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Research Article

Economic Dispatch Using Parameter-Setting-Free Harmony Search

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Economic dispatch is one of the popular energy system optimization problems. Recently, it has been solved by various phenomenon-mimicking metaheuristic algorithms such as genetic algorithm, tabu search, evolutionary programming, particle swarm optimization, harmony search, honey bee mating optimization, and firefly algorithm. However, those phenomenon-mimicking problems require a tedious and troublesome process of algorithm parameter value setting. Without a proper parameter setting, good results cannot be guaranteed. Thus, this study adopts a newly developed parameter-setting-free technique combined with the harmony search algorithm and applies it to the economic dispatch problem for the first time, obtaining good results. Hopefully more researchers in energy system fields will adopt this user-friendly technique in their own problems in the future.

1. Introduction

Economic dispatch (ED) is defined in the US Energy Policy Act of 2005 as the operation of electrical generation facilities to produce energy at the least cost to reliably serve consumers while satisfying any operational limits of generation and transmission facilities. ED became a popular optimization problem in energy system field, which has been tackled by various optimization techniques such as genetic algorithm (GA) [1], tabu search (TS) [2], evolutionary programming (EP) [3], particle swarm optimization (PSO) [4], harmony search (HS) [5], honey bee mating optimization (HBMO) [6], and firefly algorithm (FA) [7].

As observed in the literature, better results have been obtained by phenomenon-mimicking metaheuristic algorithms rather than gradient-based mathematical techniques. Indeed, the metaheuristic algorithm has advantages over the mathematical technique in terms of several factors: (1) the former does not require complex derivative functions; (2) the former does not require a feasible starting solution vector which is sensitive to the final solution quality; and (3) the former has more chance to find the global optimum.

However, the metaheuristic algorithm also has the weakness in the sense that it requires "proper and appropriate" value setting for algorithm parameters [8]. For example, in GA, only carefully chosen values for crossover and mutation rates can guarantee good final solution quality, which is not an easy task for algorithm users in practical fields who seldom know how the algorithm exactly works.

In order to overcome this troublesome parameter setting process, researchers have proposed adaptive GA techniques [9], which adjust crossover and mutation rates adaptively, instead of using fixed rates, to find good solutions without manually setting the algorithm parameters. This adaptive technique has been applied to various technical applications such as environmental treatment [10], structural design [11], and sewer network design [12].

In energy system field, the adaptive GA was also applied to a reactive power dispatch optimization as early as 1998 [13]. Afterwards, however, there have been seldom applications in major research databases using the adaptive technique. Thus, this study intends to apply a newly developed adaptive parameter-setting-free (PSF) technique [8], which is combined with the HS algorithm, to the economic dispatch problem for the first time.

2. Economic Dispatch Problem

The economic dispatch problem can be optimally formulated. The objective function can be as follows:

$$\text{Min } z = \sum_i C_i(P_i), \tag{1}$$

where $C_i(\cdot)$ is generation cost for generator i and P_i is electrical power generated by generator i. Here, $C_i(\cdot)$ can be further expressed as follows:

$$C_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \times \sin\left(f_i \times \left(P_i^{\min} - P_i \right) \right) \right|, \tag{2}$$

where a_i, b_i, c_i, e_i, and f_i are cost coefficients for generator i. The fourth term in the right-hand side of (2) represents valve-point effects.

The above objective function is to be minimized while satisfying the following equality constraint:

$$\sum_i P_i = D, \tag{3}$$

where D is total load demand. Also, each generator should generate power between minimum and maximum limits as the following inequality constraint:

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

3. Parameter-Setting-Free Technique

The parameter-setting-free harmony search (PSF-HS) algorithm was first proposed for optimizing the discrete-variable problems such as structural design [14], water network design [15], and recreational magic square [8]. PSF-HS was also applied to a continuous-variable problem such as hydrologic parameter calibration [16].

However, it was never applied to a continuous-variable problem with technical constraints. Thus, this study first applies PSF-HS to the ED problem, whose type is the continuous-variable problem with a technical constraint, because its decision variable P_i has the continuous value and it has the equality constraint of total power demand as expressed in (3). Here, the inequality constraint in (4) can be simply considered as value ranges without using any penalty method.

The basic HS algorithm manages a memory matrix, named harmony memory, as follows:

$$\mathbf{HM} = \left[\begin{array}{cccc|c} P_1^1 & P_2^1 & \cdots & P_n^1 & z(\mathbf{P}^1) \\ P_1^2 & P_2^2 & \cdots & P_n^2 & z(\mathbf{P}^2) \\ \vdots & \cdots & \cdots & \cdots & \vdots \\ P_1^{\mathrm{HMS}} & P_2^{\mathrm{HMS}} & \cdots & P_n^{\mathrm{HMS}} & z(\mathbf{P}^{\mathrm{HMS}}) \end{array} \right]. \tag{5}$$

Once this **HM** is fully filled with randomly generated vectors $(\mathbf{P}^1, \ldots, \mathbf{P}^{\mathrm{HMS}})$, a new vector $\mathbf{P}^{\mathrm{New}}$ is generated as follows:

$$P_i^{\mathrm{New}} \longleftarrow \begin{cases} P_i^{\min} \le P_i \le P_i^{\max} & \text{w.p. } R_{\mathrm{Random}} \\ P_i(k) \in \left\{ P_i^1, P_i^2, \ldots, P_i^{\mathrm{HMS}} \right\} & \text{w.p. } R_{\mathrm{Memory}} \\ P_i(k) + \Delta & \text{w.p. } R_{\mathrm{Pitch}}, \end{cases} \tag{6}$$

where R_{Random} is random selection rate, R_{Memory} is pure memory consideration rate, R_{Pitch} is pure pitch adjustment rate, and Δ is pitch adjustment amount.

If the newly generated vector $\mathbf{P}^{\mathrm{New}}$ is better than the worst vector $\mathbf{P}^{\mathrm{Worst}}$ in **HM**, those two vectors are swapped as follows:

$$\mathbf{P}^{\mathrm{New}} \in \mathbf{HM} \wedge \mathbf{P}^{\mathrm{Worst}} \notin \mathbf{HM}. \tag{7}$$

The basic HS algorithm performs (6) and (7) until a termination criterion is satisfied.

For PSF-HS, one additional matrix, named operation type matrix (OTM), is also managed as follows:

$$\begin{bmatrix} o_1^1 = \text{Random} & o_2^1 = \text{Pitch} & \cdots & o_n^1 = \text{Memory} \\ o_1^2 = \text{Memory} & o_2^2 = \text{Memory} & \cdots & o_n^2 = \text{Pitch} \\ \vdots & \cdots & \cdots & \cdots \\ o_1^{\mathrm{HMS}} = \text{Memory} & o_2^{\mathrm{HMS}} = \text{Random} & \cdots & o_n^{\mathrm{HMS}} = \text{Memory} \end{bmatrix}. \tag{8}$$

OTM memorizes which operation (random selection, memory consideration, and pitch adjustment) each value comes from. For example, if the value of P_2^2 in **HM** comes from memory consideration operation, the value of o_2^2 in OTM is also set as "Memory." This process happens when initial vectors are populated or when a new vector is inserted into **HM**.

Thus, instead of using fixed algorithm parameter values, PSF-HS can utilize adaptive parameter values by calculating them at each iteration as follows:

$$\begin{aligned} R_{i,\mathrm{Random}} &= \frac{ct\left(o_i^j = \text{Random},\ j = 1, 2, \ldots, \mathrm{HMS}\right)}{\mathrm{HMS}}, \quad i = 1, 2, \ldots, n, \\ R_{i,\mathrm{Memory}} &= \frac{ct\left(o_i^j = \text{Memory},\ j = 1, 2, \ldots, \mathrm{HMS}\right)}{\mathrm{HMS}}, \quad i = 1, 2, \ldots, n, \\ R_{i,\mathrm{Pitch}} &= \frac{ct\left(o_i^j = \text{Pitch},\ j = 1, 2, \ldots, \mathrm{HMS}\right)}{\mathrm{HMS}}, \quad i = 1, 2, \ldots, n, \end{aligned} \tag{9}$$

where $ct(\cdot)$ is a function which counts specific elements that satisfy the condition.

4. Numerical Example

The PSF-HS is applied to a popular bench-mark ED problem with three generators. The input data for the three-generator problem is shown in Table 1.

When the total system demand is set to 850 MW, the optimal solution is known as \$8234.07 [2–4], which was replicated by using a popular gradient-based technique (generalized reduced gradient (GRG) method), which has

TABLE 1: Data for three-generator example with valve-point loading.

Generator	$P_i^{\min}$	$P_i^{\max}$	a_i	b_i	c_i	e_i	f_i
1	100	600	0.001562	7.92	561	300	0.0315
2	50	200	0.00482	7.97	78	150	0.063
3	100	400	0.00194	7.85	310	200	0.042

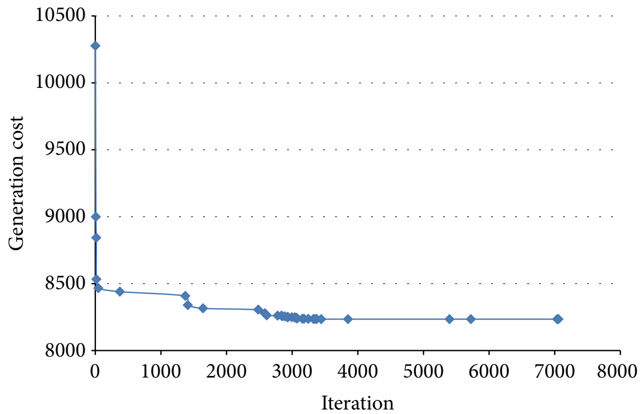

FIGURE 1: Convergence History of Generation Cost.

been also successfully applied to other energy optimization problems such as building chiller loading [17], combined heat and power ED [18], and hybrid renewable energy system design [19]. However, the GRG method was able to obtain the identical best solution only when it started with a vector ($P_1 = 300$; $P_2 = 150$; $P_3 = 400$). Instead, when, different starting vector ($P_1 = 600$, $P_2 = 200$, $P_3 = 400$) was used, solution quality was worsened as \$8241.41.

When PSF-HS was also applied to the problem, it obtained a near-optimal solution of \$8234.47 after 100 runs, which has small discrepancy from the optimal solution (\$8234.07) by 0.005%. For the results from 100 runs, maximum and mean solutions are \$8429.74 (2.4% discrepancy) and \$8292.88 (0.7% discrepancy), respectively. Here, PSF-HS was performed using MS-Excel VBA environment with Intel CPU 3.3 GHz. Each run takes only one second in this computing environment.

Figure 1 shows the convergence history of power generation cost for the case of the near-optimal solution \$8234.47. As seen in the figure, PSF-HS closely approached to the near-optimal solution in early iterations.

Table 2 shows the final **HM** with HMS = 30. As observed in the table, there are many similar vectors in **HM** because PSF-HS tried local search, instead of global search, in late stage of computation.

Figure 2 shows the history of random selection rate R_{Random}. As observed in the figure, all three parameters ($R_{1,\text{Random}}$, $R_{2,\text{Random}}$, and $R_{3,\text{Random}}$) started with higher values (0.5). In less than 1,000 iterations, $R_{1,\text{Random}}$ went up to around 0.4, $R_{2,\text{Random}}$ to around 0.5, and $R_{3,\text{Random}}$ to around 0.8. Then, they abruptly wend down to less than 0.1 after 3,000 iterations.

Figure 3 shows the history of pure memory consideration rate R_{Memory}. As observed in the figure, all three parameters

TABLE 2: Values of final HM.

Number	P_1	P_2	P_3	$\sum_i P_i$	$\sum_i C_i(P_i)$
1	300.944	149.782	399.274	850.000	8234.472
2	300.944	149.782	399.274	850.001	8234.477
3	300.944	149.782	399.274	850.001	8234.479
4	300.973	149.754	399.274	850.002	8234.481
5	301.006	149.751	399.244	850.001	8234.482
6	300.974	149.782	399.244	850.000	8234.483
7	300.974	149.754	399.274	850.002	8234.487
8	300.977	149.779	399.244	850.001	8234.489
9	300.977	149.751	399.274	850.003	8234.496
10	300.945	149.782	399.274	850.002	8234.497
11	300.912	149.815	399.274	850.001	8234.501
12	300.934	149.822	399.244	850.000	8234.509
13	300.973	149.784	399.244	850.002	8234.510
14	300.944	149.784	399.274	850.002	8234.511
15	300.912	149.815	399.274	850.002	8234.511
16	300.934	149.794	399.274	850.002	8234.511
17	300.905	149.822	399.274	850.001	8234.514
18	300.974	149.784	399.244	850.002	8234.516
19	300.944	149.784	399.274	850.003	8234.517
20	301.013	149.786	399.202	850.001	8234.520
21	301.013	149.786	399.202	850.002	8234.535
22	300.945	149.784	399.274	850.004	8234.535
23	301.009	149.751	399.244	850.004	8234.536
24	301.006	149.754	399.244	850.004	8234.538
25	300.973	149.786	399.244	850.003	8234.542
26	300.977	149.782	399.244	850.003	8234.542
27	300.944	149.786	399.274	850.004	8234.542
28	301.006	149.794	399.202	850.002	8234.543
29	300.977	149.782	399.244	850.004	8234.547
30	300.974	149.786	399.244	850.004	8234.548

($R_{1,\text{Memory}}$, $R_{2,\text{Memory}}$, and $R_{3,\text{Memory}}$) abruptly went up from the starting point of 0.25. After 4,000 iterations, they became more than 0.8 and stayed.

Figure 4 shows the history of pure pitch adjustment rate R_{Pitch}. As observed in the figure, all three parameters ($R_{1,\text{Pitch}}$, $R_{2,\text{Pitch}}$, and $R_{3,\text{Pitch}}$), from the starting point of 0.25, monotonically stayed less than 0.3 except for one situation when $R_{3,\text{Pitch}}$ spiked near 3,000 iterations.

Furthermore, the sensitivity analysis of initial parameter values was performed. While the original parameter set ($R_{\text{Random}} = 0.5$, $R_{\text{Memory}} = 0.25$, and $R_{\text{Pitch}} = 0.25$) resulted in minimal solution of \$8,243.56 and average solution of \$8,287.69 after 10 runs, equal-valued parameter set ($R_{\text{Random}} = 0.33$, $R_{\text{Memory}} = 0.33$, and $R_{\text{Pitch}} = 0.33$) resulted in minimal solution of \$8,242.12 and average solution of \$8,322.11; memory-consideration-oriented parameter set ($R_{\text{Random}} = 0.1$, $R_{\text{Memory}} = 0.7$, and $R_{\text{Pitch}} = 0.2$) resulted in minimal solution of \$8,241.34 and average solution of \$8,314.45; random-selection-oriented parameter set ($R_{\text{Random}} = 0.8$, $R_{\text{Memory}} = 0.1$, and $R_{\text{Pitch}} = 0.1$) resulted in minimal solution of \$8,241.29 and average solution of

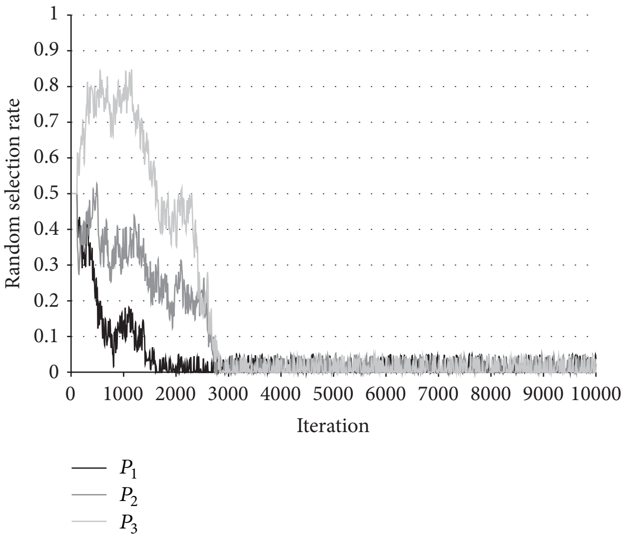

FIGURE 2: History of Random Selection Rate.

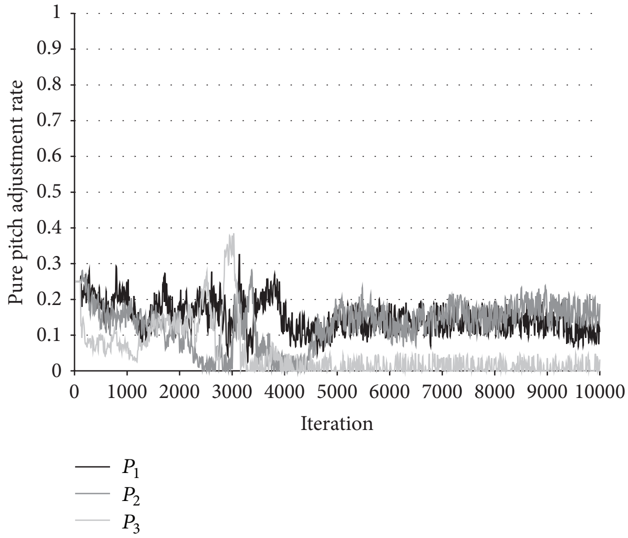

FIGURE 4: History of Pure Pitch Adjustment Rate.

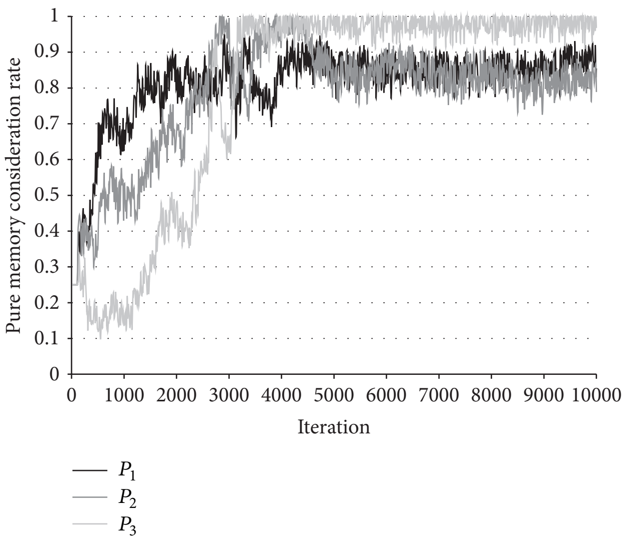

FIGURE 3: History of Pure Memory Consideration Rate.

\$8,272.40. It appeared that the initial parameter values are not very sensitive to final solution quality.

Especially, when the results from memory-consideration-oriented parameter set ($R_{\text{Random}} = 0.1$, $R_{\text{Memory}} = 0.7$, and $R_{\text{Pitch}} = 0.2$) and those from random-selection-oriented parameter set ($R_{\text{Random}} = 0.8$, $R_{\text{Memory}} = 0.1$, and $R_{\text{Pitch}} = 0.1$) were statistically compared, although their variances are different based on F-test ($p = 0.04$), their averages are not significantly different based on t-test ($p = 0.16$).

5. Conclusions

This study applied PSF-HS to the ED problem for the first time, obtaining a good solution which is very close to the best solution ever found. While existing metaheuristic algorithms require carefully chosen algorithm parameters, PSF-HS did not require that tedious process. Thus, there surely exists a tradeoff between original HS and PSF-HS. Also, it should be noted that PSF-HS respectively considers individual algorithm parameters for each variable, which is more efficient way than using lumped parameters for all variables.

For future study, the structure of PSF-HS should be improved to do better performance. Also, it can be applied to large-scale real-world problems to test scalability. Also, other researchers are expected to apply this novel technique to their own energy-related problems.

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