FOREX Publication
Open Access | Rapid and quality publishing

International Journal of Electrical and Electronics Research (IJEER)
Research Article | Volume 12, Issue 3 | Pages 926-933 | e-ISSN: 2347-470X

Economic Load Dispatch of Thermal-Solar-Wind System using Modified Grey Wolf Optimization Technique

Y V Krishna reddy[1*], Naga Venkata Ramakrishna G[2], Prof. (Dr.) Mohammad Israr[3], Buddaraju Revathi[4], Dr. Pavithra G[5], and Dr Nageswara Rao Lakkimsetty[6]

[1]Associate Professor, Department of EEE, SV College of Engineering, Tirupati, India, Email: krishnareddy.yv@svcolleges.edu.in
[2]Faculty of Engineering, University of Technology and Applied Sciences-Al Musannah, Sultanate of Oman, Email: Naga.Krishna@utas.edu.com
[3]President, Maryam Abacha American University of Nigeria, Hotoro GRA, Kano State, Federal Republic of Nigeria, Email: president@maaun.edu.ng
[4]Assistant Professor, Department of Electronics and Communication Engineering, SRKR Engineering college, Bhimavaram 534204. Email: buddaraju.revathi@gmail.com
[5]Associate Professor, Dept. of Electronics & Communication Engineering, Dayananda Sagar College of Engineering Bangalore, Karnataka, India, Email: dr.pavithrag.8984@gmail.com
[6]School of Engineering, Department of Chemical Engineering, American University of Ras Al Khaimah, United Ara Emirates. Email: Lnrao1978@gmail.com

*__Correspondence:__ Y V Krishna Reddy, e-mail: *krishnareddy.yv@svcolleges.edu.in*

ABSTRACT- The growing demand for electrical energy, coupled with the uneven distribution of natural resources, necessitates the integration of power plants. Coordinating the operation of interconnected generating units is crucial to meet the fluctuating load demand efficiently. This research focuses on the Economic Load Dispatch (ELD) problem in hybrid power systems that incorporate solar thermal and wind energy. Renewable energy resources, such as wind and solar thermal energy, depend on atmospheric conditions like wind speed, solar radiation, and temperature. This study addresses the ELD problem using a Modified Grey Wolf Optimization (MGWO) approach to obtain the most optimal solution for generator fuel costs. The Grey Wolf Optimization (GWO) approach, inspired by natural processes, is utilized but may exhibit both exploratory and exploitative behavior. To enhance its performance, we propose a novel version called MGWO, integrating memory, evolutionary operators, and a stochastic local search approach. The suggested MGWO approach is applied to two distinct test systems comprising 13 and 26 units, respectively, to solve the ELD with variable load requirements. Comparative analyses with other strategies demonstrate the effectiveness of MGWO in addressing the ELD problem. This modification enhances the GWO method, making it more robust and efficient for optimizing ELD in hybrid power systems.

Keywords: Economic load Dispatch, Solar thermal and wind energy, Modified grey wolf optimization, exploratory, exploitative, evolutionary operators, stochastic local search.

ARTICLE INFORMATION

Author(s): Y V Krishna Reddy, Naga Venkata Ramakrishna G, Prof. (Dr.) Mohammad Israr, Buddaraju Revathi Dr. Pavithra G, and Dr Nageswara Rao Lakkimsetty;

Received: 09/04/2024; **Accepted:** 04/07/2024; **Published:** 10/08/2024;
E- ISSN: 2347-470X;
Paper Id: IJEER240403;
Citation: 10.37391/ijeer.120324
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-12/ijeer-120324.html

Publisher's Note: FOREX Publication stays neutral with regard to jurisdictional claims in Published maps and institutional affiliations.

1. INTRODUCTION

Research on Economic Load Dispatch (ELD) for Thermal-Solar-Wind systems has attracted attention. Previous studies have examined different optimization methods to achieve an optimal energy source balance. However, conventional techniques may lead to suboptimal solutions or overlook complexities like valve-point loading. Soft computing methods suffer from slow convergence, parameter fine-tuning requirements, and premature convergence risks, constraining their ability to fully explore the solution space.

Electricity is essential for modern technology, especially in India where energy source distribution varies widely across regions. To address this, an integrated electrical system is crucial for efficient transfer and distribution based on demand. Effective scheduling of generating units [1, 2] is vital to align with demand fluctuations and optimize costs. Challenges like valve-point loading, multifuel systems, and operational constraints complicate Economic Load Dispatch (ELD) [3-9], which aims to minimize costs while meeting various constraints.

Renewable energies offer numerous benefits such as energy savings, emission reduction, environmental sustainability, and significant potential for conservation [13]. Wind power is the fastest-growing and most economical renewable source, while solar energy, particularly through photovoltaic panels, efficiently converts sunlight into electricity [10-12]. Both wind and solar energy are abundant and less dependent on specific geographic locations, making them easier to harness for power generation.

Renewable energy sources offer significant opportunities in modern grid systems. This study explores a combined system of solar, wind, and steam units. However, integrating green energy adds complexity to Economic Dispatch (ED) due to their unpredictable nature and erratic power outputs [13-16]. This research focuses on solar and wind power, with wind energy's future uncertainty stemming from its reliance on random wind speeds, introducing unpredictability into the ELD problem formulation [17].

Cost functions in ELD problems often exhibit non-smooth characteristics, complicating the search for optimal solutions. Prior research has utilized soft computing methods like Particle Swarms Optimization [18] and Artificial Bee's Colony algorithm [19] to tackle optimization challenges. Reliability indices for ELD were computed in one study [20], while an Artificial Collaborative Search algorithm [21] addressed non-convex ELD problems with valve point impacts in another. Other methods like Shrunken Gaussian Distribution Quantum-Behaved Optimization [22] have been introduced for multi-constraint optimization. Various techniques such as Equilibrium Optimizer, Cuckoo Optimization, and combinations thereof have also been explored [24-26]. Recent studies [27-31] have further expanded methodologies to address ELD with renewable and thermal energy integration, broadening the range of solutions in this field.

This study introduces a novel grey wolf optimization technique to address ELD optimization challenges effectively [32, 33]. The approach aims to handle complexities like valve point loading and integrating renewable sources into the system. Renewable energy units are assumed to be strategically located near the load center, reducing transmission losses and enhancing optimization strategy robustness. The method provides a simple, adaptable, and precise solution for optimizing ELD problems.

This research addresses overlooked challenges in ELD for a Thermal-Solar-Wind system. Conventional methods and soft computing techniques often yield suboptimal solutions due to complexities like valve-point loading and slow convergence. Integrating renewable sources further complicates operations, requiring coordinated parameter management and robust grid stability modeling. The Modified Grey Wolf Optimization (MGWO) method is proposed to efficiently optimize ELD in this integrated system, offering a novel approach with superior performance through effective parameter tuning.

2. ELD PROBLEM WITH WIND AND SOLAR ENERGY INCLUSION

The Economic Load Dispatch (ELD) problem becomes intricate with the integration of wind energy due to numerous equality and inequality standards associated with both thermal and wind energy producing units. Given that solar energy production does not involve fuel costs, the primary objective is to minimize the expenses associated with thermal generators and the cost of electricity produced by wind units (denoted as Ftotal). The optimization's objective function, in high-level language, aims to strike a balance by minimizing the overall costs of thermal generators and wind unit electricity production in the context of ELD with wind integration.

$$F_{total} = \sum_{i=1}^{n} F_{th}(P_i) + \sum_{j=1}^{m} F_w(P_{wj}) \tag{1}$$

The cost for generating thermal electricity via the VPL effect is stated as:

$$F_{th}(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| d_i * \sin(e_i * (P_i^{min} - P_i)) \right| \quad (\$/hr) \tag{2}$$

The cost for generating thermal electricity with a cubic function is represented as follows:

$$F_{th}(P_i) = a_i P_i^3 + b_i P_i^2 + c_i P_i + d_i \qquad (\$/hr) \tag{3}$$

The cost of the wind energy output determined with the wind power coefficient τ_j is given *equation (4)*

$$F_w(P_{wj}) = \sum_{j=1}^{m} \tau_j * P_{wj} \tag{4}$$

2.1 Equality Constraints

$$P_D = \sum_{i=1}^{n} P_i + \sum_{j=1}^{m} P_{wj} + P_{pv} \tag{5}$$

2.2 Inequality Constraints

$$P_i^{min_{i}^{max}} \tag{6}$$

$$P_{wj}^{min_{wj}^{max}} \tag{7}$$

2.3 Wind power plants modelling

The speed of the wind is inherently unpredictable, and its correlation with wind energy exhibits a non-linear nature. Data on wind speeds from various locations are structured to adhere to the Weibull distribution, a statistical model widely used to characterize the variability of wind speeds and assess wind energy potential. *Equation (8)* represents the probability density function (pdf) for wind speed. In simpler terms, this approach entails modeling the unpredictable and variable nature of wind speed using the Weibull distribution, providing an effective means to analyze and manage the fluctuations in wind speed and their implications for wind energy generation.

$$pdf(u) = \frac{\beta}{\alpha} * \left(\frac{v}{\alpha}\right)^{\beta-1} * exp\left[-\left(\frac{v}{\alpha}\right)^{\beta}\right] \tag{8}$$

Wind energy (Wp) is a random variable that may be approximated from wind speed, as illustrated by *eq. (9)*.

$$P_{wj} = \begin{cases} 0(v < v_{ci} or v > v_{co}) \\ P_{wj}^{R}(v_r \leq v \leq v_{co}) \\ \frac{(v-v_{in})P_{wj}^{R}}{v_r - v_{in}}(v_{ci} \leq v \leq v_r) \end{cases} \quad (9)$$

When the wind speed between v_{ci} and v_r, the wind farm's power production is deliberated to be an uninterrupted variable, and its pdf is given by *eq. (8)*. The total yield from all the wind turbines is treated as a single random variable *Pwj*, with the pdf supplied by

$$pdf(P_w) = \frac{\beta * \gamma * v_{in}}{P_{wj}^{R} * \alpha}\left[\frac{\left(1+\frac{\gamma P_{wj}}{P_{wj}^{R}}\right)v_{in}}{\alpha}\right]^{(\beta-1)} exp\left[-\left\{\frac{\left(1+\frac{\gamma P_{wj}}{P_{wj}^{R}}\right)v_{in}}{\alpha}\right\}^{\beta}\right] \quad (10)$$

Here $\gamma = \left(\left(\frac{v_r}{v_{ci}}\right) - 1\right)$ (11)

To characterize the uncertainty of wind power availability, a probabilistic tolerance δ_a is chosen to define the scenario in which available power is insufficient to meet total power demand. As a result, the balance of power limitation in *equation (12)* with solar and wind energy is being modified as follows.

$$P_r\left(\sum_{j=1}^{m} P_w^j + \sum_{i=1}^{n} P_i + P_{pv}\right) \leq (P_D) \leq \delta_a \quad (12)$$

2.4 The modelling of photovoltaic (PV) system

A PV generator's power production is primarily governed by the sunlight and temperature. The hourly electrical production of the PV generator may be calculated using *equation (13).*

$$P_S = I_T \eta A_{pv} \quad (13)$$

The average solar radiation (I_T) for a PV system on an inclined surface may be computed as follows *equation (14)*.

$$I_T = I_a R_a + I_b R_b + (I_a + I_b)R_r \quad (14)$$

Efficiency of the system (η) is expressed as follows *equation (15).*

$$\eta = \eta_m \eta_{pce} P_f \quad (15)$$

Here, $\eta_m = \eta_{re}[1 - \beta(T_k - T_{re})]$ (16)

3. MODIFIED GREY WOLF OPTIMIZATION

Mirjalli developed the Grey Wolf Optimization (GWO) [32] method, drawing inspiration from the hierarchical structure and hunting strategies of grey wolves. The method incorporates alpha, beta, omega, and delta wolves, mirroring their social hierarchy. The alpha wolf holds the dominant position, guiding crucial decisions for the pack. Beta wolves support the alpha and can take leadership roles in their absence. Omega wolves ensure the pack's dominance under the alpha's direction, while delta wolves follow without question. The GWO method follows the four-stage hunting process of grey wolves: encircling, herd testing, target selection, and chasing/finishing.

3.1. Looking for food

In the Grey Wolf Optimization method, potential solutions from the search space, referred to as wolf solutions, are randomly initiated to commence the search process. Similarly to real grey wolves hunting, when they locate their prey, they tend to pursue it individually rather than as a group.

3.2. Encircling prey

Mathematical *equations (17) and (18)* are provided below to explain the behaviour of grey wolves circling their prey after searching it.

$$\vec{E} = \left| \vec{O} * \vec{X}_p(k) - \vec{X}(k) \right| \quad (17)$$

$$\vec{X}(k+1) = \vec{X}_p(k) - \vec{B} * \vec{E} \quad (18)$$

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:

$$\vec{B} = 2 * \vec{l} * \vec{r}_1 - \vec{l} \quad (19)$$

$$\vec{O} = 2 * \vec{r}_2 \quad (20)$$

3.3. Hunting

After surrounding their victim, grey wolves become intensely focused on the kill. $\alpha, \beta and \omega$ wolves are often used as hunters' guides. The best possible candidate solution is provided byα. Grey wolf chasing habit may be expressed mathematically as *eq. (21)-(27).*

$$E_\alpha = \left|\left(\vec{O}_1 * \vec{X}_\alpha(k)\right) - \vec{X}(k)\right| \quad (21)$$

$$E_\beta = \left|\left(\vec{O}_2 * \vec{X}_\beta(k)\right) - \vec{X}(k)\right| \quad (22)$$

$$E_\omega = \left|\left(\vec{O}_3 * \vec{X}_\omega(k)\right) - \vec{X}(k)\right| \quad (23)$$

$$\vec{X}_1 = \vec{X}_\alpha(k) - \left(\vec{B}_1 * \vec{E}_\alpha\right) \quad (24)$$

$$\vec{X}_2 = \vec{X}_\beta(k) - \left(\vec{B}_2 * \vec{E}_\beta\right) \quad (25)$$

$$\vec{X}_3 = \vec{X}_\omega(k) - \left(\vec{B}_3 * \vec{E}_\omega\right) \quad (26)$$

$$\vec{X}(k+1)=\frac{(\vec{X}_1+\vec{X}_2+\vec{X}_3)}{3} \quad (27)$$

3.4. Attacking prey

Once the chase is done, grey wolves will launch an assault on their victim. Based on the position of $\alpha, \beta and \omega$ 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.

$$a = 2(1-\frac{t}{T}) \quad (28)$$

The modified GWO [33] uses an exponential function to calculate the decay of an over iterations. Consider

$$a = 2(1-\frac{t^2}{T^2}) \quad (29)$$

Table 1: Control and Parameter setting for MGWO

Parameter	Range or Value
Search Space	[0,1]
Dimension	13 or 26
No. of Grey Wolfs	40
No. of iterations	2000 or 4000
b	1
a	decreases linearly from 2 to 0
r1, r2	Random number
Alpha-Positions	Optimal of Power Generation
Alpha-Score	Minimal of Cost

4. RESULTS AND DISCUSSION

The evaluation and application of Modified Grey Wolf Optimization (MGWO) span across three different scenarios within two test cases, demonstrating its efficacy across diverse contexts. These scenarios entail optimizing the scheduling of thermal systems, planning solar-thermal systems, and planning solar-wind-thermal systems. The code for these test cases is meticulously crafted and executed using MATLAB 9.6 R2019a. The programs run on hardware equipped with a 1.90 GHz Pentium III Processor and 4.0 GB of RAM, facilitating a thorough assessment of MGWO's performance across varying configurations.

4.1 Test case descriptions

Test Case-1: In three scenarios, a standardized setup of 13 generating units with valve point loading [34] was used. Load demand remained at 2520 MW, and transmission power losses were omitted for consistency in evaluating proposed methodologies.

Test Case-2: In this specific test scenario, 26 generating units with cubic fuel costs [35] were employed across three scenarios. The constant power demand is set at 2900 MW, with the intentional exclusion of transmission losses for a focused assessment.

In case of hybrid solar-thermal system, maximum power of 50 MW generated from solar plants. The additional parameters for the solar power plant are set to $A_{pv}=90163.04m^2$, $p.f.=0.92$, $\beta=-4.7*e^{-3}$, $\eta_{pce}=0.91$, $\eta_{re}=0.1045$, $T_{re}=25^0C$.

In case of hybrid solar- wind-thermal system, power producing unit's data are included here, alongside with an extra wind farm. A wind farm has a cost coefficient of krw = 1, kpw = 5, and a maximum electrical capacity of 155 MW. The remaining constants are v_{ci}=5, v_{co}=45, and v_r=15. The shape and scale factor are both set to one and fifteen. *Figure 1* depicts the whole network used for simulation analysis in this test case.

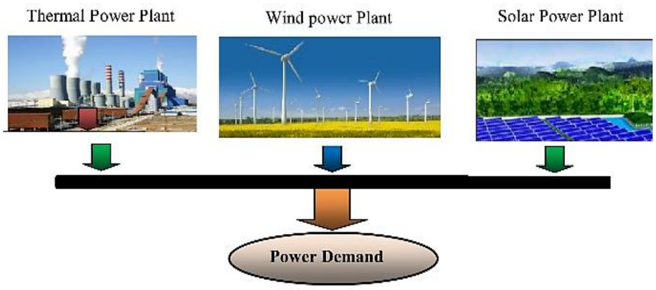

Figure 1. Thermal-Solar-Wind System

4.2 Thirteen Unit System

The presence of the valve point loading effect introduces a highly nonlinear and complex multi-model issue, posing a significant challenge in finding the global optimal solution. In this context, the Modified Grey Wolf Optimization (MGWO) method applied to the scheduling of thermal units reveals an optimal cost of $24,164.8260 per hour. This result surpasses the performance of the most recently published approach, establishing MGWO as a more effective solution. *Table 2* provides a detailed overview of the optimum dispatch solution achieved by MGWO, offering a comprehensive comparison of findings with other methods. Additionally, *Table 3* presents a statistical analysis of the results, further emphasizing the superiority of the MGWO approach.

By integrating the thermal plant with solar power generation, the optimal cost achieved is $23,907.1861 per hour. The solar power generation component contributes 25.3250 MW to the total power output of 2520 MW, with the negligible cost of generating this small quantity of power omitted in this particular scenario. *Table 2* provides a comprehensive overview of the optimal power dispatch for this integrated system; however, there are currently no existing works available for comparison with the findings. This signifies a unique contribution to the field, showcasing the effectiveness of the integrated thermal and solar power generation approach.

FOREX Publication
Open Access | Rapid and quality publishing
International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 12, Issue 3 | Pages 926-933 | e-ISSN: 2347-470X

Table 2: Optimal Power Dispatch for 13-unit system

	Thermal System			Thermal-Solar system	Thermal-Solar-Wind system
Unit	HCRO [36]	BSA [36]	MGWO	MGWO	MGWO
P_1	628.3185	628.3185	628.3457	628.2918	628.3031
P_2	299.1993	299.1993	299.1964	299.2562	299.3991
P_3	294.9957	294.4848	302.8527	317.3192	302.0003
P_4	159.7331	159.7331	159.7231	159.7899	160.1677
P_5	159.7331	159.7331	159.8903	159.8442	110.1211
P_6	159.7331	159.7331	159.8300	159.8192	159.7681
P_7	159.7331	159.7330	159.7772	159.7566	160.0072
P_8	159.7331	159.7331	160.0487	160.1631	159.9839
P_9	159.7331	159.7331	159.8202	109.8888	159.9086
P_{10}	77.3999	77.3999	115.2347	114.8184	40.0434
P_{11}	77.3999	77.3999	40.2900	77.3784	77.4883
P_{12}	92.3999	92.3997	55.0039	92.9790	92.9196
P_{13}	91.8882	92.3997	119.986	55.3701	93.0152
P_{Solar}	NA	NA	NA	25.3250	25.3340
P_{Wind}	NA	NA	NA	NA	51.5493
Therm.Cost ($/hr)	24164.8260	24164.0524	24122.0320	23907.1861	23373.3577
Cost of wind overestimation ($/hr)	NA	NA	NA	NA	108.1418
Cost of wind underestimation ($/hr)	NA	NA	NA	NA	0.0012
Total Operating Cost ($/hr)	24164.8260	24164.0524	24122.0320	23907.1861	23481.4995
Time (Sec)	7.8698	4.8923	3.4598	3.5897	3.8956

Table 3: Statistical data for a 13-unit Thermal ELD system

Methods	**HCRO**	**CRO**	**IPSO-TVAC**	**BSA**	**MGWO**
Minimum Cost ($/h)	24164.8260	24165.1664	24166.8000	24164.0524	24164.8260
Average Cost ($/h)	24164.9837	24166.9355	24167.3700	24164.2942	24164.9025
Maximum Cost ($/h)	24165.3402	24169.3642	24169.4100	24166.5831	24165.1835
Avg. time CPU (sec)	5.04	5.56	N.A	5.12	5.02
S.D	0.93	0.94	N.A	0.75	0.56

Through the combined efforts of thermal, solar, and wind power generation, the optimal cost achieved is $23,481.4995 per hour. In this scenario, the cost of generating a modest amount of electricity is disregarded, resulting in solar power contributing 25.3340 MW to the total power output of 2520 MW. Additionally, wind power generation contributes 51.5493 MW to the overall power generation, incurring a cost of $108.1430 per hour. The thermal power plant complements this mix by generating 2443.12 MW of power at an operational cost of $23,373.3577 per hour. Given the uniqueness of this integrated approach, where multiple sources contribute to power generation, there are currently no ongoing works available for direct comparison. *Table 2* serves as a detailed representation of the optimal power dispatch for this specific case, showcasing the effectiveness of the combined thermal, solar, and wind power generation system.

Figure 2 provides a graphical representation of the convergence characteristics observed in a 13-unit system under three different test scenarios. The chart distinctly communicates that the inclusion of renewable energy sources results in a notable decrease in operational costs required to meet the overall power demands of 2520 MW. This visual presentation effectively emphasizes the positive influence of integrating renewable sources, showcasing enhanced cost efficiency within the power generation system.

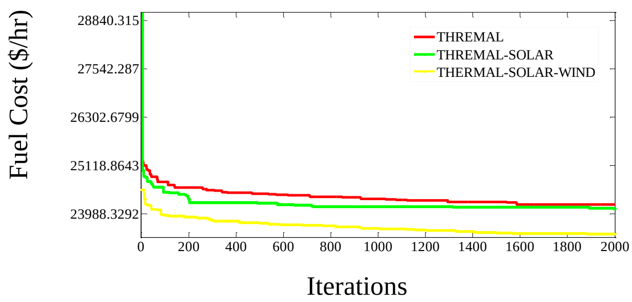

Figure 2. Convergence of a 13-unit system, with a power demand of 2520MW

4.2.1. Twenty-Six Unit System

In this scenario, the Modified Grey Wolf Optimization (MGWO) technique identifies an optimal cost of $43,436.5297 per hour to meet the power demand of 2900 MW through the scheduling of thermal Economic Load Dispatch (ELD). This result surpasses the performance of the most recently published technique. *Table 3* present detailed insights into the optimal dispatch solution achieved by MGWO, alongside a comprehensive comparison of the results.

Through the integration of the thermal plant with solar power generation, the achieved optimal cost is $42,114.5083 per hour. In this specific scenario, solar power generation contributes 49.5786 MW to the total power output of 2900 MW, with the negligible expense of generating a minor amount of power overlooked. The optimal power dispatch for this case is meticulously presented in Table 4, and the results are rigorously compared to those obtained using the BSA technique. This comparison sheds light on the effectiveness of the integrated thermal and solar power generation approach in achieving cost efficiency.

Table 4: Optimal Power Dispatch for 26-unit system

Unit	Thermal system		Thermal-Solar system		Thermal-Solar-Wind system	
	BSA	MGWO	BSA	MGWO	BSA	MGWO
P_1	2.4001	2.4019	2.4084	2.4002	12.0000	2.4024
P_2	2.4002	2.4029	2.4119	2.4000	2.4014	2.4006
P_3	2.4000	2.4023	2.4011	2.4040	2.4118	2.4000
P_4	2.4004	2.4028	2.4063	2.4101	2.4012	2.4000
P_5	2.4001	2.4003	2.4000	2.4000	2.4059	2.4003
P_6	4.0003	4.0003	4.0002	4.0000	4.0006	4.0000
P_7	4.0003	4.0003	4.0004	4.0000	4.0000	4.0005
P_8	4.0004	4.0005	4.0012	4.0002	4.0008	4.0007
P_9	4.0002	4.0005	4.0000	4.0000	4.0000	4.0000
P_{10}	76.0000	75.9999	76.0000	75.9991	76.0000	75.9993
P_{11}	76.0000	75.9999	75.9999	75.9996	75.9999	76.0000
P_{12}	76.0000	75.9999	76.0000	75.9997	76.0000	75.9985
P_{13}	76.0000	75.9999	75.9998	76.0000	76.0000	75.9998
P_{14}	100.0000	100.0000	75.9962	99.9996	99.9988	100.0000
P_{15}	100.0000	99.9999	99.9995	99.9995	99.9984	100.0000
P_{16}	100.0000	99.9998	99.9997	100.0000	99.9979	99.9991
P_{17}	155.0000	155.0000	154.9998	155.0000	155.0000	154.9999
P_{18}	155.0000	155.0000	154.9986	154.9998	154.9998	154.9999
P_{19}	155.0000	155.0000	155.0000	154.9996	154.9988	155.0000
P_{20}	155.0000	155.0000	154.9996	154.9999	155.0000	154.9992
P_{21}	190.9990	175.1190	192.3459	175.8760	119.1194	121.8040
P_{22}	166.0000	148.2370	164.8986	149.4340	93.2265	100.8790
P_{23}	141.0010	124.6710	140.7339	123.1003	71.0914	71.3260
P_{24}	350.0000	350.0000	350.0000	350.0000	349.9996	349.9986
P_{25}	400.0000	400.0000	399.9996	399.9999	399.9980	400.0000
P_{26}	400.0000	400.0000	399.9996	400.0000	399.9980	399.9989
P_{Solar}	NA	NA	NA	49.5786	49.9521	49.3456
P_{Wind}	NA	NA	NA	NA	154.9992	154.6478
Therm.Cost ($/hr)	43436.5297	42250.8926	43426.6799	42114.5083	40283.6778	38616.6916
Cost of wind overestimation ($/hr)	NA	NA	NA	NA	325.1642	324.4272
Cost of wind underestimation ($/hr)	NA	NA	NA	NA	0.0015	0.0016
Total Operating Cost ($/hr)	43436.5297	42250.8926	43426.6799	42114.5083	40608.8435	38941.1186
Time (Sec)	5.5672	4.5893	5.9845	4.7962	6.0278	4.9868

By combining thermal, solar, and wind power generation, the system achieves an optimal cost of $38,941.1186 per hour. In this integrated setup, solar power contributes 49.3456 MW to the overall power output of 2900 MW. Additionally, wind power adds 154.6478 MW to the generation capacity, incurring a cost of $324.4288 per hour. The thermal power plant complements this diverse mix by generating 2696.1 MW at an operational cost of $38,616.6916 per hour. This comprehensive integration showcases a balanced utilization of different energy sources, contributing to cost-efficient and sustainable power generation. *Table 4* provides a comprehensive presentation of the optimal dispatch for a 26-unit system, allowing for an in-depth comparison with the BSA technique. Simultaneously, *Figure 3* visually captures the convergence characteristics observed in the 26-unit system under three distinct test scenarios. The graph compellingly communicates that the integration of renewable sources results in a notable decrease in operating expenses needed to fulfill the entire power requirement of 2900 MW. This graphical representation serves as a compelling visual testament to the positive impact of incorporating renewable sources, underscoring their contribution to enhancing the cost efficiency of the power generation system.

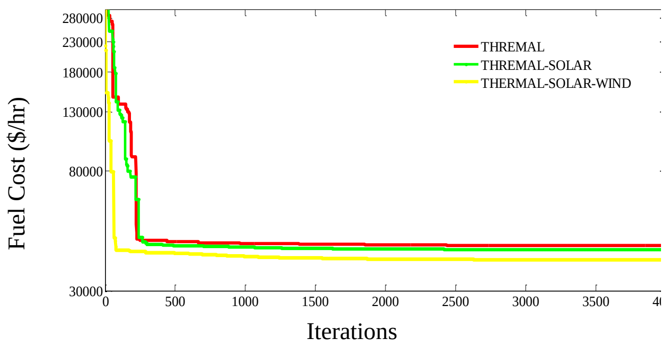

Figure 3. Convergence of a 26-unit system, with a power demand of 2900MW

5. CONCLUSIONS

This study introduces Modified Grey Wolf Optimization (MGWO) for solving the Economic Load Dispatch (ELD) problem, accommodating scenarios with and without solar power integration. It employs a probability density function (pdf) for modeling wind power and deterministic methods for solar photovoltaic systems. Inspired by grey wolves' hunting behavior, MGWO uses an exponentially decreasing function to dynamically balance exploration and exploitation, thereby enhancing its efficiency in finding optimal ELD solutions across diverse scenarios. The study highlights MGWO's superior performance compared to established methods like BSA, CRO, HCRO, and IPSO-TVAC. MGWO consistently meets operational criteria and efficiently identifies optimal dispatch solutions across varied test cases of different complexities. Its scalability and user-friendly nature position MGWO as a robust tool for addressing intricate optimization challenges in power system management and control, particularly in large-scale applications. But MGWO exhibits sensitivity to control parameter selection, impacting performance across varied scenarios and requiring meticulous tuning. Future enhancements could focus on integrating stochastic elements to better manage uncertainties in renewable energy sources, enhancing MGWO's resilience to real-world variability.

REFERENCES

[1] Omer, S. Ghosh and R. Kaushik, “Indian power system: issues and opportunities”, Int. J. Advanc. Res. Electr., Electr. Instrument. Eng., vol. 2, pp. 232-42, 2013. Corpus ID: 53620268.

[2] A. Wood and B. Wollenberg, “Power generation, operation and control", 2nd Edition, Wiley, 2007.

[3] M. L. . Ramanaiah, Y. V. K. . Reddy, and P. V., Mahesh, “Economic Load Dispatch with Practical Constraints using Mountaineering Team-Based Optimization Technique”, Int J Intell Syst Appl Eng, vol. 12, no. 1s, pp. 201–208, Sep. 2023.

[4] Y. V. K. Reddy, M. L. Devi, A. V. S. Reddy and P. V. Kumar, "Economic dispatch solutions with piecewise quadratic cost functions using Spotted hyena Optimizer," 2021 IEEE Madras Section Conference (MASCON), Chennai, India, 2021, pp. 1-6, doi: 10.1109/MASCON51689.2021.9563437.

[5] Krishna Reddy, Y.V., Damodar Reddy, M. "Flower pollination algorithm to solve dynamic economic loading of units with piecewise fuel options" Indonesian Journal of Electrical Engineering and Computer Science, 2019, 16(1), http://doi.org/10.11591/ijeecs.v16.i1.pp9-16

[6] Krishna Reddy, Y.V., Damodar Reddy, M., Sudhakara Reddy, A.V. "Flower pollination algorithm to solve dynamic economic loading of units with practical constraints", International Journal of Recent Technology and Engineering, 2019, 8(3), pp. 535–542.

[7] Reddy, Y.V.K., Reddy, M.D., "Economic load dispatch problem with ant lion optimization using practical constraints" Gazi University Journal of Science, 2019, 32(2), pp. 524–542.

[8] Sudhakra Reddy, A.V., Krishna Reddy, Y.V. "Application of ALO to economic load dispatch without network losses for different conditions", 2nd IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems, ICPEICES 2018, 2018, pp. 244–248, 8897279. DOI: 10.1109/ICPEICES.2018.8897279

[9] Krishna Reddy, Y.V., Damodar Reddy, M., "Flower pollination algorithm for solving economic dispatch problems with prohibited operating zones and multiple fuel options", International Journal of Engineering and Advanced Technology, 2018, 7(6), pp. 1–7. Doi: JETIR1810466

[10] E. Elanchezhian, S. Subramanian and S. Ganesan, “Economic power dispatch with cubic cost models using teaching learning algorithm”, IET Gener. Transm. Distrib., vol. 8, pp. 1187-202, 2013. DOI: 10.1049/iet-gtd.2013.0603

[11] H. Jadhav et al., “An enlist artificial bee colony algorithm for combined economic emission dispatch incorporating wind power”, Int. Conf. Comp. Comm. Tech., 2011. https://doi.org/10.3390/en14134014

[12] M. Deshmukh and S. Deshmukh, “Modelling of hybrid renewable energy systems”, Elsevier Renew. Sustain. Energy Rev., vol. 12, pp. 235-49, 2006. https://doi.org/10.1016/j.rser.2006.07.011

[13] M. Kuo, S. Lu and M. Tsou, “Economic dispatch planning based on considerations of wind power and pumped storage hydroelectric plants for isolated power system”, IEEE conf. Ind. Commer. Power Syst., 2015. DOI: 10.1109/ICPS.2015.7266405

[14] K. Jagtap, G. Patil, and S. Kulkarni, “Techno-economic modelling of wind-solar PV-Biomass hybrid energy system”, IEEE Int. Conf. Power Electr. Energy Syst., 2017. DOI: 10.1109/PEDES.2016.7914546

[15] J. Hetzer, D. Yu and K. Bhattarai, “An economic dispatch model incorporating wind power”, IEEE Trans. Energy Conv., vol. 23, pp. 603-11, 2008. DOI: 10.1109/TEC.2007.914171

[16] H. Chen et al., “Economic dispatch of wind integrated power systems with energy storage considering composite operating cost”, IET Gener. Transm. Distrib., vol. 10, pp. 1294-1303, 2016. DOI: 10.1049/iet-gtd.2015.0410

[17] S. Li, E. Wunsch and M. Giesselmann, “Using neural networks to estimate wind turbine power generation”, IEEE Trans. Energy Conv., vol. 16, pp. 276-82, 2001. DOI: 10.1109/60.937208

[18] A. Selvakumar and K. Thanushkodi, “A new particle swarm optimization solution to nonconvex economic dispatch problems”, IEEE J. Innov. Energy Syst. Power, vol. 1, pp. 1-7, 2006. DOI: 10.1109/TPWRS.2006.889132

[19] S. Bhongade et. al, “An optimal solution for combined economic and emission dispatch problem using artificial bee colony algorithm”, IEEE conf. Power Energy Syst. Sustain. Energy, pp. 1-7, 2016. DOI: 10.1109/PESTSE.2016.7516478

[20] E. Babaei and N. Ghorbani, “Combined economic dispatch and reliability in power system by using PSOSIF algorithm”, J. Oper. Autom. Power Eng., vol. 3, pp. 23-33, 2015. https://doi.org/10.1265/2015/67512

[21] S. Kaboli and A. Alqallaf, “Solving nonconvex economic load dispatch problem via artificial cooperative search algorithm”, Expert Syst. Appl., vol. 128, pp. 14-27, 2019. https://doi.org/10.1016/j.eswa.2019.02.002

[22] L. Ping, J. Sun and Q. Chen, "Solving power economic dispatch problem with a novel quantum-behaved particle swarm optimization algorithm", Math. Problems Eng., 2020. https://doi.org/10.1155/2020/9741595
[23] M. El-Shorbagy and A. Mousa, "Constrained multiobjective equilibrium optimizer algorithm for solving combined economic emission dispatch problem", Complexity, 2021. https://doi.org/10.1155/2021/6672131
[24] M. Mellal and E. Williams, "Cuckoo optimization algorithm with penalty function and binary approach for combined heat and power economic dispatch problem", Energy Reports, vol. 6, pp. 2720-23, 2020. https://doi.org/10.1016/j.egyr.2020.10.004
[25] A. Nezhad, F. Ghanavati and A. Ahmarinejad, "Determining the optimal operating point of CHP Units with nonconvex characteristics in the context of combined heat and power scheduling problem", IETE J. Res., 2020. https://doi.org/10.1080/03772063.2020.1724522
[26] A. Potfode, S. Bhongade "Economic Load Dispatch of Renewable Energy Integrated System Using Jaya Algorithm", Journal of Operation and Automation in Power Engineering Vol. 10, No. 1, Apr. 2022, Pages: 1-12. doi:10.22098/JOAPE.2022.7562.1538
[27] Leena Rose Robert et.al "Economic emission dispatch of hydrothermal-wind using CMQLSPSN technique", IET Renewable Power Generation, September, 2020, pp: 2680-2692, doi: 10.1049/iet-rpg.2019.1232.
[28] Xiaoyu Wang, Kan Yang, "Economic load dispatch of renewable energy-based power systems with high penetration of large-scale hydropower station based on multi-agent glowworm swarm optimization, Energy Strategy Reviews", Volume 26, 2019, https://doi.org/10.1016/j.esr.2019.100425.
[29] Guibin Wang et.al, "Cross entropy optimization based on decomposition for multi-objective economic emission dispatch considering renewable energy generation uncertainties", Energy, Volume 193, 15 February 2020. https://doi.org/10.1016/j.energy.2019.116790
[30] Xu Chen et.al "Multi-region combined heat and power economic dispatch based on modified group teaching optimization algorithm", International Journal of Electrical Power & Energy Systems, Volume 155, Part B, January 2024. https://doi.org/10.1016/j.ijepes.2023.109586
[31] Burak Urazel et.al "A new solution approach for non-convex combined heat and power economic dispatch problem considering power loss", Energy, Volume 278, Part B, 1 September 2023. https://doi.org/10.1016/j.energy.2023.128031
[32] S. Mirjalli et.al, "Grey Wolf Optimizer", Advances in Engineering Software, Volume 69, March 2014, Pages 46-61. DOI:10.1016/bs.adcom.2016.05.001
[33] Nitin Mittal, Urvinder Singh, Balwinder Singh Sohi, "Modified Grey Wolf Optimizer for Global Engineering Optimization", Applied Computational Intelligence and Soft Computing, vol. 2016, https://doi.org/10.1155/2016/7950348.
[34] Sinha N., Chakrabarti R and Chattopadhyay PK., "Evolutionary programming techniques for economic load dispatch" IEEE Trans Evol Comput., Vol.7, No.1, pp.83–94, 2003. https://doi.org/10.1016/j.epsr.2004.08.001
[35] Chandram K., Subrahmanyam N.and Sydulu M., "Equal embedded algorithm for economic load dispatch problem with transmission losses", Int J Electr Power Energy Syst, Vol.33, pp.500-507, 2011. https://doi.org/10.1016/j.ijepes.2010.12.002
[36] Nitin Tyagi et.al, "Economic load dispatch of wind-solar-thermal system using backtracking search algorithm", International Journal of Engineering, Science and Technology Vol. 8, No. 4, 2016, pp. 16-27. DOI:10.4314/ijest.v8i4.3.