



A New Method of Artificial to Solve the Optimization Problems without the Violated Constraints

Jangkung Raharjo^{1*}, Hermagasantos Zein², Adi Soeprijanto³, Kharisma Bani Adam³

^{1,4}School of Electrical Engineering, Telkom University

²Energy Engineering Department, State of Polytechnic Bandung, POLBAN, Bandung

³Electrical Engineering Department, Institut Teknologi Sepuluh Nopember, Surabaya

^{1,4}Jl. Terusan Buah Batu dayeuhkolot Bandung, 40257, Indonesia

²Ciwaruga, bandung, Indonesia

³Keputih, Sukolilo, Surabaya, Indonesia

Corresponding email: jangkungraharjo@telkomuniversity.ac.id

Received 14 February 2021, Revised 24 April 2021, Accepted 8 May 2021

Abstract—There are some problems in optimization that cannot be derived mathematically. Various methods have been developed to solve the optimization problem with various functional forms, whether differentiated or not, to overcome the problem, which is known as artificial methods such as artificial neural networks, particle swarm optimization, and genetic algorithms. The literature says that there is an artificial method that frequently falls to the minimum local solution. The local minimum results are proof that the artificial method is not accurate. This paper proposes the Large to Small Area Technique for power system optimization which works to reduce feasible areas. This method can work accurately, which never violates all constraints in reaching the optimal point. However, to conclude that this method is superior to others, logical arguments and tests with mathematical simulations are needed. This proposed method has been tested with 24 target points using ten functions consisting of a quadratic function and a first-order function. The results showed that this method has an average accuracy of 99.97% and an average computation time of 62 seconds. The proposed technique can be an alternative in solving the economic dispatch problem in the power system.

Keywords – artificial method, accurate, global minimum, optimization, simple.

Copyright © 2021 JURNAL INFOTEL

All rights reserved.

I. INTRODUCTION

The method to solve the optimization problem can be divided into two groups the mathematical base and the artificial based method. The mathematical methods are based on derivatives of the Lagrange function, and that makes each method is adequate to solve only the problems that can be derived mathematically. The methods consist of Lagrangian Method (LM) [1], Gradient Method (GM) [2], Linear Programming (LP) [3], [4], Dynamic Programming (DP) [5], and Direct Method (DM) [6], Lambda Iteration (LI) [7]. These methods ensure that solutions will always accurately fall to a global minimum, but they could not work on a function that cannot be derived.

The artificial methods take the artificial intelligent concept as their basis. The methods included in this

group are, among others: Genetic Algorithm (GA) [8], Particle Swarm Optimization (PSO) [9]–[11], Firefly Algorithm (FA) [12], Flower Pollination Algorithm (FPA) [13], Artificial Neural Network (ANN) [14], Thunderstorm Algorithm (TA) [15], Fuzzy Algorithm [16], Coulomb's and Franklin's Algorithm [17], Whale Optimization Algorithm (WOA) [18], [19], and Simulated Annealing (SA) Algorithm [20].

The main problem related to the technique is controlling the required parameters. Sometimes the selection of improper control parameters will cause considerable computational time. The methods mentioned above are complex. The methods also have many parameters to control, and their accuracy depends on the initial solution chosen. If the initial solution is close to a local minimum, it will fall within

the local minimum. This condition is sometimes experienced by PSO [21]. Meanwhile, on the other hand, several methods, such as the Direct Method, could guarantee convergence. However, these methods could only solve the economic dispatch (ED) problem when the objective function's order is lower or equal to two and failed at the higher order.

Another simpler artificial method, namely the Large to Small Area Technique (LSAT) [22], was developed from the Coarse to Fine Search method, which has been used in information signal processing, especially for estimating the motion of video signals [23]. The basic principle of LSAT is based on feasible area scaling. The basic principle of LSAT is based on feasible area scaling. The Feasible Area is continuously reduced until a very small feasible area is obtained, and the best candidate is considered the solution point. The optimum point is indicated by a situation where the difference between the best candidate in the iteration k and the best candidate in the iteration to $(k-1)$ is very insignificant.

In reaching the optimum point, this LSAT guarantees that it will not violate the constraints that have been set. If a candidate is outside the feasible area formed by the mathematical function and limitation function, the candidate is left out in the next iteration. This study proposed the LSAT method to reach the optimal point by ensuring that the results obtained never violate the constraints. This method juga can solve the optimization problem in high order function, not limited only to a second-order or quadratic function.

This paper consists of four main chapters. The first chapter explains the proposed method, its algorithms, and the flow charts. After explaining the material and method of the research, the second chapter analyzes the simulation results. The third chapter examines the discussion of the simulation results, and the last chapter contains the conclusions and the future works.

II. RESEARCH METHODS

A. Objective Functions and Constrains

Optimization is a topic that has been widely used for various purposes and by various methods. Optimization aims to reach an optimal point, either a minimum point or a maximum point depending on the goals. In optimization, the objective function must be determined first.

The objective function of the optimization in this paper is to minimize the sum of several quadratic and first-order functions, with the characteristics of each function being different and the constraints of the functions are different, as shown in (1) to (5).

$$y_i = f_i(x_i) \quad (1)$$

The objective function in this problem is:

$$\min y_{total} = \min \sum_{i=1}^n y_i \quad (2)$$

$$f_i(x_i) = \alpha_i x_i^2 + \beta x_i + \gamma \quad (3)$$

Function limitations are;

$$x_{ij} \leq x_i \leq \hat{x}_i, i = 1, 2, \dots, n \quad (4)$$

$$\sum_{i=1}^n (x_i - v_i) = 0 \quad (5)$$

where $\alpha, \beta,$ and γ are coefficient of function, v_i is the point that will be aimed at the optimization process, x_i is the optimization result in the i^{th} function.

The relationship between y_i and x_i is shown in Table 1, column-2, while the limitations of the function are shown in column-3.

Table 1. Mathematical Function and Limitations

No	Mathematical functions	Limitation Function
1	$y_1 = 1.100 x_1^2 + 375 x_1 + 250$	$40 \leq x_1 \leq 400$
2	$y_2 = 1.020 x_2^2 + 360 x_2 + 200$	$60 \leq x_2 \leq 600$
3	$y_3 = 1.120 x_3^2 + 370 x_3 + 400$	$28 \leq x_3 \leq 280$
4	$y_4 = 550 x_4 + 600$	$13 \leq x_4 \leq 126$
5	$y_5 = 500 x_5 + 800$	$18 \leq x_5 \leq 175$
6	$y_6 = 1.105 x_6^2 + 300 x_6 + 325$	$66 \leq x_6 \leq 661$
7	$y_7 = 0.110 x_7^2 + 400 x_7 + 300$	$10 \leq x_7 \leq 100$
8	$y_8 = 1.200 x_8^2 + 410 x_8 + 400$	$2 \leq x_8 \leq 20$
9	$y_9 = 0.850 x_9^2 + 365 x_9 + 375$	$40 \leq x_9 \leq 400$
10	$y_{10} = 0.850 x_{10}^2 + 365 x_{10} + 375$	$3 \leq x_{10} \leq 28$

B. The Proposed Method

Another artificial method guarantees that it does not violate the constraints of reaching the minimum global point, i.e., the Large to Small Area Technique (LSAT) can fill in those shortcomings that come with the other methods in solving the economic dispatch problem [22]. Figure 1(a) shows the optimization process from two methods: the PSO and the LSAT. Yellow Graph consists of the minimum global (shown by point D, which is the star position) and a minimum local (shown by point C). Optimization using the PSO method starts from the starting point of the candidate's movement as indicated by point A, which moves towards the global minimum point and reaches a global minimum. However, if the candidate's movement starts from point B, the iteration may stop when the candidate's movement reaches point C. In other words, iterations can stop when the optimization results reach point C or at the local minimum. The local minimum result means that PSO method is easily falling into a local minimum. Moreover, this analysis is in accordance with the paper published by [23]. Thus the PSO method depends on the starting point of the candidate's movement.

Optimization using the LSAT method starts by evenly spreading the M number of solution candidates on the feasible area formed from each generator's

constraint functions. Each candidate is tested with an objective function, a minimum cost function, and the candidate with the lowest generation cost is selected as the best candidate. Figure 1(a) shows that candidate 1 is the closest to minimum global, and it is chosen as the best candidate in this condition (iteration 1). After the best candidate has been selected, the feasible area is reduced to half of the previous feasible area's size, as shown in Fig. 1(b), and M number of candidates has spread again. Testing with the objective function and selecting the best candidate is repeated, and after that, candidate-2 is obtained. This second iteration is shown in Fig. 1(b). Here, in Fig. 1(b), candidate-2 is closer to the minimum global compared to candidate 1 (in iteration -1). Figure 1(c) shows that candidate-3 is closer to the global minimum when compared to candidate-2 (in iteration-2). All these processes (spreading, testing, and selecting) are repeated continuously until iteration-k when a very narrow feasible area is obtained. The best candidate selected from there is called an optimal solution or convergent point. The difference between the best candidate on iteration-k and the best candidate on iteration k-1 is no longer significant in such conditions. Figure 1(d) shows that the best candidate in the iteration is k, where its location coincides with the global minimum point.

The accuracy level of this method depends on the following things: (i). The number of candidates (M), the more candidates, the higher the accuracy level. (ii). Threshold value (ζ) is the difference between the best candidate on iteration-k and the best candidate on iteration k-1. The smaller ζ , the more accurate result will obtain, and it could approach the results of calculus methods such as the Direct method, Gradient method, but it took a long time to finish. Those explanations show that the LSAT method will never fall on minimum local and always give a convergent result.

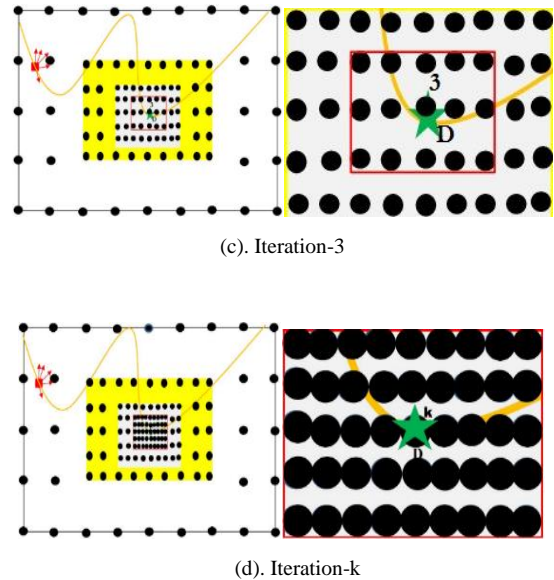


Fig. 1. Optimization Process using LSAT

In simple terms, the Large to Small Area Technique (LSAT) can be explained in Fig. 2,

Define an area formed by the limit of the generator unit having dimensions n, \mathfrak{R}_0 .

$$\mathfrak{R}_0 = \{(\tilde{x}_1, \tilde{x}_1), (\tilde{x}_2, \tilde{x}_2), \dots, (\tilde{x}_n, \tilde{x}_n)\} \quad (6)$$

The area where candidates are scattered can be a line (1-dimension), a plane (2-dimensions), a space (3-dimensions) or a higher dimension depending on the number of functions involved.

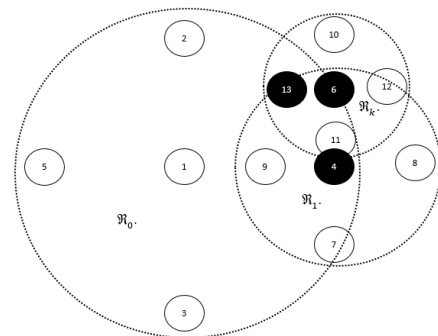
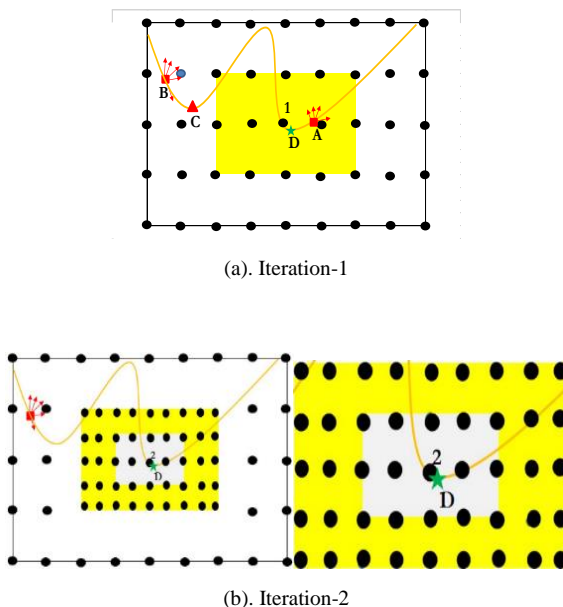


Fig. 2. The Certainty for Reaching a Global Minimum

In \mathfrak{R}_0 , M candidates are scattered, as shown in Figure 2, with M = 5 (i.e., candidate 1, 2, 3, 4, and 5). The best candidate is determined, namely the candidate with the smallest value of total y, so that candidate-4 is the best in the 0 iterations, x_0^{best} . \mathfrak{R}_0 is reduced to form a new area, \mathfrak{R}_1 and it is confirmed that candidate 4 (x_0^{best}) is in the \mathfrak{R}_1 .

Then five candidates were spread again on \mathfrak{R}_1 , so that the candidate density increased. In Fig. 2, candidate-8 does not meet, and it will not be involved



in the optimization process because it is outside of \mathfrak{R}_0 which causes it to violate the limits of x . Determine the best candidate in \mathfrak{R}_1 , obtained candidate-6 as the best candidate in the 1st iteration (x_1^{best}).

The process is continued until a tiny area of \mathfrak{R}_k is obtained and the best candidate, namely candidate 6 as x_k^{best} , can be considered as the optimal solution, and the iteration process stops. Each candidate C in the k -iteration can be written as (7).

$$C_i^k = (x_{i1}^k, x_{i2}^k, \dots, x_{iM}^k) \quad (7)$$

To stop the iteration process, set ζ is a constant that is not significant compared to y_{tot} . So that if the difference between the best candidates in \mathfrak{R}_k and in \mathfrak{R}_{k-1} is smaller or equal to ζ , the iteration is stopped.

$$\mu = x_k^{best} - x_{k-1}^{best} \leq \zeta \quad (8)$$

Each best candidate in each iteration must be in \mathfrak{R}_0 , as shown in (9).

$$x_k^{best} \in \mathfrak{R}_0 \quad (9)$$

This ensures that this technique will never violate the x constraints.

C. Algorithm and Flowchart

In simple terms, LSAT's basic principles have been explained in the research method in Fig. 2. The initial step is to determine the feasible area which is formed from the limits of all x .

In general, the algorithm from the LSAT can be expressed as follows:

1. Input data.
2. Determine the area formed from the limit of all x , namely \mathfrak{R}_0 and spread M candidates into \mathfrak{R}_0 .
3. Determine the best candidate, namely the candidate with the minimum y .
4. Reduction of the feasible area to get a new feasible area and the best candidate in step-3 is inside the new feasible area.
5. Spread M candidates and if there are candidates who are outside \mathfrak{R}_0 , then the candidates are ignored.
6. Determine the best candidate.
7. Check if $\mu \leq \zeta$, then a solution point is found, go to step 9. If $\mu > \zeta$, then determine the new feasible area.
8. Spread M candidates and determine the best candidate.
9. Go to step 3.
10. Result
11. Stop

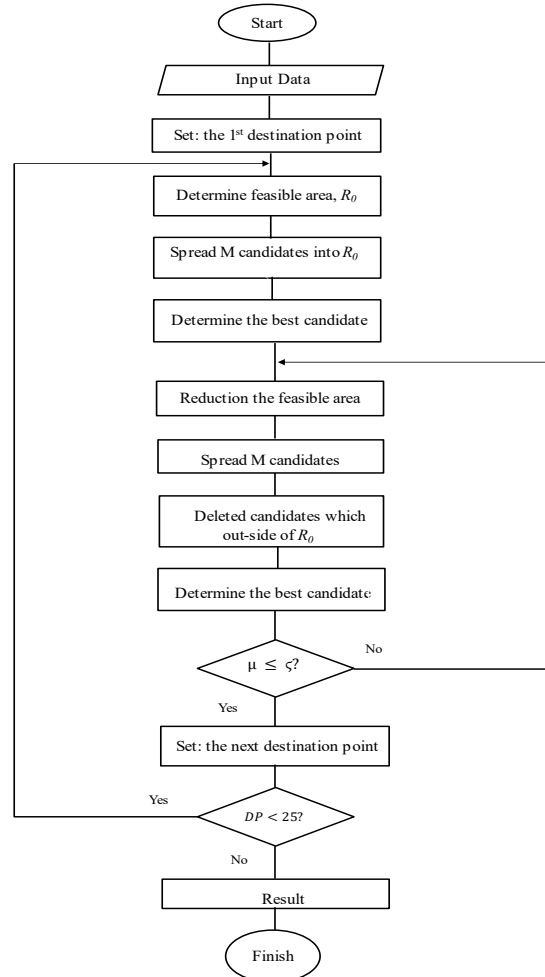


Fig. 3. Flow Chart of The Proposed Method

This method is done based on the repetition of the best candidate search process from a feasible area, \mathfrak{R}_0 . Some candidates are spread on \mathfrak{R}_0 and the best candidate is chosen among them. After that, the smaller feasible area around the best candidate, \mathfrak{R}_0 is determined. The same process is repeated until a very small feasible area where the best candidate can be considered a convergence point. The testing uses 24 target points to validate the proposed technique. To guarantee the convergence, if there are candidates on iteration k which placed outside \mathfrak{R}_0 , the candidates are deleted, even though they are located in \mathfrak{R}_k .

This is an advantage of LSAT, which will not fall at local minimum conditions, so the convergence is guaranteed. The LSAT's convergence guarantee is shown in Fig. 2. The flow chart of the proposed method is shown in Fig. 3.

III. RESULTS

A. Simulation Results

The proposed system is tested using the target points (TP) as shown in Fig. 4 and in Table 2 to test the proposed technique's performance, especially regarding accuracy. This system can reach these goal

points accurately, the results are shown in Table 2, where ζ is set at 10000. The results of each x are shown in Fig. 5.

Table 2. Optimization Results

TP _i	v _i	$\sum_{i=1}^{10} x_i$	y _i	$\left[\frac{x_i - v_i}{v_i} \right] * 100$	Acc. (%)
1	1,299	1,299.50	687,130.86	0.03849	99.962
2	1,314	1,314.83	686,620.61	0.06317	99.937
3	1,238	1,238.30	642,611.74	0.02423	99.976
4	1,214	1,214.69	634,539.57	0.05684	99.943
5	1,157	1,157.43	583,984.68	0.03717	99.963
6	1,238	1,238.30	642,611.74	0.02423	99.976
7	1,292	1,292.76	674,432.28	0.05882	99.941
8	1,299	1,299.50	687,130.86	0.03849	99.962
9	1,385	1,385.52	736,611.34	0.03755	99.962
10	1,390	1,390.32	742,507.40	0.02302	99.977
11	1,570	1,570.86	883,627.42	0.05478	99.945
12	1,634	1,634.01	932,338.99	0.00061	99.999
13	1,815	1,815.11	1,095,707.55	0.00606	99.994
14	1,878	1,878.43	1,157,256.93	0.02290	99.977
15	2,375	2,375.18	1,701,903.42	0.00758	99.992
16	2,669	2,669.42	2,110,541.19	0.01574	99.984
17	2,724	2,724.94	2,199,366.40	0.03451	99.965
18	2,471	2,471.25	1,835,295.67	0.01012	99.990
19	2,385	2,385.18	1,706,123.42	0.00755	99.992
20	1,868	1,868.43	1,152,796.93	0.02302	99.977
21	1,815	1,815.11	1,095,707.55	0.00606	99.994
22	1,632	1,632.34	931634.56	0.02083	99.979
23	1,356	1,356.40	720343.70	0.02950	99.971
24	1,311	1,311.67	702532.34	0.05111	99.949

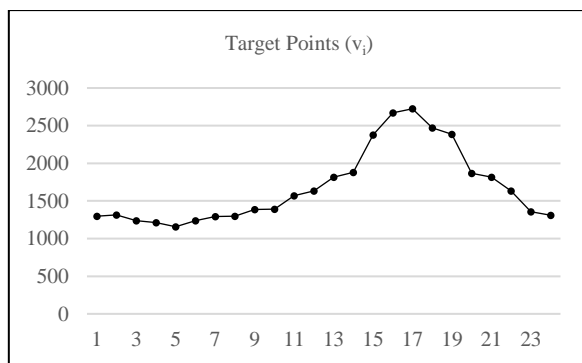


Fig. 4. Target Points (TP)

The accuracy is calculated using (10) to see the system performance.

$$Acc = \left(1 - \frac{x_i - v_i}{v_i} \right) * 100\% \tag{10}$$

Table 2 shown the target point of 1299 (v₁=1299, in column-2) testing. This technique shows the optimization result of 1299.5 (x₁=1299.5, in column-3). This shows that the accuracy of the proposed

technique for this condition is 99,962%. From Table 2, the average accuracy for the 24 target points is 99.97%.

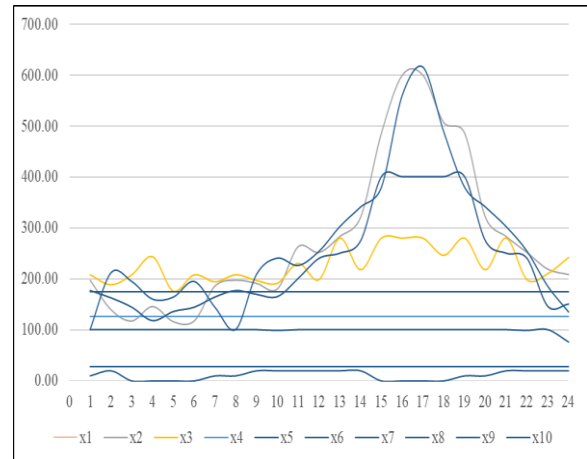


Fig. 5. Optimum points for each x

The accuracy of the proposed technique for reaching the target points is shown in Table 2, where ζ is set to 10,000, and the number of candidates M is 250. Figure 5 shows the result of each x. The values x are in the range of the limitation function. It is indicated that the proposed method guarantees that it does not violate the constraints. Table 3 compares the proposed techniques' accuracy and computation time for various threshold values (ζ).

Table 3. Accuracy of The LSAT and Computation Time

Threshold Value (ζ)	Average of Accuracy (%)	Average of Computation time (s)
10 ⁶	99.842	17
10 ⁵	99.945	23
10 ⁴	99.974	62

IV. DISCUSSION

This paper discusses the certainty of a new artificial LSAT method in reaching the optimum point or global minimum point. The test involves ten functions $y = f(x)$, with the objective function is to minimize the value of y. This technique is tested with 24 target points that must be achieved. The simulation results through testing at the 24 target points show that the proposed technique has an accuracy of 99.97% when ζ is set to 10,000. Meanwhile, Table 3 shows that the smaller the ζ value, the higher the accuracy, but it requires a longer computation time. So that to increase accuracy can be done by reducing the value of ζ .

Referring to Table 1, the optimization results for each of the x values shown in Fig. 5, do not violate the limits of x. It is caused this problem was anticipated in the algorithm of the LSAT.

The basic principle of LSAT, which has been explained in the research method section, shows that LSAT is a simple artificial method. This technique has

a different approach from other artificial methods, where this technique does not use a point-to-point approach to reach the optimal point but uses an area-to-area approach. Table 3 shows that the LSAT has a short computation time, wherein the computation time is approximately 1 minute.

For several reasons mentioned above, the LSAT can be used as an alternative method to solve optimization problems. An example of optimization in the power system is the economic dispatch (ED) problem. In ED problems, then v is the load demand that must be met by generator power, x is the power generated by each generator, y is the fuel costs function that should be minimized, and TP (1 to 24) is the hour during the day. In ED problems, the computation time is very important because the optimization results will be used for generator scheduling. If the computation time is long, the application program will not satisfy the scheduling usage.

V. CONCLUSION

The LSAT can be well applied to solve optimization problems. In addition to providing the guarantee of convergence so that it does not fall into local minimum conditions, LSAT also has several advantages: being simple, fast, and achieving a global minimum that will never violate all these constraints. The certainty of this convergence lies in this method. If candidates in the feasible area of iteration- k but candidates are outside the feasible area before the iteration, they are discarded. The average accuracy of the proposed method is 99.92%. Thus, the proposed method can solve optimization problems in the power system, especially in solving ED or Economic and Emission Dispatch (EED) problems. However, there is no research concerning the optimal value and randomization of the candidates. Thus, future research is needed to optimize the number of candidates and the randomization processes to obtain optimal computational time of simulation and optimal value.

REFERENCES

- [1] S. Sabach and M. Teboulle, *Lagrangian methods for composite optimization*, 1st ed., vol. 20. Elsevier B.V., 2019.
- [2] D. M. Devia Narvaez, G. C. Velez, and D. F. Devia Narvaez, "Application of the gradient method in the economic dispatch," *Contemp. Eng. Sci.*, vol. 11, no. 96, pp. 4761–4768, 2018, doi: 10.12988/ces.2018.89513.
- [3] S. Pan, J. Jian, H. Chen, and L. Yang, "A full mixed-integer linear programming formulation for economic dispatch with valve-point effects, transmission loss and prohibited operating zones," *Electr. Power Syst. Res.*, vol. 180, no. December 2019, p. 106061, 2020, doi: 10.1016/j.epsr.2019.106061.
- [4] Z. Feng, W. Niu, S. Wang, C. Cheng, and Z. Song, "Mixed integer linear programming model for peak operation of gas-fired generating units with disjoint-prohibited operating zones," *Energies*, vol. 12, no. 11, 2019, doi: 10.3390/en12112179.
- [5] N. Awadah, R. A. S. Ali, S. AlBaijan, G. Al-Qallaf, M. Al-Hassawi, and S. Kasap, "Dynamic Programming approach to unit commitment problem for Kuwait power generations," *Proc. Int. Conf. Ind. Eng. Oper. Manag.*, vol. 2018, no. JUL, pp. 1939–1947, 2018.
- [6] H. Zein, Y. Sabri, and A. Mashar, "Implementation of electricity competition framework with economic dispatch direct method," *Telkomnika*, vol. 10, no. 4, pp. 667–674, 2012, doi: 10.12928/telkomnika.v10i4.854.
- [7] B. M. S. M. Ramadan, T. Logenthiran, R. T. Naayagi, and C. Su, "Accelerated Lambda Iteration Method for solving economic dispatch with transmission line losses management," *IEEE PES Innov. Smart Grid Technol. Conf. Eur.*, no. Mli, pp. 138–143, 2016, doi: 10.1109/ISGT-Asia.2016.7796375.
- [8] M. Abu Siam, O. Mohamed, and H. Al-Nazer, "Comparative Study between Genetic Algorithms and Iterative Optimization for Economic Dispatch of Practical Power System," *Int. Rev. Electr. Eng.*, vol. 13, no. 2, p. 128, Apr. 2018, doi: 10.15866/iree.v13i2.13870.
- [9] L. Daniel and K. T. Chaturvedi, "A Crazy Particle Swarm Optimization with Time Varying Acceleration Coefficients for Economic Load Dispatch," *Int. J. Eng. Adv. Technol.*, vol. 9, no. 2, pp. 1205–1213, 2019, doi: 10.35940/ijeat.b3614.129219.
- [10] P. Wongchai and S. Phichaisawat, "Load feasible region determination by using adaptive particle swarm optimization," *Eng. J.*, vol. 23, no. 6, pp. 239–263, 2019, doi: 10.4186/ej.2019.23.6.239.
- [11] K. Chayakulkheeree, V. Hengsriratwat, and P. Nantivatana, "Particle swarm optimization based equivalent circuit estimation for on-service three-phase induction motor efficiency assessment," *Eng. J.*, vol. 21, no. 6 Special Issue, pp. 101–110, 2017, doi: 10.4186/ej.2017.21.6.101.
- [12] B. M. Hussein and A. S. Jaber, "Unit commitment based on modified firefly algorithm," *Meas. Control (United Kingdom)*, vol. 53, no. 3–4, pp. 320–327, 2020, doi: 10.1177/0020294019890630.
- [13] A. Y. Abdelaziz, E. S. Ali, and S. M. Abd Elazim, "Combined economic and emission dispatch solution using Flower Pollination Algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 80, pp. 264–274, 2016, doi: 10.1016/j.ijepes.2015.11.093.
- [14] G. Villarrubia, J. F. De Paz, P. Chamoso, and F. De la Prieta, "Artificial neural networks used in optimization problems," *Neurocomputing*, vol. 272, pp. 10–16, Jan. 2018, doi: 10.1016/j.neucom.2017.04.075.
- [15] A. N. Afandi *et al.*, "Designed Operating Approach of Economic Dispatch for Java Bali Power Grid Areas Considered Wind Energy and Pollutant Emission Optimized Using Thunderstorm Algorithm Based on Forward Cloud Charge Mechanism," *Int. Rev. Electr. Eng.*, vol. 13, no. 1, p. 59, Feb. 2018, doi: 10.15866/iree.v13i1.14687.
- [16] V. P. Sakthivel, M. Suman, and P. D. Sathya, "Nonconvex Economic Environmental Load Dispatch Using Fuzzy Based Squirrel Search Algorithm," *Int. J. Energy Convers.*, vol. 8, no. 2, p. 61, Mar. 2020, doi: 10.15866/irecon.v8i2.18593.

- [17] V. P. Sakthivel, M. Suman, and P. D. Sathya, "Environmental/Economic Dispatch Problem: Coulomb's and Franklin's Laws Based Optimization Algorithm," *Int. Rev. Electr. Eng.*, vol. 15, no. 5, p. 421, Oct. 2020, doi: 10.15866/iree.v15i5.18568.
- [18] "Application of Whale Optimization Algorithm for Environmental Constrained Economic Dispatch of Fixed Head Hydro-Wind-Thermal Power System," *Int. J. Eng. Adv. Technol.*, vol. 9, no. 1, pp. 5608–5616, Oct. 2019, doi: 10.35940/ijeat.A2261.109119.
- [19] F. C. K. and H. Vennila, "Economic and Emission Dispatch using Whale Optimization Algorithm (WOA)," *Int. J. Electr. Comput. Eng.*, vol. 8, no. 3, p. 1297, Jun. 2018, doi: 10.11591/ijece.v8i3.pp1297-1304.
- [20] H. Hardiansyah, J. Junaidi, and Y. Yandri, "Combined Economic Emission Dispatch Solution using Simulated Annealing Algorithm," *IOSR J. Electr. Electron. Eng.*, vol. 11, no. 05, pp. 141–148, May 2016, doi: 10.9790/1676-110502141148.
- [21] M. Li, W. Du, and F. Nian, "An adaptive particle swarm optimization algorithm based on directed weighted complex network," *Math. Probl. Eng.*, vol. 2014, 2014, doi: 10.1155/2014/434972.
- [22] J. Raharjo, H. Zein, and K. B. Adam, "Optimal economic load dispatch with prohibited operating zones using large to small area technique," *Int. J. Energy Convers.*, vol. 9, no. 1, pp. 29–34, 2021, doi: 10.15866/irecon.v9i1.19548.
- [23] R. Korah and J. R. P. Perinbam, "A Novel Coarse-to-Fine Search Algorithm for Motion Estimation," in *2006 IEEE International Conference on Industrial Technology*, 2006, pp. 1121–1126, doi: 10.1109/ICIT.2006.372325.