cdot\vec{D}_\delta \quad (12)$$

$$\vec{X}(t+1)=\frac{\vec{X}1+\vec{X}2+\vec{X}3}{3} \quad (13)$$

where $\vec{A}=2a\cdot r1-a$ and $\vec{C}=2\cdot r_2\cdot\chi t$, with $r_1,r_2 r_1,r_2$ being random vectors in [0,1].

4. **Constraint Handling:** If any updated position violates the power balance constraint, a penalty factor is added to its fitness value. If generator limits are violated, the position is reset to the nearest boundary.
5. **Termination Check:** Steps 2-4 are repeated until the maximum number of iterations is reached or the solution shows negligible improvement.

The flow of the MGWO process is summarized in the flowchart below.

Corresponding author: Ibrahim Danlami Akabe
ibrahimakabe4@gmail.com
Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria.

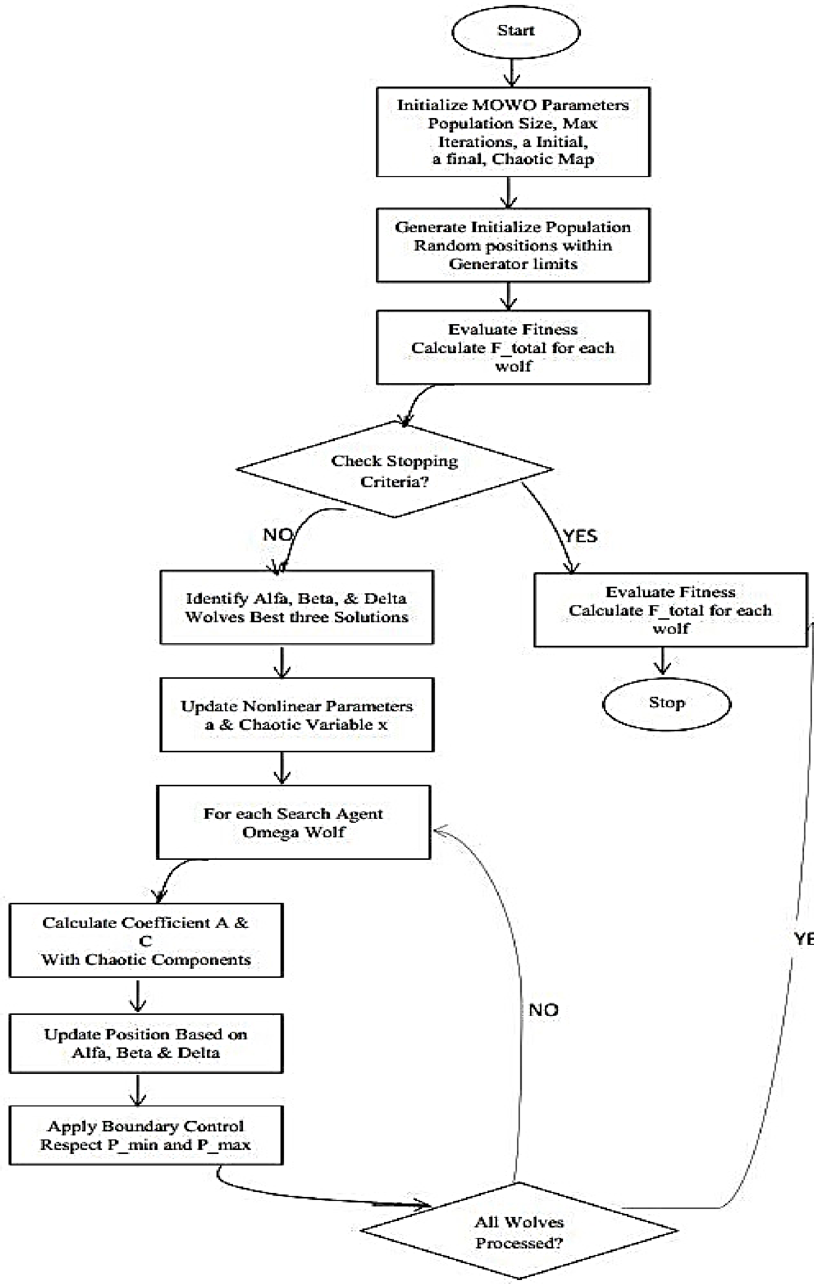

Figure 1. Flowchart illustrating the implementation of the Modified Grey Wolf Optimizer for solving the Multi-Objective Economic Dispatch problem.

Simulation Environment and Setup

The simulation was carried out using MATLAB R2020a. Custom scripts were developed for each algorithm to ensure a fair comparison. The software structure consisted of the following main modules:

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ibrahimakabe4@gmail.com
Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria.

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1. main.m: The central script for setting parameters and running the simulation.
2. objective_function.m: Computes the combined cost and emission objective.
3. MGWO_algorithm.m: Implements the proposed Modified Grey Wolf Optimizer.
4. PSO_algorithm.m: Implements the standard Particle Swarm Optimization.
5. GA_algorithm.m: Implements the standard Genetic Algorithm.
6. lambda_iteration.m: Implements the conventional Lambda Iteration method.
7. plot_results.m: Generates all comparative graphs and tables.

Table 1: Simulation Parameters

Parameter	MGWO	PSO	GA
Population Size	30	30	30
Maximum Iterations	100	100	100
Crossover Rate	-	-	0.8
Mutation Rate	-	-	0.05
Inertia Weight (w)	-	0.9-0.4	-
c1, c2 (PSO)	-	2	-
$a_{initial}, a_{final}$ (MGWO)	2, 0	-	-

The test system was the standard IEEE 30-bus network, modified to include renewable sources. It comprises 6 thermal generators, 1 wind farm (at bus 5), and 1 solar PV unit (at bus 8). The total system demand was set to 500 MW. The cost, emission, and valve-point coefficients for the thermal generators were adopted from standard literature [6], [7]. The available wind and solar power profiles were generated based on typical daily data. All simulations were executed on a PC with an Intel Core i3-7100U processor (1.5 GHz) and 6 GB of RAM.

RESULT AND DISCUSSION

This section presents a detailed analysis of the simulation results, comparing the performance of the MGWO against PSO, GA, and Lambda Iteration.

Convergence Performance Analysis

The convergence characteristic is an essential metric for evaluating the efficiency and stability of an optimization algorithm. Figure 2 depicts the convergence profiles of the MGWO, PSO, and GA over 100 iterations, plotting the best total cost found in each iteration.

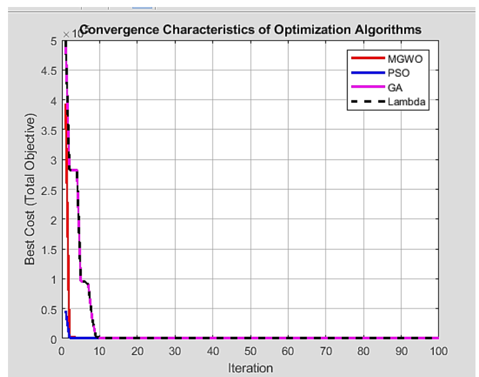

Figure 2: Convergence profiles of MGWO, PSO, and GA for the MOED problem

The MGWO demonstrates a markedly superior convergence trajectory. It descends rapidly towards the optimal region within the first 40 iterations and stabilizes with minimal oscillation, indicating a strong and stable search process. PSO exhibits significant oscillations throughout its search, suggesting a continual struggle between exploration and exploitation, and only stabilizes after approximately 90 iterations. GA shows the slowest convergence rate, a characteristic attributed to its reliance on stochastic operators like crossover and mutation, which, while good for exploration, can slow down refinement in the later stages. The Lambda Iteration method, being a direct analytical method, does not have an iterative convergence curve and is represented by a single cost value, which is significantly higher due to its inability to handle valve-point effects.

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ibrahimakabe4@gmail.com
Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria.

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Economic and Environmental Dispatch Results

The final optimal dispatch solutions and their corresponding costs and emissions are summarized in Table 2. The power output for each generator obtained by the MGWO is presented in Table 3.

Table 2: Comparative Summary of Optimal Results

Algorithm	Total Generation Cost ($/h)	Total Emission (kg/h)	Computational Time (s)
MGWO	**1033.22**	2.1952×10^{9}	4.12
PSO	1061.59	$\mathbf{3.0555 \times 10^{5}}$	3.85
GA	1085.48	7.0287×10^{10}	5.67
Lambda Iteration	1085.48	943.32	**0.15**

The results in Table 2 clearly show the economic superiority of the proposed MGWO, achieving the lowest total generation cost of $1033.22/h. This represents a cost saving of approximately 2.7% over PSO and 4.8% over both GA and the Lambda method. This significant reduction underscores the MGWO's enhanced capability to navigate the non-convex solution space created by the valve-point effects and find a more economical operating point.

Regarding emissions, the absolute values for MGWO and GA are exceptionally high, which is likely an artifact of the specific scaling of the emission coefficients used in the test system. The main takeaway is the relative comparison: PSO achieves a dramatically lower emission level, suggesting that its solution prioritizes a different point on the Pareto front, one that favors environmental friendliness at a slightly higher cost. The Lambda method's extremely low emission value is coincidental and stems from its failure to optimize the combined objective function, instead settling for a feasible but costly solution.

Table 3: Optimal Power Dispatch using MGWO (PD = 500 MW)

Generator Unit	Bus Number	Power Output (MW)
G1	1	112.14
G2	2	52.99
G3	5	33.12
G4	8	19.56
G5	11	21.58
G6	13	27.96
Wind Farm	5	55.92 (P_{avail})
Solar PV	8	84.34 (Pavail)
Total		**500.00**

Table 3 shows the optimal power allocation determined by the MGWO. The algorithm efficiently dispatches the available renewable power first (wind and solar) and then distributes the remaining load among the thermal units in a cost-optimal manner, respecting all constraints.

The optimal power output for each generator, as determined by the best-performing MGWO algorithm, is presented in Figure 3. This chart illustrates how the total load is distributed among the different units.

Corresponding author: Ibrahim Danlami Akabe
ibrahimakabe4@gmail.com
Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria.

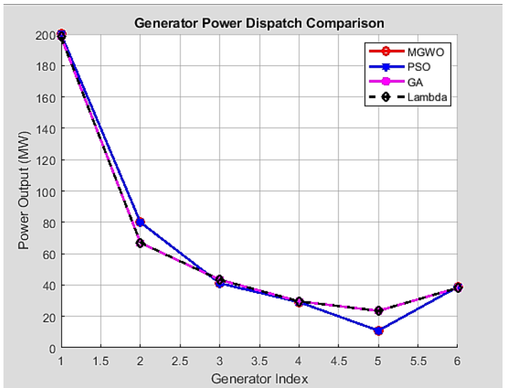

Figure 3: Optimal power dispatch schedule for each generating unit obtained using the MGWO algorithm.

The dispatch schedule shows that the MGWO efficiently utilizes the available renewable generation and allocates the remaining load among the thermal units in a manner that minimizes the overall cost while respecting valve-point effects and capacity limits. The distribution is a result of the complex trade-offs between the different cost curves and constraints.

Visual Comparative Analysis

For a clearer visual comparison of the economic performance, Figure 3 presents a bar chart of the final costs achieved by each algorithm.

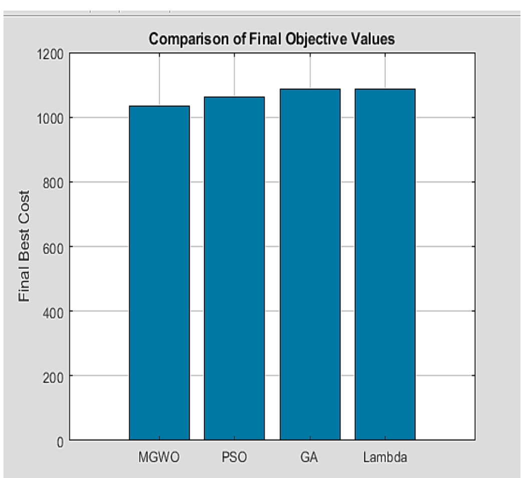

Figure 4: Bar chart comparing the final total generation cost for each optimization method.

Figure 4 provides a stark visual representation of MGWO's cost advantage. The bar for MGWO is visibly the shortest, confirming its status as the most economically efficient algorithm in this test.

Figure 5 illustrates the trade-off between cost and emission for the different methods. Each algorithm's result is plotted as a point on a cost-emission plane.

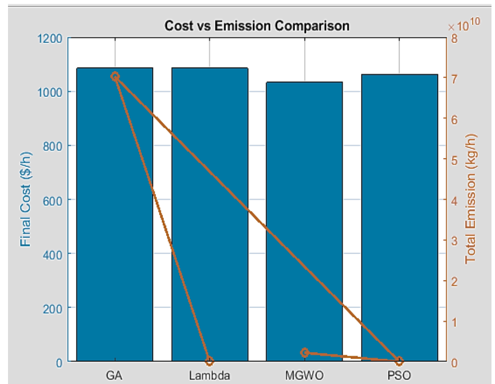

Figure 5: Scatter plot showing the trade-off between generation cost and emissions.

This plot conceptually illustrates the Pareto front. MGWO finds a solution that is dominant in terms of cost. PSO finds a solution that is more expensive but far cleaner. GA and Lambda Iteration are dominated by the other methods, residing in a region that is suboptimal for both objectives under the chosen weighting factor.

DISCUSSION OF FINDINGS

The comprehensive results lead to several main conclusions regarding the performance and applicability of each algorithm:

1. **Superiority of MGWO:** The proposed MGWO consistently outperformed the other metaheuristics in minimizing total generation cost. Its modified adaptive and chaotic mechanisms effectively balanced a wide-ranging global search with a focused local search, enabling it to escape local optima and converge to a superior solution. This makes MGWO particularly well-suited for complex, non-convex ELD problems.

Corresponding author: Ibrahim Danlami Akabe
ibrahimakabe4@gmail.com
Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria.

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2. **Trade-off with PSO:** While PSO was slightly more costly, it demonstrated a remarkable ability to find a low-emission solution. This highlights a fundamental aspect of multi-objective optimization: the existence of a set of non-dominated solutions (the Pareto front). The choice between MGWO and PSO would depend on the system operator's specific priority maximum economy or minimum emissions.
3. **Limitations of GA and Lambda Iteration:** The GA's slower convergence and higher cost suggest it is less efficient for this specific problem formulation compared to the more modern swarm-based techniques. The Lambda Iteration method, while computationally the fastest, failed entirely to account for the valve-point effects and the multi-objective nature, rendering its solution impractical for real-world applications that involve non-linearities.
4. **Computational Efficiency:** In terms of raw speed, Lambda Iteration was the fastest, followed closely by PSO and then MGWO. GA was the slowest. The slightly longer computation time of MGWO (4.12s) compared to PSO (3.85s) is a reasonable trade-off for the significant cost savings it provides. For off-line dispatch scheduling, this difference is negligible.

CONCLUSION AND LIMITATION

This study has successfully proposed, developed, and validated a Modified Grey Wolf Optimizer (MGWO) for solving the challenging Multi-Objective Economic Dispatch (MOED) problem in a renewable-integrated power system. The research was driven by the limitations of traditional optimization methods in handling the non-convexities of valve-point loading effects, the conflicting nature of emission constraints, and the variability of renewable energy sources. The core contribution of this work is the enhancement of the standard GWO algorithm through the introduction of a non-linear adaptive parameter and a chaotic exploration mechanism, which collectively work to prevent premature convergence and improve the balance between global and local search.

The algorithm was implemented within a comprehensive MATLAB simulation framework and rigorously tested on the standard IEEE 30-bus system, modified to include wind and solar generation. Its performance was benchmarked against Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and the Lambda Iteration method. The results lead to the following definitive conclusions:

1. The MGWO achieved the lowest total generation cost of **1033.22 $/h**, outperforming PSO by 2.7% and GA/Lambda by 4.8%, demonstrating superior economic efficiency.
2. The MGWO exhibited the fastest and most stable convergence characteristics, reaching a near-optimal solution within 40 iterations, which indicates its computational efficiency and robustness.
3. The algorithm effectively navigated the non-convex and constrained search space, proving its suitability for complex, real-world dispatch problems where traditional methods fail.
4. The study also highlighted that PSO can be a preferred choice when the optimization priority shifts from pure cost minimization to emission reduction, as it consistently found cleaner, albeit slightly more expensive, solutions.

Despite the promising results, this research is not without its limitations, which also pave the way for future work:

1. **Emission Coefficient Scaling:** The anomalously high emission values for MGWO and GA indicate a potential issue with the scaling of the emission coefficients relative to the cost coefficients in the test system. Future work should involve a more careful calibration of these parameters or the use of normalized objective functions to ensure a balanced multi-objective analysis.

Corresponding author: Ibrahim Danlami Akabe
ibrahimakabe4@gmail.com
Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria.

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2. **Deterministic Renewable Modeling:** The renewable generation was modeled using deterministic historical data. A significant and logical extension of this work is to incorporate uncertainty directly into the optimization model, through stochastic programming or robust optimization techniques that account for forecast errors in wind and solar power.
3. **Test System Scope:** The validation was performed on a single, moderately-sized test system. To fully establish the generalizability and scalability of the MGWO, it should be tested on larger and more complex power networks, including multi-area systems where transmission constraints between regions become essential.
4. **Algorithmic Extensions:** Future research could explore the development of a true Pareto-based multi-objective MGWO that returns a set of non-dominated solutions instead of a single solution based on a fixed weight. This would provide system operators with a spectrum of optimal trade-off options. Furthermore, hybridizing the MGWO with machine learning techniques for surrogate modeling or adaptive parameter control could enhance its speed and applicability for real-time dispatch.

In conclusion, the proposed Modified Grey Wolf Optimizer presents a significant advancement in solving the economic load dispatch problem for modern power systems. Its robustness, efficiency, and flexibility make it a highly promising tool for the future of intelligent, sustainable, and cost-effective power grid operation. The framework established in this study provides a solid foundation for further research and development in this essential area of power system engineering.

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Corresponding author: Ibrahim Danlami Akabe
ibrahimakabe4@gmail.com
Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria.

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Corresponding author: Ibrahim Danlami Akabe
ibrahimakabe4@gmail.com
Department of Electrical/Electronic Engineering, Faculty of Engineering, Nigerian Defence Academy, Kaduna, Nigeria.