Implementation of HEBMO in Solving Convex Economic Dispatch Problems

Nor Laili Ismail[1,a)], Ismail Musirin[2,b)], Nofri Yenita Dahlan[3,c)], Mohd Helmi Mansor[4,d)], A.V. Senthilkumar[5,e)]

[1]Department of Electrical and Electronic Engineering, Faculty of Engineering, UPNM, Kem Sungai Besi 57000 Kuala Lumpur, Malaysia
[2,3]School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia.
[4]Department of Electrical and Electronics Engineering, College of Engineering, Universiti Tenaga Nasional, Putrajaya Campus, Jalan IKRAM-UNITEN, 43000 Kajang Selangor, Malaysia
[5]Hindusthan College of Arts and Science, Coimbatore, India.

Author Emails
[a)]norlaili@upnm.edu.my
[b)]ismailbm@uitm.edu.my
[c)]nofriyenita012@uitm.edu.my
[d)]mhelmi@uniten.edu.my
[e)]avsenthilkumar2007@gmail.com

[b)] Corresponding author: ismailbm@uitm.edu.my

Abstract. Minimization of the cost of generation for any utilities is crucial to ensure the utilities will be able to maintain continuous supply and their survivability. Non-optimal amount of power generated by all generating stations in a country will possibly lead to monetary loss and ineffective operation of the power system. Thus, a robust and reliable optimization technique is the prerequisite to ensuring the lowest cost of generation can be achieved. This paper proposes a hybridized optimization technique that integrates the element of evolutionary programming (EP) into the barnacle mating optimizer (BMO), termed Hybrid Evolutionary Programming-Barnacles Mating Optimization (HEBMO). HEBMO is utilized to address the convex economic dispatch (ED) in a power transmission system. Its implementation on the IEEE 30-Bus Reliability Test System (RTS) in addressing the convex ED is remarkable, through the comparison with the traditional EP and BMO. The cost of generations in chosen cases such as base case conditions, stress conditions due to real power, and reactive power increments revealed the superiority of the proposed HEBMO over EP and BMO.

INTRODUCTION

Economic dispatch is one of the important components in power system operation and planning. The continuous progressing demand is sometimes unplanned and unpredictable. This phenomenon will lead to lose increment due to high current flow through the transmission line resulting from the low voltage level at the receiving end of the transmission line. To address the issue of loss reduction or minimization, appropriate remedial action such compensation scheme can be one of the possible solutions. This will also concurrently solve other associated problems such as economic dispatch which desires the possible cost of generation as reported in several previous works [1]–[10]. The issues of ED have been addressed in a broad spectrum such as the dynamic mode [1], solar generation consideration [2], cost-effective emission consideration [3],[4], and economic load dispatch [5]. Minimization of the cost of generation for any utilities is crucial to ensure the utilities will be able to maintain continuous supply and their survivability. Non-optimal amount of power generated by all generating stations in a country will possibly lead to monetary loss and ineffective operation of the power system. Thus, a robust and reliable optimization technique is the prerequisite to ensuring the lowest cost of generation can be achieved. Numerous optimization techniques have been invented which are based on the behaviour of insects and animals such as bats, particle swarms [5],[6], dolphins [1], and flora [7]. Most of them are search-based algorithms as addressed by W. Aribowo et. al. in [8-10]. Researchers also tended to improve the traditional optimization approaches to gain better optimization performance as can be referred to in the work by I. Alzubi et. al. [11]–[14]and appreciated the behavior of insects to solve complex optimization problems such as the ant colony optimization (ACO) [15]. Other than ACO and PSO, the multiverse optimization (MVO) technique has also been incorporated into solving power system problems [16]; other than moth flame as addressed by N. F. Ramli et al. [17]. Most of the optimization techniques are meta-heuristic [18][19]. Most recent optimization techniques proposed the hybridization of several optimization techniques to alleviate the current weakness and setback experienced in the traditional techniques [20]–[22]. ED can also be addressed together with unit commitment [23], especially in the smart grid environment. In general, all ED studies involved with optimization process [24][25][13]. One of the important optimization techniques is the invention of the barnacle mating optimizer (BMO) as addressed by M. H. Sulaiman et. al. [22]. It was discovered that BMO has performed very well in solving ED problems.

This paper presents an implementation of HEBMO in solving convex economic dispatch problems. In this study, a new hybrid optimization technique is proposed which integrates the element of EP into the traditional BMO. Its implementation on the IEEE 30-Bus Reliability Test System (RTS) in addressing the convex ED is remarkable, through the comparison with the traditional EP and BMO. The cost of generations in chosen cases such as base case conditions, stress conditions due to real power, and reactive power increments revealed the superiority of the proposed HEBMO over EP and BMO. The proposed HEBMO optimization technique can be feasibly used to solve other optimization problems in the power system or other engineering fields.

PROBLEM FORMULATION

The goal of economic power dispatch is to make sure that all of the generating units in the system receive an equal distribution of the system's power demand. The revenue will be increased while the operating expenses are minimized. The smooth generation cost is expressed as (1), and the smooth generation cost function is depicted in Figure 1.

$$C_i(P_i) = \sum_{i=1}^{N} a_i + b_i P_{Gi} + C_i P_{Gi}^2 \quad (1)$$

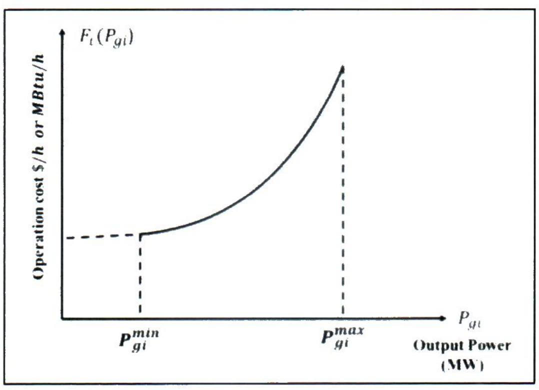

FIGURE 1. The smooth production cost function

Some optimization constraints in ED must also be considered. The equality and inequality restrictions in economic load dispatch are the active power balancing criterion and power generating capacity. The equation of the active power balance criterion is given in (2), where PD is total real power demand and PL is total real power loss. The inequality equation is formulated in (3) where PGi max and PGi min are the maximum and minimum real power at generation unit, ith respectively. For a stable operation to be completed, the real power constraint must be taken into account.

$$\sum_{i=1}^{N} P_{Gi} = P_D + P_L \tag{2}$$

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \tag{3}$$

METHOD

In this research, a novel hybrid optimization technique for solving economic dispatch is proposed. This hybrid technique is capable of determining the optimal generator allocation for a thermal power system while accounting for all the generator constraints. The proposed hybrid algorithm was formulated by the hybridization of Barnacles Mating Optimizer (BMO) and Evolutionary Programming (EP). BMO is one of the most recent meta-heuristic optimization methods, developed by H. Sulaiman et. al. [22] and inspired by the mating behavior of barnacles. It also can be categorized as a group of evolutionary algorithms. While the Darwinian model, a traditional theory of evolution, sets the backbone of the EP technique. A group of individuals must compete in an environment with few resources to put the survival principle into practice. This competition leads to natural selection, or "survival of the fittest." This newly proposed technique is termed Hybrid Evolutionary Programming-Barnacles Mating Optimization (HEBMO) technique.

Initialization

Implementation of the proposed HEBMO algorithm begins with the initialization of the solution set so that the candidate solutions are dispersed throughout the whole search space. The generators are given a random load distribution that falls within their operating limit. The generated random numbers are generally expressed in matrix form as shown in (4);

$$X = \begin{bmatrix} x_1^1 & x_1^2 & \dots & x_1^N \\ x_2^1 & x_2^2 & \dots & x_2^N \\ \vdots & \vdots & \vdots & \vdots \\ x_n^1 & x_n^2 & \dots & x_n^N \end{bmatrix} \tag{4}$$

where n is the number of populations and N is the number of control variables. In ED optimization, the generated power Pg at the generator buses will be represented by x1, x2,...xn. The upper and lower boundaries of the problem to be solved are indicated as the control variable numbers, N. The fit individuals will fill the initialization pool for 20 individuals after the initialization process is complete. The highest value of the fitness evaluation determines which candidates for the solution will survive. The total generation cost, determined by equation (1) for the convex ELD problem, is the fitness to be optimized in this study. To breed the offspring in the BMO operator, ml must be set up at the maximum location for mating. The maximum number of ml determined in this study is 14 barnacles, which represents 70% of the entire population size. This number is used to reach the global optimum since the processes of exploitation and exploration are well-balanced.

Mutation

The two types of mutation carried out by this proposed technique are BMO reproduction and Gaussian mutation. In equation (5), the Gaussian Mutation formula is described; while equations (6) and (7) provide the details of the BMO reproduction equation.

$$X_{i+m,j} = X_{i,j} + N\left(0, \beta\left(X_{jmax} - X_{jmin}\right)\left(\frac{f_i}{f_{max}}\right)\right) \tag{5}$$

where $X_{(i,j)}$ are the parents, β is the search step, Xj_{max} is the maximum parent, Xj_{min} is the minimum parent, f_i is the fitness of ith individual and f_{max} is the maximum fitness. In this study, $N=20$, which is the number of candidates, and $\beta=0.005$.

$$X^{N}_{i}\_new = px^{N}\ barnacle\_d + qx^{N}\ barnacle\_m \tag{6}$$

$$X_{i}^{\,n\_new} = rand\,() \times x^{n}\ barnacle\_m \tag{7}$$

where p=randn, q=(1-p), barnacle_m, and barnacle_d are the parents to be mated.

The alteration was made during the reproduction process using the $p=randn\ (1,1)\ *\ a+b$ formula to generate the random numbers. The regularly distributed pseudo-random numbers between 0 and 1 make up the p formula. Determining the minimum, b, and offset, a is necessary to guarantee satisfactory results. To choose the best offspring, the fitness test is once more necessary. 20 best offspring were produced in total, which corresponds to the population size. The offspring pool preserves the best values for the following phase.

Combination I

The combination is a merging process of two offspring populations, between EP and BMO offspring. The size of the offspring population becomes larger, with a size of 40. The combined offspring population is written as in (8).

$$Combine\ offspring\ population = \begin{bmatrix} EP\ offspring\ population \\ BMO\ offspring\ population \end{bmatrix} \tag{8}$$

Ranking and Selection

The combined population of offspring is then ranked based on its best fitness values. It is termed the elitism approach. The objective function in this study is a minimization of the cost, hence the best value is the lowest value, which will be put at the top of the row. The last row will be occupied by the worst individuals. The maximizing process works the other way around. The top 20 offspring will then be chosen to move on to the next round of the process.

Combination II

The 20 accepted parents who are first determined by the fitness equation will be recombined with the top 20 individuals from the prior step. Once again, the total population numbers doubled. The combination process formed one large matrix as shown in (9).

$$Population = \begin{bmatrix} Accepted\ parent \\ Offspring\ individuals \end{bmatrix} \tag{9}$$

Ranking and Selection

The survivors will be nominated once again by ranking them according to their fitness value. The survivor with the best fitness value will be on top of the row, while the survivor with the worst fitness value will be at the bottom row. The 20 survivors are classified as a new generation, indicating that they are getting ready to be employed in the following iteration until HEBMO converges.

Convergence Test

When an optimization process converges to a specific value, it is termed converge. As illustrated in the equation, this process is signaled by a halting criterion, which is defined as the difference between the maximum and minimum fitness (15). Until the problem is solved, the algorithm will keep repeating the same process. The desired difference value is determined by the relevance of the experiment.

$$fitness_{max} - fitness_{min} \leq 0.0001 \tag{10}$$

If the final results achieved an optimal solution, all the individuals will achieve similar values.

RESULT AND DISCUSSION

Three case studies were carried out to realize the potential of HEBMO to resolve convex ED problems in the power system. The results provided by the proposed algorithm were compared with two single optimization techniques, EP and BMO. The IEEE 30-Bus RTS is selected to explore our idea on how to use HEBMO to identify the optimal economic power generation. The detailed power generator limits and cost coefficient for IEEE 30-Bus RTS are tabulated in Table 1 and the details scenario is listed in Table 2.

TABLE 1. Power generator limits and cost coefficient for IEEE 30-Bus RTS system

Generator	$P_{g,min}$	$P_{g,max}$	Cost Coefficient		
			a_i (\$/h)	b_i (\$/MWh)	c_i (\$/MW^{2}h)
P_{g1}	50	200	240	7	0.0070
P_{g2}	20	80	200	10	0.0095
P_{g3}	15	50	220	8.5	0.0090
P_{g4}	10	35	200	11	0.0090
P_{g5}	10	30	220	10.5	0.0080
P_{g6}	12	40	190	12	0.0075

TABLE 2. Implemented Cases for Solving ED Problem

Scenario No	Description
Scenario-1	Base case: The system is operating in a normal condition.
Scenario-2	Stressed condition: Increment of real power load, P_d with a factor value, k.
Scenario-3	Stressed condition: Increment of reactive power load, Q_d with a factor value, k.

Base Case Scenario

The presented results in Table 3 are the comparison of generation cost for base case conditions. The result shows that HEBMO exhibits the lowest cost when compared to EP and BMO. HEBMO managed to achieve the lowest generation cost worth \$/MWh 3.8740 x10^3, while EP gives a higher cost of \$/MWh of 3.9321x10^3 while BMO achieved \$/MWh 3.8999 x 10^3. To achieve the lowest generation cost, the optimal power to be generated by the generators in the system are; $P_{g1}=187.7232$ *MW*, $P_{g2}=20.0695$ *MW*, $P_{g5}=49.9999$ *MW*, $P_{g8}=10.0000$ *MW*, $P_{g11}=10.7707$ *MW, and* $P_{g13}=13.7415$ *MW*. This requires 57 iterations to achieve the lowest optimal solution. EP and BMO required 13 and 51 iterations, respectively, to converge. Even though EP was the first to achieve convergence, the cost of the generation is the highest, which is not the desired solution in this study. However, BMO performs slightly faster convergence than HEBMO, while having a higher generation cost. As a result, it is fair to state that HEBMO is outstanding because it reduced the cost of generating to the absolute minimum.

TABLE 3. Comparison of generation cost of base case condition for IEEE 30-Bus RTS (Scenario-1) 1.

P_g	EP	BMO	HEBMO
P_{g1}	180.6016	188.0491	187.7232
P_{g2}	23.8136	26.0831	20.0695
P_{g5}	27.6318	35.9240	49.9999
P_{g8}	11.3988	14.7002	10.0000
P_{g11}	25.3222	13.4197	10.7707
P_{g13}	23.5443	14.5275	13.7415
Generation cost ($/MWh)	3.9321 x 10^3	3.8999 x 10^3	3.8740 x 10^3

Stressed Condition Due to the Real Power Loading Increment

Table 4 summarises the results obtained by EP, BMO, and HEBMO after solving the ED problem under stressed conditions, imposed by an increase in real power load. It can be observed that the minimum generation cost that HEBMO can accomplish when the active power is increased from the base case value to 110 % is $/MWh 4.1895 x 10^3. On the other hand, BMO and EP achieved the optimal solution with 4.1994 x 10^3 and 4.2219 x 10^3, respectively. The optimal power generated by HEBMO for each generator, in acquiring the lowest generation cost is *$Pg1$=197.5220 MW, P_{g2}=28.7193 MW, and P_{g5}=46.4069 MW, P_{g8}=13.9996 MW, P_{g11}= 20.1768 MW, and P_{g13}=15.1919 MW.*

Likewise, the outcomes when the real power load is increased up to 120 % of the base case value, the lowest generation cost is $/MWh 4.4938 x 10^3, optimized by HEBMO. EP and BMO solved the stressed condition ED problem with $/MWh 4.5168 x 10^3 and $/MWh 4.5082 x 10^3, respectively which is higher than HEBMO. This implies that the proposed HEBMO outperformed EP and BMO in achieving the lowest cost of generation. The optimal sizing of power to be generated in producing the lowest generation is listed as *P_{g1}=214.9800 MW, P_{g2}=37.0071 MW, P_{g5}=49.9095 MW, P_{g8}=18.3621 MW, P_{g11}= 19.6812 MW, and P_{g13}=12.4787 MW.*

TABLE 4. Comparison of generation cost of stressed condition due to the real power loading increment for IEEE 30-Bus RTS (Scenario-2)

Load Multiplier		**1.1**			**1.2**	
P_g	EP	BMO	HEBMO	EP	BMO	HEBMO
P_{g1}	162.9192	194.4584	197.5220	193.8640	222.2333	214.9800
P_{g2}	42.7568	36.2352	28.7193	42.8095	34.0484	37.0071
P_{g5}	46.7599	43.6876	46.4069	46.7740	43.4622	49.9095
P_{g8}	29.0582	13.59	13.9996	29.0730	18.9874	18.3621
P_{g11}	19.9451	17.0241	20.1768	19.9280	20.0689	19.6812
P_{g13}	18.4335	17.1459	15.1919	18.4562	14.2734	12.4787
Generation Cost ($/MWh)	4.2219 x 10^3	4.1994 x 10^3	4.1895 x 10^3	4.5168 x 10^3	4.5082 x 10^3	4.4938 x 10^3
Iteration	17	68	57	16	55	34

The convergence performance for the 110% increment of power loading was dominated by EP with 17 iterations; while HEBMO requires 57 iterations and BMO requires 68 iterations. EP technically seems to be faster than the proposed HEBMO. However, this is acceptable as the main objective is to gain the lowest cost of generation. HEBMO still performs well and better than BMO in terms of achieving the optimal solution. From the convergence performance perspective, for the 120% increment of power loading, it shows that EP reaches its optimal value after 16 iterations, but BMO and HEBMO reach their optimal solutions after 55 and 34 iterations, respectively. Even though EP offers the fastest convergence, it has the largest generation cost. HEBMO performed significantly faster than BMO to achieve the optimal solution. Then, HEBMO defeated BMO by having lower generation costs and fewer iterations. HEBMO demonstrates excellent performance indicated by its lowest optimal solution over EP and BMO.

Stressed Condition Due to the Reactive Power Loading Increment

The results for the next case which considers stressed conditions due to reactive power loading increment are tabulated in Table 5. From Table 5, the minimum generation cost achieved by HEBMO is \$/MWh 3.8836 x 10^3 when the reactive power is increased to 110 % from the base case value. It is obvious from the statistical measure, HEBMO is an effective technique to solve ELD problems. BMO and EP are less efficient indicated by their higher generation cost of \$/MWh 3.9027 x 10^3 and \$/MWh 3.9162 x 10^3, respectively. Using the proposed HEMBO technique, the optimal size of the power to be generated for achieving the lowest generation cost is P_{g1}*=190.3650 MW,* P_{g2}*=21.2854 MW, and* P_{g5}*=42.0838 MW,* P_{g8}*=11.6492 MW,* P_{g11}*= 15.2429 MW,* P_{g13}*=12.0213 MW.*

TABLE 5. Comparison of generation cost of stressed condition due to the reactive power loading increment for IEEE 30-Bus RTS (Scenario-3)

Load Multipler	**1.1**			**1.2**		
P_g	**EP**	**BMO**	**HEBMO**	**EP**	**BMO**	**HEBMO**
P_{g1}	165.0276	197.4902	190.3650	180.7278	189.029	189.4041
P_{g2}	30.0000	24.8491	21.2854	23.8137	26.3521	22.7253
P_{g5}	42.6667	31.1923	42.0838	27.6319	39.3113	45.7633
P_{g8}	18.2562	10.6285	11.6492	11.3988	12.7502	10.0026
P_{g11}	12.5290	16.5044	15.2429	25.3222	12.9157	12.7602
P_{g13}	22.6914	12.8662	12.0213	23.5443	12.4764	12.0105
Generation Cost (\$/MWh)	3.9162 x 10^3	3.9027 x 10^3	3.8836 x 10^3	3.9333 x 10^3	3.8911 x 10^3	3.8784 x 10^3
Iteration	16	61	36	16	62	52

A similar pattern of results was obtained when the reactive power was increased to 120 % from the base case value. The generation cost computed by HEBMO is the lowest, attaining \$/MWh 3.8784 x 10^3, compared to BMO and EP which managed to solve the cost worth \$/MWh 3.8911 x 10^3 and \$/MWh 3.9333 x 10^3. HEBMO required P_{g1}*=189.4041 MW,* P_{g2}*=22.7253 MW,* P_{g5}*=45.7633 MW,* P_{g8}*=10.0026 MW,* P_{g11}*= 12.7602 MW, and* P_{g13}*=12.0105 MW* to achieve the lowest generation cost. For a 110% increment of reactive power loading, HEBMO attained convergence after 36 iterations, whereas EP and BMO needed 16 and 61 iterations, respectively, to converge to an optimal solution. EP was the first to achieve convergence, although the generating cost is the highest.

When the load was increased to 120 % from the base value, a similar trend also emerged, with HEBMO requiring 52 iterations to converge, EP requiring 16 iterations, and BMO requiring 62 iterations. Even though EP has a rapid rate of convergence, it fails to offer the lowest generation cost. BMO generates more iterations and costs than HEBMO. Thus, it is fair to state that the proposed HEBMO technique shows an unbelievably fast convergence ability over EP. It also exhibits the lowest cost of generation over the other two techniques. It will be very useful to power system operators and planners at the relevant utilities to do their planning.

CONCLUSION

This paper has presented the implementation of HEBMO in solving the convex economic dispatch problems. In this study, a hybrid optimization-based technique for convex economic dispatch is described. The three implemented cases revealed the superiority of the proposed HEBMO over EP and BMO in terms of achieving the lowest generation cost. The validation of the proposed technique, implemented on IEEE 30-Bus RTS gives \$/MWh 3.8740 x 103 as the generation cost for the base case condition. This implies its superiority over EP and BMO. In the second case, where the system was subjected to real power loss increment; HEBMO managed to achieve the lowest cost of generation again worth \$/MWh 4.1895 x 10^3 for 110% load increment and \$/MWh 4.4938 x 0^3 120% real load increment. For the third case, HEBMO managed to achieve \$/MWh 3.8836 x 10^3 and \$/MWh 3.8784 x 10^3 for a 120% reactive power load increment. This demonstrates its superiority over EP and BMO. In terms of convergence performance, it is also acceptable and comparable with other techniques. In general, it is worth utilizing the proposed HEBMO optimization technique to solve the convex ELD. The proposed HEBMO optimization technique will have the feasibility to solve other optimization problems in the power system subject to minor alteration, depending on the problem formulations and the control variables.

REFERENCES

1. A. Srivastava and D. K. Das, "A bottlenose dolphin optimizer: An application to solve dynamic emission economic dispatch problem in the microgrid," *Knowledge-Based Syst.*, pp. 108455, 2022
2. H. S. Hoang, V. B. Nguyen, V. D. Phan, and H. N. Nguyen, "Marine Predator Optimization Algorithm for Economic Load Dispatch Target Considering Solar Generators," *GMSARN Int. J.*, vol. 16, no. 1, pp. 11–26, 2022.
3. M. H. Hassan, E. H. Houssein, M. A. Mahdy, and S. Kamel, "An improved Manta ray foraging optimizer for cost-effective emission dispatch problems," *Eng. Appl. Artif. Intell.*, vol. 100, no. January, p. 104155, 2021.
4. L. L. Li, Z. F. Liu, M. L. Tseng, S. J. Zheng, and M. K. Lim, "Improved tunicate swarm algorithm: Solving the dynamic economic emission dispatch problems," *Appl. Soft Comput.*, vol. 108, p. 107504, 2021.
5. A. Kaur, L. Singh, and J. S. Dhillon, "Krill Herd Algorithm to Solve Economic Load Dispatch Problem considering Generation Constraints," no. April, 2021.
6. P. Vasant, F. P. Mahdi, J. A. Marmolejo-Saucedo, I. Litvinchev, R. R. Aguilar, and J. Watada, "Quantum-behaved bat algorithm for solving the economic load dispatch problem considering a valve-point effect," *Int. J. Appl. Metaheuristic Comput.*, vol. 11, no. 3, 2020.
7. H. M. Rosli, S. A. Halim, L. J. Awalin, and S. M. Mustaza, "Economic-emission load dispatch for power system operation using enhanced sunflower optimization," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 27, no. 1, p. 1, 2022.
8. W. Aribowo, Supari, and B. Suprianto, "A hunger game search algorithm for economic load dispatch," *IAES Int. J. Artif. Intell.*, vol. 11, no. 2, pp. 632–640, 2022.
9. M. Said, E. H. Houssein, S. Deb, R. M. Ghoniem, and A. G. Elsayed, "Economic Load Dispatch Problem Based on Search and Rescue Optimization Algorithm," *IEEE Access*, vol. 10, pp. 47109–47123, 2022.
10. M. T. Riaz *et al.*, "Design of Optimization Methodology for Economic Dispatch of Thermal Generating Units," *2022 5th Int. Conf. Energy Conserv. Effic. ICECE 2022 - Proc.*, pp. 1–5, 2022.
11. I. Alzubi, H. M. K. Al-Masri, and A. Abuelrub, "Modified Particle Swarm Optimization Algorithms for Solving Economic Load Dispatch," 3rd Int. Conf. Smart Grid Renew. Energy, SGRE 2022 - Proc., pp. 2–6, 2022.
12. M. Zare, M. R. Narimani, M. Malekpour, R. Azizipanah-Abarghooee, and V. Terzija, "Reserve constrained dynamic economic dispatch in multi-area power systems: An improved fireworks algorithm," Int. J. Electr. Power Energy Syst., vol. 126, no. PA, p. 106579, 2021.
13. W. Yang, Z. Peng, Z. Yang, Y. Guo, and X. Chen, "An enhanced exploratory whale optimization algorithm for dynamic economic dispatch," Energy Reports, vol. 7, pp. 7015–7029, 2021.
14. X. Chen and G. Tang, "Solving static and dynamic multi-area economic dispatch problems using an improved competitive swarm optimization algorithm," Energy, vol. 238, p. 122035, 2022.
15. A. Kumar, M. Thakur, and G. Mittal, "Planning optimal power dispatch schedule using constrained ant colony optimization," Appl. Soft Comput., vol. 115, p. 108132, 2022.
16. M. H. Suhaimi, I. Musirin, M. Hidayab, S. Jelani, and M. H. Mansor, "Multiverse optimisation based technique for solving economic dispatch in power system," Indones. J. Electr. Eng. Comput. Sci., vol. 20, no. 1, pp. 485–491, 2020.
17. N. F. Ramli, N. A. M. Kamari, M. A. Zulkifley, and I. Musirin, "Optimal power scheduling for economic dispatch using moth flame optimizer," Indones. J. Electr. Eng. Comput. Sci., vol. 20, no. 1, pp. 379–384, 2020.
18. A. Sheta, A. Ali, A. Baareh, and S. Aljahdali, "Meta-heuristic Search Algorithms for Solving the Economic Load Dispatch Problem," pp. 87–92, 2022.

19. A. S. Alghamdi, "Greedy Sine-Cosine Non-Hierarchical Grey Wolf Optimizer for," Appl. Artif. Intell., vol. VOL. 35, no. NO. 2, pp. 171–191, 2021.
20. R. M. Rizk-Allah, A. E. Hassanien, and V. Snášel, "A hybrid chameleon swarm algorithm with superiority of feasible solutions for optimal combined heat and power economic dispatch problem," Energy, vol. 254, 2022.
21. M. N. Iqbal, A. R. Bhatti, A. D. Butt, Y. A. Sheikh, K. N. Paracha, and R. H. Ashique, "Solution of Economic Dispatch Problem Using Hybrid Multi-Verse Optimizer," Electr. Power Syst. Res., vol. 208, no. March, p. 107912, 2022.
22. M. H. Nadimi-shahraki, A. Fatahi, H. Zamani, S. Mirjalili, and D. Oliva, Hybridizing of Whale and Moth-Flame Optimization Algorithms to Solve Diverse Scales of Optimal Power Flow Problem, vol. 11, no. 5. 2022.
23. R. Habachi, A. Touil, A. Boulal, A. Charkaoui, and A. Echchatbi, "Solving economic dispatch and unit commitment problem in smart grid system using eagle strategy based crow search algorithm," Indones. J. Electr. Eng. Comput. Sci., vol. 14, no. 3, pp. 1087–1096, 2019.
24. R. A. Abttan, A. H. Tawafan, and S. J. Ismael, "Economic dispatch by optimization techniques," Int. J. Electr. Comput. Eng., vol. 12, no. 3, pp. 2228–2241, 2022.
25. M. H. Sulaiman, Z. Mustaffa, and O. Aliman, "An application of barnacles mating optimizer for solving economic dispatch problems," 2019 IEEE Jordan Int. Jt. Conf. Electr. Eng. Inf. Technol. JEEIT 2019 - Proc., pp. 835–839, 2019.