International Journal of Engineering Inventions
e-ISSN: 2278-7461, p-ISSN: 2319-6491
Volume 12, Issue 5 [May. 2023] PP: 460-466

Application of Grey Wolf Optimization Algorithm to Dynamic Economic Dispatch Problems in Power System

Ramamoorthi R[1], Balamurugan R[2]
[1]*Department of Electrical and Electronics Engineering, Government College of Engineering - Dharmapuri,Tamilnadu-636704, India.*
[2]*Department of Electrical and Electronics Engineering, Government College of Engineering - Thanjavur,Tamilnadu-613402, India,*
Corresponding Author: ram_moorthi2007@yhaoo.com

ABSTRACT: *This article present a meta-heuristic algorithm named Grey Wolf Optimization (GWO). GWO represents the foraging activities of the grey wolfs. Dynamic Economic dispatch is a vital technical problem in the field of power system engineering. It is a highly nonlinear and non-convex optimization problem. In this research work GWO algorithm is employed to solve the challenging DED problems of the power system. To assess the efficacy of the GWO algorithm power system generators with different real-time constraints are considered. GWO algorithm is applied to one test system with 5 thermal generating units. Simulation outcomes are contrasted with the well-known algorithms in the literature such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), etc.; the results show that the proposed algorithm has better results and consistency.*
KEYWORDS**:** *Dynamic economic dispatch, Heuristic algorithm, Grey wolf optimization, Valve point effect, Economic load dispatch*

Date of Submission: 16-05-2023 Date of acceptance: 30-05-2023

I. INTRODUCTION

Dynamic economic dispatch (DED) is a problem in power system operations that involves finding the optimal generation schedule for power plants in real-time, taking into account the varying load demand and the constraints of the system. The goal is to minimize the total cost of generating electricity while ensuring that the supply meets the demand and all operational constraints are satisfied. In a power system, various power plants, such as thermal, hydro, and renewable energy sources, are responsible for generating electricity. The DED problem arises because electricity demand is constantly changing throughout the day due to factors like consumer behavior and weather conditions. The DED problem involves determining the optimal output levels for each power plant at each time interval, typically in increments of 15 minutes or 1 hour. Overall, the dynamic economic dispatch problem plays a crucial role in ensuring the efficient and reliable operation of power systems by optimizing the generation schedule in response to changing demand and system conditions.

The DED problem is typically solved using optimization techniques such as mathematical programming or heuristic methods. Heuristic approaches offer certain advantages compared to mathematical approaches when solving the DED problem in power systems. Here are some advantages of heuristic approaches: Handling Nonlinearities: Power systems often have nonlinearities in their cost functions, ramp rate constraints, and transmission constraints. Heuristic approaches, such as evolutionary algorithms or particle swarm optimization, can handle nonlinear objective functions and constraints more effectively compared to mathematical programming techniques, which may require linearization or approximation of nonlinearities. Scalability: Heuristic algorithms are typically more scalable and can handle larger problem instances. Power systems are complex, and as the size of the system and the number of power plants increase, the mathematical formulation becomes more challenging due to the exponential growth in variables and constraints. Heuristic approaches can effectively handle large-scale DED problems with a reasonable computational effort. Exploration of Solution Space: Heuristic algorithms provide the capability to explore the solution space more extensively, which can lead to finding alternative solutions or trade-offs that may not be captured by a single mathematical formulation. Heuristics can search for near-optimal solutions that are not constrained by a specific mathematical model, allowing for greater flexibility in finding solutions that satisfy the operational requirements and objectives of the power system. It's worth noting that while heuristic approaches have these advantages, they may not guarantee to find the globally optimal solution. The trade-off for their computational efficiency and flexibility is a potential sub-optimality in the solution quality. However, in practice, heuristic approaches have been widely used and proven effective in solving the dynamic economic dispatch problem, providing reasonable and satisfactory solutions for power system operation. Flexibility: Heuristic algorithms are more flexible and adaptable to different problem settings and constraints. The DED problem can involve numerous constraints and variables, and it may be challenging to formulate the problem mathematically in a concise and tractable manner.

Heuristic approaches can handle various types of constraints and allow for more complex and realistic problem representations. [1] has solved the DED problem using the Symbiotic Organisms Search (SOS) algorithm. [2] has solved the DED problem using Harmony Search Algorithm (HSA). [3] has solved the DED problem using Simulated Annealing (SA) technique. The results obtained were compared with other results in the literature such as the SA [3], the GA [4], the PSO [5], Imperial Competitive Algorithm (ICA) [4], Ant colony optimization [6], Chaotic Sequence- Differential Evolution (CS-DE) algorithm [7], A Hybrid bee colony optimization (BCO) and sequential quadratic programming (SQP) is proposed for solving DED problem [8], Artificial Immune System (AIS) [9], self-learning teaching-learning based optimization (SL-TLBO) [10], improved pattern search based method [11]. In this research article, a new meta-heuristic algorithm named Grey Wolf Optimization (GWO) algorithm was proposed by Mirjalili et.al., [12]. The GWO algorithm models the forging activities of a grey wolf. To validate the effectiveness of the GWO method the proposed algorithm is tested for dynamic economic dispatch of 5 generators power system. The outcomes have been contrasted with several other optimization approaches reported in the literature.

The rest of the sections of the article are structured as follows: Explanation and expression of DED are given in Section 2. The Grey Wolf optimization algorithm is briefly discussed, and the implementation of GWO for DED is presented in Section 3. Section 4 presents the simulation results and discusses the outcomes. Finally, Section 5 provides the conclusion of the research work.

II. PROBLEM FORMULATION

DED is a well-known power system complex problem. The mathematical modeling of the cost function is considering the cost of thermal generators along with the valve-point effect as under,

$$\mathrm{minF(X)} = \sum_{t=1}^{T}\sum_{i=1}^{N}(a_iP_i^2 + b_iP_i + c_i) + \left|d_i * \sin\left(e_i * \left(P_i^{min} - P_i\right)\right)\right| \tag{1}$$

Here a, b, and c are the fuel coefficients, e, and f represent valve point parameters to model the ripples produced in the cost curve. N represents the maximum number of generating units in the test case, T is the total time interval in hours for which the objective function is calculated, P_i^{min} is the minimum power generation by i th generator, and Pi is the power generation by i th generator in t th interval. The different constraints accompanying DED are

2.1 Power Balance Constraint

The Power balance constraint is an equality constraint, in which the stability criterion is met when the total power generation equals the total demand and the real power loss in transmission lines. This relation can be expressed as given in Equation

$$\sum_{i-1}^{N} P_i = P_D + P_L \tag{2}$$

Over long distances, the transmission loss is considered as an element of generator's output power through Kron's loss coefficients. The Kron's loss formula can be expressed as given in Equation

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_iB_{ij}P_j + \sum_{i=1}^{N} B_{oi}P_i + B_{oo} \tag{3}$$

Here P_D is the total load demand and P_L is the system loss. To calculate the system loss the method based on penalty factor and constant loss formula coefficient or B coefficient is adopted. B_{ij}, B_{oi}, B_{oo} are the loss coefficient of the generators.

2.2 Generation Capacity Constraint

This is an inequality constraint for each generator. The real power output of each generator for a normal system operation is within its lower and upper limits as given in Equation

$$P_i^{min} \le P_i \le P_i^{max} \tag{4}$$

Where P_i^{max} and P_i^{min} is the upper and lower limit of the power generated by *i* th generator.

2.3 Generator Ramp Rate Limits

The online generator's operating range is constantly confined by its ramp rate limits. When the generator units are online, there exist three possible situations as shown in Figure 1.

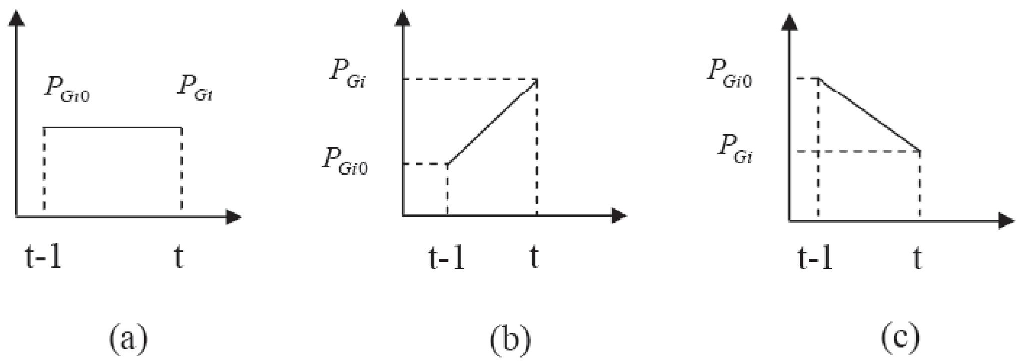

Fig 1 : Three possible situations of online generator (a) Steady-state operation, (b) Increasing the level of power generation, and (c) Decreasing the level of power generation

Based on the above situations, the inequality constraints due to ramp rate limits can be written as given in Equation

$$\begin{aligned} P_i - P_i^o &\leq UR_i \\ P_i^o - P_i &\leq DR_i \end{aligned} \quad (5)$$

Where the up-ramp limit of the generator is denoted as URi; the down-ramp limit of the generator is denoted as DRi.

III. GREY WOLF OPTIMIZATION ALGORITHM

GWO algorithm was first introduced by Mirjalili et al. in 2014 [12]. Since then it is widely used in finding optimal solutions for complex optimization problems in various fields including engineering applications. This algorithm mimics the hunting nature of the Gray Wolfs. Based on the hunting nature of the Grey Wolfs, movements of the Gray wolfs classified into four phases. There is Exploration for prey, Encircling prey, Hunting, and attacking prey (exploitation). These operators are briefly explained and mathematically expressed in the following subsection.

3.1 Exploration for prey

The grey wolves diverge from each other positions for searching a victim. Make use of AM with random values to compel the search agent to diverge from the victim. The component CM provides random weights for searching for prey in the search space. Hence exploration through AM and CM permits this algorithm to globally search the area. CM vector also presents the effect of obstacles to impending the prey.

3.2 Encircling prey

The alpha, beta, and delta estimate the position of the three best wolves, and other wolves update their positions using the positions of these three best wolves. Encircling behavior can be represented by DM. The expected boundary is mathematically represented by the following equations:

$$DM = |CM.XP(t) - X(t)| \quad (6)$$

$$X(t+1) = XP(t) - AM.DM \quad (7)$$

Here t indicates the current iteration, AM and CM are coefficient vectors, XP(t) is the position vector of prey, X(t) represents the position vector of a grey wolf. r1 and r2 are random vectors in [0, 1].a is linearly decreased from 2 to 0.

$$AM = 2a * r_1 - a \quad (8)$$

$$CM = 2 * r_2 \quad (9)$$

3.3 Hunting

Conservation of regional habitat connectivity has the potential to facilitate the recovery of the grey wolf. After encircling, the alpha wolf guides for hunting. Later, the delta and beta wolves join in hunting. It is tough to predict the optimum location of prey. The hunting behavior of grey wolf, based on the position of alpha, beta, and gamma (candidate solution) wolf can be represented by

$$DM_\alpha = |CM_\alpha . XP_\alpha(t) + X| \quad (10)$$

$$DM_\beta = \left|CM_\beta . XP_\beta(t) + X\right| \tag{11}$$

$$DM_\delta = \left|CM_\delta . XP_\delta(t) + X\right| \tag{12}$$

Finally, the position of various categories of wolves is modified as follows:

$$X_{\alpha 1} = X_\alpha - AM . DM_\alpha \tag{13}$$

$$X_{\beta 1} = X_\beta - AM . DM_\beta \tag{14}$$

$$X_{\delta 1} = X_\delta - AM . DM_\delta \tag{15}$$

$$X(t+1) = \frac{X_{\alpha 1} + X_{\beta 1} + X_{\delta 1}}{3} \tag{16}$$

3.4 Attacking prey (exploitation)

The grey wolves stop hunting by attacking the prey when it stops moving. It depends on the value of a* AM is a random value in the interval [-2a, 2a]. In GWO, search agents update their positions based on the location of alpha, beta, and delta wolves mentioned in the hunting phase and attack the prey.

3.5 Grey wolf optimization applied to DED

The different steps of GWO algorithm for solving DED problems are described below.

Step 1: Active power generation of all the generating units initialized randomly within their lower and upper real power operating limits

Step 2: Evaluate the fitness of each solution of the current population using (1)–(3). Each fitness value represents the distance of the individual wolf from the prey.

Step 3: Sort the population from best to worst. The best, second best and third best solutions respectively, represent the positions of α, β, and δ categories of wolves.

Step 4: Modify the position of each search agent using the searching prey, encircling prey, hunting, and attacking prey concepts. The position of each search agent represents a potential solution comprised of active power generation of DED problem.

Step 5: Check whether the operating limits of the active power of all generating units except the last unit are violated or not. If any power generation is less than the minimum level, it is made equal to a minimum value. Similarly, if it is greater than the maximum level, it is assigned its maximum value. Subsequently, the last unit of the power generation is evaluated using (5) and whether it satisfies all the inequality constraints or not is checked. The infeasible solutions are exchanged for the best feasible solutions.

Step 6: Go to Step 2 until termination criteria are met. The GWO is stopped executing when the maximum number of iterations (generations) is reached or there is no noteworthy improvement in the solution. In this paper, the ending criterion is the maximum number of iterations for which most of the grey wolves or search agents are idle.

IV. CASE STUDIES AND NUMERICAL RESULTS

The five-unit test system with a non-smooth fuel cost function is used to demonstrate the performance of the proposed GWO method. The system data are given in Table 1. The demands of the system spread over 24 intervals are given in Table 2 and the graphical representation of the load profile is shown in Figure 2. To justify the efficacy of the proposed algorithm, the developed algorithm is simulated and tested in MATLAB 7.1 Software on a 2 GHz Pentium IV, 1 GB RAM personal computer. The population size and the maximum iteration number are taken as 50 and 500 respectively for the test systems under consideration. Simulated results are tabulated in Table 3. The total generation cost is 43850.6481 $ and it is much lesser than the best cost obtained by the other methods reported in the literature.

Table 1 Load profile for the test case

Parameters	P1	P2	P3	P4	P5
a	0.0080	0.0030	0.0012	0.0010	0.0015
b	2.0	1.8	2.1	2.0	1.8
c	25	60	100	120	40

e	100	140	160	180	200
f	0.042	0.040	0.038	0.037	0.035
P_{min}	10	20	30	40	50
P_{max}	75	125	175	250	300
UP	30	30	40	50	50
DW	30	30	40	50	50

$$B = \begin{bmatrix} 0.000049 & 0.000014 & 0.000015 & 0.000015 & 0.000020 \\ 0.000014 & 0.000045 & 0.000016 & 0.000020 & 0.000018 \\ 0.000015 & 0.000016 & 0.000039 & 0.000010 & 0.000012 \\ 0.000015 & 0.000020 & 0.000010 & 0.000040 & 0.000014 \\ 0.000020 & 0.000018 & 0.000012 & 0.000014 & 0.000035 \end{bmatrix}$$

Table 1 Load profile for the test case

Time	Load (MW)	Time	Load (MW)	Time	Load (MW)	Time	Load (MW)
1	410	7	626	13	704	19	654
2	435	8	654	14	690	20	704
3	475	9	690	15	654	21	680
4	530	10	704	16	580	22	605
5	558	11	720	17	558	23	527
6	608	12	740	18	608	24	463

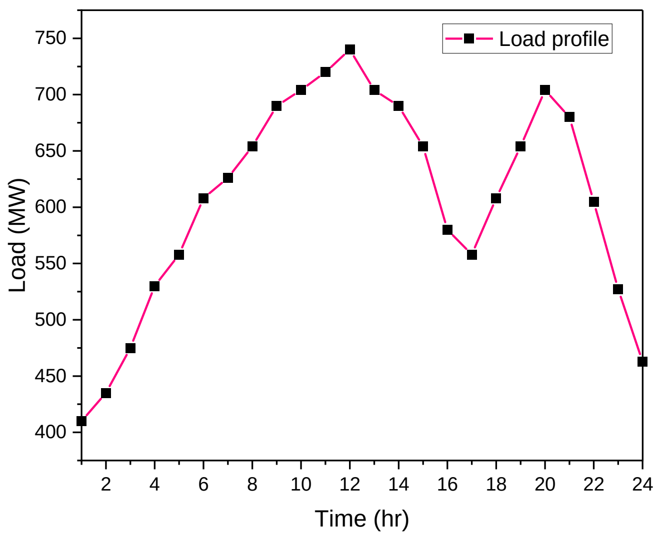

Fig 2 Load distribution for test system

Table 2 Obtained best schedule for the test case

Time (hr)	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	Loss (MW)
1	74.88438	48.81788	113.4783	126.3293	50	3.5125
2	57.7814	95.05868	111.7584	124.4152	50	4.0133
3	74.99962	102.7918	30	132.1406	140.0996	5.0315
4	68.17475	98.82979	103.4593	124.8591	140.5326	5.8578
5	51.18066	108.681	134.4332	129.7983	140.377	6.4703
6	49.15392	97.93039	114.4828	124.4829	229.7892	7.8418
7	71.65904	97.14169	112.487	123.8187	229.1995	8.3058
8	74.99587	109.9696	114.7502	131.7589	231.6061	9.0805
9	61.10696	95.14176	108.4366	206.2938	229.1783	10.1572
10	62.06835	102.412	111.7866	208.5306	229.7739	10.5722
11	74.97138	104.485	112.7467	209.8895	228.9522	11.0446
12	74.99845	99.00959	136.2906	210.7713	230.4638	11.5338
13	64.44817	98.14352	112.4179	210.0907	229.4588	10.5601
14	51.88175	98.29637	111.7473	208.7715	229.4691	10.1657
15	69.62994	124.0346	113.6152	126.3513	229.4938	9.1249
16	20.11891	100.099	112.7011	126.1346	228.1501	7.2039
17	19.95139	93.15601	112.0784	108.2322	231.2694	6.6875
18	10.20357	96.72618	154.3721	125.1875	229.3416	7.831
19	14.88444	97.58557	112.4131	209.7923	228.5706	9.2458
20	60.85063	99.95215	112.408	212.5207	228.8423	10.5733
21	38.22047	98.60156	114.0183	209.6947	229.362	9.8971
22	13.10357	99.46768	114.0606	156.288	229.9323	7.8521
23	10.00927	60.54811	113.168	124.2348	224.9637	5.9216
24	10.03498	20.00903	82.64669	125.4596	229.5613	4.7116
					Best fuel Cost ($)	43850.6481
					Transmission loss (MW)	193.1959

Table 3 Comparison of best cost with other algorithms

Method	SA [3]	APSO [13]	GA[14]	PSO[14]	ABC[14]	AIS [9]	RCGA[15]	IRCGA[15]	GWO
Best cost ($)	47,356	44,678	44,862	44,253	44,046	47,564	47,564	47,185	43,850.64

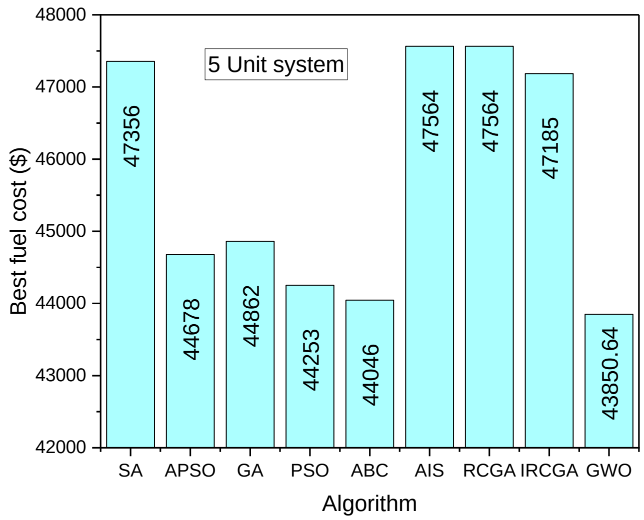

Fig 3 : Best cost comparison for the test case

V.CONCLUSION

The DED problem is very important in power system optimization. It is used to minimize the fuel cost of the generator to obtain the best optimal generation schedule for a given day. In this research work, GWO is utilized to find the best optimal solution for the DED problem and it is applied to the 5-unit test case. The results show that the GWO produces the best optimal solution than the compared algorithms such as SA, APSO, GA, PSO, ABC, AIS, RCGA, and IRCGA. Hence the applied GWO algorithm can be a potential meta-heuristic algorithm for the DED problems in power systems.

REFERENCES

[1] Y. Sonmez, H. T. Kahraman, M. K. Dosoglu, U. Guvenc, and S. Duman, “Symbiotic organisms search algorithm for dynamic economic dispatch with valve-point effects,” *J. Exp. Theor. Artif. Intell.*, vol. 29, no. 3, pp. 495–515, May 2017, doi: 10.1080/0952813X.2016.1198935.

[2] A. K. Sahoo, T. K. Panigrahi, J. Paramguru, and A. P. Hota, “Dynamic Economic Dispatch Using Harmony Search Algorithm,” 2021, pp. 425–435.

[3] C. K. Panigrahi, P. K. Chattopadhyay, R. N. Chakrabarti, and M. Basu, “Simulated Annealing Technique for Dynamic Economic Dispatch,” *Electr. Power Components Syst.*, vol. 34, no. 5, pp. 577–586, May 2006, doi: 10.1080/15325000500360843.

[4] B. Mohammadi-ivatloo, A. Rabiee, A. Soroudi, and M. Ehsan, “Imperialist competitive algorithm for solving non-convex dynamic economic power dispatch,” *Energy*, vol. 44, no. 1, pp. 228–240, Aug. 2012, doi: 10.1016/j.energy.2012.06.034.

[5] X. YUAN, A. SU, Y. YUAN, H. NIE, and L. WANG, “An improved PSO for dynamic load dispatch of generators with valve-point effects,” *Energy*, vol. 34, no. 1, pp. 67–74, Jan. 2009, doi: 10.1016/j.energy.2008.09.010.

[6] D. C. Secui, “A method based on the ant colony optimization algorithm for dynamic economic dispatch with valve-point effects,” *Int. Trans. Electr. Energy Syst.*, vol. 25, no. 2, pp. 262–287, Feb. 2015, doi: 10.1002/etep.1841.

[7] D. He, G. Dong, F. Wang, and Z. Mao, “Optimization of dynamic economic dispatch with valve-point effect using chaotic sequence based differential evolution algorithms,” *Energy Convers. Manag.*, vol. 52, no. 2, pp. 1026–1032, Feb. 2011, doi: 10.1016/j.enconman.2010.08.031.

[8] M. Basu, “Hybridization of bee colony optimization and sequential quadratic programming for dynamic economic dispatch,” *Int. J. Electr. Power Energy Syst.*, vol. 44, no. 1, pp. 591–596, Jan. 2013, doi: 10.1016/j.ijepes.2012.08.026.

[9] S. Hemamalini and S. P. Simon, “Dynamic economic dispatch using artificial immune system for units with valve-point effect,” *Int. J. Electr. Power Energy Syst.*, vol. 33, no. 4, pp. 868–874, May 2011, doi: 10.1016/j.ijepes.2010.12.017.

[10] Z. YANG, K. LI, Q. NIU, Y. XUE, and A. FOLEY, “A self-learning TLBO based dynamic economic/environmental dispatch considering multiple plug-in electric vehicle loads,” *J. Mod. Power Syst. Clean Energy*, vol. 2, no. 4, pp. 298–307, Dec. 2014, doi: 10.1007/s40565-014-0087-6.

[11] J. S. Alsumait, M. Qasem, J. K. Sykulski, and A. K. Al-Othman, “An improved Pattern Search based algorithm to solve the Dynamic Economic Dispatch problem with valve-point effect,” *Energy Convers. Manag.*, vol. 51, no. 10, pp. 2062–2067, Oct. 2010, doi: 10.1016/j.enconman.2010.02.039.

[12] S. Mirjalili, S. M. Mirjalili, and A. Lewis, “Grey Wolf Optimizer,” *Adv. Eng. Softw.*, vol. 69, pp. 46–61, Mar. 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[13] B. K. Panigrahi, V. Ravikumar Pandi, and S. Das, “Adaptive particle swarm optimization approach for static and dynamic economic load dispatch,” *Energy Convers. Manag.*, vol. 49, no. 6, pp. 1407–1415, Jun. 2008, doi: 10.1016/j.enconman.2007.12.023.

[14] S. Hemamalini and S. P. Simon, “Dynamic economic dispatch using artificial bee colony algorithm for units with valve-point effect,” *Eur. Trans. Electr. Power*, vol. 21, no. 1, pp. 70–81, Jan. 2011, doi: 10.1002/etep.413.

[15] J. K. Pattanaik, M. Basu, and D. P. Dash, “Improved real coded genetic algorithm for dynamic economic dispatch,” *J. Electr. Syst. Inf. Technol.*, vol. 5, no. 3, pp. 349–362, Dec. 2018, doi: 10.1016/j.jesit.2018.03.002.