Research Article

A Memetic Approach for Improving Minimum Cost of Economic Load Dispatch Problems

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Economic load dispatch problem is a popular optimization problem in electrical power system field, which has been so far tackled by various mathematical and metaheuristic approaches including Lagrangian relaxation, branch and bound method, genetic algorithm, tabu search, particle swarm optimization, harmony search, and Taguchi method. On top of these techniques, this study proposes a novel memetic algorithm scheme combining metaheuristic algorithm and gradient-based technique to find better solutions for an economic load dispatch problem with valve-point loading. Because metaheuristic algorithms have the strength in global search and gradient-based techniques have the strength in local search, the combination approach obtains better results than those of any single approach. A bench-mark example of 40 generating-unit economic load dispatch problem demonstrates that the memetic approach can further improve the existing best solutions from the literature.

1. Introduction

Economic load dispatch (ELD) problem is a classical form of optimization problems and has been one of the most important decision-making processes in the operation of electrical power systems. The total system-wide generation cost is generally defined as the objective function of ELD problem. The equality and inequality power system constraints are embedded in ELD formulation, such as power balance and generation limits of each generating unit's output capacity. ELD problem has been thought of as a mathematically complex and highly nonlinear optimization problem, especially in larger systems. For many decades, many algorithms have been presented to solve the optimization problem of ELD. First, conventional deterministic approaches which resort to mathematical gradient information have been developed to obtain the minimum cost of ELD problem. To overcome the limitations of those deterministic algorithms in real-system applications which are basically associated with the simplification of mathematical formulation, a variety of evolutionary frameworks that employ metaheuristic computational intelligence have explored their capabilities to search

optimal solution of ELD problem with little abbreviation of original formulation.

Many gradient-based and enumeration-based deterministic approaches such as Lagrangian relaxation and linear, nonlinear, and dynamic programming techniques have been applied to find the optimal solution of ELD problem [1–7]. They are suitable, however, only when the problem satisfies certain conditions (complex calculus-based gradient should be derived or formulation can be approximated in terms of linearity and/or convexity), and therefore this mathematical requirement has limited the extensive applications of these deterministic algorithms in real ELD problem. In addition, extensive search algorithms which explore all the solution space such as dynamic programming [2, 3], therefore, have been employed in ELD problem to tackle the issue of the simplification in the mathematical formulation of ELD. Due to the so-called “curse of dimensionality” and local optimality, however, these approaches hardly give solutions with higher level of satisfaction in the real-world applications.

For recent decades, therefore, a variety of artificial intelligence approaches which are dependent upon heuristic and

stochastic search scheme have been intensively adopted in ELD problem. Many studies have aimed to overcome the shortcomings of the conventional deterministic algorithms and to investigate the efficiency and applicability of the algorithms in ELD problem. For example, genetic-based different types of algorithms (GA) [8–15], a variety of evolutionary programming-based algorithms (EP) [16–19], particle swarm optimization (PSO) with its variations [20–28], tabu search (TS) [29], Taguchi method [30], bioinspired optimization algorithms [31–34], harmony search (HS) [35, 36], and hybrid methods combining two or more metaheuristic algorithms [37–42] have been applied to explore the capability of stochastic artificial intelligence algorithms to solve ELD problem so far.

Up until now, we can see that several well-developed metaheuristic algorithms have shown a higher level of applicability in ELD problem with fine performance [43–53]. In spite of the acceptable level of performance in some algorithms of ELD problem, we have found that a memetic approach for ELD problem to combine the well-developed evolutionary frameworks with gradient-based local search algorithm can provide an opportunity for better solutions. Through this memetic combination, it can be seen that the minimum cost of ELD problem can be further improved because metaheuristic algorithm's weak local search performance is reinforced by calculus-based method and calculus-based method's weak global search performance is reinforced by metaheuristic algorithm.

This paper is organized as follows. Mathematical formulation of ELD problems and recent metaheuristic algorithms to solve ELD problem are described in Section 2. In Section 3, memetic implementations for those algorithms are explored to integrate gradient-based local search into the evolutionary frameworks for the solution of ELD. Simulation results and discussions on the algorithm proposed are provided in Section 4, followed by conclusion and future investigation in Section 5.

2. Problem Description: Economic Load Dispatch with Valve-Point Loading

The ELD problem can be stated as to determine the optimal set of individual generating units' generation outputs minimizing the objective function(s) as well as satisfying both the equality and inequality constraints. The ELD can, therefore, be mathematically formulated as a continuous variable optimization problem. The objective function to be minimized can be defined as the system-wide generation cost across all the generators. Equality constraint of ELD is a power balancing equation where total power supply of all the generators is equal to the total system demand plus system loss. In addition, individual generators' generation output should be in-between its minimum and maximum generation capacity, and this condition is imposed as the inequality constraint for each generator's output in ELD

problem. The mathematical formulation of the generic ELD problem can, therefore, be described as follows:

$$\begin{aligned} \text{Min } C &= \sum_{i \in I} F_i(P_i) = \sum_{i \in I} [a_i + b_i P_i + c_i P_i^2] \\ \text{subject to } \sum_{i \in I} P_i &= D + L \\ \underline{P}_i &\leq P_i \leq \bar{P}_i, \end{aligned} \quad (1)$$

where C is system-wide total generating units' cost function; F_i is generation cost function of generating unit- i ; P_i is generation output of generating unit- i ; a_i , b_i , and c_i are cost coefficients of generating unit- i ; I is index set of generating units in the system; D is total system demand; L is total system loss; $\underline{P}_i$, $\bar{P}_i$ are minimum and maximum generation output of generating unit- i .

The system loss in the transmission lines, L , can be presented as a quadratic form of generating units' output generations as follows:

$$L = \sum_{i \in I} \sum_{j \in I} P_i B_{ij} P_j + \sum_{i \in I} P_i B_{0i} + B_{00}, \quad (2)$$

where B_{ij} is the ij th element of loss coefficient matrix, B_{0i} is i th element of loss coefficient vector, and B_{00} is i th element of loss coefficient constant.

Moreover, more practical consideration of ELD problem requires an inclusion of valve-point loading effects in ELD problem, and the mathematical formulation of ELD with valve-point loading can be rephrased as follows:

$$\begin{aligned} \text{Min } C &= \sum_{i \in I} F_i(P_i) \\ &= \sum_{i \in I} [a_i + b_i P_i + c_i P_i^2 + |e_i \cdot \sin(f_i \cdot (\underline{P}_i - P_i))|], \end{aligned} \quad (3)$$

where e_i and f_i are nonsmooth fuel cost coefficients of generating unit- i .

Many gradient-based and enumeration-based deterministic approaches have been applied to find the optimal solution of ELD problem, and they are suitable only when the problem satisfies certain conditions. Extensive search algorithms have been employed in ELD problem to tackle the issue of the simplification in the mathematical formulation of ELD. These approaches hardly give solutions with higher level of satisfaction in the real-world applications due to the curse of dimensionality and local optimality. For recent decades, many artificial intelligence approaches have been intensively adopted in ELD problem to investigate the efficiency and applicability of the algorithms in ELD problem. In ELD problem, although several algorithms for solving economic dispatch are well developed up until now, we have found that memetic crossover between gradient-based algorithm and metaheuristic methodology can provide opportunity of better solutions for ELD. The memetic algorithm is based on the characteristic of the meme in human culture, which is the basic unit of knowledge that can be modified, combined with other ones, and generating new ones to propagate in

the communities [63]. Under the optimization problems like ELD, the memetic algorithm considers complex structures of conventional metaheuristic algorithms and simple gradient-based optimization operators, where the interactions of evolutionary and local search algorithm lead to an efficient solution method that is able to solve ELD problem more effectively. In this study, therefore, a memetic approach to combine stochastic metaheuristic algorithms with gradient-based local search is presented to explore the opportunity of better solution for ELD problem.

Many metaheuristic approaches using population-based evolutionary frameworks have been applied in ELD problem in order to find the optimal solution. The population-based metaheuristic algorithms for ELD primarily resort to iterated procedures for initializing, competing, and updating of population in reaching optimal solution(s), and, therefore, the general solution steps of the metaheuristic algorithms for ELD can be described as shown in Algorithm 1.

Depending upon the specific individual evolutionary framework in a metaheuristic algorithm, the initialization, competition, and update of population process for ELD in the algorithm can vary. Some algorithms employ a random initialization for the parent population, while the others attempt to use a better quality one as a starting population by using a refined heuristic. In the iterated competing and updating processes for ELD, the respective metaheuristic algorithms adopt their own computational intelligence operators based upon their functional advantages over other ones. For example, genetic and evolutionary upgrade operators are used in genetic and evolutionary algorithms. Social patterns in the behaviors of animals are modeled in particle swarm optimization, honey bee mating, and firefly algorithm. Also, physical phenomenon-based population improvement is explored in harmony search, tabu search, and simulated annealing. As for the termination, the iterated processes in the algorithms stop based upon their own termination criteria, which are typically defined as the maximum number of iterations and/or minimum extent of the improvement of the fitness value(s) for ELD.

In recent ELD studies using metaheuristic algorithms, several biogeography-based and musical improvisation methodologies are presented to find the optimal solution of ELD problem [33, 34, 36, 64]. In [33, 34], a firefly algorithm (FA) and a honey bee mating optimization (HBMO) algorithm have been developed to solve nonconvex ELD problem with valve loading effect, respectively, and they have shown a higher level of performance than conventional metaheuristic algorithms. In addition, a variation of pattern search (PS) methods and a population-variance harmony search (HS) algorithm have also been presented to solve the constrained ELD problem, in [36, 64], respectively. Two algorithms have also demonstrated their better capabilities in ELD applications than existing relevant approaches.

3. Memetic Implementations for ELD Problem

Memetic computing is a branch in computer science which regards complicate structures as the combination of

heterogeneous operators, named memes, whose evolutionary interactions contribute to intelligent structures for problem solving [65, 66].

For recent decades, memetic algorithms have been widely applied in the large-scale complex optimization problems. The problem of balance between global and local search, that is, balance between computational intelligence and gradient-based search algorithm, has been explored under a multiobjective optimization setting in [67, 68]. In [69], a memetic algorithm is presented to analyze the evolutionary artificial neural network for training of a medical application. For a large-scale combinatorial optimization problem, a parallel memetic algorithm with selective local search is proposed in [70]. In [71–73], memetic algorithms are applied to solve scheduling and planning problems such as vehicle routing and path planning. A fast adaptive memetic algorithm for a design of controller of engineering drives is presented in [74], and a compact memetic differential algorithm has been developed for a robot control in [75]. In [76], a differential evolution-based hybrid algorithm is provided to solve the optimization problem in aerodynamic design.

In order to explore the opportunity of better solution in ELD problem using the memetic combination proposed in this study, we have basically considered three metaheuristic algorithms: harmony search (HS), firefly algorithm (FA), and honey bee mating optimization (HBMO), which show the highest level of performances among all the existing relevant population-based metaheuristic approaches in the most recent ELD problem literatures [33, 34, 36]. HS algorithm was originally inspired by the improvisation process of Jazz musicians. The algorithm uses a novel stochastic derivative which utilizes the experiences of musicians in Jazz improvisation and can be applicable to optimization problem. Instead of the gradient-based inclination information of an objective function, the stochastic derivative of the algorithm gives a probability to be selected for each value of a decision variable. In [36], the evolution of the population-variance over successive generations in HS was analyzed and the algorithm showed that it can easily take care of solving nonconvex ELD problems along with different constraints. The FA was based on the idealized behavior of the flashing characteristics of fireflies such that the brightness or light intensity of a firefly is affected or determined by the landscape of the objective function to be optimized. In [33], a FA for solving nonsmooth economic dispatch with various constraints was presented and the results are compared with recent ELD solution methods. The HBMO algorithm is based upon the social characteristics of the honey bee in working together in a highly structured social order. In [34], a method to improve the mating process of HBMO combining the HBMO with a chaotic local search was proposed to overcome the disadvantage of the conventional algorithm that may miss the optimum and provide a near optimum solution in a limited runtime period. Table 1 shows the minimum cost of ELD problem using the most recent three metaheuristic algorithms in [33, 34, 36] (i.e., HS, FA, and HBMO), with the same test system of 40 generating units.

Based upon the result in Table 1, therefore, we have proposed a memetic combination of the most recent HS,

Step 1. Initialization of the population for the parent generation
Step 2. Iterations
 Step 2.1. Creation of the population for the new generation
 Step 2.2. Competition among populations
 Step 2.3. Population update
Step 3. Termination

ALGORITHM 1: The general solution steps of the metaheuristic algorithms for ELD.

TABLE 1: Minimum costs of ELD problem from three different algorithms.

Number	Generation (MW)			Cost (\$)		
	HS	FA	HMBO	HS	FA	HMBO
1	110.8312	110.8099	110.8018	925.6191	925.2642	925.1296
2	110.8234	110.8059	110.8000	925.4891	925.1976	925.0998
3	97.3999	97.4023	97.3999	1190.5485	1190.5949	1190.5485
4	179.7331	179.7332	179.7331	2143.5503	2143.5524	2143.5503
5	88.9932	92.7070	87.7998	726.2998	787.1211	706.5003
6	140.0000	140.0000	140.0000	1596.4643	1596.4643	1596.4643
7	259.6006	259.6004	259.5997	2612.9019	2612.8983	2612.8846
8	284.6143	284.6004	284.5997	2780.1031	2779.8502	2779.8368
9	284.5997	284.6004	284.5997	2798.2312	2798.2440	2798.2303
10	130.0000	130.0028	130.0000	2502.0650	2502.1290	2502.0650
11	168.7998	168.8008	94.0000	2959.4585	2959.4811	1893.3054
12	168.7998	168.8008	94.0000	2977.4549	2977.4776	1908.1668
13	214.7598	214.7606	214.7598	3792.0703	3792.0901	3792.0700
14	394.2794	304.5204	394.2794	6414.8612	5149.7187	6414.8604
15	304.5191	394.2801	394.2794	5171.1965	6436.6047	6436.5863
16	394.2794	394.2801	394.2794	6436.5870	6436.6047	6436.5863
17	489.2794	489.2801	489.2794	5296.7114	5296.7265	5296.7107
18	489.2794	489.2801	489.2794	5288.7658	5288.7809	5288.7652
19	511.2796	511.2817	511.2794	5540.9342	5540.9797	5540.9292
20	511.2794	511.2817	511.2794	5540.9099	5540.9597	5540.9092
21	523.2867	523.2793	523.2794	5071.4381	5071.2898	5071.2897
22	523.2836	523.2793	523.2807	5071.3753	5071.2898	5071.3156
23	523.2794	523.2832	523.2794	5057.2237	5057.3002	5057.2231
24	523.2794	523.2832	523.2794	5057.2237	5057.3002	5057.2231
25	523.2794	523.2793	523.2794	5275.0891	5275.0886	5275.0885
26	523.2794	523.2793	523.2794	5275.0891	5275.0886	5275.0885
27	10.0000	10.0000	10.0000	1140.5240	1140.5240	1140.5240
28	10.0000	10.0000	10.0000	1140.5240	1140.5240	1140.5240
29	10.0000	10.0000	10.0000	1140.5240	1140.5240	1140.5240
30	91.2184	87.8008	87.7999	762.9889	706.5149	706.5001
31	190.0000	189.9989	190.0000	1643.9913	1643.9869	1643.9913
32	190.0000	189.9989	190.0000	1643.9913	1643.9869	1643.9913
33	190.0000	189.9989	190.0000	1643.9913	1643.9869	1643.9913
34	164.9179	164.8036	164.8015	1587.5968	1585.6100	1585.5733
35	164.8672	164.8036	194.3928	1541.0193	1539.9348	1985.3690
36	164.8786	164.8036	200.0000	1541.2137	1539.9348	2043.7270
37	110.0000	110.0000	110.0000	1220.1661	1220.1661	1220.1661
38	110.0000	110.0000	110.0000	1220.1661	1220.1661	1220.1661
39	110.0000	110.0000	110.0000	1220.1661	1220.1661	1220.1661
40	511.2795	511.2794	511.2794	5540.9320	5540.9299	5540.9292
Sum	10500.0000	10500.0000	10500.0000	121415.4560	121415.0522	121412.5704

TABLE 2: Generating units data for test system.

Number	P	$\bar{P}$	a	b	c	e	f
1	36	114	0.0069	6.73	94.705	100	0.084
2	36	114	0.0069	6.73	94.705	100	0.084
3	60	120	0.02028	7.07	309.54	100	0.084
4	80	190	0.00942	8.18	369.03	150	0.063
5	47	97	0.0114	5.35	148.89	120	0.077
6	68	140	0.01142	8.05	222.33	100	0.084
7	110	300	0.00357	8.03	287.71	200	0.042
8	135	300	0.00492	6.99	391.98	200	0.042
9	135	300	0.00573	6.6	455.76	200	0.042
10	130	300	0.00605	12.9	722.82	200	0.042
11	94	375	0.00515	12.9	635.2	200	0.042
12	94	375	0.00569	12.8	654.69	200	0.042
13	125	500	0.00421	12.5	913.4	300	0.035
14	125	500	0.00752	8.84	1760.4	300	0.035
15	125	500	0.00708	9.15	1728.3	300	0.035
16	125	500	0.00708	9.15	1728.3	300	0.035
17	220	500	0.00313	7.97	647.85	300	0.035
18	220	500	0.00313	7.95	649.69	300	0.035
19	242	550	0.00313	7.97	647.83	300	0.035
20	242	550	0.00313	7.97	647.81	300	0.035
21	254	550	0.00298	6.63	785.96	300	0.035
22	254	550	0.00298	6.63	785.96	300	0.035
23	254	550	0.00284	6.66	794.53	300	0.035
24	254	550	0.00284	6.66	794.53	300	0.035
25	254	550	0.00277	7.1	801.32	300	0.035
26	254	550	0.00277	7.1	801.32	300	0.035
27	10	150	0.52124	3.33	1055.1	120	0.077
28	10	150	0.52124	3.33	1055.1	120	0.077
29	10	150	0.52124	3.33	1055.1	120	0.077
30	47	97	0.0114	5.35	148.89	120	0.077
31	60	190	0.0016	6.43	222.92	150	0.063
32	60	190	0.0016	6.43	222.92	150	0.063
33	60	190	0.0016	6.43	222.92	150	0.063
34	90	200	0.0001	8.95	107.87	200	0.042
35	90	200	0.0001	8.62	116.58	200	0.042
36	90	200	0.0001	8.62	116.58	200	0.042
37	25	110	0.0161	5.88	307.45	80	0.098
38	25	110	0.0161	5.88	307.45	80	0.098
39	25	110	0.0161	5.88	307.45	80	0.098
40	242	550	0.00313	7.97	647.83	300	0.035

TABLE 3: Results for Test Case 1.

Number	Generation (MW)		Cost (\$)	
	HS [36]	M_HS	HS [36]	M_HS
1	110.8312	110.8322	925.6191	925.6363
2	110.8234	110.8234	925.4891	925.4891
3	97.3999	97.3999	1190.5485	1190.5484
4	179.7331	179.7331	2143.5503	2143.5503
5	88.9932	88.9932	726.2998	726.2998
6	140.0000	140.0000	1596.4643	1596.4643
7	259.6006	259.6005	2612.9019	2612.9009
8	284.6143	284.6142	2780.1031	2780.1021
9	284.5997	284.5996	2798.2312	2798.2303
10	130.0000	130.0000	2502.0650	2502.0650
11	168.7998	168.7998	2959.4585	2959.4585
12	168.7998	168.7998	2977.4549	2977.4549
13	214.7598	214.7598	3792.0703	3792.0699
14	394.2794	394.2793	6414.8612	6414.8603
15	304.5191	304.5195	5171.1965	5171.1976
16	394.2794	394.2793	6436.5870	6436.5862
17	489.2794	489.2794	5296.7114	5296.7108
18	489.2794	489.2794	5288.7658	5288.7652
19	511.2796	511.2794	5540.9342	5540.9303
20	511.2794	511.2794	5540.9099	5540.9092
21	523.2867	523.2866	5071.4381	5071.4355
22	523.2836	523.2835	5071.3753	5071.3728
23	523.2794	523.2793	5057.2237	5057.2231
24	523.2794	523.2793	5057.2237	5057.2231
25	523.2794	523.2793	5275.0891	5275.0885
26	523.2794	523.2793	5275.0891	5275.0885
27	10.0000	10.0000	1140.5240	1140.5240
28	10.0000	10.0000	1140.5240	1140.5240
29	10.0000	10.0000	1140.5240	1140.5240
30	91.2184	91.2184	762.9889	762.9891
31	190.0000	190.0000	1643.9913	1643.9913
32	190.0000	190.0000	1643.9913	1643.9913
33	190.0000	190.0000	1643.9913	1643.9913
34	164.9179	164.9179	1587.5968	1587.5964
35	164.8672	164.8672	1541.0193	1541.0191
36	164.8786	164.8786	1541.2137	1541.2135
37	110.0000	110.0000	1220.1661	1220.1661
38	110.0000	110.0000	1220.1661	1220.1661
39	110.0000	110.0000	1220.1661	1220.1661
40	511.2795	511.2793	5540.9320	5540.9292
Sum	10500.0000	10500.0000	121415.4560	121415.4525

FA, and HBMO algorithms with gradient-based local search operator to improve the minimum cost of the ELD problem. The memetic approach to metaheuristic algorithms for ELD problem combines a local search operator with a metaheuristic algorithm, and it is a basically population-based metaheuristic which enables an evolutionary framework to search local solutions in a gradient manner within a certain generation cycle. As the memetic approach blends together a population-based computational intelligence algorithm and local search method, the memetic algorithm for ELD problem

can provide a better opportunity for the optimal solution by combining two individual robust operators, which have higher capability of global search and local search, in the solution space, respectively. Therefore, the general structure of the memetic algorithm for ELD can be rephrased as shown in Algorithm 2 to mimetically associate gradient-based search algorithm with conventional population-based metaheuristic.

Step 1. Initialization of the population for the parent generation
 Step 2. Iterations
 Step 2.1. Creation of the population for the new generation
 Step 2.2. Competition among population
 Step 2.3. Population update
 Step 3. **Gradient-based local search**
 Step 4. Termination

ALGORITHM 2: The general structure of the memetic approach to metaheuristic for ELD.

4. Gradient-Based Local Search Algorithm

For the gradient-based local search algorithm, this study adopted BFGS (Broyden-Fletcher-Goldfarb-Shanno) method [77], which can solve nonlinear optimization problems by eliminating technical constraints. The solution steps of the BFGS method are as follows.

Step 1. Identify an initial feasible solution, $\mathbf{x}^{k=0} = (x_1^0, x_2^0, \dots, x_n^0)$.

Step 2. Calculate the searching direction, $\mathbf{d}^k$.

Step 3. Calculate a new solution, $\mathbf{x}^{k+1} = \mathbf{x}^k + \beta^k \mathbf{d}^k$, where β^k is the step size which minimizes $f(\mathbf{x}^k + \beta^k \mathbf{d}^k)$.

Step 4. If convergence criterion is not satisfied, set $k = k + 1$ and go to Step 2.

The searching direction in Step 2 can be obtained by various methods such as steepest descent, conjugate gradient, quasi-Newton, and Newton methods. Out of various approaches, this study chose the quasi-Newton method, named BFGS, because it is one of the most powerful techniques. The BFGS method emulates the inverse Hessian matrix instead of directly calculating it as follows:

$$\mathbf{d}^{k+1} = \mathbf{G}^{k+1} \nabla f(\mathbf{x}^{k+1}), \quad (4a)$$

$$\nabla f(\mathbf{x}) = \left[\frac{\partial f}{\partial \mathbf{x}} \right] = \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \dots, \frac{\partial f}{\partial x_n} \right)^T, \quad (4b)$$

$$\mathbf{G}^{k+1} = \mathbf{G}^k + \left(\frac{1 + (\mathbf{Y}^k)^T \mathbf{G}^k \mathbf{Y}^k}{(\mathbf{Y}^k)^T \mathbf{S}^k} \right) \frac{\mathbf{S}^k (\mathbf{S}^k)^T}{(\mathbf{S}^k)^T \mathbf{Y}^k} - \frac{\mathbf{Y}^k (\mathbf{S}^k)^T \mathbf{G}^k + \mathbf{G}^k \mathbf{S}^k (\mathbf{Y}^k)^T}{(\mathbf{Y}^k)^T \mathbf{S}^k}, \quad (4c)$$

$$\mathbf{Y}^{k+1} = \nabla f(\mathbf{x}^{k+1}) - \nabla f(\mathbf{x}^k), \quad (4d)$$

$$\mathbf{S}^{k+1} = \mathbf{x}^{k+1} - \mathbf{x}^k. \quad (4e)$$

The convergence criterion in this study is the relative error as follows:

$$\left| \frac{f(\mathbf{x}^k) - f(\mathbf{x}^{k+1})}{f(\mathbf{x}^k)} \right| < \varepsilon. \quad (5)$$

The BFGS method, which is a calculus-based technique, has the advantages over metaheuristic algorithms in terms of (1) fast convergence (it takes less than one second in this study), (2) good local search performance, and (3) having no algorithm parameter requirement (e.g., crossover rate in GA and harmony memory considering rate in HS). However, it also has the disadvantages over metaheuristic algorithms in terms of (1) less global search performance and even (2) divergence [77–79].

5. Numerical Experiments and Discussions

5.1. Test System. The numerical test system used to explore the applicability of memetic algorithms in ELD problem in this study consists of forty generating units with valve-point loading effects, and the total system demand is 10,500 MW [18]. Table 2 shows the data of the forty generating units with valve-point for the test system. In order to compare the performance proposed in this paper to those of existing metaheuristic only algorithms, we have adopted the same test system that is used in previous studies [18].

5.2. Test Case 1: Memetic Implementation with Harmony Search. First, we have implemented a memetic approach using HS algorithm. The best minimum generation cost of ELD for the given test system using HS reported until now is \$121,415.4560 [36], and each generator's output generation at the optimal point is presented in Table 3. The better minimum cost of ELD using a memetic approach to HS (M_HS) proposed in this study, however, can be obtained as \$121,415.4525, and the results are also provided in Table 3.

5.3. Test Case 2: Memetic Implementation with Firefly Algorithm. As a second experiment, we have carried out a memetic implementation using FA. In [33], the best minimum generation cost of ELD for the same test system using FA has been reported as \$121,415.0522, and each generator's output generation at this point is given in Table 4. However, the better minimum cost of ELD can be obtained using a memetic approach to FA (M_FA) presented in this paper as \$121,414.9137, and the results are also provided in Table 4.

TABLE 4: Results for Test Case 2.

Number	Generation (MW)		Cost (\$)	
	FA [33]	M_FA	FA [33]	M_FA
1	110.8099	110.8341	925.2642	925.6675
2	110.8059	110.8059	925.1976	925.1976
3	97.4023	97.3999	1190.5949	1190.5484
4	179.7332	179.7330	2143.5524	2143.5501
5	92.7070	92.7077	787.1211	787.1319
6	140.0000	140.0000	1596.4643	1596.4643
7	259.6004	259.5996	2612.8983	2612.8845
8	284.6004	284.5997	2779.8502	2779.8377
9	284.6004	284.5996	2798.2440	2798.2303
10	130.0028	130.0000	2502.1290	2502.0650
11	168.8008	168.7998	2959.4811	2959.4583
12	168.8008	168.7999	2977.4776	2977.4566
13	214.7606	214.7598	3792.0901	3792.0700
14	304.5204	304.5195	5149.7187	5149.6989
15	394.2801	394.2792	6436.6047	6436.5857
16	394.2801	394.2792	6436.6047	6436.5857
17	489.2801	489.2799	5296.7265	5296.7230
18	489.2801	489.2799	5288.7809	5288.7772
19	511.2817	511.2793	5540.9797	5540.9291
20	511.2817	511.2793	5540.9597	5540.9091
21	523.2793	523.2793	5071.2898	5071.2898
22	523.2793	523.2793	5071.2898	5071.2898
23	523.2832	523.2794	5057.3002	5057.2231
24	523.2832	523.2794	5057.3002	5057.2231
25	523.2793	523.2793	5275.0886	5275.0886
26	523.2793	523.2793	5275.0886	5275.0886
27	10.0000	10.0000	1140.5240	1140.5240
28	10.0000	10.0000	1140.5240	1140.5240
29	10.0000	10.0000	1140.5240	1140.5240
30	87.8008	87.8009	706.5149	706.5162
31	189.9989	190.0000	1643.9869	1643.9913
32	189.9989	190.0000	1643.9869	1643.9913
33	189.9989	190.0000	1643.9869	1643.9913
34	164.8036	164.8028	1585.6100	1585.5961
35	164.8036	164.8032	1539.9348	1539.9274
36	164.8036	164.8032	1539.9348	1539.9274
37	110.0000	110.0000	1220.1661	1220.1661
38	110.0000	110.0000	1220.1661	1220.1661
39	110.0000	110.0000	1220.1661	1220.1661
40	511.2794	511.2789	5540.9299	5540.9289
Sum	10500.0000	10500.0000	121415.0522	121414.9137

TABLE 5: Results for Test Case 3.

Number	Generation (MW)		Cost (\$)	
	HBMO [34]	M_HBMO	HBMO [34]	M_HBMO
1	110.8018	110.8014	925.1296	925.1218
2	110.8000	110.8000	925.0998	925.0998
3	97.3999	97.3999	1190.5485	1190.5489
4	179.7331	179.7331	2143.5503	2143.5507
5	87.7998	87.7999	706.5003	706.5002
6	140.0000	140.0000	1596.4643	1596.4643
7	259.5997	259.5997	2612.8846	2612.8850
8	284.5997	284.5997	2779.8368	2779.8372
9	284.5997	284.5997	2798.2303	2798.2307
10	130.0000	130.0000	2502.0650	2502.0650
11	94.0000	94.0000	1893.3054	1893.3054
12	94.0000	94.0000	1908.1668	1908.1668
13	214.7598	214.7598	3792.0700	3792.0702
14	394.2794	394.2794	6414.8604	6414.8606
15	394.2794	394.2794	6436.5863	6436.5865
16	394.2794	394.2794	6436.5863	6436.5865
17	489.2794	489.2794	5296.7107	5296.7112
18	489.2794	489.2794	5288.7652	5288.7656
19	511.2794	511.2794	5540.9292	5540.9296
20	511.2794	511.2794	5540.9092	5540.9096
21	523.2794	523.2794	5071.2897	5071.2902
22	523.2807	523.2806	5071.3156	5071.3153
23	523.2794	523.2794	5057.2231	5057.2236
24	523.2794	523.2794	5057.2231	5057.2236
25	523.2794	523.2794	5275.0885	5275.0890
26	523.2794	523.2794	5275.0885	5275.0890
27	10.0000	10.0000	1140.5240	1140.5240
28	10.0000	10.0000	1140.5240	1140.5240
29	10.0000	10.0000	1140.5240	1140.5240
30	87.7999	87.7999	706.5001	706.5005
31	190.0000	190.0000	1643.9913	1643.9913
32	190.0000	190.0000	1643.9913	1643.9913
33	190.0000	190.0000	1643.9913	1643.9913
34	164.8015	164.8015	1585.5733	1585.5732
35	194.3928	194.3928	1985.3690	1985.3693
36	200.0000	200.0000	2043.7270	2043.7270
37	110.0000	110.0000	1220.1661	1220.1661
38	110.0000	110.0000	1220.1661	1220.1661
39	110.0000	110.0000	1220.1661	1220.1661
40	511.2794	511.2794	5540.9292	5540.9296
Sum	10500.0000	10500.0000	121412.5704	121412.5702

5.4. *Test Case 3: Memetic Implementation with Honey Bee Mating Optimization.* HBMO algorithm is selected as a final experiment for the memetic implementation in this study. Up until now, the best minimum generation cost of ELD for the same test system using HBMO has been reported as \$121,412.5704 [34], and each generator's output generation at this point is presented in Table 5. Using a memetic combination to HBMO (M_HBMO) proposed in this paper,

the better minimum cost of the same ELD problem can be obtained as \$121,414.5702, and the results are presented in Table 5.

6. Conclusions

In summary, this study introduced a memetic scheme of metaheuristic algorithm and gradient-based technique

TABLE 6: Test results and comparison.

Algorithm	Minimum cost (\$)
Chaotic differential evolution and quadratic programming [54]	121,741.9700
PSO [55]	121,735.4700
Hybrid differential evolution [56]	121,698.5100
New PSO [57]	121,664.4300
Antipredatory PSO [55]	121,663.5200
Self-organizing hierarchical PSO [58]	121,501.1400
Biography-based optimization [59]	121,479.5000
GA-PS-SQP [60]	121,458.0000
Bacterial foraging [61]	121,423.6300
Harmony search (HS) [36]	121,415.4560
Memetic harmony search (this study)	121,415.4525
Pattern search [62]	121,415.1400
Firefly algorithm (FA) [33]	121,415.0522
Memetic firefly algorithm (this study)	121,414.9137
Honey bee mating optimization (HBMO) [34]	121,412.5704
Memetic HBMO (this study)	121,412.5702

and then applied it to a popular benchmark problem of 40 generating-unit ELD problem with valve-point loading, obtaining better solutions than other solutions ever found in the literature. As shown in Table 6, the result (\$121415.4560) of HS was further improved into \$121415.4525 as shown in bold font; that (\$121415.0522) of FA was further improved into \$121414.9137 as shown in bold font; and that (\$121412.5704) of HBMO was further improved into \$121412.5702 as shown in bold font. We have extended the simulation comparisons against the other recent metaheuristic approaches, and it is also listed in Table 6. We also hope that this table and corresponding references become a good literature survey for future researches.

While metaheuristic algorithms perform well in global search, they do not perform well in local search. On the contrary, while gradient-based techniques perform well in local search, they do not perform well in global search. Thus, the memetic approach in this study can be mutually complementary to obtain better solutions than either metaheuristic-only solution or gradient-based-only solution. Not only this ELD problem, but also hydrologic flood model calibration had better results using the memetic approach [79].

With this successful approach, we would like to explore more complex real-world ELD problems as well as other optimization problems. The proposed method can be applied to improve the simulation results of existing approaches [80, 81] in the future.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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