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A Method for Completing Economic Load Dispatch Using the Technique of Narrowing Down Area

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ABSTRACT Economic load dispatch solutions based on published methods, both conventional and artificial, have been very well-formulated through point-to-point movement methodologies to reach a convergence point. Iteration always starts from the starting point to obtain the following solution point, leading to the convergence point. This paper presents a new method to solve economic load dispatch problems by narrowing the minimum and maximum power limits between generator units. This idea approximates the solution point with a tiny space formed by the very narrow power limits of each generator. The methodology used is the distance between the minimum and maximum power limits of each generator divided into several segments. Then, the best segment is determined by the minimum total cost calculated based on the center point of the segment. Continue to the following iteration process until the best segment is the smallest. This iteration process is another artificial method that works without calculus calculations, so it does not depend on the objective function. This method has been validated using two generator units with differentiable objective functions, with calculation accuracy less than 0.00001 MW of the power distance of the generator limit, and the iteration stops at the 23^{rd} step. Furthermore, this method has been successfully applied to the nondifferentiable objective function, piecewise and valve point effects.

INDEX TERMS Economic load dispatch, narrow power limits, segment, tiny space.

I. INTRODUCTION

Economic dispatch problem (EDP) practices are always an interesting study. The EDP can generally be differentiated into differentiable EDPs and nondifferentiable EDPs. The objective function in the form of differentiable EDP is continuous and differentiable, generally quadratic. In contrast, the objective function in nondifferentiable EDP can be either noncontinuous or non-differentiable. Examples of nondifferentiable EDP objective functions are non-smooth functions, having prohibited operation zones and steps. The development of this objective function has prompted experts to study it. Conceptually, EDP is a simple optimization problem in a power system. All committed generator units are assumed to collect in one bus with a single load. The consequence of this concept is that transmission loss has been neglected. Conventionally, the ELD (economic load dispatch) problem is a differentiable problem, and the methods for solving it have been widely published. The conventional ELD problem has been defined by [1], which involves equivalence and inequality constraints. However, the actual operation of the power plant can cause undifferentiated ELD problems, such as a non-smooth objective function and the presence of POZ in the fuel cost curve [2]–[4]. This makes the EDP problem even more complicated because it changes its objective function. This method consists of an artificial network and a Lagrange multiplier. The methodology uses the artificial network to control the Lagrange parameter. However, it can repair the computation time, but information regarding its accuracy has not been discussed [2]. A solution of the non-convex optimization for ELD problems using the Fuzzy Technique studied by [3]. This technique has been

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successfully applied to the ELD problems, but the formulations are enough complex, and applying to POZ needs to advance study. Economic Dispatch (ED) problem solving by considering valve point effect (VPE), transmission loss, and restricted operating zone (POZ) has been studied by [3] using a full mixed-integer linear programming (FMILP) formulation. In this study, a reformulation trick is used, by converting the objective function into a set of traceable quadratic constraints [4].

Experts have published a few methods for solving EDP based on calculus methods (CMs) and artificial intelligent methods (AIMs). CMs are specially used for differentiable EDPs, as studied by [5]–[9]. The methodology developed by [5]–[8] is based on the LaGrange technique with its completion through iterative steps as in the lambda iteration, gradient, and Newton methods. In addition to CMs, there is also a direct method studied by [9]. This methodology is based on deriving mathematics to obtain formulas with straightforward solutions. The advantages are that the method can be applied to large systems and has the shortest computation time. However, the method is limited to objective functions in quadratic form only. The accuracy of the CMs is so high (the certainty of the solution falls on the global minimum point) that they are often used to validate the other methods (or AIMs). The optimal point is achieved by deriving the LaGrange function so that the CMs cannot resolve the nondifferentiable EDP.

Various AIMs have been published as in [10]–[31]. Based on artificial intelligence, two concepts have been developed, namely, point-to-point and area reduction. A point-to-point AIM is a method in the optimization process through a point-to-point approach to reach a solution point. These methods include the neural network method (NNM), particle swarm optimization (PSO), and genetic algorithm (GA). For AIM-based area reduction, the solution is obtained by reducing the viable area to a very small value.

NNM is based on the process of the human brain of working in parallel and exchanging information via the synaptic connectors on neurons. These neurons encapsulate all the information that comes to them, and if the result is higher than the given potential called an action potential, the neurons send pulses through the axons to the next stage. An artificial neural network consists of simple computing units (artificial neurons), and each unit is connected to other units via heavy connectors. Then, these units calculate the total input weight and know the output using the squashing function or activation function. The applications of this neural network have been studied by [10], while applications to EDP have been presented by [11] and [12]. Although NNM can be applied to complete EDP, a high-speed processor is needed because artificial nerves work in parallel. In addition, a large memory is required for data storage. In addition, there are no specific rules for determining an artificial neural network structure; a suitable network structure is achieved through experience and trial and error. Therefore, the speed and memory of computers will be a problem if NNM is implemented in large systems.

PSO is also overgrowing, as studied by [13]–[17]. The methodology starts from a randomly selected initial spot (initial point); continues to scatter many candidates around it at a certain distance (step-length); then, the best candidate is selected as the next spot until a solution point is obtained. This method will not be accurate if the local minimum is close to the initial point chosen because the method can ascertain that the solution point falls on that local minimum. Accuracy is also dependent on the number of candidates; the optimal number of candidates is still uncertain. Parameter control is required in each iteration step, and the processed dataset is vast, which will influence the computation time when applied to large systems.

GA is a metaheuristic based on the process of natural selection. The applications for generating high-quality solutions in optimization and search problems rely on biological operators such as mutation, crossover, and selective operators. The method has been applied to solve EDP, as studied by [18]–[25]. Similar to PSO, GA is no guarantee of finding global maxima. A decent-sized population and many generations must be processed so that it is burdensome to work on computers to obtain solutions over a long time, especially for large systems. GA also needs fine-tuning all parameters in determining mutation, which is often just trial and error.

The other methods stress the complexity of the optimization problem presented by [27]–[31]. The model with the conditional value at risk recourse function [27] has solved the robust dynamic economic dispatch distribution problem. Inspiration by the moth flame moving toward the moon was developed by [28]. Optimizing an electric power system is very complex, so a heuristic method is needed to solve it. The basic heuristic optimization techniques for application to power systems have been presented by [29]. The complicated methods used to solve optimal power flow were studied by [30] and [31]. The Newton-Rapson method determines power flows based on PSO, which has been satisfactorily developed [26]. These methods are also artificial; they will face problems if applied to large systems. The other method is based on calculus, the interior point, presented by [31]. The interior algorithm has been developed through predictor-corrector and reduction techniques to work very fast and to be applicable for large systems. Nevertheless, the method cannot be applied to nondifferentiable optimizations.

All methods mentioned above use a point-to-point optimization process to reach a convergence solution. The following are published based on reducing feasible areas developed by [32]–[35]. This method is commonly used to detect two-dimensional image objects in telecommunication, as studied by [32]–[34], with a coarse-to-fine technique. The feasibility area is divided into grids, and each grid is tracked to determine the best grid. Furthermore, this best grid reduces until a tiny grid is obtained, representing a convergent solution. The development of this multidimensional method was presented by [35]. The purpose of this development is to complete the EDP. The multidimensional feasibility area is formed by the minimum and maximum power limits of the generator units. The feasibility area is divided into several areas with the same dimensions. Each area represents a candidate with a coordinate point at the center. In addition to determining the best candidate, the candidate must also meet the power balance between total power generation and load.

Fig. 1 shows a difference illustration between the point-to-point and reducing area methods. Based on the point-to-point method in Fig. 1a, the iteration step starts from the initial point (x_0), and through iteration steps, the solution points will lead to the convergence point (x_{op}). As the reducing area in Fig. 1b shows, the iteration step starts from the feasibility area and reduces to the best area-1 and best area-2. This method will successfully yield when the optimal points are in their respective best areas.

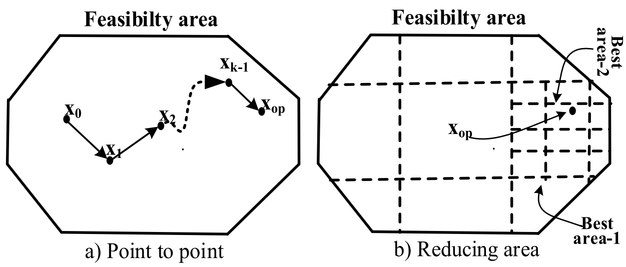

FIGURE 1. Iteration processes in: (a) point-to-point; (b) reducing area methodologies.

This paper develops a new method, called the technique of narrowing down area (ToNDA), to work for all kinds of objective functions (differentiable or not). The methodology is to narrow the power distance of the generator limits (PDGL) of each generator, expressed in (1), until it approaches the solution point, P_{op}, as illustrated in Fig. 2.

$$X_i = \hat{P}_i - \check{P}_i \tag{1}$$

where X_i is the PDGL of Generator i. $\hat{P}_i$ and $\check{P}_i$ are the maximum and minimum power limits of Generator-i. Meanwhile, feasible areas are formed by PDGL from all generators.

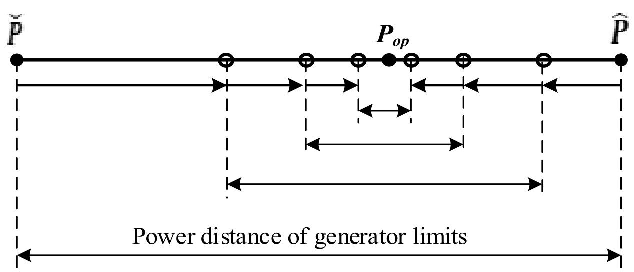

FIGURE 2. Iteration process in ToNDA methodology.

In each iteration, the PDGL is divided into segments, and each segment boundary is represented as a solution point. Once the best candidate is obtained, the PDGL is narrowed to reduce that candidate. The iteration process continues to update the PDGL (after being narrowed down from the previous one) until the smallest segments are reached. The smallest space is formed in a feasible area from a very narrow PDGL. where the smallest space can be stated as a solution point (convergence point).

While the narrowing process can be explained in Fig. 3, if the PDGL of each generator is divided into k−1 segments, k potential solution points (P^1, P^2, ..., P^{k-1}, P^k) of each generator are obtained, where the first point (P^1) is at $\check{P}$, and the endpoint (P^k) is at $\hat{P}$. For n generators, the candidate is a vector of dimension n, where the elements are the potential solution points of each generator and are expressed in Equation (2).

$$Cd_i = x(P_1^i, P_2^j, \ldots, P_{n-1}^l, P_n^m) \tag{2}$$

where cd_i is as a candidate and P_1^i is,

$$P_1^i \in \left\{P_i^1, P_i^2, \ldots, P_i^{k-1}, P_i^k\right\} \tag{3}$$

The candidates formed must meet the balance of power, namely:

$$P_1^i + P_2^j + \cdots + P_{n-1}^l + P_n^m = P_D \tag{4}$$

where P_D is total load. Then the best candidate (Cd_b) is selected when the total cost is least compared to the others. Area reduction is carried out by establishing a new generator power limit involving the left and right segments. However, the new minimum or maximum power limit should not violate the initial minimum or maximum power limit.

After obtaining Cd_b or point (P^{j+2}) on the generator, as shown in Fig. 3, which is marked with **x**, the distance of the power limit is narrowed by involving the left and right segments. Narrowing the distance of the power limit aims to anticipate the possibility of the convergence point outside the new distance of generator limits, such as the convergent point (P_{op}) seen in Fig. 3. In this case, the convergence point is improbable to be outside the new distance of the generator limits.

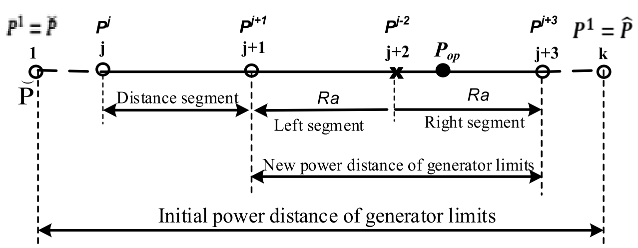

FIGURE 3. Narrowing process.

Next, the generator limits are updated through Equations (5) and (6).

$$\check{P}^{new} = P^{j+2} - Ra, \quad \check{P}^{new} \geq \check{P}^{old} \tag{5}$$
$$\hat{P}^{new} = P^{j+2} + Ra, \quad \hat{P}^{new} \leq \hat{P}^{old} \tag{6}$$

where $\check{P}^{new}$ and $\hat{P}^{new}$ are the new generator limits, $\check{P}^{old}$ and $\hat{P}^{old}$ are the old generator limits. Ra is a quantity to determine the size of the area reduction. The smaller the Ra value is, the larger the reduced area. For a very large Ra it will allow the solution point to be outside the minimized area, so it is not accurate. This inaccuracy is shown in Table 2 with a Vra value of more than 80%. It is certain that a small Ra value (≤50%) in the table can guarantee accuracy.

II. ToNDA METHODOLOGY

Generally, the EDP consists of an objective function, some inequality constraints, and an equality constraint, written in (7), (8), and (9), respectively.

$$TC = \sum_{i=1}^{n} F_i \tag{7}$$

$$\check{P}_i \leq P_i \leq \hat{P}_i, \quad i = 1, 2, \ldots, n \tag{8}$$

$$\sum_{i=1}^{n} P_i - P_D = 0 \tag{9}$$

where TC is the total cost, P_i is the active power generator, and F_i is the function of fuel cost to generator output power and is expressed by (10).

$$F_i = f_i(P_i) \tag{10}$$

Then, $\mathcal{S}_0$ is defined as the initial space (initial feasible area) formed by generator limits from n generator units so that this space will have n dimensions, as written in (11).

$$\mathcal{S}_0 = \left\{ \left(\check{P}_1^0, \hat{P}_1^0\right), \left(\check{P}_2^0, \hat{P}_2^0\right), \ldots, \left(\check{P}_n^0, \hat{P}_n^0\right) \right\} \tag{11}$$

The initial PDGL of the generator is defined in (1) for generator i expressed by (12).

$$\mathcal{X}_i^0 = \hat{P}_i^0 - \check{P}_i^0 \tag{12}$$

If $\mathcal{X}_i^0$ is divided into k−1 segments, the number of k points will be obtained as the potential solutions that are spread evenly between the minimum and maximum limits. Where $\hat{P}_i^0$ and $\check{P}_i^0$ are the maximum and minimum initial power limits. Based on the description, an initial segment length of generator i ($\mathcal{L}s_i^0$) is written in (13) is obtained.

$$\mathcal{L}s_i^0 = \frac{\hat{P}_i^0 - \check{P}_i^0}{k-1} \tag{13}$$

For n generators, a candidate is formed; for example, $x_1^0(P_1^{0,i}, P_2^{0,j}, \ldots, P_{n-1}^{0,l}, P_n^{0,m})$ is selected in $\mathcal{S}_0$ that meets (9) so that $P_n^{0,m}$ can be calculated through (14).

$$P_n^{0,m} = P_D - P_1^{0,i} - P_2^{0,j} - \cdots - P_{n-1}^{0,l} \tag{14}$$

For the kth iteration step, equation (14) becomes,

$$P_n^{k,m} = P_D - P_1^{k,i} - P_2^{k,j} - \cdots - P_{n-1}^{k,l} \tag{15}$$

where $P_1^{k,i}$ is the power generator 1, it is in segment i at the k iteration step which satisfies the power balance in equation (4) or (14).

This last equation ensures that the equality constraint in (9) is consistently met. In this case, the segments of an nth generator are not the same length because the value of $P_n^{k,m}$ must meet (14). From the explanation above, some candidates will be obtained, namely, $\mathcal{J}_c$ and expressed in (15).

$$\mathcal{J}_c = k^{n-1} \tag{16}$$

Suppose Cd_1^0 is a potential candidate. If Generator 1 to Generator n−1 is set with their solution potential points at the minimum power limit, the solution potential point for Generator n is:

$$P_n = P_D - \check{P}_1 - \check{P}_2 - \cdots - \check{P}_{n-1} \tag{17}$$

So, Cd_1^0 is:

$$Cd_1^0 = x\left(\check{P}_1, \check{P}_2, \ldots, \check{P}_{n-1}, P_n\right) \tag{18}$$

where $Cd_1^0 \in \mathcal{S}_0$. Of all the candidates distributed to $\mathcal{S}_0$, then the best candidate is chosen with a minimum value of total cost (TC_b^k) and it falls on Cb_b^k, expressed in (19). All the candidates are distributed to the appropriate areas.

$$Cb_b^k = \mathbf{x}\left(P_{1-b}^k, \ldots, P_{n-b}^k\right) \tag{19}$$

while Cb_b^k can be determined by (19).

$$Cb_b^k = Min\left\{TC_1^k, TC_2^k, \ldots, TC_n^k\right\} \tag{20}$$

Next, $\mathcal{S}_0$ can be reduced to $\mathcal{S}_1$ (a new space), where $\mathcal{S}_1 \in \mathcal{S}_0$. $\mathcal{S}_0$ is obtained by narrowing the limits of generators and is formulated in (21) and (22).

$$\check{P}_i^k = P_i^{k-b} - \mu\mathcal{L}s^k \tag{21}$$

$$\hat{P}_i^k = P_i^{k-b} + \mu\mathcal{L}s^k \tag{22}$$

where $\check{P}_i^k$ and $\hat{P}_i^k$ are the minimum and maximum power limits of the iteration k for Generator i. The greater the value of μ is, the slower the narrowing of the generator power limit, where:

$$0 \leq \mu \leq 0.5(k-1) \tag{23}$$

From (12), (22), and (23), the value of $\mathcal{X}_0$ can be determined, namely:

$$\mathcal{X}_0^{new} = 2\mu\mathcal{L}s, \quad \mathcal{X}_0^{new} < \mathcal{X}_0^{old} \tag{24}$$

So, the area reduction speed (Vra) is:

$$Vra = \frac{\mathcal{X}_0^{ald} - \mathcal{X}_0^{new}}{\mathcal{X}_0^{old}} 100\% \tag{25}$$

The process of narrowing the generator limit continues until it becomes tiny, namely, $\mathcal{X}_{small}$. For example, in the kth step, the space of the feasible area, $\mathcal{S}_k$, can already be considered to represent the solution point, where the value of $\mathcal{X}_{small}$ is calculated by (26).

$$\mathcal{X}_{small} = max\left\{\mathcal{X}_1^k, \mathcal{X}_2^k, \ldots, \mathcal{X}_n^k\right\} \leq \varepsilon \tag{26}$$

where ε is a very small number as the convergence. Algorithm steps can explain detailed procedures of ToNDA through a simple example of EDP consisting of two generator units.

Total cost in (27), power of the generator limits in (28) and (29), and equality constraint in (30).

$$TC = (200+10P_1+0,5P_1^2)+(300+5P_2+P_2^2) \quad (27)$$

$$50 \leq P_1 \leq 100 \quad (28)$$

$$10 \leq P_2 \leq 50 \quad (29)$$

$$P_1 + P_2 = 110 \quad (30)$$

The first step is to determine the desired number of segments (for example, four segments or k = 5 and $\mu = 1$), obtaining 16 rectangles and 25 points as much as possible, as shown in Fig. 4. Two horizontal axes present the generator power of P_1 (first generator) and P_2 (second generator). In contrast, the vertical axis presents the total cost. The ABCD rectangle (area 2500 MW^2) is $\mathcal{S}_0$ from the initial minimum and maximum power limits of the generators. The PB-line is to be formed by equality constraint stating as power balance, and all candidates must lie on this line.

From Fig. 4, there are five potential candidates of 25 points in space $\mathcal{S}_0$ (PB line), i.e., Cd_1, Cd_2, Cd_3, Cd_4, and Cd_5. From the potential candidates are chosen the best candidate that has a minimum total cost, where the minimum cost falls on the candidate Cd_4 (said to be the first best candidate, BC_1). Then, the PDGLs are narrowed based on (21) and (22) to be $A_1B_1C_1D_1$, as shown in Fig. 4 and Fig. 5. With the same procedures, five new candidates are obtained, and the best candidate is BC_2 and the new area ($A_2B_2C_2D_2$), where the new area is less than the old area ($A_1B_1C_1D_1$).

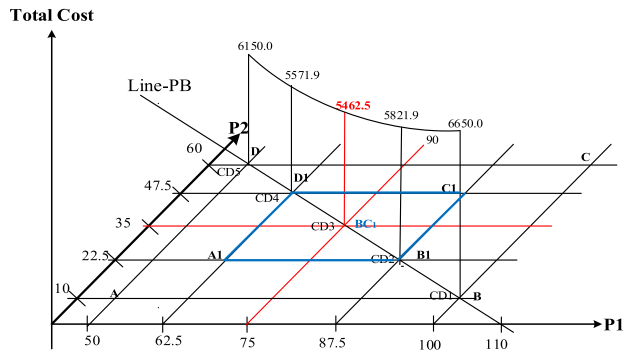

FIGURE 4. Plot the candidates in the initial space.

The results of all steps are loaded in Table 1. The total cost going down along with narrowing feasible area from $A_0B_0C_0D_0$ is 50 × 40 MW^2 = 2000 MW^2 to $A_{23}B_{23}C_{23}D_{23}$ is $2.88x10^{-11}MW^2$ in the 23rd step. Where the PDGL of Generator 1 of 50 MW decreases to 0.0000060 MW, and the PDGL of Generator 2 decreases from 40 MW to 0.0000048 MW.

The iteration will stop after reaching the convergence point with the largest PDGL value of less than 0.00001 MW, namely, 50 MW from Generator-1. In this simulation, convergence is reached in the 23rd step with an accuracy of 5 digits of decimal number accuracy and a total cost of $5445. 83333. Accurate solution points fall in P_1 = 7166762 ± 0.0000060 MW and P_2 = 38.33238 ± 0.0000048 MW

TABLE 1. Results of simulation analysis.

Iteration Step	$\check{P}_1$ (MW)	P_1^b (MW)	$\hat{P}_1$ (MW)	X_{0-1} (MW)	$\check{P}_2$ (MW)	P_2^b (MW)	$\hat{P}_2$ (MW)	$\mathcal{X}_2$ (MW)	Total Cost (TC)	Reduce Area (%)
0	50.00000	-	100.00000	50.000000	10.00000	-	50.00000	40.000000	-	-
1	62.50000	75.00000	87.50000	25.000000	25.00000	35.00000	45.00000	20.000000	5462.500000	50.00
2	62.50000	68.75000	75.00000	12.500000	36.25000	41.25000	46.25000	10.000000	5458.593750	50.00
3	68.75000	71.87500	75.00000	6.2500000	35.62500	38.12500	40.62500	5.000000	5445.8984375	50.00
4	70.31250	71.87500	73.43750	3.1250000	36.87500	38.12500	39.37500	2.500000	5445.8984375	50.00
5	70.09375	71.87500	72.65625	1.5625000	37.50000	38.12500	38.75000	1.250000	5445.8984375	50.00
6	71.09375	71.48438	71.87500	0.7812500	38.20313	38.51563	38.82813	0.625000	5445.8831787	50.00
7	71.48438	71.67969	71.87500	0.3906250	38.16406	38.32031	38.47656	0.312500	5445.8335876	50.00
8	71.58203	71.67969	71.77734	0.1953125	38.24219	38.32031	38.39844	0.156250	5445.8335876	50.00
9	71.63086	71.67969	71.72852	0.0976563	38.28125	38.32031	38.35938	0.078125	5445.8335876	50.00
10	71.63086	71.65527	71.67969	0.0488281	38.32520	38.34473	38.36426	0.039063	5445.8335280	50.00
11	71.65527	71.66748	71.67969	0.0244141	38.32275	38.33252	38.34229	0.019531	5445.8333343	50.00
12	71.66128	71.66748	71.67358	0.0122070	38.32764	38.33252	38.33740	0.009766	5445.8333343	50.00
13	71.66443	71.66748	71.67053	0.0061035	38.33008	38.33252	38.33496	0.008448	5445.8333343	50.00
14	71.66443	71.66595	71.66748	0.0030518	38.33282	38.33405	38.33527	0.002441	5445.8333341	50.00
15	71.66595	71.66672	71.66748	0.0015259	38.33267	38.33328	38.33389	0.001221	5445.8333333	50.00
16	71.66634	71.66672	71.66710	0.0007629	38.33298	38.33328	38.33359	0.000610	5445.8333333	50.00
17	71.66653	71.66672	71.66691	0.0003815	38.33313	38.33328	38.33344	0.000305	5445.8333333	50.00
18	71.66653	71.66662	71.66672	0.0001907	38.33330	38.33338	38.33345	0.000153	5445.8333333	50.00
19	71.66663	71.66667	71.66672	0.0000954	38.33329	38.33333	38.33337	0.000076	5445.8333333	50.00
20	71.66665	71.66667	71.66669	0.0000477	38.33331	38.33333	38.33335	0.000038	5445.8333333	50.00
21	71.66666	71.66667	71.66668	0.0000238	38.33332	38.33333	38.33334	0.000019	5445.8333333	50.00
22	71.66666	71.66666	71.66667	0.0000119	38.33333	38.33334	38.33334	0.000009	5445.8333333	50.00
23	71.66666	71.66667	71.66667	0.0000060	38.33333	38.33333	38.33334	0.000005	5445.8333333	50.00

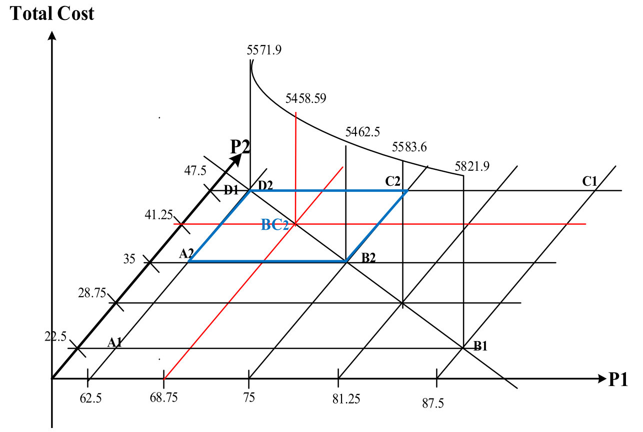

FIGURE 5. Plot the candidates in the $A_1B_1C_1D_1$.

TABLE 2. The effect of area reduction on the number of iterations.

Number of Iterations	P_1 (MW)	P_2 (MW)	Total Cost ($)	Reduction Area (%)
301	71.66667	38.33333	5445.83333	5
147	71.66667	38.33333	5445.83333	10
95	71.66667	38.33333	5445.83333	15
70	71.66667	38.33333	5445.83333	20
54	71.66667	38.33333	5445.83333	25
44	71.66667	38.33333	5445.83333	30
36	71.66667	38.33333	5445.83333	35
31	71.66667	38.33333	5445.83333	40
26	71.66667	38.33333	5445.83333	45
23	**71.66667**	**38.33333**	**5445.83333**	**50**
20	71.66667	38.33333	5445.83333	55
17	71.66667	38.33333	5445.83333	60
16	71.66667	38.33333	5445.83333	65
13	71.66667	38.33333	5445.83333	70
12	71.66667	38.33333	5445.83333	75
10	71.66667	38.33333	5445.83333	80
9	71.63051	38.36949	5445.83529	85
7	72.22222	37.77778	5446.29630	90
6	73.68421	36.31579	5451.93906	95

When comparing the ToNDA method and the calculus method for 5 digits of decimal number accuracy, the same results were obtained, namely, $P_1^b = 71.66667$ MW, $P_2^b = 38.333343$ MW, and TC = $5445.83333.

Vra affects the number of iterations, as shown in Table 2, where the larger *Vra* is, the fewer iteration steps. However, an area reduction of more than 80% causes the calculation to be inaccurate. From Table 2, the smaller area reduction will guarantee the accuracy, but the iteration step required is getting larger. For example, a *Vra* value of 5% requires 301 iteration steps. This paper suggests the *Vra* value of 50% as a reconciliation so that the accuracy of the calculation results is guaranteed.

III. ALGORITHM AND FLOWCHART OF ToNDA

The ToNDA described above can be applied to the various objective functions, differentiable and nondifferentiable. The procedure steps of solving EDP can be explained in detail by the flowchart in Fig. 6. The calculation process starts with determining the segment distance of the limits of each power generator. The generator range (between the max limit and the min limit) is divided into several segments/areas. Each segment is represented by a point located in the middle of the area to determine the best area indicated with the lowest cost. The, a reduced area is formed involving the best area and the neighboring area.Then, the process is continued by choosing potential candidates who had to meet equality and inequality constraints and then determining the best candidate with the minimum total cost. Finally, the power limits of generators are narrowed based on the point of the best candidate, where the position of the point is the center. Convergence will be reached if the maximum distance of the power limits of the generator is smallest and satisfies (24). In this paper, the best very small area that is considered to represent the point of convergence is the area with a size of 0.012accuracy of 0.001.

The algorithm of the ToNDA method is written step by step as:

1. Start
2. Input data (number of generators, cost characteristics, generator power limit)
3. Set the maximum and minimum power limits of each generator.
4. Calculate the PDGL for each generator using (12).
5. Set the value of k
6. The PDGL is divided into k−1 to obtain segment; for example, k = 5 to obtain 4 segment
7. Calculate length segment through (13)
8. Determine k potential solution points that fall on the segment boundaries in the PDGL for each generator.
9. Determine candidates that meet balance of power in equation (4) or (14). Candidates for each generator are determined from the smallest k sequence starting from the first generator to the (n−1) generator. Candidates for the nth generator are determined later through equation (15).
10. Determine the best candidate with the lowest total cost of generation from all candidates.
11. Set the *Vra* (recommended 50%).
12. Create a new PDGL with the best candidate as the center involving neighboring segments.
13. If the minimum limit obtained is less than the initial minimum limit, then the minimum limit is set equal to the initial minimum.
14. If the maximum limit obtained is greater than the initial maximum limit, then the maximum limit is set equal to the initial maximum limit.
15. If the largest PDGL has been reduced to be the smallest value (for example, 0.00001 MW), then the convergence point is reached, and go to Step 16. Otherwise, go back to Step 6.
16. Finish

IV. SIMULATION AND ANALYSIS

The ToNDA work performance and this method were tested with the EDP with a fuel cost model in the form of a piecewise quadratic cost function and valve point effect. Simulation for

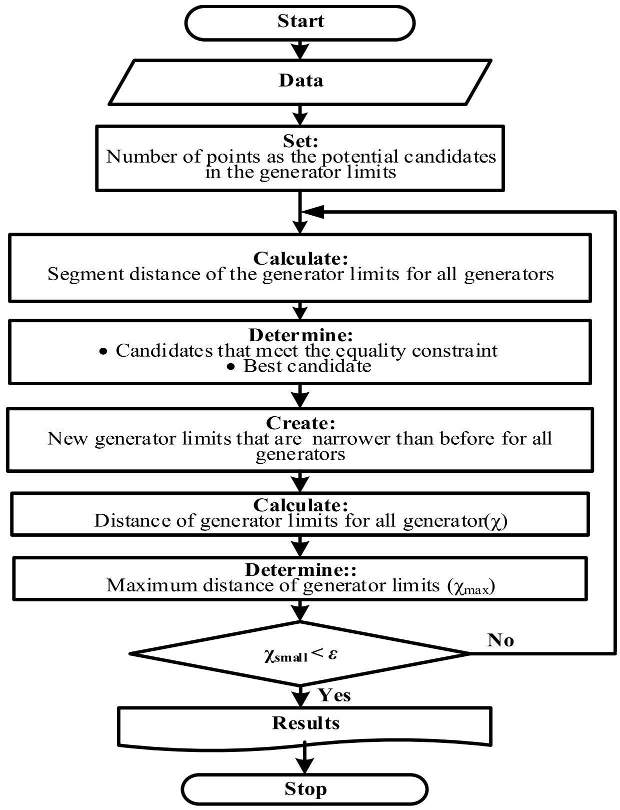

FIGURE 6. Flowchart of ToNDA.

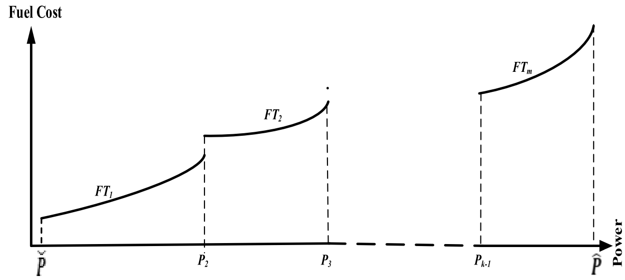

FIGURE 7. Characteristics of the generating unit with various fuel types.

TABLE 3. Economic dispatch results of three load demands with three fuel types.

Unit	Load demand					
	2500 MW		2600 MW		2700 MW	
	Fuel Type	P_{OPT} (MW)	Fuel Type	P_{OPT} (MW)	Fuel Type	P_{OPT} (MW)
1	2	212.5	2	212.5	2	212.5
2	1	185.0	1	230.0	1	230.0
3	3	350.0	3	350.0	3	350.0
4	3	223.5	3	223.5	3	223.5
5	1	265.0	1	265.0	1	265.0
6	3	220.0	3	220.0	3	220.0
7	1	275.0	1	275.0	1	275.0
8	3	223.5	3	223.5	3	223.5
9	1	285.0	1	362.5	3	440.0
10	1	260.5	1	238.0	1	260.5
Total Cost ($/h)	519.895		564.990		612.835	

TABLE 4. Comparison of six methods.

Method	Total fuel cost ($/h)		
	2500 MW	2600 MW	2700 MW
SAMF	526.24	574.78	623.88
PSO	-	-	623.81
HM	526.70	574.03	625.18
HNN	526.13	574.26	626.12
HGA	526.24	574.38	623.81
ToNDA	**519.90**	**564.99**	**612.84**

EDP with a piecewise quadratic cost function uses a 10-unit system. In comparison, simulation for VPE uses two size systems, a 13-unit system, and a 40-unit system.

A. EDP WITH PIECEWISE QUADRATIC FUEL COST FUNCTION

The mathematical model of the fuel cost function is in piecewise quadratic forms depicted in Fig. 7 and formulated in (31). The case study uses a 10-unit system with three fuel types obtained from [36]. The ToNDA successfully simulated the case for three load demands of 2500 MW, 2600 MW, and 2700 MW, and the detailed results are presented in Table 3.

$$f(P) = \begin{cases} a_{i,1} + b_{i,1}P_i + c_{i,1}P_i^2, & \check{P}_i \le P_i < P_{i,1} \\ a_{i,2} + b_{i,2}P_i + c_{i,2}P_i^2, & P_{i,1} \le P_i < P_{i,2} \\ \vdots & \\ a_{i,k-1} + b_{i,k-1}P_i + c_{i,k-1}P_i^2, & P_{i,k-1} \le P_i < \hat{P}_i \end{cases} \quad (31)$$

The simulation uses the Laptop Asus core i3 using the Fortran Programming Language. For an error rate of 0.0001 MW, the iteration stops at the 19th step with a CPU time of 3.74 seconds.

Calculation results of the EDP for the other methods are obtained from [36], namely, Sequential Approach with Matrix Framework (SAMF), Hierarchical Method (HM), Hopfield Neural Network (HNN), Adaptive Hopfield Neural Network (AHNN), and Hybrid Genetic Algorithm (HGA). A detailed comparison of the results is presented in Table 4.

Table 4 shows that the reference methods give almost no different results for load demands of 2500 MW, 2600 MW, or 2700 MW. The ToNDA method provides better results than the results of the reference methods. When referring to the SAMF results, the ToNDA method provides a lower total cost with an average fuel savings of 9.06 $/h or 1.55% (detailed in Table 5).

Fuel savings will increase when the load demand is greater; the percentage of fuel savings increases from 1.12% (load demand of 2500 MW) to 1.80% (load demand of 2700 MW). This fuel savings shows that the ToNDA method is always accurate even though the load demand is increasing.

Based on Table 4, the proposed method has a performance improvement of 10.97 $/h or 1.7586% against the best comparison method (PSO or HGA), which costs 623.81.

TABLE 5. Fuel saving refer to SAMF method.

Load Demand	Fuel Cost Saving ($/h)	Percentage Cost Saving (%)
2500 MW	6.34	1.20
2600 MW	9.79	1.70
2700 MW	11.05	1.77
Average	526.70	1.55

B. EDP WITH VPE

1) THE 13-UNIT SYSTEM

EDP simulation with VPE uses the IEEE testing system. The simulations carried out are for two systems with different sizes, namely, a system of 13 units and 40 units [37] with a demand load of 1800 MW and 10500 MW, respectively. Data of the 13-unit system and ToNDA results are presented in Table 6. The optimal power of generators (P_{opt}) is not out of power limits ($\check{P}$ and $\hat{P}$). Under this optimal condition, the VPE is 13.9829 $/h caused by the second unit of 12.3762 $/h. The optimal condition, fuel, and VPE costs must be minimized. The coefficient e is so large that the cost of VPE is minimized as low as possible. Therefore, the high fuel units will be optimal at the minimum power limit, the VPE cost is zero (5, 6, and 7 units) or above the minimum power limit, and the VPE cost is close to zero (4 units). The lowest fuel units will be optimal around the maximum limit, and the VPE cost is close to zero (unit 1).

Balance power between generating and load demand is shown by the IPSO-TVAC, HCRO-DE, DSD, and ToNDA methods. There are four different solution points shown in Table 7, namely, the results of QPSO (SSA, IPSO-TVAC, HCRO-DE, and DSD) and (HGA and FAPSO-VDE) ToNDA. The result of the SSA method is smallest compared to the IPSO-TVAC, HCRO-DE, and DSD methods, but the power is not balanced. The DSD method shows the best results (total cost of $17963.29/h) with balanced power compared to the HGA method at different solution points. The SHDE method (total cost of $17963.891/h) is better than the HGA method because it satisfies the power balance. The power balance must be satisfied because small power changes significantly affect the results. For example, unit 4 with the power is 109.7453 MW at the cost of $1129.5971/h, when the power increases to 0.1 MW (to 109.8453 MW), the cost reduces to 1129.4972 $/h. The ToNDA method yields a different solution point, but the total cost of 17974.67$/h

TABLE 6. Results for the 13-system unit with VPE.

Unit	$\check{P}$ (MW)	$\hat{P}$ (MW)	a	b	c	e	f	P_{opt}(MW)	Fuel Cost ($/h)	VPE ($/h)
1	0	680	550	8.1	0.00028	300	0.035	628.3185	5749.919	0.0003
2	0	360	309	8.1	0.00056	200	0.042	297.7250	2770.211	12.3762
3	0	360	307	8.1	0.00056	200	0.042	224.3447	2152.377	0.4601
4	60	180	240	7.74	0.00324	150	0.063	109.7453	1128.451	1.1458
5	60	180	240	7.74	0.00324	150	0.063	60.0000	716.064	0.0000
6	60	180	240	7.74	0.00324	150	0.063	60.0000	716.064	0.0000
7	60	180	240	7.74	0.00324	150	0.063	60.0000	716.064	0.0000
8	60	180	240	7.74	0.00324	150	0.063	109.8665	1129.476	0.0005
9	60	180	240	7.74	0.00324	150	0.063	60.0000	716.064	0.0000
10	40	120	126	8.6	0.00284	100	0.084	40.0000	474.544	0.0000
11	40	120	126	8.6	0.00284	100	0.084	40.0000	474.544	0.0000
12	55	120	126	8.6	0.00284	100	0.084	55.0000	607.591	0.0000
13	55	120	126	8.6	0.00284	100	0.084	55.0000	607.590	0.0000
Total	550	2960						1800.0000	17958.960	13.9829

TABLE 7. Comparison results for 13-unit test system with VPE.

Unit	QPSO	SSA	IPSO-TVAC	HCRO-DE	DSD	SHDE	HGA	FAPSO-VDE	ToNDA
	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)
1	538.5600	628.31788	628.3185	628.3185	628.3185	628.3172	628.3185	628.3185	628.3185
2	224.7000	149.57315	149.5996	149.5930	149.5997	149.5986	222.7491	222.7490	297.7250
3	150.0900	224.38835	222.7489	222.7559	222.7491	222.7987	149.5996	149.5990	224.3447
4	109.8700	109.86655	109.8666	109.8665	109.8666	109.8673	109.8665	109.8665	109.7453
5	109.8700	109.86652	109.8666	109.8665	109.8666	109.8418	109.8665	109.8665	60.0000
6	109.8700	109.86592	109.8666	109.8665	109.8666	109.8641	109.8665	109.8665	60.0000
7	109.8700	109.86439	109.8666	109.8665	109.8666	109.8547	109.8665	109.8665	60.0000
8	159.7500	109.86644	109.8666	109.8665	109.8666	109.8576	109.8665	109.8665	109.8665
9	109.8700	60.00000	60.0000	60.0000	60.0000	60.0000	60.0000	60.0000	60.0000
10	77.4100	40.00000	40.0000	40.0000	40.0000	40.0000	40.0000	40.0000	40.0000
11	40.0000	40.00000	40.0000	40.0000	40.0000	40.0000	40.0000	40.0000	40.0000
12	55.0100	55.00000	55.0000	55.0001	55.0000	55.0000	55.0000	55.0000	55.0000
13	55.0100	55.00000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000
Tot. Power	1849.8800	1801.60920	1800.0000	1800.0000	1800.0003	1800.0000	1799.9997	1799.9990	1800.0000
Tot. Cost	18398.8480	17963.7660	17963.8330	17963.8610	17963.8290	17963.8910	17963.8290	17963.8290	17972.9434

TABLE 8. Test results for 40-unit system with VPE.

Unit	P_{opt}(MW)	Cost ($/hr.)	Unit	P_{opt}(MW)	Cost ($/hr.)
1	110.7998	925.1	21	533.2790	5071.29
2	110.7998	925.1	22	533.2790	5071.29
3	97.3999	1190.55	23	533.2790	5071.29
4	179.7000	2143.48	24	533.2790	5071.29
5	87.8000	706.5	25	533.2790	5071.29
6	139.9980	1596.46	26	533.2790	5071.29
7	259.6000	2612.88	27	10.0000	1140.52
8	284.6000	2779.84	28	10.0000	1140.52
9	284.6000	2798.23	29	10.0000	1140.52
10	130.0000	2502.07	30	87.8000	706.50
11	94.0000	1893.31	31	190.0000	1643.96
12	94.0000	1908.17	32	190.0000	1643.96
13	214.7600	3792.08	33	190.0000	1643.96
14	394.2800	6414.88	34	164.8000	1585.55
15	394.2800	6436.6	35	200.0000	2043.73
16	394.2800	6436.6	36	194.4270	1985.75
17	489.2800	5296.72	37	109.9980	1220.15
18	489.2800	5288.78	38	110.0000	1220.17
19	511.2790	5540.93	39	110.0000	1220.17
20	511.2790	5540.91	40	511.2840	5541.03
Load Demand = 10500 MW and Total Cost = $121412.87					

TABLE 9. Comparison results of 9 methods for IEEE 40 units with VPE.

No.	Method	Total Cost ($/hr.)
1	SSA	121412.55
2	QPSO	121448.21
3	HGA	121418.27
4	IPSO-TVAC	121412.54
5	FAPSO-VDE	121412.56
6	ACRO-DE	121412.55
7	DSD	121412.53
8	CCPSO	121412.54
9	FMILP	121412.54
10	**ToNDA**	121412.87

is almost equal to the others, except for the QPSO method (18398.848 $/h). For quadratic and the results of various fuel types in Table 4, the proposed method is competitive, which gives 1.7586% better results than the best comparison method (PSO or HGA), which offers a cost of 623.81 $/h). However, for the case of VPE (in Table 7), the proposed method differs only in the results of 0.05072% worse than the best method (IPSO-TVAC)

2) THE LARGE UNIT SYSTEM

The test results for a 40-unit system with VPE are presented in Table 8. The lowest fuel units fall in the minimum power limit (units 10, 11, 12, 27, 28, and 29). The optimal power (P_{opt}) does not violate the power limits. The total cost of the ToNDA method (121412.87 $/h) is slightly larger than the others, as shown in Table 9.

In Tables 8 and Table 9, the proposed method is superior to QPSO and HGA, while when compared to DSD, there is a difference of 0.00028%. When the proposed method is compared with the method from the latest reference [4] which uses full mixed-integer linear programming (FMILP) formula, the results are also not significantly different.

Figure 8 shows the execution times for various numbers of generators. From the time, it looks quite feasible to apply to

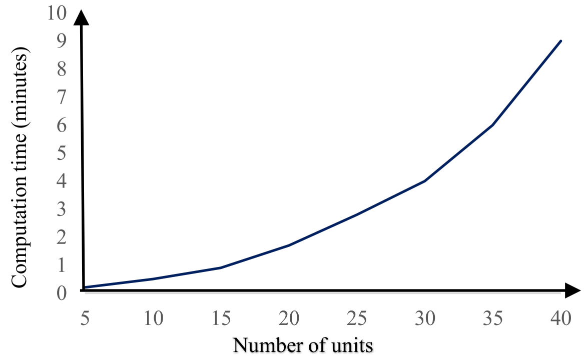

FIGURE 8. Execution time for various number of generators.

the generator schedule for the next 1 hour, where generally the generator schedule is 1 hour ahead.

V. CONCLUSION

A new paradigm based on narrowing the area in solving any EDP problem has been described in this paper through the ToNDA method. The methodology developed narrows the feasible area at each iteration step to obtain a tiny feasible area (as the solution point). The feasible area is evenly traced to ensure very high accuracy. The advantage is that it does not depend on the forms of the objective function. All economic load dispatch problems can be solved satisfactorily, regardless of whether the economic load dispatch problems are differentiable.

The simulation of two generators (differentiable EDP) shows that the results are close to the results of the calculus method in step 14, with a limit range of 0.09766 MW or a feasible area size of 0.0000596 MW^2 (it is a tiny area that can be considered a convergence point).

The ToNDA method successfully applies to the nondifferentiable EDP, piecewise fuel cost, and fuel cost with the valve point effect. From the simulation results of EDP with a piecewise quadratic fuel cost function for ten units, the ToNDA can save 9.06 $/h of fuel. or 1.55% compared to the SAMF, HM, HNN, AHNN, and HGA) methods.

While the EDP simulation results with VPE are 13 units, the proposed method shows almost the same results as other methods, although the solution points are different. This method always balances the power generated and the load demand. This power balance must be maintained because a slightly unbalanced power can reduce fuel costs due to VPE.

The ToNDA method has also been successfully applied to large systems (40 generator units) in the case of the valve point effect. Moreover, this method still consistently shows optimal results compared to the other eight methods.

REFERENCES

[1] H. Sadat, *Power System Analysis*. New York, NY, USA: McGraw-Hill, 1999.
[2] S. Phommixay, M. L. Doumbia, and D. L. St-Pierre, "Review on the cost optimization of microgrids via particle swarm optimization," *Int. J. Energy Environ. Eng.*, vol. 11, no. 1, pp. 73–89, Mar. 2020.
[3] 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, pp. 61–70, 2020.

[4] 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, pp. 1–12, Mar. 2020.

[5] A. J. Wood, B. F. Wollenberg, and G. B. Sheblé, *Power Generation, Operation, and Control*. New York, NY, USA: Wiley, 1984.

[6] M. Salama, "Economic control for generation in thermal power system," *Energy Convers. Manage.*, vol. 40, pp. 669–681, Apr. 1999.

[7] *Present Practices in the Economic Operation of Power Systems*, IEEE Committee Report, IEEE Trans. Power Apparatus Syst., vol. 90, 1971, pp. 1768–1775.

[8] E. Yousif, Z. Suli, M. Zhongjing, and Z. Baihai, "Decentralized gradient projection method for economic dispatch problem with valve point effect," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 16, pp. 844–3851, Sep. 2018.

[9] H. Zein, Y. Sabri, and A. Mashar, "Implementation of electricity business competition framework with economic dispatch direct method," *TELKOMNIKA Telecommun., Comput., Electron. Control*, vol. 10, no. 4, pp. 667–674, Dec. 2012.

[10] A. Zayegh and N. Al Bassam, "Neural network principles and applications," IntechOpen, Provisional Chapter, Tech. Rep., 2018.

[11] K. Y. Lee, A. Sode-Yome, and J. H. Park, "Adaptive Hopfield neural network for economic load dispatch," *IEEE Trans. Power Syst.*, vol. 13, no. 2, pp. 26–519, May 1998.

[12] T. Deng, X. He, and Z. Zeng, "Recurrent neural network for combined economic and emission dispatch," *Appl. Intell.*, vol. 48, no. 8, pp. 1–19, 2017.

[13] Z.-L. Gaing, "Constrained dynamic economic dispatch solution using particle swarm optimization," in *Proc. IEEE Power Eng. Soc. Gen. Meeting*, Jun. 2004, pp. 153–158.

[14] J.-B. Park, K.-S. Lee, J.-R. Shin, and K. Y. Lee, "A particle swarm optimization for economic dispatch with nonsmooth cost functions," *IEEE Trans. Power Syst.*, vol. 20, no. 1, pp. 34–42, Feb. 2005.

[15] D. N. Jeyakumar, T. Jayabarathi, and T. Raghunathan, "Particle swarm optimization for various types of economic dispatch problems," *Int. J. Electr. Power Energy Syst.*, vol. 28, no. 1, pp. 36–42, Jan. 2006.

[16] R. Al-Rubayi, M. K. Abd, and F. M. F. Flaih, "A new enhancement on PSO algorithm for combined economic-emission load dispatch issues," *Int. J. Intell. Eng. Syst.*, vol. 13, no. 1, pp. 77–85, Feb. 2020.

[17] H. Shahinzadeh, S. M. Nasr-Azadani, and N. Jannesari, "Applications of particle swarm optimization algorithm to solving the economic load dispatch of units in power systems with valve-point effects," *Int. J. Electr. Comput. Eng.*, vol. 4, no. 6, pp. 858–867, Dec. 2014.

[18] D. C. Walters and G. B. Sheble, "Genetic algorithm solution of economic dispatch with valve point loading," *IEEE Trans. Power Syst.*, vol. 8, no. 3, pp. 1325–1332, Aug. 1993.

[19] J. Tippayachai, W. Ongsakul, and I. Ngamroo, "Parallel micro genetic algorithm for constrained economic dispatch," *IEEE Trans. Power Syst.*, vol. 17, no. 3, pp. 790–797, Aug. 2002.

[20] A. Bakirtzis, V. Petridis, and S. Kazarlis, "Genetic algorithm solution to the economic dispatch problem," *IEEE Proc.-Gener., Transmiss. Distrib.*, vol. 141, no. 4, pp. 377–382, Jul. 1994.

[21] W. M. Mansour, M. M. Salama, S. M. Abdelmaksoud, and H. A. Henry, "Dynamic economic load dispatch of thermal power system using genetic algorithm," *IRACST Eng. Sci. Technol., Int. J.*, vol. 3, no. 2, pp. 345–352, Apr. 2013.

[22] L. Mellouk, M. Boulmalf, A. Aaroud, K. Zine-Dine, and D. Benhaddou, "Genetic algorithm to solve demand-side management and economic dispatch problem," in *Proc. 9th Int. Conf. Ambient Syst., Netw. Technol. (ANT)*, 2018, pp. 612–618.

[23] P. H. Chen and H. C. Chang, "Large-scale economic dispatch approach by genetic algorithm," *IEEE Trans. Power Syst.*, vol. 10, no. 4, pp. 1918–1926, Nov. 1995.

[24] Y. H. Song, F. Li, R. Morgan, and D. T. Y. Cheng, "Comparison studies of genetic algorithms in power system economic dispatch," *Power Syst. Technol.*, vol. 19, no. 3, pp. 28–33, Mar. 1995.

[25] G. B. Sheble and K. Brittig, "Refined genetic algorithm-economic dispatch example," *IEEE Trans. Power Syst.*, vol. 10, no. 1, pp. 117–124, Feb. 1995.

[26] L. Dai, D. You, X. Yin, G. Wang, and Q. Zou, "Distributional robust dynamic economic dispatch model with conditional value at risk recourse function," *Int. Trans. Elect. Energy Syst.*, vol. 29, no. 4, pp. 1–17, 2018.

[27] S. Hazr and P. K. Roy, "Optimal dispatch using moth-flame optimization for hydrothermal-wind scheduling problem," *Int. Trans. Electr. Energy*, vol. 30, no. 8, pp. 1–24, 2020.

[28] K. Y. Lee and M. A. El-Sharkawi, "Tutorial on modern heuristic optimization techniques with applications to power systems IEEE power engineering society," in *Proc. IEEE Catalog*, 2013.

[29] S. Bhupender, S. Shivani, and N. Ajay, "Particle swarm optimization and genetic algorithm-based optimal power flow solutions," *Int. J. Appl. Innov. Eng. Manage.*, vol. 2, no. 7, pp. 307–315, 2013.

[30] H. Zein, A. S. Kurniasetiawati, and C. K. Wachjoe, "Fuel cost optimization of the power system by involving all operating limits based on the developed interior point algorithm," *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 5, pp. 1–14, May 2020.

[31] S. Duman, S. Rivera, J. Li, and L. Wu, "Optimal power flow of power systems with controllable wind-photovoltaic energy systems via differential evolutionary particle swarm optimization," *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 4, pp. 1–28, Apr. 2019.

[32] R. Girshick, "Object detection with heuristic coarse-to-fine search," M.s. thesis, Univ. Chicago, Chicago, IL, USA, 2009.

[33] K. Anderson, N. Sturtevant, R. Holte, and J. Schaeffer, "Coarse-to-fine search techniques," Dept. Comput. Sci., Univ. Alberta, Edmonton, AB, Canada, Tech. Rep. TR 08-05, 2008.

[34] R. Korah and J. Perinbam, "A novel coarse-to-fine search motion estimator," *Inf. Technol. J.*, vol. 5, no. 6, pp. 1073–1077, Oct. 2006.

[35] R. Jangkung, S. Adi, and Z. Hermagasantos, "Multi dimension of coarse to fine search method development for solving economic dispatch," *Indonesian J. Electr. Eng. Comput. Sci.*, vol. 3, no. 1, pp. 1–9. Jul. 2016.

[36] S. Subramanian and S. Ganesan, "A simplified approach for economic dispatch with piecewise quadratic cost functions," *Int. J. Comput. Electr. Eng.*, vol. 2, no. 5, pp. 793–798, Oct. 2010.

[37] C. E. Lin and G. L. Viviani, "Hierarchical economic dispatch for piecewise quadratic cost functions," *IEEE Trans. Power App. Syst.*, vol. PAS-103, no. 6, pp. 1170–1175, Jun. 1984.

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