A Multiobjective Bacterial Optimization Method Based on Comprehensive Learning Strategy for Environmental/Economic Power Dispatch

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Abstract. This article extends the bacterial foraging optimization (BFO) for addressing the multi-objective environmental/economic power dispatch (EED) problem. This new approach, abbreviated as MCLBFO, is proposed based on the comprehensive learning strategy to improve the search capability of BFO for the optimal solution. Besides, the fitness survival mechanism based on a health sorting technique is employed and embedded in reproduction mechanism to enhance the quality of the bacteria swarm. The diversity of the solutions is achieved by the combination of two typical techniques, i.e. non-dominance sorting and crowded distance. Experimental tests on the standard IEEE 30-bus, 6-generator test system demonstrate that the novel algorithm, MCLBFO, is superior to other well developed methods such as MOEA/D, SMS-EMOA and FCPSO. The results of the comparison indicate that MCLBFO is outstanding in handling optimization problems with multiple conflicting objectives.

Keywords: Multi-objective problems · Bacterial foraging optimization · Comprehensive learning strategy · Environmental/economic power dispatch

1 Introduction

Traditional electric power systems, known as Economic Power Dispatch (ED), are operated to minimize the cost in supply and transmission related processes while meeting all generation and systems constraints [1, 2]. However, the traditional model is proved to be not the best as the increasing public appeal to environmental protection [3]. Therefore, when it is related to environment issues, this single objective model, which only considers the cost, does not satisfy the public any more.

Actually, amendments to some rules of the clean air act have carried out to limit the emission of SO_2 and NO_x in 1990. Soon afterwards strategies used to reduce emissions were proposed and discussed accordingly [4]. Thus, the traditional problem of ED is

Y. Tan et al. (Eds.): ICSI 2016, Part II, LNCS 9713, pp. 400–407, 2016.
DOI: 10.1007/978-3-319-41009-8_43

transformed to the problem of Environmental/Economic Power Dispatch (EED) considering the conflicting objectives to minimize the generation cost and pollution emissions. Population based algorithms are demonstrated to have the advantages to address the EED by handling all the conflicting objectives simultaneously, and providing the results consisting of a set of satisfactory solutions (Pareto-optimal front). Since now, population based algorithms have been wildly used in solving EED, such as multi-objective particle swarm optimization (MOPSO) algorithms [5, 6], multi-objective evolutionary algorithms (MOEAs) [7, 8], Bees Algorithms [9, 10].

By getting inspiration from the foraging behavior of *E. coli* bacteria, bacterial foraging optimization was proposed by Passion in 2002 [11] and it has been improved for handling multi-objective problems [12–15]. However, most of them have only been tested by benchmark functions which are comparatively simple multi-objective issues with uncomplicated structure in objectives. Some of them are also applied for EED problem and solve it as multi-objective optimization problems [16–18], while the algorithms adopted for comparison seem to be outdated and numerous improvements have been proposed by other researchers.

In this article, an extension of the original Multi-objective Bacterial Foraging Optimization (MBFO) [14], referred as Multi-objective Comprehensive Learning Bacterial Foraging Optimization (MCLBFO), is presented to address the environmental/economic power dispatch (EED) problem. This newly proposed method considers the comprehensive learning between bacteria, the health sorting approach for reproduction, as well as the external achieves to handle the non-dominance choice for the improvement of the solution diversity.

The rest of the article is structured as follows: Sect. 2 provides a brief description of the original BFO, and the proposed MCLBFO are presented in this Sect. 3. Comparative studies and pertinent discussions are elaborated in Sect. 4, Finally, Sect. 5 provides the conclusions of this article.

2 Bacterial Foraging Optimization

Passion proposed Bacterial Foraging Optimization (BFO) in 2002 by getting inspiration from the foraging behavior of *E. coli* [11]. Generally, the foraging behavior of bacteria mainly includes three steps: chemotaxis, reproduction, and elimination and dispersal. A brief description of these three steps is illustrated as follows.

(1) Chemotaxis: Define $\theta^i(j,k,l)$ as the position of the i^{th} bacterium at the j^{th} chemotactic, the k^{th} reproductive and the l^{th} elimination and dispersal. The moving direction of each bacterium is adjusted as:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + c(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{1}$$

where: $C(i)$ indicates the unit moving length, and $\Delta(i)$ represents the direction angle of the i^{th} step. The typical behaviors, e.g. running, tumbling during the bacterial foraging process are also incorporated into the chemotactic step.

(2) Reproduction: Reproduction as a basic life behavior of all kinds of species is also the key point for life preservation. The search efficiency of the bacterial colony increases along with the generation times. Define $J_t\ (i, j, k, l)$ as the fitness value of the t^{th} (t = 1, 2) function of the i^{th} bacterium at the j^{th} chemotaxis, the k^{th} reproduction and the l^{th} dispersal. The health status of the i^{th} bacterium can be formulated as:

$$J_t^i health = \sum_{j=1}^{N_c} J_t(i, j, k, l) \tag{2}$$

According to their health status, all bacteria are arranged in ascending order. The better ranking half which have better health status can be kept and the rest half should be eliminated. That is:

$$\theta^{i+\mathrm{Sr}}(j, k, l) = \theta^i(j, k, l) \tag{3}$$

The healthy $S_r = S/2$ bacteria are now supposed to reproduce to keep the total population number unchanged while improving the quality of the population.

(3) Elimination and Dispersal: The bacteria individuals have the high chance to be impacted by the dynamic environment surrounding them. The one of main advantages of this strategy is to improve the diversity of the bacteria swarm. It could be formulated as:

$$\theta^i = x_{\min} + (x_{\max} - x_{\min}) * rand \tag{4}$$

where x_{max} and x_{min} are the upper and the lower limitation of the initial position, and *rand* is a random value ranging from 0 to 1. The principle of elimination and dispersal in this paper refers to the literature published by Passino [11].

3 Multiobjective Comprehensive Learning Bacterial Foraging Optimization

In this section, MCLBFO is presented for addressing the multi-objective optimization problems. Two strategies, i.e. non-dominated sorting and crowding distance [19–21], are employed in MCLBFO. These two methods are regarded as the superiority tactics in addressing multi-objective problems. Except these two strategies, additional two mechanisms are modified for multi-objective optimization, i.e. comprehensive learning mechanism and health evaluation.

3.1 Comprehensive Learning Mechanism

The original comprehensive learning mechanism is proposed by Liang et al. [22] to enhance the capability of PSO. However, it is less applicable for multi-objective problems for Pareto optimal sets. To enhance the search accuracy, the comprehensive learning mechanism is modified for multi-objective optimization. In this learning mechanism, the moving direction of the i^{th} bacterium in the d^{th} dimension is updated as follows:

$$\theta_d(i,j+1,k,l) = \theta_d(i,j,k,l) + c(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} + r*(pbest_{id} - \theta_d(i,j,k,l)) + (1-r)*(rep_d - \theta_d(i,j,k,l)) \tag{5}$$

$$pbest_{id} = \alpha * pbest_{compet} + (1-\alpha) * pbest_{id} \tag{6}$$

$$pbest_{compet} = b * pbest_n + (1-b)pbest_m \tag{7}$$

where n and m are two random generated individuals from population. $n \in \{1,\ldots,S\}$, $m \in \{1,\ldots,S\}$, and $n \neq m$. Three parameters r, a and b are randomely selected from $\{0, 1\}$, whilst are two constants given previously. $Pbest_{id}$ indicating the personal best of the d^{th} dimension is obtained from either current position of individual $Pbest_{id}$ or from the best position of two randomly selected individual $Pbest_{compet}$. To obtain the satisfied solutions approaching to the Pareto optimal front, the position of individuals are also learned from external non-dominated archives *Rep*.

3.2 Health Assessment Based on Population Segmentation

In BFO, the bacteria with higher performance are used for reproduction according to their health indexes. For each bacterium in the colony, the ability to search for nutrients varies and is marked by the health indexes $J_t^i health$ (t = 1, 2) which are influenced by objective function values. In the multi-objective problems, the health condition of bacteria are different in definition. The particles approaching to the true Pareto front would be regarded as the better performance. Therefore, the reproduction of bacteria is formulated as follows:

Pseudo-code 1: *Reproduction based on health assessment*

For each bacterium (i =1,2,…, n)

$$J^i_{1health} = \sum_{j=1}^{Nc} J_1(i,j,k,l), \quad J^i_{2health} = \sum_{j=1}^{Nc} J_2(i,j,k,l), \quad J^i_{health} = J^i_{1health} + J^i_{2health}$$

end

Sort $\{J^i_{1health}\}$ in increasing order, and select the first 20% population, i.e. Pop_1

Sort $\{J^i_{2health}\}$ in increasing order, and select the first 20% population, i.e. Pop_2

Sort $\{J^i_{health}\}$ in increasing order, and select the first 60% population, i.e. Pop_3

Then, the new population is updated as: Pop=[Pop_1, Pop_2, Pop_3]

3.3 MCLBFO Algorithm

Based on the strategies described above, the Pseudo-code of MCLBFO for multi-objective problems are presented as follows.

Pseudo-code 2*: Multiobjective Comprehensive Learning Bacterial Foraging Optimization (MCLBFO)*

```
Begin
Initialization: Parameters' value, bacterial position, etc.
 For k =1: Upper limitation of elimination process N_e
  For j =1: Upper limitation of reproduction process N_r
    For i = 1: Upper limitation of chemotaxis process N_c
      For Each bacterium
        Do Chemotaxis step using Eq. 5;
      End for
      Updating the archives: Non-Dominate sorting and crowded distance
    End chemotaxis process
    Do: Reproduction based on health assessment (refer to Pseudo-code 1)
  End reproduction process
  Do Elimination step using Eq. 4
End elimination process
Output: solutions in archives, i.e. Pareto optimal font
```

4 Application

To investigate its effectiveness, the proposed algorithm (MCLBFO) has been applied in the standard IEEE 30-bus 6-generator test system [23]. The objectives and constrains of the EED problem is described as a nonlinear combinatory multiple objective problem with multiply constraints in [24]. The total demand of the system is 2.834 *p.u.*

4.1 Parameter Settings and Multiobjective Methods

Transmission loss coefficient B_{ij}, upper and lower real power output of each generator, and values of fuel cost and emission coefficients are defined as the same in [25]. The numerical results of the novel algorithm are compared with six multi-objective approaches: BB-MOPSO [25], NSGAII [20], FCPSO [24], MOEA/D [21], MBFO [14] and SMS-EMOA [19].

Values of parameter used in the new technique are as follows: $p = 2$, $S = 100$, $N_c = 100$, $N_s = 5$, $N_{re} = 4$, $N_{ed} = 2$, $P_{ed} = 0.2$, $C = 0.1$. The parameter P_r in MCLBFO is a constant, and equals 0.5. Furthermore, the learning probability P_c is set as 0.1, and the algorithm is conducted for 20 runs to obtain the statistical results. Algorithms are initiated according to the above settings. The optimization process is implemented through the MATLAB.

4.2 Experimental Results and Analysis

For comparison purposes, the system is chosen as a typical case considering the transmission losses. This case considers several constraints, such as the generation capacity, the transmission losses and the power balance constraints. Two objectives, minimizing the fuel cost and minimizing emissions, are optimized simultaneously. The best values of fuel cost and emission optimized using the proposed algorithm as well as six other reported approaches are shown as Tables 1 and 2, respectively.

Table 1. Best results out of 20 trials for fuel cost

	BB-MOPSO	NSGAII	FCPSO	MOEA/D	SMS-EMOA	MBFO	MCLBFO
P_{G1}	0.1229	0.1151	0.1130	0.1186	0.1183	0.1271	0.1121
P_{G2}	0.2880	0.3055	0.3145	0.2971	0.2977	0.2171	0.2979
P_{G3}	0.5792	0.5972	0.5826	0.6123	0.6140	0.6256	0.5692
P_{G4}	0.9875	0.9808	0.9860	0.9514	0.9466	1.0018	0.9775
P_{G5}	0.5255	0.5142	0.5264	0.5080	0.5103	0.5278	0.5491
P_{G6}	0.3564	0.3541	0.3450	0.3780	0.3471	0.3346	0.2640
Cost	605.9817	607.77	607.79	607.6872	607.6896	606.6184	**605.7128**
Emis.	0.22019	0.2198	0.2201	0.2179	0.2176	0.2231	0.2198

Table 2. Best results out of 20 trials for emission

	BB-MOPSO	NSGAII	FCPSO	MOEA/D	SMS-EMOA	MBFO	MCLBFO
P_{G1}	0.4103	0.4101	0.4063	0.4034	0.4002	0.5000	0.4071
P_{G2}	0.4661	0.4631	0.4586	0.4589	0.4521	0.4552	0.4621
P_{G3}	0.5432	0.5434	0.5510	0.5420	0.5394	0.5508	0.5421
P_{G4}	0.3883	0.3895	0.4084	0.3973	0.4101	0.3838	0.3891
P_{G5}	0.5447	0.5438	0.5432	0.5381	0.5413	0.4754	0.5401
P_{G6}	0.5168	0.5151	0.4974	0.4008	0.4909	0.4688	0.5112
Cost	646.21	646.06	643.58	645.16	643.58	653.67	646.16
Emis.	**0.194179**	**0.194179**	0.194212	0.194198	0.194219	0.194955	**0.194179**

MCLBFO could obtain the smallest fuel cost in comparison to all six compared algorithms in terms of emission objective, and there is no big difference between studied methods in terms of fuel cost. FCPSO obtain the comparatively biggest fuel cost, and NSGAII, SMS-EMOA as well as MOEA/D generate more fuel cost, while the remaining methods BB-MOPSO and MBFO get smaller values. Besides, Table 1 also verifies the effectiveness of the MCLBFO for being got the smallest emission, while MBFO is difficult in solving the complex objectives.

Through the experiment results on the standard IEEE 30-bus 6-generator test system, the effectiveness of the novel algorithm has been investigated. All in all, the performance of the novel technique MCLBFO has confirmed its superiority compared to reported traditional multi-objective optimization algorithms in prior literature.

5 Conclusion and Future Work

In this paper, a multi-objective algorithm extended from bacterial foraging optimization is presented to handle the Environmental/Economic Dispatch problem. Through the experiments on the IEEE 30-node, 6-generator system, the proposed algorithm (MCLBFO) has proved to be promising in dealing with multi-objective optimization problems. Studies on solving EED optimization problem are helpful for choosing and modifying bacterial based algorithms for the optimization of multi-objective optimization problems. Even so, BFO, with its own limitations, has a high computation complexity which cannot be ignored. In future, more work will be done to overcome this computational problem, and more powerful and complicated multi-objective bacterial foraging optimization variants will be studied.

Acknowledgments. This work is partially supported by The National Natural Science Foundation of China (Grants Nos. 71571120, 71271140, 71461027, 71471158) and the Natural Science Foundation of Guangdong Province (Grant Nos. 1614050000376, 2014A030310314).

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