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Grey Wolf Optimizer Algorithm for Multi-Objective Optimal Power Flow

Y. V. Krishna Reddy[1], R. Sireesha[2], BP Mishra [3], Pavithra G.[4], Soban Badonia*[5]

[1, 2] Department of Electrical and Electronics Engineering, SV College of Engineering, Tirupati, 517507, India
[3]JSS Academy of Technical Education, Sector-62, Noida, India
[4] Department of Electronics & Communication Engineering, Dayananda Sagar College of Engineering (DSCE), Bangalore- 560078, Karnataka, India.
[5]Master of Information Technology, University of Wollongong, Wollongong New South Wales, Australia
Emails: yvkrishnareddy36@gmail.com; sireesha.rachapalli@svcolleges.edu.in; bpmishra@jssaten.ac.in; dr.pavithrag.8984@gmail.com; sb032@uowmail.edu.au
*Corresponding Author: sb032@uowmail.edu.au

Abstract

This article introduces the Grey Wolf Optimizer (GWO) algorithm, a novel method aimed at tackling the challenges posed by the multi-objective Optimal Power Flow (OPF) problem. Drawing inspiration from the foraging behavior of grey wolves, GWO stands apart from traditional approaches by enhancing initial solutions without relying on gradient data collection from the objective function. In the domain of power system optimization, the OPF problem is widely acknowledged, involving constraints related to generator parameters, valve-point loading, reactive power, and active power. The proposed GWO technique is applied to IEEE 14-bus and 30-bus power systems, targeting four case objectives: minimizing cost with quadratic cost function, minimizing cost with inclusion of valve point, minimizing power loss, and minimizing both cost and losses simultaneously. For the IEEE-14 bus system, which requires meeting a power demand of 259 MW, GWO yields optimal costs of 827.0056 $/hr, 833.4691 $/hr, 1083.2410 $/hr, and 852.2255 $/hr across the four cases. Similarly, for the IEEE-30 bus system aiming to satisfy a demand of 283.4 MW, GWO achieves optimal costs of 801.8623 $/hr, 825.9321 $/hr, 1028.6309 $/hr, and 850.4794 $/hr for the respective cases. These optimal results are then compared with existing research outcomes, highlighting the efficiency and cost-effectiveness of the GWO algorithm when juxtaposed with alternative methods for solving the OPF problem.

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Keywords: Grey Wolf Optimizer; Optimal Power Flow; Valve-point loading; Active power loss; Power loss with fuel cost.

1. Introduction:

The Optimal Power Flow (OPF) challenge surfaced in the 1960s, as noted by Carpentier in 1962. Utilizing network configurations in OPF facilitates the optimization of various power system objective functions, including greenhouse gas emissions from generators, total generating unit cost, and real power loss in the system, and operational constraints of equipment. Despite the existence of numerous outdated techniques for solving the OPF problem [1,2], many of them encounter limitations such as local optima or issues with inequality constraints. To overcome these challenges, several heuristic approaches have been proposed. Various mathematical methods have been applied to address the OPF problem, including the Newton method [3], the interior point method [4], and linear programming [5]. While these techniques have shown effectiveness, relying solely on linear function approximations and constraints for problem-solving has its limitations. Specifically, depending solely on linear approximations in addressing the OPF may result in significant inaccuracies.

In practical scenarios, addressing the Optimal Power Flow (OPF) problem becomes more challenging when considering valve-point effects and nonconvex fuel cost functions. Heuristic optimization methods prove valuable in overcoming these challenges due to their flexibility in accommodating various objective functions and constraints. A multitude of heuristic approaches has been applied to tackle the OPF problem, encompassing methods such as Differential Evolution (DE) [6], Particle Swarm Optimization (PSO) [7], Simulated Annealing (SA) [8], and Gravitational Search Algorithm (GSA) [9].

Mohamed [10] introduced the Moth Swarm Algorithm (MSA) as a solution for the OPF problem, incorporating an associative learning process with instantaneous memory and group diversity crossovers for Levy-mutation to enhance both exploratory and exploitative capabilities. Recognizing the robust problem-solving efficiency of the Binary Salp Swarm Algorithm (BSA) across different initial parameter settings, Kilic U [11] adapted BSA for addressing the OPF problem. Abdel-Rahim [12], based on atomic mobility principles, employed the Atom Search Optimizer (ASO) algorithm to address the OPF problem. The ASO algorithm considers atom interactions through mutual forces derived from the Lenard-Jones potential and constraint forces arising from bond-length potentials.

In order to comprehensively evaluate the effectiveness of heuristic algorithms for addressing the Optimal Power Flow (OPF) problem, it becomes imperative to explore enhanced or hybridized versions of existing approaches. Bakirttzis [13] introduced an Improved Genetic Algorithm (EGA) by incorporating a problem-specific activator into the genetic algorithm (GA) framework, aiming to enhance its performance in resolving the OPF. Kumare [14] devised a hybrid approach named EGAeDQLF by integrating the EGA with a novel Decoupled Quadratic Load Flow (DQLF) solution. This combination aimed to capitalize on the strengths of both components for more effective OPF resolution. Vaisakh (2015) proposed the Evolving Ant Direction Particle Swarm Optimization (EADPSO) method specifically designed for addressing the non-convex generation cost characteristics within the OPF problem.[15] This technique involves the evolutionary adaptation of ant colony variables through a genetic process to identify a suitable velocity update operator for Particle Swarm Optimization (PSO). Naderi [16] introduced a novel hybrid configuration tailored for the multiobjective OPF problem. This unique approach integrates fuzzy adaptation into a Joint Self-Adaptive PSO (SePSO), providing a directed and adaptive solution to the challenges posed by the OPF problem.

Shahen [17] introduced a Forced Initiation Multi-Objective Differential Evolutionary Algorithm (MO-DEA) designed for solving the Optimal Power Flow (OPF) problem. This novel approach effectively addresses the computational complexity associated with Optimum ranking by integrating a distinctive variant of Differential Evolution (DE) and the e-constraint technique. This integration ensures rapid convergence and the generation of a diverse set of Optimum solutions. To enhance the local search capability of the SFLA technique, Shahen [17] incorporated Simulated Annealing (SA), significantly boosting its effectiveness. In the pursuit of improving the Sine-Cosine Algorithm's (SCA) ability to steer clear of local optimal solutions, Attia [18] introduced a Modified Sine-Cosine Algorithm (MSCA) tailored for solving the OPF. These enhanced or hybrid variants have demonstrated effectiveness in yielding outstanding outcomes. However, a noteworthy challenge lies in their ability to regulate exploration and exploitation throughout different stages of evolution.

This study employs the Grey Wolf Optimization (GWO) [19], a method rooted in the Newton-Raphson algorithm, to minimize the overall cost encompassing generation, transmission losses, and emissions for IEEE 14-bus and 30-bus test systems. A comparative analysis is conducted between the optimal solutions obtained through the GWO approach and the outcomes reported in contemporary literature for other methods. The findings reveal that GWO outperforms the results reported in the existing literature, providing superior solutions in terms of minimizing total costs associated with generation, transmission losses, and emissions.

The paper is structured into several pivotal sections.

Initially, Section 2 extensively discusses the mathematical model underpinning the Optimal Power Flow (OPF) problem, elucidating its intricacies and formulation. Following this, Section 3 conducts a thorough exploration of the implementation of the Grey Wolf Optimizer (GWO) method, with a specific focus on its adaptation to various objective functions within the OPF framework. Subsequently, Section 4 delves into the empirical aspect of the study, providing insights into the application of test systems and presenting a diverse array of case study simulation results pertinent to OPF scenarios. Lastly, Section 5 encapsulates the conclusions drawn from the study's findings, summarizing the implications and contributions of the research.

2. Problem Formulation

The goal of the Optimal Power Flow (OPF) is to optimize the objective function by adjusting the control parameters of power systems to adhere to various practical and physical constraints imposed on the power grid. The mathematical formulation of the OPF problem appears as follows:

$$\min:\ f(x, u) \tag{1}$$

$$\text{s.t.}\quad g(x, u) = 0 \tag{2}$$

$$h(x, u) \le 0 \tag{3}$$

$$\begin{cases} f(x, u) \rightarrow \text{objective function}, \\ g(x, u) \rightarrow \text{equality constraint}, \\ h(x, u) \rightarrow \text{inequality constraint}. \end{cases}$$

A. Formulation of Objective function

Each generator incorporates a shared fuel cost function, which can be represented in a quadratic form, as illustrated below:

$$F_{Obj} = F_i(P_i) = \sum_{i=1}^{N} (a_i P_i^2 + b_i P_i + c_i) \tag{4}$$

Nevertheless, Equation (4) does not consider the valve-point effect (VPE), introducing oscillations in the input/output curve. To accommodate for the valve-point effects, researchers can express the objective function as shown in Equation (5).

$$F_{Obj} = F_i(P_i) = \sum_{i=1}^{N} \left(a_i * P_i^2 + b_i * P_i + c_i + \left| e_i * \sin(f_i * (P_{min} - P_i)) \right| \right) \tag{5}$$

As the quantity of transmission system lines rises, so does the associated increase in the dissipation of active power. The following represents a formulation of the objective function:

$$F_{Obj} = F_i(P_i) = \sum_{i=1}^{Nl} \sum_{j \ne i}^{Nl} G_{ij} * V_i^2 + V_j^2 - 2 * V_i * V_j \cos(\delta_j - \delta_i) \tag{6}$$

By integrating Equation (4) and Equation (6), the aim is to concurrently minimize both cost and losses, as depicted in Equation (7).

$$F_{Obj} = \sum_{i=1}^{N} (a_i * P_i^2 + b_i * P_i + c_i + \left| e_i * \sin(f_i * (P_{min} - P_i)) \right|) + w_2 * \sum_{i=1}^{Nl} \sum_{j \ne i}^{Nl} \{G_{ij} * V_i^2 + V_j^2 - 2 * V_i * V_j \cos(\delta_j - \delta_i)\} \tag{7}$$

B. Constraints of equality and inequality

Conventionally, the load flow balancing equations are expressed in the subsequent manner to represent equality constraints:

$$P_{Gi} - P_{Di} = V_i * \sum_{j=1}^{Nb} V_j * [G_{ij} * \cos(\delta_{ij}) + B_{ij} * \sin(\delta_{ij})] \tag{8}$$

$$Q_{Gi} - Q_{Di} = V_i * \sum_{j=1}^{Nb} V_j * [G_{ij} * \cos(\delta_{ij}) + B_{ij} * \sin(\delta_{ij})] \tag{9}$$

In the pursuit of discovering an improved optimum condition, the OPF problem's inequality constraints are deemed to impose the following functional limitations:

***Generator limits*:**

$$V_i^{min} \le V_i \le V_i^{max} \tag{10}$$

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \qquad \text{Where i = 1, 2... Ng.} \tag{11}$$

Voltages at loading buses:

$V_j^{min} \leq V_j \leq V_j^{max}$ Where j = 1, 2… npq; (12)

The Newton-Raphson method can be employed for conducting load flow analysis, and the GWO methodology can be utilized to achieve the optimal solution, all within the specified constraints mentioned above.

3. Grey Wolf Optimizer

Mirjalli introduced the Grey Wolf Optimization (GWO) [19] approach, inspired by the hunting strategies observed in natural grey wolves. Grey wolves exhibit a social hierarchy comprising alpha, beta, omega, and delta types, forming a structured dominance order within their pack. The alpha wolf holds the highest rank and makes crucial decisions, with beta wolves collaborating closely. Omega wolves, as apex predators, follow directives from the alpha, while delta wolves obediently follow pack leadership. The subsequent text delves into the four-stage hunting process employed by grey wolves.

i. **Looking for food**

The search method initiates with wolf solutions, or potential solutions from the search space, randomly selected to commence the process. In the natural hunting behavior of grey wolves, when they locate their prey, they typically engage in separate hunting activities.

ii. **Encircling prey**

The behavior of grey wolves encircling their prey after locating it is elucidated through the mathematical expressions (13) and (14), presented below.

$$\vec{E} = \left| \vec{O} * \vec{X}_p(k) - \vec{X}(k) \right| \quad (13)$$

$$\vec{X}(k+1) = \vec{X}_p(k) - \vec{B} * \vec{E} \quad (14)$$

In this context, k represents the present iteration. Vectors coefficients are denoted by $\vec{O}$ and $\vec{B}$.

$\vec{B}$ is used to prevent grey wolves (GW) from attacking searchers' livestock. $\vec{O}$ represents obstacles encountered by the prey during a hunt. The position vector of grey wolves is illustrated by $\vec{X}$ and a prey's position indicated by a vector by $\vec{X}_p$. The vectors $\vec{O}$ and $\vec{B}$ are determined by the following equations:

$$\vec{B} = 2 * \vec{l} * \vec{r}_1 - \vec{l} \quad (15)$$

$$\vec{O} = 2 * \vec{r}_2 \quad (16)$$

iii. **Hunting**

After surrounding their victim, grey wolves become intensely focused on the kill. α, β and ω wolves are often used as hunters' guides. The best possible candidate solution is provided by α. Grey wolf chasing habit may be expressed mathematically as (17)-(23).

$$E_\alpha = \left| \left(\vec{O}_1 * \vec{X}_\alpha(k) \right) - \vec{X}(k) \right| \quad (17)$$

$$E_\beta = \left| \left(\vec{O}_2 * \vec{X}_\beta(k) \right) - \vec{X}(k) \right| \quad (18)$$

$$E_\omega = \left| \left(\vec{O}_3 * \vec{X}_\omega(k) \right) - \vec{X}(k) \right| \quad (19)$$

$$\vec{X}_1 = \vec{X}_\alpha(k) - \left(\vec{B}_1 * \vec{E}_\alpha \right) \quad (20)$$

$$\vec{X}_2 = \vec{X}_\beta(k) - \left(\vec{B}_2 * \vec{E}_\beta \right) \quad (21)$$

$$\vec{X}_3 = \vec{X}_\omega(k) - \left(\vec{B}_3 * \vec{E}_\omega \right) \quad (22)$$

$$\vec{X}(k+1) = \frac{(\vec{X}_1 + \vec{X}_2 + \vec{X}_3)}{3} \quad (23)$$

iv. **Attacking prey**

Once the chase is done, grey wolves will launch an assault on their victim. Based on the position of α, β and ω wolves, the GWO algorithm enables the wolves, to relocate so that they can more effectively ambush their prey. Two factors, $\vec{a}$ and $\vec{A}$, need be taken into account before making a move on the target. Here, $\vec{a}$ linearly decreases from 2 to 0 as the iterations grows, and the variability of $\vec{A}$ likewise diminishes as $\vec{a}$ does.

A Implementation of the GWO for the OPF problem

Below are the procedures used to put the GWO into action for the OPF issue addressed in this paper.
Methods for using the GWO algorithm for OPF issues

Step 1: The initialization process

i. The cost coefficients, bus data, and line data may all be read.
ii. Limit the amount of energy each generator may produce.
iii. Choose a maximum number of search agents.
iv. Find the minimum and maximum search depths using the GWO settings.

Step 2: Make a random guess for the α, β and ω-positions and the starting fitness values

α_pos=zeros(1,d)	β_pos=zeros(1,d)	ω_pos=zeros(1,d)
α_value=infinity	β_value = infinity	ω_value = infinity

$$Pos = rand\left(No.of\_searchAgents, d\right).*\left(u\_b - l\_b\right) + l\_b$$

Step 3: Place t=0 as the time step.

Step 4: Perform the computations necessary to determine the beginning points of the goal function. Replace each alpha's present position with the best position they've ever had in the past.

Step 5: t=t+1 denotes an increment of the variable t by 1.

Step 6: Choose each alpha's neighbour and calculate the goal function.

Step 7: Refresh each alpha's best performance record against the best performance record of all other search agents.

```
for i=1:size(Pos,1)
  for j=1:size(Pos,2)
        E_α =abs(O1* α _pos(j)-Pos(i,j)),        X1= α _pos(j)-A1*D_ α
        E_β =abs(C2* β _pos(j)-Pos (i,j)) ,      X2= β _pos(j)-A2*D_ β
        E_ω =abs(C3* ω _pos(j)-Pos (i,j)),       X3= ω _pos(j)-A3*D_ ω
        Pos(i,j)=avg_of(X1,X2,X3)
    end
 end
```

Step 8: Continue iterating Step 6 until the best value for the objective function is attained, determined by the specified tolerance (0.00001), rather than stopping before reaching the total number of iterations.

Step 9: Find the optimum generating powers that match to the goal function.

4. Simulation Results

GWO is applied to solve the OPF for the IEEE 14-bus [20] and IEEE 30-bus [30] test systems, covering cases 1-4. A maximum of 500 iterations is set for both systems. The simulations are conducted using Matlab-2014 on a Windows 10 desktop with a 1.80 GHz processor and 4.00 GB of RAM. Power outputs are measured in MW, fuel costs in $/h, and voltage magnitudes in per unit, uniformly presented across all tables and graphs.[22]

A. IEEE 14-Bus Test System

The testing system follows the IEEE standard, comprising 14 buses, with 5 buses designated as voltage-controlled (PV) and 9 as load (PQ) buses. The total load demand for the system is 259 MW. Detailed information on the fuel price coefficients for the system's generators is sourced from [25].

i. CASE 1: Quadratic fuel cost function

Equation 4 represents the objective function without considering valve-point effects, which distinguishes it from other heuristic methods. Table 1 displays optimal values for control variables determined by the Grey Wolf Optimizer, including the objective function, active power outputs from generating units, and system losses, considering a demand of 259 MW. The GWO method achieves an operating cost of 827.0056 ($/hr) with transmission losses totaling 10.5912 MW. Figure 1 illustrates the convergence characteristics, showing that the objective value is attained within 10 iterations. However, the absence of valve-point effects in the convex fuel cost leads to unsatisfactory results, highlighting the need to address this limitation by considering the valve-point influence on the cost function.

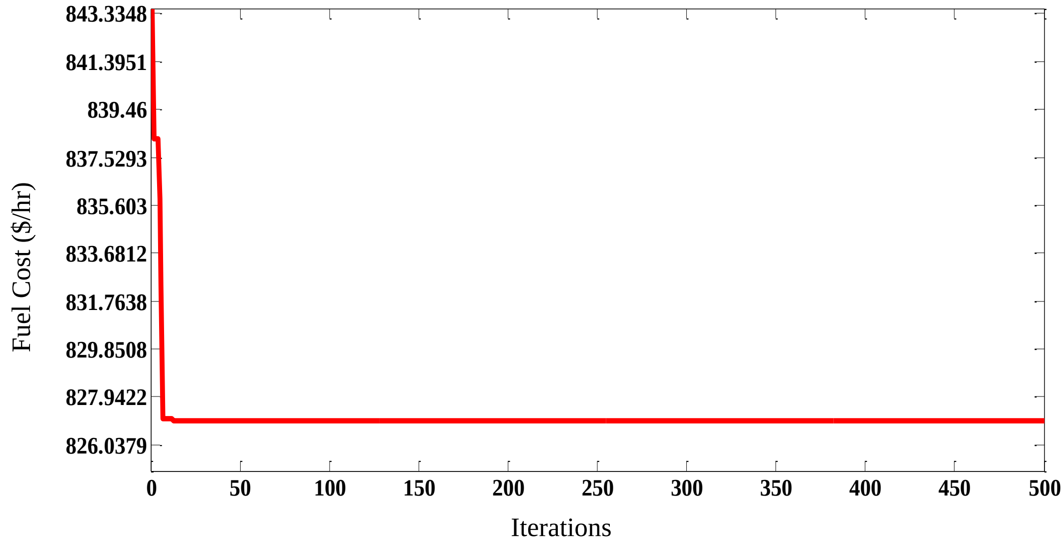

Figure 1: IEEE 14-bus system case1 convergence characteristics

ii. CASE 2: Valve Point Loading in a Quadratic Fuel Cost Function

To comprehensively validate the effectiveness of the GWO algorithm in addressing a complex OPF problem, including valve-point effects is crucial. Equation 5 represents the objective function with detailed valve-point effect generating cost coefficients from [25]. Table 1 presents optimal control variable configurations determined by GWO, covering transmission losses, active power outputs, and objective function results for a demand of 259 MW. To ensure comparability with other algorithms, generator 1's maximum operational output is increased to 250. Figure 2 illustrates GWO's convergence curves, showing instances of premature convergence due to multiple local minima influenced by valve-point effects. The non-convex nature of the objective function requires nearly 130 iterations to reach the global optimum.

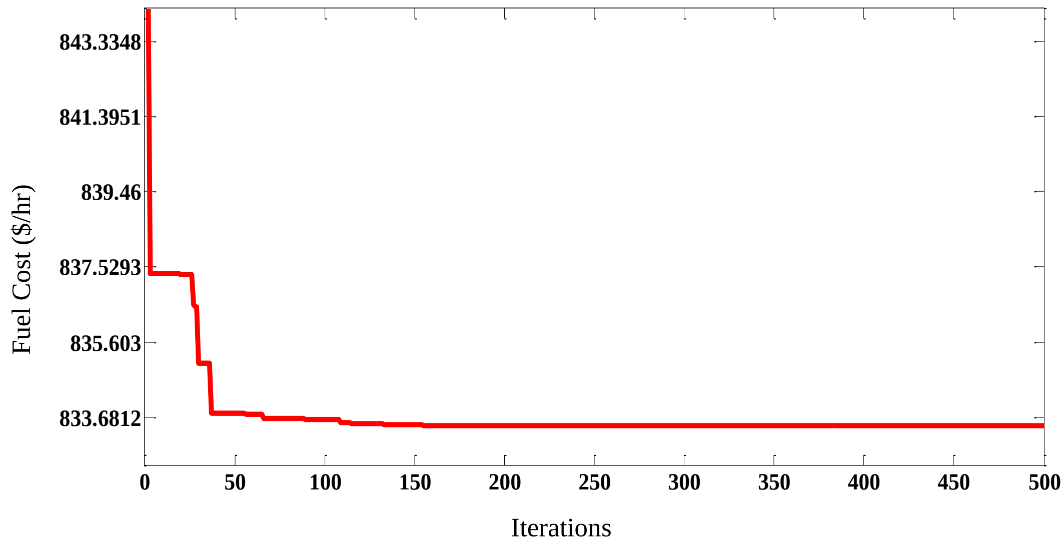

Figure 2: IEEE 14-bus system case2 convergence characteristics

Comparing Optimal Power Flow (OPF) outcomes using the Grey Wolf Optimizer (GWO) with studies in the literature reveals significant differences in cost results. Previous reports document costs of 926.55 and 905.54 $/h for Genetic Algorithm (GA) and Hybrid Genetic Algorithm (HGA) [42], while Sine-Cosine Algorithm with Simulated Annealing (SFLA-SA) achieved 834.36 $/h [44]. The transmission losses vary across different methods: GA reports 7.82 MW, Modified Sine-Cosine Algorithm with Simulated Annealing (MSG-HS) reports 9.32 MW, SFLA-SA reports 9.56 MW, and Particle Swarm Optimization (PSO) reports 9.26 MW. In contrast, implementing GWO in this research estimates system losses at 6.2530 MW, with an operating cost of 801.8623 $/hr. Comparatively, the GWO enhanced approach in this study yields notably lower overall generating cost and losses compared to standard GWO and other methods in the literature.[31]

iii. CASE 3: Active Power Loss Minimization

In this specific scenario, active power loss is chosen as the exclusive criterion for assessment, and its corresponding formula is expressed in Equation 6. The recommended values for the controlling factors of the proposed Grey Wolf Optimizer (GWO) are presented in Table 1. For a demand of 259 MW, the output of the objective function, the active power outputs of the generating units, and the transmission losses of the test system are detailed. In this context, active power losses amount to 3.2062 MW, signifying a reduction of 48.72% compared to case 2 and a decrease of 69.72% compared to case 1.

The cost increment resulting from the loss reduction objective is observed in example 3, where it is 29.96% higher than case 2 and 30.98% higher than case 1. To overcome this drawback, costs and losses are simply combined in case 4, each assigned an appropriate weighting factor. Figure 3 visually represents the convergence characteristics, demonstrating that no more than ten iterations are necessary to reach the global objective value.

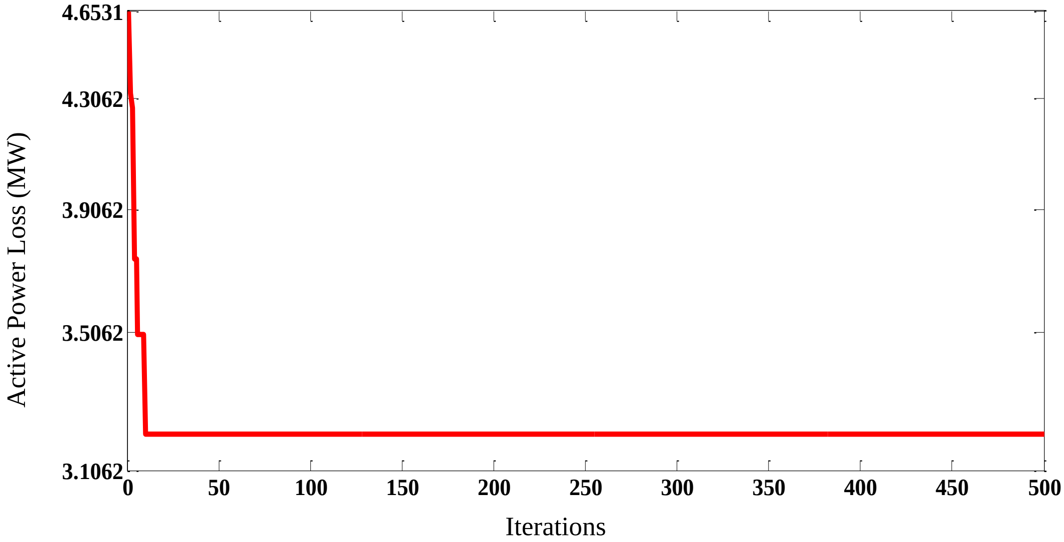

Figure 3: IEEE 14-bus system case3 convergence characteristics

iv. CASE 4: Cost of Fuel with Power Loss

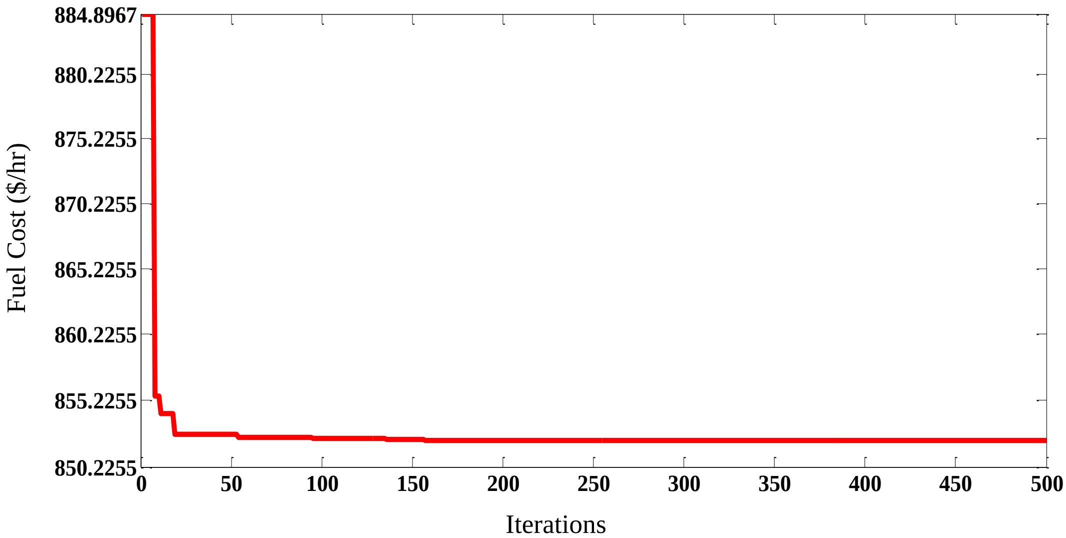

Figure 4: IEEE 14-bus system case6 convergence characteristics

In this specific scenario, the objective is to concurrently reduce the magnitude of transmission active power dissipation and the primary fuel expenditure. The fitness function for Case 4 is articulated in Equation 7, with the weighting factor represented by the symbol 'w' set at a value of 40, as reported in Reference [25]. Table 1 provides a comprehensive breakdown of the optimal values for the controlling variables of the proposed Grey Wolf Optimizer (GWO).

The study presents the results of the objective function, the active power outputs of the power-producing units, and the overall transmission losses of the test system in response to a demand of 259 MW. For Case 4, the fuel cost obtained is 852.2255 ($/hr), accompanied by transmission losses amounting to 9.3694 MW. Figure 4 visually depicts the convergence characteristics. Due to the intricate nature of the objective function, achieving its global objective value necessitates approximately 162 iterations.

Table 1: The optimum control variable settings for an IEEE 14-bus system

Variable Parameter	Lower Limit	Upper Limit	Case1 Outcomes	Case2 Outcomes	Case3 Outcomes	Case4 Outcomes
Pg1	50	250	213.6059	199.5997	67.2062	199.5997
Pg2	20	80	20.00	20.0000	80.0000	20.0000
Pg3	15	50	15.9853	21.0568	50.0000	21.4374
Pg6	10	35	10.0000	16.1674	35.0000	15.4127
Pg8	10	30	10.0000	11.5635	30.0000	11.9197
Vg1	0.94	1.06	1.0600	1.0600	1.0600	1.0600
Vg2	0.94	1.06	1.0438	1.0412	1.0442	1.0450
Vg3	0.94	1.06	1.0204	1.0216	1.0266	1.0215
Vg6	0.94	1.06	1.0479	1.0477	1.0482	1.0478
Vg8	0.94	1.06	1.0474	1.0472	1.0473	1.0471
Gen.Cost($/hr)	**-**	**-**	827.0056	833.4691	1083.2410	852.2255
Losses(MW)	-	-	10.5912	6.2530	3.2062	9.3694

B. IEEE 30-BUS TEST SYSTEM

The IEEE 30-bus test configuration consists of 26 buses, with six buses designated as "generation buses" (PV) and the remaining 21 as "load buses" (PQ) [25]. The total load demand for the system is 283.40 MW.

i. CASE 1: Quadratic fuel cost function

The objective function, as currently formulated, does not account for valve-points to ensure fair comparison with other heuristic methods. Table 3 outlines optimal values for controlling variables of the proposed Grey Wolf Optimizer (GWO) to meet a demand of 283.4 MW. GWO yields an optimal cost of 801.8623 $/hr and active power losses totaling 9.3803 MW. Table 2 provides a comprehensive analysis of results for the IEEE 30-bus system. Notably, GWO demonstrates superior values compared to GA [23], GA-OPF [24], EP-OPF [24], ACO [27], NLP [29], MDE-OPF [30], MSFLA [34], and EGA [32] methods reported in the literature. The introduction of these innovative optimization approaches proves effective in solving the OPF problem, overcoming the complexity associated with local optimal value disadvantages.

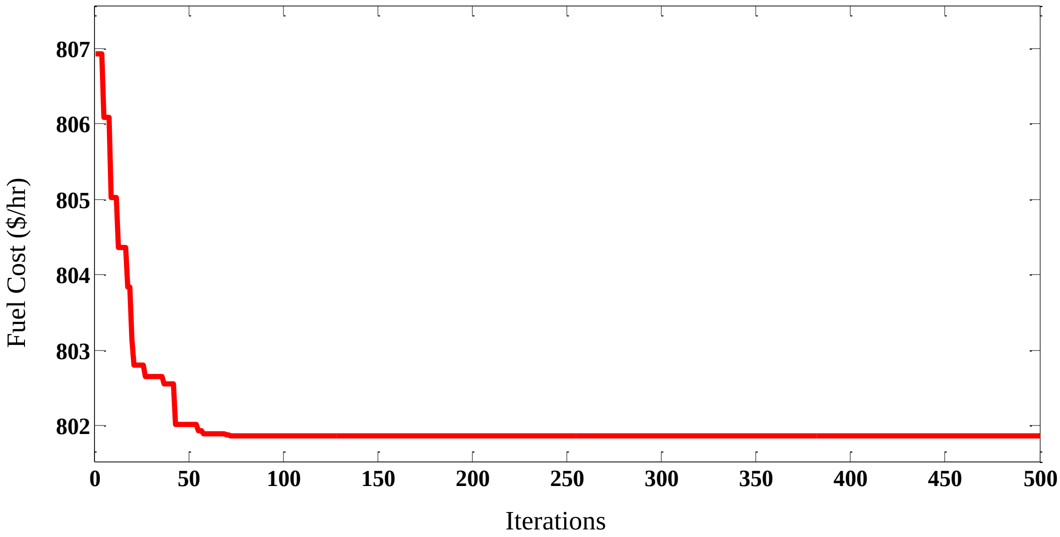

Figure 5: IEEE 30-bus system case1 convergence characteristics

Figure 5 illustrates the convergence patterns of the IEEE 30-bus system in scenario 1. Remarkably, the GWO approach reaches a global optimum value within the initial 80 iterations, hitting the maximum limit of 500 iterations. However, introducing the valve-point effect into the objective function for case 1 increases the complexity of the GWO approach.

ii. CASE 2: Valve Point Loading in a Quadratic Fuel Cost Function

When addressing a more complex Optimal Power Flow (OPF) problem, including valve-point effects is crucial to verify the overall effectiveness of the GWO algorithm. Table 3 details recommended values for control variables of the proposed GWO. Outcomes of the objective function, active power outputs of generating units, and transmission losses for a demand of 283.4 MW are presented. Figure 6 illustrates convergence curves achieved by GWO. It's evident that when used to solve OPF problems with multiple local minima, GWO encounters the challenge of premature convergence to varying extents due to valve-point influences. Achieving the global optimum value requires nearly 200 iterations, reflecting the non-convex nature of the objective function.[43]

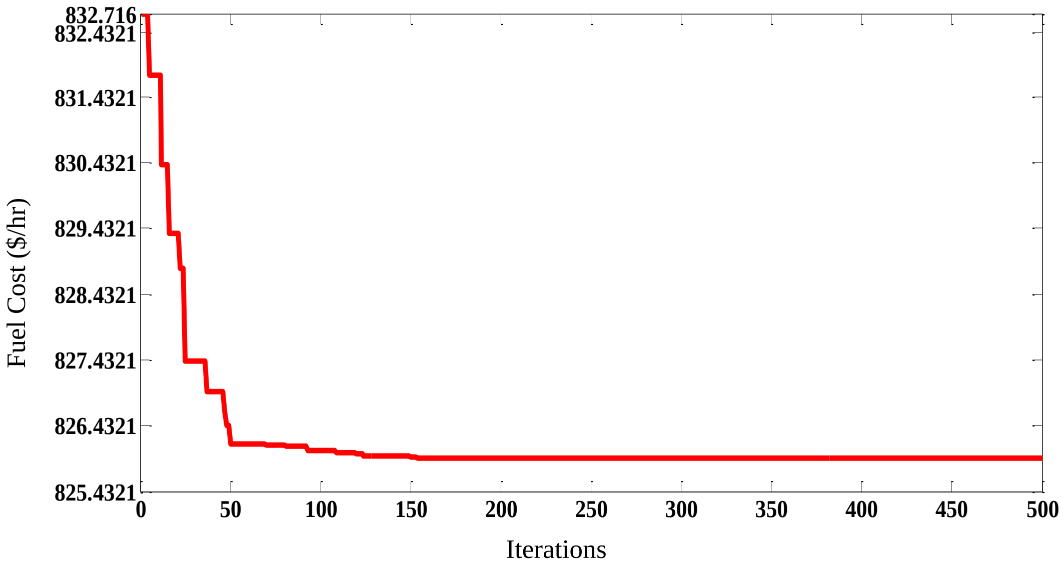

Figure 6: IEEE 30-bus system case2 convergence characteristics

The GWO method yields an optimal cost of 825.9321 $/hr and active power losses totaling 12.3046 MW. Table 2 provides a comprehensive analysis of results for the IEEE 30-bus system. Notably, GWO demonstrates superior performance compared to ICBO [36], NISSO [37], SA [23], SA [38], EEA [32], EGA-EA [39], PSO [38], DE-OPF [30], EGA [32], and SFLA [23] techniques described in published works.

iii. CASE 3: Active Power Loss Minimization

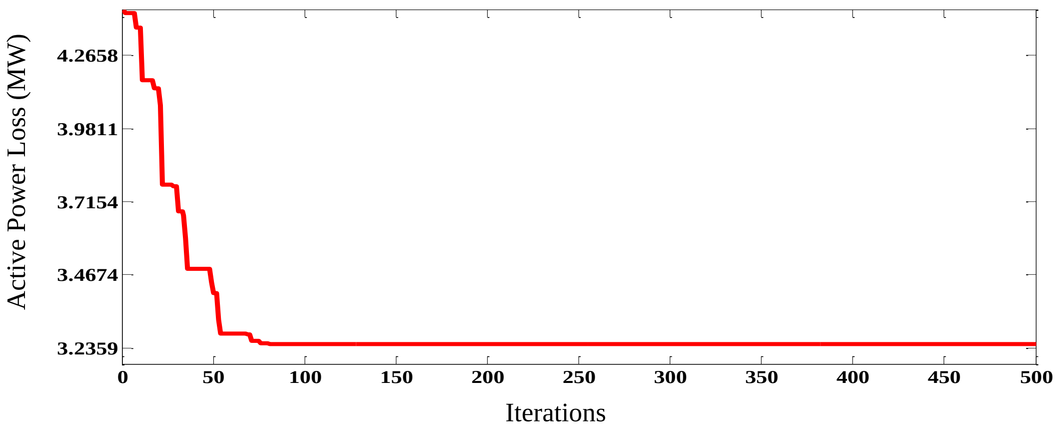

Figure 7: IEEE 30-bus system case3 convergence characteristics

In scenarios with significant power losses, relying solely on minimizing fuel costs becomes less reliable. Active power loss is the sole criterion for this analysis, as denoted by Equation 6. Table 3 provides suggested values for controlling parameters of the Grey Wolf Optimizer (GWO), along with detailed information on transmission losses, active power outputs, and the objective function output for a demand of 283.4 MW. In this case, active power losses amount to 3.2473 MW, indicating a reduction of 73.60% compared to Case 2 and a decrease of 65.38% compared to Case 1. However, costs increase by 24.54% compared to Case 2 and 28.28% compared to Case 1 due to the loss reduction objective in Case 3. To address this, costs and losses in Case 4 were aggregated and assigned weights reflecting their relative importance. Figure 7 illustrates convergence characteristics, with no more than sixty iterations needed to reach the global objective value.

Table 3 provides a thorough examination of results obtained for the IEEE 30-bus system. Notably, the GWO method demonstrates superior performance when compared to various other optimization techniques, including PSO [38], EEA [32], GA [40], EGA-EA [39], DSA [41], and EGA [32], as detailed in the previously published works listed in Table 2. This superiority can be attributed to the hybridization of approaches and the optimization of control variables, which collectively contribute to achieving the global optimum value in less iteration. Furthermore, the GWO method outperforms previous studies by providing the best ideal value, showcasing its efficacy and robustness in tackling optimization challenges within power systems.

Table 2: Comprehensive analysis of the results for IEEE 30-bus

METHOD	**MGWO**	**EGA[32]**	**MSFLA[34]**	**MDE-OPF[30]**	**NLP[29]**	**ACO[27]**	**EA-OPF[24]**
Case1 cost($/hr)	801.8623	802	802.06	802.211	802.287	802.29	802.37
METHOD	MGWO	SFLA[23]	EGA[32]	MDE-OPF[30]	NLP[29]	PSO[28]	EGA[39]
Case2 cost($/hr)	825.9321	825.9906	826.3176	826.54	826.5898	826.6962	826.8492
METHOD	MGWO	EGA[32]	DSA[41]	EGA-GA[39]	GA[40]	EEA[32]	PSO[38]
Case3 losses (MW)	3.2470	3.2490	3.2502	3.2601	3.2772	3.2883	3.3180

iv. CASE 4: Cost of Fuel with Power Loss

In this scenario, the objective is to address two critical aspects simultaneously: reducing active power loss during transmission and minimizing fuel expenses, as outlined in Equation 7. To achieve this, a weighting factor 'w' of 40, referenced from [25], is incorporated into the fitness function for Case 4. The optimal control variable values determined by the Grey Wolf Optimizer are presented in Table 3.

For a power demand of 283.4 MW, Case 4 results in a fuel cost of 850.4794 $/hr and transmission losses of 12.2431 MW. Notably, the only heuristic approach identified in the literature capable of tackling this specific objective function is the Moth Swarm Algorithm (MSA) [10], which achieves a fuel cost of 859.1915 $/h as referenced in [10]. Despite the comparable fuel costs, the proposed GWO method exhibits superior performance over MSA [10].

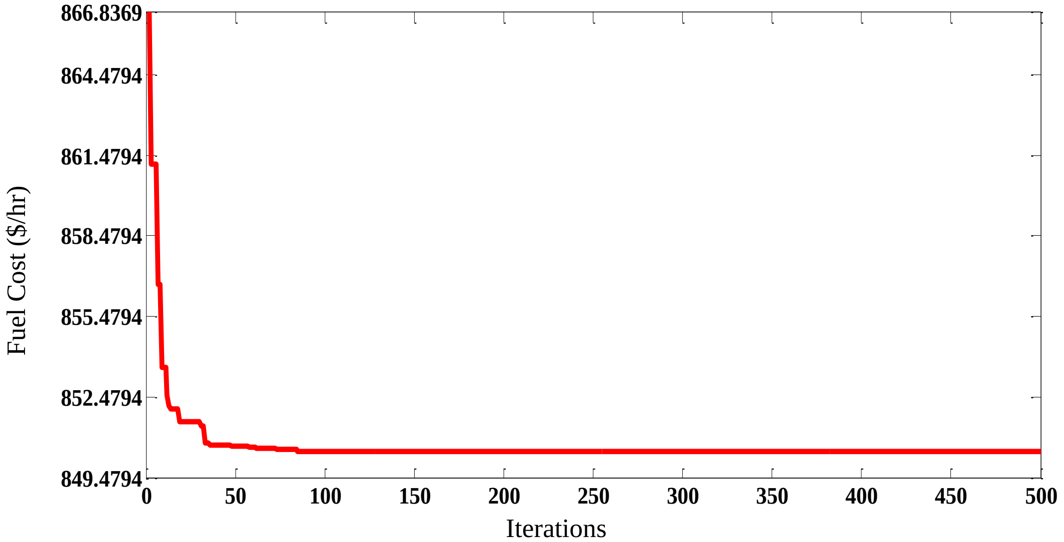

Figure 8: IEEE 30 bus system case4 convergence characteristics

Figure 8 provides insights into the convergence characteristics of the algorithm, indicating that approximately 100 iterations are required to attain the global objective value owing to the complexity of the function. This convergence behavior underscores the robustness and efficacy of the GWO method in addressing multifaceted optimization problems in power systems.

Table 3: Optimum control variable settings for an IEEE 30 bus test system

Variable Parameter	Lower Limit	Upper Limit	Case1 Outcomes	Case2 Outcomes	Case3 Outcomes	Case4 Outcomes
Pg1	50	250	176.7788	219.8158	51.8973	219.8158
Pg2	20	80	48.8419	28.0167	80.0000	27.0771
Pg5	15	50	21.4774	15.8721	50.0000	16.7501
Pg8	10	35	21.5783	10.0000	34.0080	10.0000
Pg11	10	30	12.1038	10.0000	29.0005	10.0000
Pg13	12	40	12.0000	12.0000	40.0000	12.0000
Vg1	0.94	1.06	1.0600	1.0600	1.0600	1..0600
Vg2	0.94	1.06	1.0430	1.0432	1.0428	1.0439
Vg5	0.94	1.06	1.0100	1.0108	1.0118	1.0098
Vg8	0.94	1.06	1.0100	1.0115	1.0125	1.0105
Vg11	0.94	1.06	1.0420	1.0418	1.0407	1.0398
Vg13	0.94	1.06	1.0410	1.0489	1.0465	1.0359
Gen.Cost($/hr)	-	-	801.8623	825.9321	1028.6309	850.4794
Losses(MW)	-	-	9.3803	12.3046	3.2473	12.2431

5. Conclusions

This study proposes the utilization of the Grey Wolf Optimizer (GWO) to address the complex challenges inherent in Optimal Power Flow (OPF) within the IEEE 14-bus and IEEE 30-bus test power systems. Through systematic validation across four distinct cases, each characterized by a unique objective function, GWO's effectiveness is clearly demonstrated. Findings from cases 1 to 4 consistently highlight GWO's superior performance compared to other initial algorithms. Particularly noteworthy is GWO's capability to navigate away from local optimal solutions, attributed to its proficient handling of non-convex cost functions and the valve-point effect. In systems with heightened levels of active power losses, GWO excels in prioritizing loss reduction over cost reduction. Moreover, the strategic integration of a weighting factor enables GWO to concurrently minimize both costs and losses. This successful implementation underscores GWO's adaptability and efficiency, drawing parallels with the strategic foraging behavior observed in wolves. It further underscores GWO's promise in effectively addressing the intricate challenges posed by the OPF problem and broadens its applicability to domains such as Distributed Generation (DG) and the optimization of multiple fuel utilization simultaneously.

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Author Contribution

- **Y V Krishna Reddy and Soban Badonia:** Methodology, Writing original draft, Review and Editing Supervision
- **R Sireesha** and **Dr. Pavithra G**: Literature Review, Investigation,
- **Dr. BP Mishra:** Conceptualization

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