A Novel Economic Dispatch in Power Grids Based on Enhanced Firework Algorithm

Iman Niazazari, Oveis Asgari Gashteroodkhani, and Amir Niaz Azari

Abstract— This paper proposes a novel single objective optimization technique for economic dispatch (ED) in power grids. This new technique is developed based on firework algorithm (FWA) and is implemented in the IEEE 24 bus reliability test system. In this paper, the single-objective enhanced fireworks (EFWA) is developed to find the economic operating condition to minimize the generation cost. This method is a swarm intelligence algorithm that solves a single-objective optimization problem much faster than other well-known algorithms such as genetic algorithm (GA). The experimental results show that the proposed EFWA method is indeed capable of obtaining higher quality solutions efficiently in ED problems.

Index Terms— Economic dispatch, enhanced firework algorithm, genetic algorithm, optimization

I. INTRODUCTION

Optimization problems are one of the most important problems in power system planning and operation. Economic dispatch (ED) problem is probably the most widespread use of optimization in power systems. Its purpose is the minimization of the overall generation cost with respect to multiple constraints. The output of ED gives the optimal allocation of the power generated by each generator [1]. The cost function of generating units is modeled in numerous ways [2-5]. As the complexity of the model and the number of generating unit increases the difficulty of the problem increases especially in the presence of renewable energy integration [6-7]. It is usually assumed the cost function of the generators are quadratic function [8].

Several methods for solving ED problems have been proposed so far. The optimization methods for solving the problem mostly include classical mathematical techniques [9-12] or evolutionary techniques [13-17]. The mathematical optimization methods such as linear programming and quadratic programming are usually susceptible to the starting point and may get stuck in the local minima or even diverge [18]. However, recently evolutionary techniques have become very popular in the optimization problems in power systems [19]. Optimization techniques such as genetic algorithms (GA), imperialistic competitive algorithm (ICA) and particle swarm optimization (PSO) have been successfully used to solve power optimization problems such as loss minimization, fault location estimation, and determining the number of protective and devices in power systems [20-23]. In [20], the authors utilized GA as a scenario reduction tool to implement a multi-objective optimization problem for loss minimization under DGs' uncertainty. In [21], the authors propose a new application of ICA for fault

estimation in a power system that has high accuracy in the estimation even for very complicated systems. Furthermore, based on [23], it has been shown that the GA is a powerful tool in the optimal allocation of protective and control devices in a smart grid in order to make the grid's self-healing characteristic reinforced to be able to restore as many interrupted loads as possible in the least possible time. GA methods proved to be most successful in solving the power system optimization problems; however, they do not perform very well when the problem parameters are highly correlated and they tend to fail in finding the global optimum [24-25].

Firework algorithm (FWA) is one of the evolutionary optimization methods that recently become very popular [26-29]. It is first introduced by Ying Tan and Yuanchun Zhu, as a swarm based evolutionary algorithms [30]. The FWA can generate high-quality solutions within shorter calculation time and stable convergence characteristic than other stochastic methods. Zheng et al. presented a modified form of FWA called enhanced firework algorithm (EFWA) to improve the performance of FWA [31].

In this paper, an EFWA method for solving the ED problem in power system is proposed. The performance of the proposed method was validated on the IEEE 24 bus test reliability system, as compared with the GA method in the solution quality and computation efficiency. The rest of this paper is organized as follows. In section 2, the problem formulation is presented. Section 3 introduces the EFWA. Section 4 presents the simulation results followed by the conclusion in Section 5.

II. PROBLEM FORMULATION

The objective of ED is to find the optimal output power of generating units to supply the system load demand while satisfying system constraints. It is a subset of the unit commitment problem and the optimal values of generators power are determined based on scheduled power of each generating units at each period of operation [3]. It is customary to assume a quadratic cost function for the generating units [32]. Due to the quadratic form of the cost function, the ED problem is a non-linear optimization programming. In addition, the generating power of each generator should lie between the maximum and minimum limits represented. Therefore, the problem can be formulated as follows:

The total fuel cost function is formulated as follows:

$$\min f = \sum_{t=1}^T [\sum_{i=1}^n F_i^t (P_i^t)] \quad (1)$$

where F_i^t is the total fuel cost for the i^{th} generator (in \$/h) at time t , which is defined by

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$$F_i^t(P_i^t) = a_i P_i^{t^2} + b_i P_i^t + c_i \quad (2)$$

where a_i , b_i , and c_i are cost coefficients of i^{th} generator.

Two constraints need to be satisfied as well:

Equality constraint: The generators powers should be the same as the load consumption, therefore,

$$(\sum_{i=1}^n P_i^t) - P_D^t = 0 \quad (3)$$

where P_i^t is the power of i^{th} generator (in MW) at time t , n is the number of generating units in the system, P_D^t is the system's total demand (in MW) at time t .

Inequality constraint: the generating units' power should stay in an acceptable range, therefore,

$$P_i^{\min} \leq P_i^t \leq P_i^{\max} \quad (4)$$

where $P_i^{\min}$ and $P_i^{\max}$ are, the minimum and maximum power of i^{th} generating unit (in MW).

III. ENHANCED FIREWORK ALGORITHM

The firework algorithm (FWA) is developed by the idea of the fireworks explosion. When a firework is set off, a number of sparks are generated around the firework. In summary, in this algorithm, a number of fireworks generated as individuals, and in each generation, after the explosion of these fireworks their sparks search the local space to find the optimum location and at the end of each iteration the best locations are selected for the next generation. This process is carried on until the stopping criterion is met and the optimum location is found.

It is reasonable that fireworks which are closer to the optimal solutions should have the permission to generate more sparks, and with less amplitude compared to the ones which are far away from the optimal solutions. Similar to real-life experience, most of the sparks tend to explode around the firework. However, there is a chance that some of those sparks explode far away from the firework. We call the former regular/uniform sparks, and the latter mutation/Gaussian sparks. The mutation sparks are necessary when the optimization process is stuck in a local minimum. Fig.1 shows three different fireworks with corresponding sparks.

There are some issues related to FWA that needs to be addressed. For instance, its performance worsens when it is applied to shifted functions. It means that with increasing the distance between objective function optimum and origin of the search space the performance of the algorithm is affected. In addition, FWA has a high computational cost per iteration, with respect to other evolutionary algorithms. To address these issues, four major improvements of FWA are proposed in [31]: (i) a new explosion amplitude check Eq. (7), (ii) a new way of generating regular sparks Eq. (10), (iii) a new way of generating mutation sparks Eq. (11), and (iv) a new mapping strategy for out of bounds sparks Eq. (12). In addition, a randomly based selection criterion for choosing the next iteration population is suggested as well. However, after comparing the results with the original FWA, the authors have decided to stick to the distance based selection strategy as presented in the original work [30]. The flowchart of the EFWA is presented in Fig. 2. The algorithm formulations are presented as follows:

Fig.1. Scattering of different types of fireworks

The number of generated sparks and the explosion amplitude for each firework can be acquired by (5):

$$N_i = \hat{N} \times \frac{f_{\max} - f(x_i) + \epsilon}{\sum_{i=1}^N (f_{\max} - f(x_i)) + \epsilon} \quad (5)$$

where $\hat{N}$ is a constant to control the number of explosion sparks, and ϵ is a small constant to prevent the zero-division-error. To limit the number of generated sparks in a controllable range, N_i is bound according to (6):

$$N_i = \begin{cases} N_{\max} & \text{if } N_i > N_{\max} \\ N_{\min} & \text{if } N_i < N_{\min} \\ \text{round}(N_i) & \text{otherwise} \end{cases} \quad (6)$$

To calculate the amplitude of the generated sparks it is noticed that it is better that in the early stage of the search, the amplitude is set to a higher value in order to facilitate exploration, and as we go along the amplitude is decreased to allow for better exploitation capabilities around good locations. Therefore, the amplitude is formulated as (7)

$$A_i = \begin{cases} A_{\min} & \text{if } A_i < A_{\min} \\ A_i & \text{otherwise} \end{cases} \quad (7)$$

where A_i is calculated as

$$A_i = \hat{A} \times \frac{f(x_i) - f_{\min} + \epsilon}{\sum_{i=1}^N (f(x_i) - f_{\min}) + \epsilon} \quad (8)$$

where $\hat{A}$ is a constant to control the number of explosion sparks, and $A_{\min}$ is calculated using a non-linear decreasing function as

$$A_{\min} = A_{\text{init}} - \frac{A_{\text{init}} - A_{\text{final}}}{t_{\max}} \sqrt{(2 \times t_{\max} - t)t} \quad (9)$$

where A_{init} and A_{final} are the initial and final minimum explosion amplitude, respectively, and t and $t_{\max}$ are the current and maximum number of iterations, respectively.

Fig.2. Flowchart of EFWA

After finding the number of sparks and amplitude of each firework, it is time to determine how the sparks are distributed in the space. The location of each spark is determined in two ways:

For most of the sparks, the regular sparks, the location of sparks are obtained with a uniform function displacement with respect to the firework location. i.e.:

$$X_i'^k = X_i^k + A_i \times \text{rand}(-1,1) \quad (10)$$

Where k shows the direction of k .

In order to keep the diversity of the population, a few numbers of sparks, mutation sparks, are distributed with a Gaussian distribution, i.e.:

$$X_i'^k = X_i^k + (X_B^k - X_i^k) \times N(0,1) \quad (11)$$

where X_B is the position of the best firework found so far.

It should be noted that if the spark location is dropped out of the search area, it is mapped to another location in the area using (12).

$$X_i^k = X_{\min}^k + (X_{\max}^k - X_{\min}^k) \times \text{rand}(0,1) \quad (12)$$

At the end of each iteration, N locations are chosen for the next iteration. All original fireworks along with all regular and mutation sparks can be chosen for the next iteration. The current best location is always retained for the next iterations. The remaining $N - 1$ locations are selected based on a distance-based selection operator to improve the diversity in the population. For location X_i , the selection probability p is calculated by

$$p(X_i) = \frac{R(X_i)}{\sum_{j \in K} R(X_j)} \quad (13)$$

$$R(X_i) = \sum_{j \in K} d(X_i, X_j) = \sum_{j \in K} \|X_i - X_j\| \quad (14)$$

where K is the entire set of original fireworks and both types of sparks except for the best location. Consequently,

Fig. 3. The IEEE 24 bus test system

fireworks or sparks in low crowded regions will have a higher chance to be chosen for the next iteration than fireworks or sparks in crowded regions [30].

IV. SIMULATIONS AND RESULTS

A. Case Study

To verify the efficiency of the proposed EFWA method, it has been applied to the ED problem in the IEEE 24 bus reliability test system as shown in Fig. 3. Table I demonstrates the units generating capacities along with their cost coefficients [31]. There are 12 units in the system, with two nuclear, five coal/stream, one coal/3 stream, three oil/stream, and one hydro unit. The total generation capacity of the system is 3325 MW. The total demand power in 24 hours is presented in Table II [32]. The tuning parameters for EFWA are determined using extensive trial and error: the $N_{\min}$, $N_{\max}$, $\hat{N}$ are selected as 10, 40, and 300, respectively.

Also, A_{final} is set to 0.01 and A_{init} is set to the minimum of difference between locations in all directions. Noted that for all the simulations in this paper, the experimental platform is: Win7; Intel with CPU X5482 2×3.2 GHz; RAM 16 GB.

B. Discussions

The simulation is conducted with both EFWA and GA methods. Table III compares two methods in terms of simulation time. This table only shows some time steps of the day as the representatives of all hours, but the last row of the table shows the total time needed for each method to find the optimal solution for the entire scheduling horizon, i.e., 24 hours. As it is observed from the Table, although GA needs less computational time for each iteration, it requires much more number of iteration and subsequently computational time to find the true optimal solution compared to EFWA.

TABLE I. GENERATING UNIT CAPACITY AND COEFFICIENTS

Unit	$P_{\max}$ [MW]	$P_{\min}$ [MW]	a [\$/MW ²]	b [\$/MW]	c [\$]
18	400	100	0.000213	4.4231	395.374
21	400	100	0.000213	4.4231	395.374
1	152	30.4	0.014142	16.0811	212.307
2	152	30.4	0.014142	16.0811	212.307
15b	155	54.25	0.008342	12.3883	382.239
16	155	54.25	0.008342	12.3883	382.239
23a	310	108.5	0.008342	12.3883	382.239
23b	350	140	0.004895	11.8495	665.109
7	300	75	0.052672	43.6615	781.521
13	591	206.9	0.00717	48.5804	832.757
15a	60	12	0.328412	56.564	86.3852
22	300	60	0	0.001	0.001

TABLE II. LOAD PROFILE IN 24 HOURS

Hour	System Demand [MW]	Hour	System Demand [MW]
1	1598.252	13	2266.178
2	1502.834	14	2266.178
3	1431.27	15	2218.469
4	1407.416	16	2218.469
5	1407.416	17	2361.596
6	1431.27	18	2385.45
7	1765.233	19	2385.45
8	2051.487	20	2290.032
9	2266.178	21	2170.76
10	2290.032	22	1979.924
11	2290.032	23	1741.379
12	2266.178	24	1502.834

TABLE III. COMPARISON OF EFWA AND GA SPEED

Hour	GA Time per Iteration [s]	GA Total Time [s]	EFWA Time per Iteration [s]	EFWA Total Time [s]
1	0.0312	6.7073	0.1291	4.0321
9	0.0278	6.5945	0.096	3.7240
17	0.0392	7.6738	0.1372	3.7168
Whole day	N/A	189.6543	N/A	90.2541

Moreover, the last row of the table indicates that to find the same optimal answer, the EFWA method is almost 2 times faster than GA.

Fig. 4 shows the minimum total cost for both EFWA and GA methods for the entire scheduling horizon. It is assumed that the end condition for both methods is the number of iterations which is 100 for each scheduling subintervals (i.e., each hour). Also, the number of initial population for both methods are equal to 10. As it is observed from Fig. 4, for almost all scheduling horizon, the minimum total cost related to EFWA is smaller than the one associated with GA.

Fig. 5 and Fig. 6 depict the optimal generation output of each generator at each hour using GA and EFWA methods, respectively. These figures have been plotted with the same parameters of Fig. 4. In this figure, from the darkest color to the brightest one, each color represents the scheduled power

Fig. 4. minimum total cost for both EFWA & GA methods for whole day after 100 times iterations for each hour

Fig. 5. optimal generation output of each generator at each hour using GA

Fig. 6. optimal generation output of each generator at each hour using EFWA

generation with the sequence mentioned in Table I. Therefore, after solving the single-objective optimization by GA and EFWA methods, the best operation points for all generations are according to the ones in Fig. 5 and Fig. 6, respectively.

V. CONCLUSIONS

This paper presents a new single objective optimization technique for performing economic dispatch in power networks. This new technique is developed based on real-life

firework explosion and is called enhanced firework algorithm (EFWA). In order to validate the efficiency of the proposed EFWA method, it has been applied to the ED problem in the IEEE 24 bus reliability test system and then compared to the GA method as the benchmark. The simulation results show the superiority of EFWA to find the optimal solution with less computation time compared to GA. In addition, the simulation results validate the better performance of the EFWA method, to achieve the minimum total cost, within the certain computational time limit for each scheduling hour.

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