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A NOVEL APPROACH TO UNIVERSAL SYSTEM WITH LOSSES THAT FOCUS ON THE ECONOMIC DISPATCH FOR THE ENERGY INTEGRATION IN MICRO GRID AND ACCENTUATE THE HEURISTIC OPTIMIZATION

V. SAI GEETHA LAKSHMI[1], M. VANITHASRI[2], M. VENU GOPAL RAO[3]

[1]Research Scholar, Department of Electrical Engineering, Faculty of Engineering & Technology, Annamalai University, Annamalai Nagar, Chidambaram, Tamil Nadu-608002, India

[2]Assocoate professor, Department of Electrical and Electronics Engineering, Annamalai University, Annamalai Nagar 608002, Tamil Naadu, India

[3] Professor, Department of Electrical and Electronics Engineering, QIS College of Engineering and Technology, JNTUK, Ongole, Andhra Pradesh, India

E-mail: [1]sahrudha.v@gmail.com , [2] vanithasimman@gmail.com, [3] venumannam@gmail.com

ABSTRACT

Rapid development of renewable infrastructure and popular support for green energy have led to the emergence of hybrid generating systems in power networks that is micro grid. The effective scheduling of all power producing facilities to meet the increasing power demand is one of the most significant challenges in the design and operation of an electric power generation system. Scheduling power generating units to minimize costs and meet system restrictions is an example of economic load dispatch (ELD), a generic operation in the electrical power system. Due to their greater global solution capacity, flexibility, and derivative-free construction, metaheuristic algorithms are rising in favor for addressing ELD problems. This study develops a novel hybrid optimization–based solution model for the ELD problem of integrating renewable resources. In addition, this work takes into account multiple objectives, including the full cost of wind generation, the full cost function of thermal units, and a penalty cost function. The optimal output of thermal power plants is maximized using the hybrid optimization model. Limits, both upper and lower. In addition, the hybrid optimization model selects the best turbines to maximize wind energy production in response to specific needs. The efficiency and viability of the suggested algorithm were demonstrated using test system with 10 units. The Heuristic Optimization techniques is applied to get numerical results for the static and dynamic ELD problem show that the suggested elephant herding optimization (EHO) algorithm outperforms state-of-the-art methods in most of the test situations, proving its superiority and practicality.

Keywords: *Green Energy, Hybrid Generating Systems, Economic Load Dispatch, Heuristic Optimization, Elephant Herding Optimization.*

1. INTRODUCTION

The cost of generating the power is developing as a critical concern in the management and control of a power system as a result of the rise in power demand and the corresponding rise in the price of energy in the residential and commercial sectors. This report systematically discusses the results of extensive research into the problem at hand. It is more important than ever to reduce electric energy costs because of the interdependence of distributed electrical networks. The economics of the power system are greatly impacted by even a little decrease in the price of electric energy. Power system engineers' primary responsibility is to investigate the economics of power systems, and one

significant difficulty they face is economic load dispatch (ELD) [1], [6], a subset of the unit commitment issue. Recently Generation dispatch includes both thermal generators and renewable sources [26]. Proper modelling of wind energy sources is necessary for this purpose. The intermittent and random nature of wind energy, however, presents significant obstacles to power system management. Many researchers have put forth a lot of time and effort, yet many of the existing systems' use of wind is still not ideal. with this, the combination of wind energy and thermal plants and maintaining economic load dispatch is crucial. In this work Researchers are driven to find ways to significantly reduce the cost of power generation by the economics of each electricity generation system. Previous work on the ELD problem has made use of numerical techniques like gradient and Lambda iteration methods to find an optimal solution using Heuristic Optimization.

Many fields have been using metaheuristic optimization techniques recently [9]. This study integrates the wind power system with the conventional thermal power-producing unit to provide a solution to ELD, taking into account multiple factors such as combined thermal unit cost function and penalty cost function. And also, in this paper discussed about enhancing usage of wind energy in recent years have seen a meteoric rise in the popularity of wind power, and this trend is expected to continue in the near future. The ELD could be defined as the process of setting generation targets for power plants in order to optimally meet the needs of the entire system's load. The price of a connected system must be maintained low. Electric production expenses can be reduced with careful planning. The primary focus of this research is to determine how to generate the required amount of electricity at the lowest cost. However, environmental issues including fossil fuel emissions and increased energy demand are on the rise. Efficient and cheap transportation helps lessen the amount of pollution released into the air and the amount of fuel consumed. Moreover, addressing the ELD issue is crucial for improving electric system security to prevent accidents like power system collapse.

Gradient and Lambda iteration methods are two examples of popular numerical techniques used to address the ELD problem. As renewable energy sources become more prevalent, however, the optimization problem may become more challenging due to the introduction of nonlinear control variables. However, metaheuristic methods are often believed to be highly effective at quickly resolving high-dimensional ELD problems. The ELD issue in a renewable energy system that combines thermal and wind power was addressed in this study. The ELD issue in a renewable energy system that combines thermal and wind power plants has been addressed in this study. For this work the figure 1 is shown.

One method of reducing the strain on coal-based thermal power plants in terms of coal consumption and, by extension, environmental emissions is to increase the share of electricity generated from nonconventional sources by combining them with coal-based thermal power plants using a Synchronous Generator (SG). Clean and inexpensive, wind power generating lessens environmental impact, generation expenses, the greenhouse effect, and global warming. Wind power [15] is becoming an increasingly important means of electricity generation. Limited predictability, uncertainty, and unpredictability make it troublesome for power system operation. To further operational flexibility for congestion management in both day-ahead and real-time markets, the topic of adaptive scheduling of generation resources is discussed. Stochastic programming and resilient programming are two mainstays of uncertainty-driven optimization issues [19].

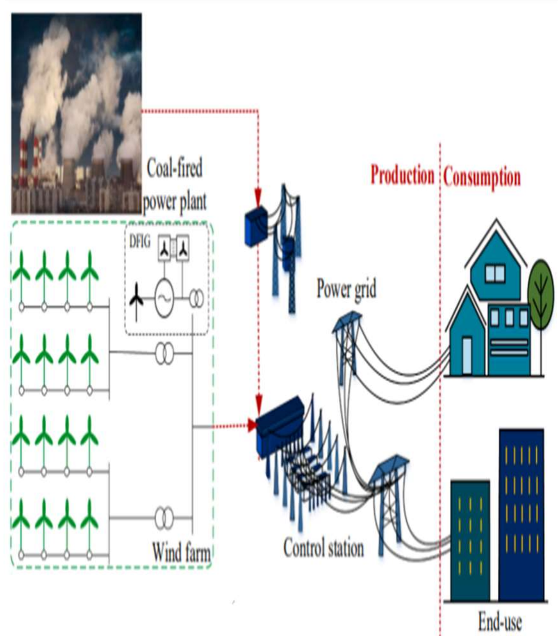

Figure:1 Micro Grid

In this paper problem is solved by optimizations techniques such as particle swarm optimization (PSO), Quantum Particle Swarm Optimization (QPSO), Grey Wolf Optimization (GWO), Ant Colony Optimization (ACO) and elephant herding optimization (EHO) and compared with each other. From this solution it may give optimized solution for constraints based economic load dispatch with losses. These Heuristic Optimizations techniques are considered.

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2. FORMULATION OF THE PROBLEM

The participation of generators in meeting the demand might reduce their operating costs by using economic dispatch. The cost-minimizing objective function is

$$F_i(P_i) = \sum_{i=1}^{n}(a_i P_i^2 + b_i P_i + c_i)$$

where the i^{th} generator's cost coefficients are a_i, b_i, c_i

The problem's equality and inequality constraints are

Balance of power equations:

$$\sum_{i=1}^{m} P_i - P_D - P_L = 0$$

Transmission loss:

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j$$

Distinct Boundaries for Operation:

$$P_i^{min} \le P_i \le P_i^{max}$$

2.1 INTEGRATION OF WIND FARM INTO ECONOMIC DISPATCHING

When it comes to doling out resources, "Weibull" has a cumulative distribution function of

$$F_v(V) = 1 - e^{(-\frac{v}{c})^k}$$

For the Weibull distribution, we have the probability function

$$F_v(V) = (\frac{K}{C})(\frac{V}{C})^\wedge(K-1)e^{(-\frac{v}{c})^k}$$

where the shape factors and scale factors, k and c, are respectively.

According to the type of power generating system [23] that is being investigated, the number of variables that affect the relationship between the initial wind power and the entire electrical power include the efficiency of the "generator, the wind rotor, the gearbox," as well as the inverter. The purpose of the streamlined framework that is used for the standard wind penetration device is to classify the connection between wind power and wind speed.

$$W = \begin{cases} 0, \ (V < v_{in} \ or \ V \ge v_{out}) \\ w_r, \quad (v_r \le V < v_{out}) \\ \frac{(V - v_{in})}{v_r - v_{in}}, \ (v_{in} \le V < v_r) \end{cases}$$

For a particular time period, we can estimate the power production by using

$$P = P_w \times f_v(V)$$

Production costs for wind energy are

$$C_j(P_j) = d_j(P_j)$$

Currently, the revised power-balance equation is

$$\sum_{i=1}^{m} P_i + \sum_{j=1}^{n} P_j - P_D - P_L = 0$$

Algorithm 1 EHO

Input:
Initialize the maximum generation $t_{\max}$, the size of population N, the number of clans c, and the upper and lower bounds $x_{\max}$ and $x_{\min}$.

Output:
The best solution x_{best}.

```
Initialize population and parameters α, β, r.
Calculate and sort the fitness of every initialized agents.
Save the best m elephants.
Divide the initial population into c clans.
while t < t_max do
    for ci = 1 : c do
        Generate x_new,ci,j and update x_ci,j based on (8) to (9).
        for j = 2 : n_ci (the number of elephants in clan ci) do
            Generate x_new,ci,j and update x_ci,j based on (7).
        end for
    end for
    for ci = 1 : c do
        Replace the agent with the worst fitness x_worst,ci based on (10).
    end for
    Calculate and update the fitness values according to each position.
    Sort the entire population according to fitness.
    Replace the worst agents with the m generated agents' elites.
    t = t + 1
end whilereturn x_best
```

3. ELEPHANT HERDING OPTIMIZATION

The primary objective of EHO is to simulate the herding behaviour of elephants in their natural environment, where the collective intelligence of the herd enables the elephants to locate the safest and most efficient routes to resources and to avoid potential threats. This collective behaviour, when applied to the context of optimization [27], is utilized to identify optimal solutions to complex problems. The algorithm begins by randomly seeding a population of candidates for the optimal solution to the problem. Each of these answers stands in for a different elephant's location in the search space. The elephants are herded and organized into different groups. Each herd is a different collection of options. Each herd's elephants share their location updates based on both their own observations and the information provided by other members of the herd. A leader elephant is chosen from each herd using its fitness or objective function score. A herd of elephants will follow their leader into potentially fruitful regions of the search space. The elephants in a herd shift about according to the leader's instructions and their own inclination to explore new areas. Both the current leader and the best answer found so far are guiding forces for the movement. Elephants from different herds will periodically speak to one another in order to provide information about the relative fitness of the leaders and to encourage mutual exploration. When a termination requirement, such as a fitness threshold or exhaustion of computer resources, is fulfilled, the algorithm stops iterating the herding and movement steps.

Instructional Strategy Illustration show in fig2

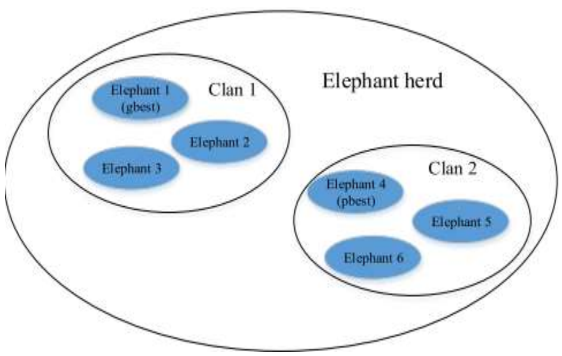

Fig: 2 Instructional Strategy Illustration

4. Additional Approaches:

Particle swarm optimization (PSO) is a population-based optimization method that takes its cues from the herd mentality of animals like birds and schools of fish. Particle swarm optimization (PSO) iteratively updates the positions and velocities of a collection of particles (potential solutions) as they travel around the search space in pursuit of the best possible answer. Every particle's motion is affected by both its own and its neighbours' best-known positions. By tweaking these coordinates and rates of travel across multiple iterations, the algorithm seeks to converge on the global optimum. Incorporating quantum mechanical ideas into the algorithm, Quantum Particle Swarm Optimization (QPSO) is a variation of PSO. QPSO exploits quantum superposition and entanglement to update particle positions, rather than conventional probability. The goal is to make the algorithm better at exploring the search space and less likely to converge too quickly. Inspired by the social structure and hunting strategies of grey wolves, Grey Wolf Optimization (GWO) is a natural-based optimization method. The program effectively explores and exploits the search space by modelling the leadership hierarchy of alpha, beta, and delta wolves. Wolves locations stand in for different solutions, and the program iteratively adjusts their locations to discover the best one shown fig4 - Process Diagram. The foraging habits of ants served as inspiration for the development of Ant Colony Optimization (ACO), an optimization method. The travelling salesman problem is one type of combinatorial optimization that works especially well with this method. Artificial ant colonies (ACO) work together to systematically investigate a search space by leaving pheromone trails as they travel. In general, ants will take the route with the highest concentration of pheromones, and this will encourage the trajectories that lead to the best solutions over time shown in fig3ACO Process Diagram:

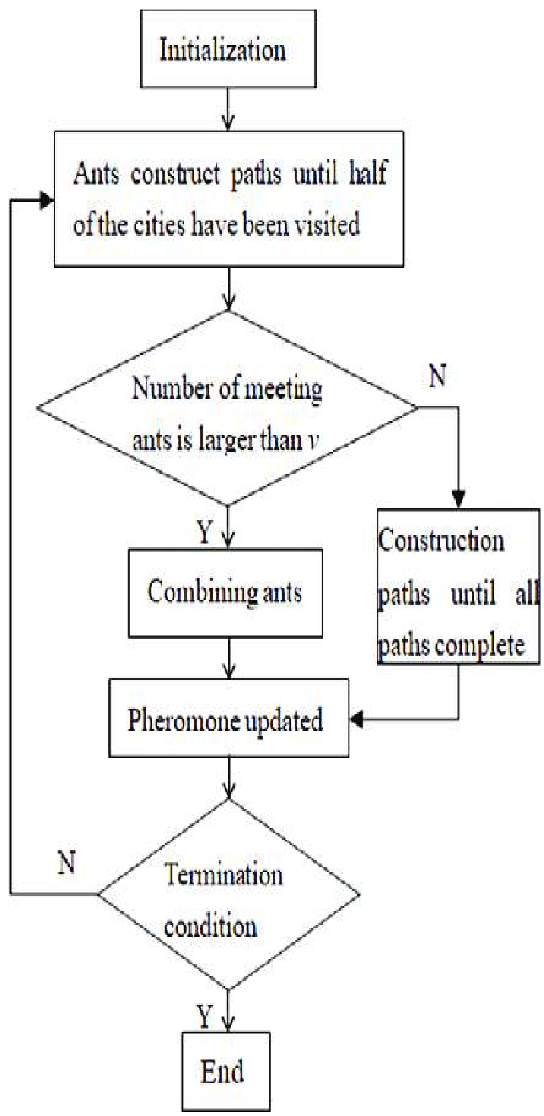

Fig3: Process Diagram

GWO Process Diagram:

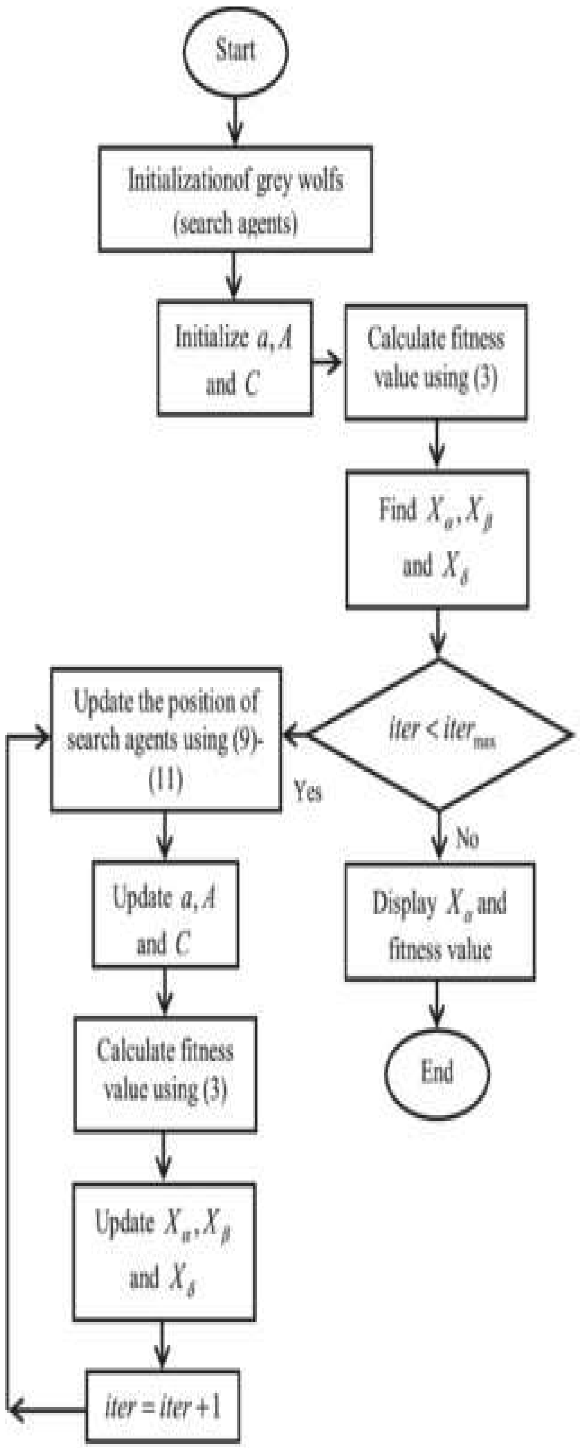

Fig4: Process Diagram

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5. RESULTS AND DISCUSSIONS

We put the proposed Heuristic Optimization methods to the test on one system. In the table 1 below, we can see the cost coefficients for ten thermal power generators, as well as the test system that was examined to minimize operating costs. First Issue: Testing Systems with ten Generators

Table 1: Coefficients Of Fuel Cost For Ten Generator Test Systems

Unit	a_i	b_i	c_i
1	0.00123	8.92	730
2	0.009800	7.42	525
3	0.001420	8.52	823
4	0.002263	8.88	818
5	0.001164	8.83	823
6	0.001625	8.12	841
7	0.001122	8.41	745
8	0.001318	8.91	543
9	0.001418	8.53	568
10	0.001432	8.00	653

From the above data of a, b, c with some iterations using Elephant Herding Optimization (EHO) the cost value for ten units is given below in table 2 and compared with ant colony algorithm (ACO), Grey Wolf Optimization (GWO), particle swarm optimization (PSO) and Quantum Particle Swarm Optimization (QPSO) for 10 units.

Table 2: The Convectional Test System's Dispatch Compared And Contrasted Is Given Below

Parameter	PSO	QPSO	ACO	GWO	EHO
P1(MW)	32.89	31.86	33.12	35.89	33.12
P2(MW)	64.60	62.15	66.60	66.23	68.60
P3(MW)	54.85	55.85	52.19	49.25	53.22
P4(MW)	33.47	34.47	35.47	34.12	34.26
P5(MW)	64.10	65.10	62.25	67.10	64.12
P6(MW)	55.1	56.1	55.1	49.3	50.2
P7(MW)	28.6	29.6	30.6	31.6	32.6
P8(MW)	58.27	57.23	58.23	61.27	50.99
P9(MW)	50.12	51.12	52.12	53.12	54.12
P10(MW)	36.12	34.15	34.12	32.15	34.88
PT(MW)	478.12	477.63	479.82	479.98	476.13
PL(MW)	2.7	2.56	2.51	2.56	2.45
TOC (Rs/h)	708	708.12	705.99	706.11	705.11

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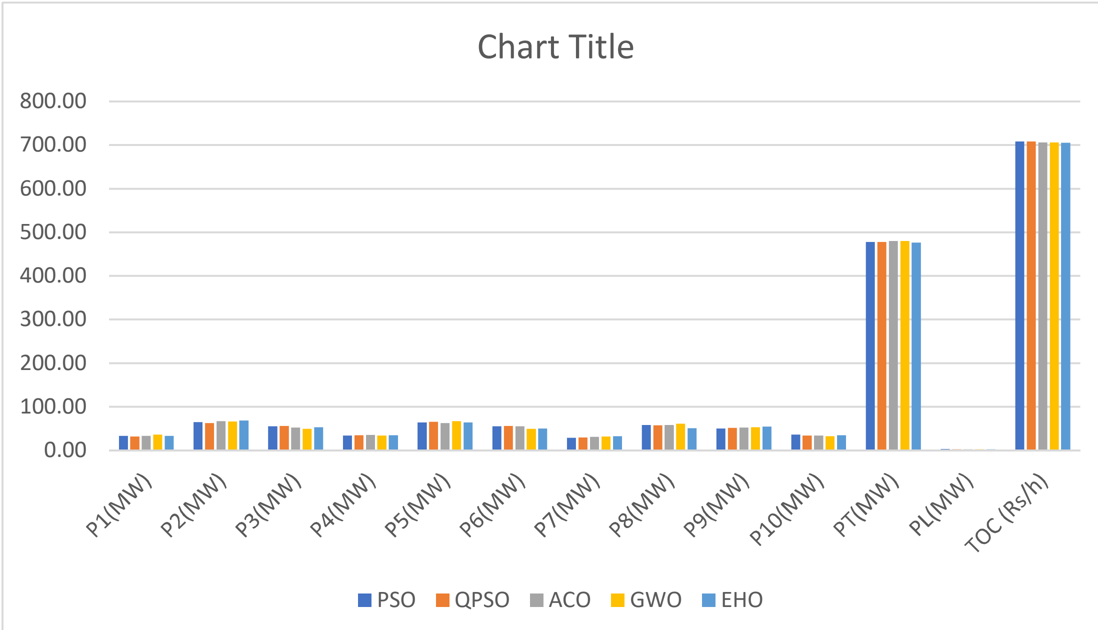

Table3: Economic Dispatch For Wind Thermal System Using Elephant Herding Optimization (EHO):

P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	PW1	PW2	PL	TOC(Rs/h)
28.55	66.55	48.99	29.15	60.11	47.55	29.66	48.22	50.28	30.88	29.44	15.78	1.88	672.4181

In Table 3, ED is performed by taking into account both thermal and wind energy systems [29] concurrently The table clearly shows that when wind power is added to the system, costs and losses are minimized

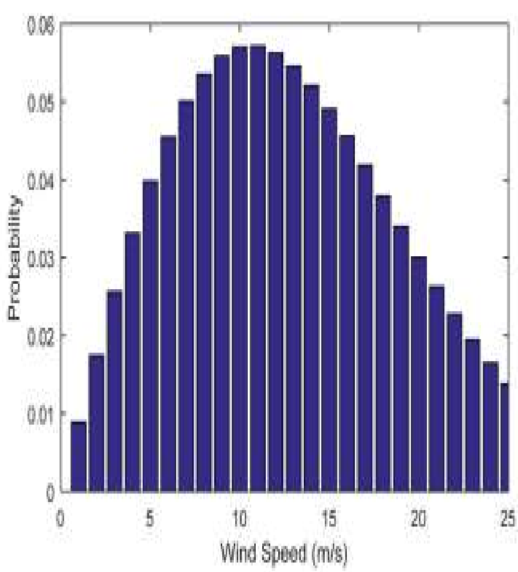

Fig 5: Distribution Of Wind Speed Probabilities

Using the Weibull distribution function, we can predict how much power will be generated by wind farms and factor that into the test system as a negative demand. For different gust strengths, the probability density curve is shown in Fig. 5.

10 unit system with losses is considered and renewable energy sources such as wind energy is included.

6. CONCLUSION

In this study, economic dispatch model for combined wind and thermal power systems is introduced. For wind thermal systems, Elephant Herding Optimization (EHO) is used to tackle the static economic dispatch problem. The IEEE 30 bus system is used to with wind-powered scenarios, and the results are compared to those of several alternative approaches. Maximum wind power extraction can be achieved with careful planning and accurate forecasting, as shown by the outcomes. It has been noticed that power generators gain from greater use of renewable energy sources, and that this trend also aids in reducing emissions. The utilization Heuristic Optimization i.e., Elephant Herding Optimization algorithm for the purpose of economic load dispatch in systems that make use of both wind energy and thermal sources is a method that shows promise. The capability of EHO to manage complexity, optimize costs, and promote grid stability may help to the development of energy systems that are more efficient and sustainable.

REFERENCES

[1] P. Samal, A. Mohapatra and S. Samal, "Application of Artificial Rabbits Optimization Algorithm to the Economic Load Dispatch Problem," 2023 4th International Conference for Emerging Technology (INCET), Belgaum, India, 2023, pp. 1-5, doi: 10.1109/INCET57972.2023.10170612.

[2] S. M. Dubey, H. M. Dubey and M. Pandit, "Optimal Generation Scheduling of Hybrid Systems using Manta Ray Foraging Optimizer," 2022 2nd International Conference on Emerging Frontiers in Electrical and Electronic Technologies (ICEFEET), Patna, India, 2022, pp. 1-6, doi: 10.1109/ICEFEET51821.2022.9848314.

[3] M. W. Tahir, G. Abbas, M. A. Ilyas, N. Ullah and S. M. Muyeen, "Economic Emission and Energy Scheduling for Renewable Rich Network Using Bio-Inspired Optimization," in IEEE Access, vol. 10, pp. 79713-79729, 2022, doi: 10.1109/ACCESS.2022.3194012.

[4] K. Pawani and M. Singh, "Economic Load Dispatch using Black Widow Optimization Algorithm," 2021 IEEE 2nd International Conference On Electrical Power and Energy Systems (ICEPES), Bhopal, India, 2021, pp. 1-4, doi: 10.1109/ICEPES52894.2021.9699512.

[5] T. -T. Nguyen, T. -D. Nguyen, T. -G. Ngo and T. -K. Dao, "A Load Power Distribution Optimization based on Improving Biogeography-Based Optimization," 2021 IEEE International Conference on Machine Learning and Applied Network Technologies (ICMLANT), Soyapango, El Salvador, 2021, pp. 1-5, doi: 10.1109/ICMLANT53170.2021.9690539.

[6] A. Kumar, R. Singhi, S. Das, T. Malakar, O. Prakash and P. Das, "Economic Load Dispatch Using Salp Swarm Algorithm," 2020 IEEE 9th Power India International Conference (PIICON), Sonepat, India, 2020, pp. 1-6, doi: 10.1109/PIICON49524.2020.9112882.

[7] Y. Jia, Z. Y. Dong, C. Sun and K. Meng, "Cooperation-Based Distributed Economic MPC for Economic Load Dispatch and Load Frequency Control of Interconnected Power Systems," in IEEE Transactions on Power Systems, vol. 34, no. 5, pp. 3964-3966, Sept. 2019, doi: 10.1109/TPWRS.2019.2917632.

[8] W. R. Barcelo and P. Rastgoufard, "Dynamic economic dispatch using the extended security constrained economic dispatch algorithm," in IEEE Transactions on Power Systems, vol. 12, no. 2, pp. 961-967, May 1997, doi: 10.1109/59.589791.

[9] M. Ellahi, G. Abbas, G. B. Satrya, M. R. Usman and J. Gu, "A Modified Hybrid Particle Swarm Optimization With Bat Algorithm Parameter Inspired Acceleration Coefficients for Solving Eco-Friendly and Economic Dispatch Problems," in IEEE Access, vol. 9, pp. 82169-82187, 2021, doi: 10.1109/ACCESS.2021.3085819.

[10] Ahmed Fathy, Hegazy Rezk, Seydali Ferahtia, Rania M. Ghoniem, Reem Alkanhel, An efficient honey badger algorithm for scheduling the microgrid energy management, Energy Reports, Volume 9, 2023, Pages 2058-2074, ISSN 2352-4847, https://doi.org/10.1016/j.egyr.2023.01.028.

[11] Yubin Jia, Tengjun Zuo, Yaran Li, Wenjun Bi, Lei Xue, Chaojie Li, Finite-time economic model predictive control for optimal load dispatch and frequency regulation in interconnected power systems, Global Energy Interconnection, Volume 6, Issue 3, 2023, Pages 355-362, ISSN 2096-5117, https://doi.org/10.1016/j.gloei.2023.06.009.

[12] Xing-Yue Zhang, Wen-Kuo Hao, Jie-Sheng Wang, Jun-Hua Zhu, Xiao-Rui Zhao, Yue Zheng,
Manta ray foraging optimization algorithm with mathematical spiral foraging strategies for solving economic load dispatching problems in power systems, Alexandria Engineering Journal, Volume 70, 2023, Pages 613-640, ISSN 1110-0168, https://doi.org/10.1016/j.aej.2023.03.017.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[13] Mohamed H. Hassan, Salah Kamel, Francisco Jurado, Mohamed Ebeed, Mohamed F. Elnaggar, Economic load dispatch solution of large-scale power systems using an enhanced beluga whale optimizer, Alexandria Engineering Journal, Volume 72, 2023, Pages 573-591, ISSN 1110-0168, https://doi.org/10.1016/j.aej.2023.04.002.

[14] Chao Chen, Linan Qu, Ming-Lang Tseng, Lingling Li, Chih-Cheng Chen, Ming K. Lim, Reducing fuel cost and enhancing the resource utilization rate in energy economic load dispatch problem, Journal of Cleaner Production, Volume 364, 2022, 132709, ISSN 0959-6526, https://doi.org/10.1016/j.jclepro.2022.132709.

[15] J. Li, H. Li, T. Huang, L. Zheng, L. Ji and S. Yin, "Model-Free Reinforcement Learning Economic Dispatch Algorithms for Price-Based Residential Demand Response Management System," in IEEE Transactions on Industrial Cyber-Physical Systems, doi: 10.1109/TICPS.2023.3294874.

[16] T. Chu, Z. Yan, X. Gong and F. Dong, "Network Attack Detection Method for Distributed Economic Dispatch of Virtual Power Plants," 2022 First International Conference on Cyber-Energy Systems and Intelligent Energy (ICCSIE), Shenyang, China, 2023, pp. 1-6, doi: 10.1109/ICCSIE55183.2023.10175256.

[17] A. Ali et al., "A Bi-Level Techno-Economic Optimal Reactive Power Dispatch Considering Wind and Solar Power Integration," in IEEE Access, vol. 11, pp. 62799-62819, 2023, doi: 10.1109/ACCESS.2023.3286930.

[18] R. Zafar, A. Esmaeel Nezhad, A. Ahmadi, T. Erfani and R. Erfani, "Trading Off Environmental and Economic Scheduling of a Renewable Energy Based Microgrid Under Uncertainties," in IEEE Access, vol. 11, pp. 459-475, 2023, doi: 10.1109/ACCESS.2022.3231158.

[19] Z. Chu, S. Lakshminarayana, B. Chaudhuri and F. Teng, "Mitigating Load-Altering Attacks Against Power Grids Using Cyber-Resilient Economic Dispatch," in IEEE Transactions on Smart Grid, vol. 14, no. 4, pp. 3164-3175, July 2023, doi: 10.1109/TSG.2022.3231563.

[20] Homayoun Berahmandpour, Shahram Montaser Kouhsari, Hassan Rastegar, A new flexibility based probabilistic economic load dispatch solution incorporating wind power,International Journal of Electrical Power & Energy Systems, Volume 135,2022,107546,ISSN 0142-0615, https://doi.org/10.1016/j.ijepes.2021.107546.

[21] Mohammed Azmi Al-Betar, Mohammed A. Awadallah, Sharif Naser Makhadmeh, Iyad Abu Doush, Raed Abu Zitar, Samah Alshathri, Mohamed Abd Elaziz, A hybrid Harris Hawks optimizer for economic load dispatch problems,Alexandria Engineering Journal,Volume 64,2023,Pages 365-389,ISSN 1110-0168, https://doi.org/10.1016/j.aej.2022.09.010.

[22] Xueqian Gao, Wenxia Liu, Mengdi Fu, Shuting Zhang, Shuai Zhang, Shan Huang, Strategy decision game approach of the combination generation system of wind and thermal power participating in the direct power purchase transaction of large consumer,Electric Power Systems Research,Volume 200, 2021,107463,ISSN 0378-7796,https://doi.org/10.1016/j.epsr.2021.107463.

[23] K.B. Porate, K.L. Thakre, G.L. Bodhe,Impact of wind power on generation economy and emission from coal based thermal power plant,International Journal of Electrical Power & Energy Systems,Volume 44, Issue 1, 2013,Pages 889-896,ISSN 0142-0615, https://doi.org/10.1016/j.ijepes.2012.08.029.

[24] Saber Arabi Nowdeh, Amirreza Naderipour, Iraj Faraji Davoudkhani, Josep M. Guerrero,Stochastic optimization – based economic design for a hybrid sustainable system of wind turbine, combined heat, and power generation, and electric and thermal storages considering uncertainty: A case study of Espoo, Finland,Renewable and Sustainable Energy Reviews,Volume183,2023,113440,ISSN1364-21,https://doi.org/10.1016/j.rser.2023.113440.

[25] Yuyu Tian, Jianxia Chang, Yimin Wang, Xuebin Wang, Mingzhe Zhao, Xuejiao Meng, Aijun Guo,A method of short-term risk and economic dispatch of the hydro-thermal-wind-PV hybrid system considering spinning reserve requirements,Applied Energy,Volume 328,2022,120161,ISSN 306-2619,https://doi.org/10.1016/j.apenergy.2022.120161.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[26] Sizhou Sun, Chenxi Wang, Yu Wang, Xuehua Zhu, Huacai Lu,Multi-objective optimization dispatching of a micro-grid considering uncertainty in wind power forecasting,Energy Reports,Volume8,2022,Pages2859-2874,ISSN23524847, https://doi.org/10.1016/j.egyr.2022.01.175.

[27] Yu Huang, Qingshan Xu, Yuanxing Xia, Dong Yue, Chunxia Dou, Wind–Thermal power generation scheduling with predictive transmission security margin,International Journal of Electrical Power & Energy Systems, Volume 141,2022,108197,ISSN 0142-0615, https://doi.org/10.1016/j.ijepes.2022.108197.

[28] Vineet Kumar, Veena Sharma, Ram Naresh,Leader Harris Hawks algorithm based optimal controller for automatic generation control in PV-hydro-wind integrated power network,Electric Power Systems Research,Volume 214, Part B,2023,108924,ISSN 0378-7796,https://doi.org/10.1016/j.epsr.2022.108924.

[29] Y. Jia, Z. Y. Dong, C. Sun and K. Meng, "Cooperation-Based Distributed Economic MPC for Economic Load Dispatch and Load Frequency Control of Interconnected Power Systems," in IEEE Transactions on Power Systems, vol. 34, no. 5, pp. 3964-3966, Sept. 2019, doi: 10.1109/TPWRS.2019.2917632.

[30] M. R. B. D. Santos et al., "A Proposed Methodology Involving Progressive Bounded Constraints And Interior-Exterior Methods in Smoothed Economic/Environmental Dispatch Problems," in IEEE Latin America Transactions, vol. 15, no. 8, pp. 1422-1431, 2017, doi: 10.1109/TLA.2017.7994788.

[31] J. Han, L. Yan and Z. Li, "A Task-Based Day-Ahead Load Forecasting Model for Stochastic Economic Dispatch," in IEEE Transactions on Power Systems, vol. 36, no. 6, pp. 5294-5304, Nov. 2021, doi: 10.1109/TPWRS.2021.3072904.

[32] W. R. Barcelo and P. Rastgoufard, "Dynamic economic dispatch using the extended security constrained economic dispatch algorithm," in IEEE Transactions on Power Systems, vol. 12, no. 2, pp. 961-967, May 1997, doi: 10.1109/59.589791.

[33] S. Gao, R. Dai, W. Cao and Y. Che, "Combined Provision of Economic Dispatch and Frequency Regulation by Aggregated EVs Considering Electricity Market Interaction," in IEEE Transactions on Transportation Electrification, vol. 9, no. 1, pp. 1723-1735, March 2023, doi: 10.1109/TTE.2022.3195567.

[34] Z. Zhang, J. Shi, W. Yang, Z. Song, Z. Chen and D. Lin, "Deep Reinforcement Learning Based Bi-layer Optimal Scheduling for Microgrids Considering Flexible Load Control," in CSEE Journal of Power and Energy Systems, vol. 9, no. 3, pp. 949-962, May 2023, doi: 10.17775/CSEEJPES.2021.06120.

[35] H. Zhang, D. Yue, C. Dou and G. P. Hancke, "PBI Based Multi-Objective Optimization via Deep Reinforcement Elite Learning Strategy for Micro-Grid Dispatch With Frequency Dynamics," in IEEE Transactions on Power Systems, vol. 38, no. 1, pp. 488-498, Jan. 2023, doi: 10.1109/TPWRS.2022.3155750.

[36] M. W. Tahir, G. Abbas, M. A. Ilyas, N. Ullah and S. M. Muyeen, "Economic Emission and Energy Scheduling for Renewable Rich Network Using Bio-Inspired Optimization," in IEEE Access, vol. 10, pp. 79713-79729, 2022, doi: 10.1109/ACCESS.2022.3194012.