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Complex System Optimization for Economic Emission Load Dispatch

Haiping Ma, Zhile Yang, Pengcheng You and Minrui Fei

Abstract—**This paper proposes a complex system optimization method to solve economic emission load dispatch. First, a real-world economic emission load dispatch is modeled as a complex system problem, and the optimization objectives include economic load dispatch, emission load dispatch and transmission network loss. Then a called BBO/complex method is introduced, which extends biogeography-based optimization to a multi-archipelago environment to suit the structure of complex systems. Finally, the proposed method is applied to the economic emission load dispatch, and the results show that it can obtain good performance for economic emission load dispatch studied in this paper, and it is a competitive algorithm for solving complex system optimization problem.**

Index Terms—**Complex system optimization; Economic emission load dispatch; Transmission network loss; Biogeography-based optimization**

I. Introduction

ECONOMIC emission load dispatch (EELD) problem is one of the fundamental issues of power system operation and planning [1-3]. Its main objective is to find the optimal generation cost and low emission demand while satisfying several equality and inequality constraints like power balance constraint and generator capacity constraint. Various investigations on EELD have been undertaken, and they mainly emphasize on economic performance and the environmental impact of fossil fuel power systems [4-6]. So in most of cases, EELD is taken as a two-objective optimization problem. Many multi-objective evolutionary algorithms, for example, the classic non-dominated sorting genetic algorithm (NSGA) [7], are used to solve the economic emission load dispatch, and obtain the good results [8-13].

With the progress of lives and industries, people put forward higher requirements for energy saving based on economy and environment protection. It undoubtedly becomes an important factor to reduce transmission network loss in power system. That is, low transmission network loss is taken as one objective in the EELD problem. Importantly, transmission network loss is subject to the constraints of system load balance, namely, the objectives, constraints, and variables have interactions with each other. Such systems are more complex than ever before, and the optimization becomes more difficult under these circumstances. In this situation, the system can not be treated as a typical multi-objective optimization problem any long. Considering these factors of the EELD problem, we here define it as a complex system, which has the following properties: (1) a complex system contains multiple objectives, multiple constraints and multiple variables; (2) these elements have interactions with each others; (3) the interactions include high degree of nonlinearity. Therefore, it is necessary to seek new optimization methods to deal with the EELD problem under new circumstances.

Complex system optimization is a class of optimization methods dedicated to solving multi-objective and multi-constraint interacting problems. Traditional complex system optimization methods are frameworks that provide basic conceptual structures without specifying the detailed underlying algorithms, including multidisciplinary feasible (MDF), individual discipline feasible (IDF) and collaborative optimization (CO). So the disadvantages of these methods are to require an additional optimization algorithm as a complementary but essential component, like gradient descent and Newton's method, which is usually based on the specific problem or the user's preference. Recently, heuristic algorithms become popular in both academic and industry, and they are modified to optimize complex system. It becomes the new trend, because they have the more flexible adaptive options compared to traditional methods. Biogeography-based optimization for complex system (BBO/complex) proposed by Du and Simon is one of the most effective heuristic algorithms to solve complex system [14-15], and it provides the best performance for some real-world applications, including the speed reducer problem, the power converter problem, the heart dipole problem and the propane combustion problem.

Since EELD is so important for power systems considering transmission network loss, more research needs to be carried out to make EELD solutions more robust and efficient. Motivated by this consideration, this paper highlights the benefits of BBO/complex for complex system, and uses it to find efficient dispatches for power system management. The remainder of this paper is organized as follows. Section II builds a complex system model of the EELD problem. Section III introduces BBO/complex as a complex system optimization method. Section IV applies BBO/complex to the EELD problem and presents optimization results. Section V provides conclusions and suggests directions for future work.

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II. Problem Formulation of EELD

The complex system model of the EELD problem is formulated as three optimization objectives and two constraints. The objectives include the generation cost, the emission cost and the transmission network loss, which should be minimized. It is defined as follows.

$$\min F(P) = \text{Minimize}\left(F_1(P), F_2(P), F_3(P)\right) \tag{1}$$

where $P = (P_1, \cdots, P_n)$ is the power outputs of generation units and n is the number of generation units in power system, $F(P)$ represents the set of three objective functions with respect to the generation units. $F_1(P)$ denotes the economic load dispatch, $F_2(P)$ denotes the emission load dispatch, and $F_3(P)$ denotes the transmission network loss. These objectives are described in detailed as follows.

A. Economic load dispatch

The economic load dispatch is expressed as minimization of the generation cost of power system, which is defined as

$$\begin{aligned} F_1(P) &= \sum_{i=1}^{n} F_i^{eco}(P_i) \\ &= \sum_{i=1}^{n}\left[\left(a_i P_i^2 + b_i P_i + c_i\right) + \left|d_i \sin\left(e_i\left(P_i^{\min} - P_i\right)\right)\right|\right] \quad (\$/\text{h}) \end{aligned} \tag{2}$$

where P_i is the power output of the ith generation unit and $P_i^{\min}$ is the lower power output limit of the ith generation unit, $F_i^{eco}(P_i)$ is the generation cost function of the ith generation unit and is usually expressed as a quadratic polynomial added sinusoidal function, which denotes valve-point loading effect [8], and a_i, b_i, c_i, d_i and e_i are the generation cost coefficients of the ith generation unit.

B. Emission load dispatch

The emission load dispatch is expressed as minimization of the emission cost released by power systems, which is defined as

$$\begin{aligned} F_2(P) &= \sum_{i=1}^{n} F_i^{emis}(P_i) \\ &= \sum_{i=1}^{n}\left[\left(\alpha_i P_i^2 + \beta_i P_i + \gamma_i\right) + \eta_i \exp\left(\delta_i P_i\right)\right] \quad (\text{Kg/h}) \end{aligned} \tag{3}$$

where $F_i^{emis}(P_i)$ is the emission cost function of the ith generation unit and is usually expressed as a quadratic polynomial associated with an exponential term [9], and $\alpha_i, \beta_i, \gamma_i, \eta_i$ and δ_i are the emission cost coefficients of the ith generation unit.

C. Transmission network loss

The total transmission network loss of power systems is defined as

$$F_3(P) = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j \quad (\text{MW}) \tag{4}$$

where B_{ij} is the transmission network loss coefficients which may be assumed to be constant under normal operating condition.

D. Constraints

Furthermore, three objective functions must satisfy the following constraints.

(a) Power capacity constraints

The power outputs of generation units should be within the capacity of each specific generation unit, so that

$$P_i^{\min} \le P_i \le P_i^{\max} \quad \text{for } i \in \{1, 2, \cdots, n\} \tag{5}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the lower limit and the upper limit of the ith power output respectively.

(b) Real power balance constraint

The sum of the generated power of all generation units must be equal to the sum of power demand response by the general traditional load demand P_D and the total transmission network loss F_3, which is shown as

$$\sum_{i=1}^{n} P_i = P_D + F_3 \tag{6}$$

Based on equation (6), we can see that the real power balance constraint contains the objective function of transmission network loss described by equation (4); that is, they are interacting with each other. In addition, equation (4) also shows the nonlinear characteristics of transmission network loss. So the EELD problem studied in this paper can be taken as a complex system. Next it comes to a question - how can we optimize such complex system?

III. Complex System Optimization

This section introduces BBO/Complex to optimize complex system. Before we discuss the details of BBO/Complex, there are some questions we need to clarify.

First, it is not realistic that most of the real-world applications are designed for multi-objective optimization problems, in which each candidate solution shares the same objective functions and constraints. In the most cases, the real-world problems are multi-input, multi-output, multi-objective and multi-constraint, and they are interrelated and complementary. Also, the constraints and independent variables of each objective may not be the same as well. At this point, we prefer to take real-world problems as complex systems than ordinary multi-objective problems.

Second, in the original BBO/Complex paper [14], the complex system consists of multiple subsystems, and each subsystem contains multiple objectives, and multiple constraints. For the EELD problem studied in this paper, we take each objective as a subsystem, that is, a subsystem only contains an objective. But when we discuss BBO/Complex in this paper, we still use the generalized framework, which can be applied to any other complex systems.

Third, the establishment of BBO/Complex is based on biogeography-based optimization. So some definitions and operating strategies of biogeography-based optimization, including migration and mutation, are reserved [16-18], and they are not described repeatedly.

Now we see some notations in BBO/Complex, which is described as follows:

(1) $P = \{A_1, A_2, A_3, \ldots\}$ is a population that is comprised of archipelagos. Each archipelago corresponds to one subsystem.

(2) $A_h = \{O_{h1}, O_{h2}, O_{h3}, \ldots; C_{h1}, C_{h2}, C_{h2}, \ldots; I_{h1}, I_{h2}, I_{h3}, \ldots\}$ is an archipelago that is comprised of objective O_{hi}, constraints C_{hi} and islands (which are called candidate solutions) I_{hi}.

(3) $I_{hi} = \{S_{hi1}, S_{hi2}, S_{hi3}, \ldots\}$ is island that is comprised of SIVs, also called candidate solution features, or independent variables, which are denotes as S_{hij}.

Next, based on the original paper [14], BBO/Complex is directly summarized as follows.

(1) Initialize the population, which is usually done with randomly generated individuals.

(2) Calculate the rank of islands in each subsystem, which will be described in the following subsection (*a*), and then perform within-subsystem migration: probabilistically choose the immigrating islands based on the obtained island ranks. Use roulette wheel selection based on the emigration rates to select the emigrating islands. Emigration rates are linearly related to the obtained island ranks. After each immigrating island selects its corresponding emigrating island, we perform within-subsystem migration. Each SIV in an immigrating island will have a chance to be replaced by an SIV from an emigrating island. Note that for within-subsystem migration, the immigrating and emigrating probabilities are relative to island ranks.

(3) Calculate the constraint and objective similarity levels between all pairs of subsystems, which will be described the following subsection (*b*), and calculate distance between each pairs of islands from different subsystems, which will be described in the following subsection (*c*). Then perform cross-subsystem migration: probabilistically find suitable pairs of subsystems to migrate, and the probability is based on the obtained similarity levels. After that, we need to choose emigrating islands for each immigrating island. We use roulette wheel selection based on distances of islands to select the emigrating islands. Islands with better distances will have better chance to be selected as the emigrating island. Each SIV in an immigrating island will have a chance to be replaced by an SIV from an emigrating island. Note that for cross-subsystem migration, the immigrating probability is relative to similarity levels, and emigrating probability is relative to distances of islands.

(4) Probabilistically perform mutation on each island based on the mutation probability, which is the same as that in the standard BBO algorithm.

(5) Save the islands in each subsystem with best performance as elite islands, and replace the worst islands in the population with the previous generation's elite islands.

(6) If the termination criterion is not met, go to step 2; otherwise, terminate.

In the structure of BBO/Complex described above, the two most important components are within-subsystem migration and cross-subsystem migration. In standard BBO, migration is a simple operator because the system consists of only one objective function. But in complex system, it consists of multiple subsystems, and we need to combine all information within subsystems and cross subsystems to determine to migration.

(*a*) *Island ranks within subsystem*

Island ranks are mainly used to calculate the migration probability within subsystems. We consider two factors that determine the island ranks: fitness values and constraint violations. Assume that we have a subsystem with the following characteristics: the population size is n, the number of objectives is m, the number of constrains is k, R_i is the rank of the ith island, and V_i is the number of constraint violations of the ith island. Algorithm 1 outlines the calculating procedure of island ranks within subsystem.

Algorithm 1: Island rank calculation within subsystem

Set $R_i = 0$ and $V_i = 0$;
For i =1 to n **do**
  For c=1 to k **do**
    If constraint c of island i is violated **then**
      $V_i = V_i + 1$;
    End if
  End for
End for
For i_1 =1 to n **do**
  For $i_2 = i_1$ to n **do**
    If $V_{i1} > V_{i2}$ **then**
      $R_{i1} = R_{i1} + m$;
    Else if $V_{i1} < V_{i2}$ **then**
      $R_{i2} = R_{i2} + m$;
    Else if $V_{i1} = V_{i2}$ **then**
      For o_1 =1 to m **do**
        If objective o_1 of island i_1 is better than o_1 of i_2 **then**
          $R_{i2} = R_{i2} + 1$;
        Else if objective o_1 of island i_2 is better than o_1 of i_1 **then**
          $R_{i1} = R_{i1} + 1$;
        End if
      End for
    End if
  End for
End for

After performing island ranks described in Algorithm 1, we have the rank of each island in the subsystem. Note that a smaller rank means better performance.

(*b*) *Similarity levels cross subsystems*

In BBO/Complex, migration cross subsystem is different with migration within subsystem. The comparison of ranks across subsystems is meaningless, because each subsystem has its own ranking system, and ranks assigned to each island in a subsystem only represents the relative goodness of the island in that specific subsystem.

For cross-subsystems, we use similarity levels of the objectives and the constraints to determine the pair of subsystems to migrate. The calculation of similarity levels is outlined in Algorithm 2, where U and V are the sets of objectives and constraints of two islands cross subsystems.

```
Algorithm 2: Similarity level calculation cross subsystem
Set SL = 0;
For each u ∈ U do
  For each v ∈ V do
    If u and v are the same type then
      SL = SL + 1;
    End if
  End for
End for
```

Next, we calculate the migration probability between islands based on the similarity level between subsystems, which is shown as

$$P=\begin{cases}\frac{1}{2}\left(\frac{OS}{OS_{\max}}+\frac{CS}{CS_{\max}}\right), \text{if } \ OS_{\max}>0 \text{ and } CS_{\max}>0\\ \frac{1}{2}\frac{OS}{OS_{\max}}, & \text{if } \ OS_{\max}>0 \text{ and } CS_{\max}=0\\ \frac{1}{2}\frac{CS}{CS_{\max}}, & \text{if } \ OS_{\max}=0 \text{ and } CS_{\max}>0\\ 0, & \text{if } \ OS_{\max}=0 \text{ and } CS_{\max}=0\end{cases} \tag{7}$$

where OS is objective similar level between two islands, $OS_{\max}$ is the maximum inter-archipelago objective similarity level in the population, CS is constraint similar level between two islands, and $CS_{\max}$ is the maximum inter-archipelago constraint similarity level in the population.

(*c*) *Distance between islands cross subsystems*

In a complex system, subsystems usually have different island structures. This is, the independent variables in each subsystem are not the same. So we need a method to calculate the distances between islands in different subsystems. The partial distance strategy is widely used to calculate distances with different structures, which is given as follows.

$$D=\begin{cases}\frac{t}{K_{ghab}}\sqrt{\sum_{k=1}^{t}\left(S_{gak}-S_{hbk}\right)^2 K_{ghabk}}, \text{if } \ K_{ghab}>0\\ 0, & \text{if } \ K_{ghab}=0\end{cases} \tag{8}$$

where

$$K_{ghabk}=\begin{cases}0, & \text{if } S_{gak}=N/A \text{ or } S_{hbk}=N/A\\ 1, & \text{if } S_{gak}\neq N/A \text{ and } S_{hbk}\neq N/A\end{cases} \tag{9}$$

and

$$K_{ghab}=\sum_{k=1}^{t}K_{ghabk} \tag{10}$$

where D is the partial distance between island a in subsystem g and island b in subsystem h, S is independent variable in an island, t is the total number of independent variables, and N/A denotes missing data, that is, an independent variable does not exist in a certain island.

IV. SIMULATIONS AND RESULTS

In this section, we use BBO/Complex to solve the proposed EELD problems. To compare the performance of BBO/Complex, we also use MDF, IDF, and CO, which are well-known traditional complex system optimization algorithms [14]. These three algorithms require an additional essential method as a complementary, and here we adopt the standard BBO algorithm. The test problems are 6-unit and 10-unit EELD problems, and the generation unit characteristics like cost coefficients of a, b, c, d, e, emission coefficients of $\alpha, \beta, \gamma, \eta, \delta$, capacity limits of generation unit of $P^{\min}$ and $P^{\max}$, and transmission network loss coefficient B, refer to literature [19].

The algorithm parameters have been used after a series of careful experimentations. For BBO/Complex and complementary methods in MDF, IDF, and CO, a population size is set to 50, and the mutation rate is set to 0.01 per solution decision variable per generation. If mutation occurs, the mutated value of the new independent variable is uniformly distributed in the search space. Each algorithm is evaluated by 100 times, with a maximum number of function evaluations equal to 100,000 for each simulation. The algorithms are programmed in MATLAB® on a 2.40 GHz Intel Pentium® 4 CPU with 4 GB of memory.

The performance metric is based on the function values of the generation cost, the emission cost and the total transmission network loss, and the optimization goal is to find the minimum values of these costs. The optimization results for 6-unit and 10-unit EELD problems are shown in Tables 1 and 2 respectively.

From Tables 1 and 2, we see that BBO/Complex has the better performance than MDF, IDF, and CO methods for 6-unit and 10-unit EELD problems, including the best generation cost, the best emission cost, and the best transmission network loss. The reason is that BBO/Complex effectively makes use of cross-subsystem migration to increase interaction of solutions, and within-subsystem migration to adaptively converge to the optimal solutions. Based on these results, it is concluded that BBO/Complex is a competitive optimization algorithm for complex systems, including the EELD problems we studied.

Table 1 – Best power outputs of generation units and optimal objective function values for 6-unit EELD problems

Unit power output	Best solutions			
	MDF	IDF	CO	BBO/Complex
P_1 (MW)	70.36	60.75	73.42	68.12
P_2 (MW)	108.45	95.62	110.74	101.87
P_3 (MW)	135.12	175.34	120.32	160.35
P_4 (MW)	137.49	106.32	135.79	142.78
P_5 (MW)	242.80	299.43	236.62	275.31
P_6 (MW)	215.63	198.75	234.12	215.43
Generation cost ($/h)	35218.3	37452.4	35120.1	34404.3
Emission cost (Kg/h)	749.63	776.23	743.20	716.32
Network loss (MW)	22.17	27.32	21.21	17.65

Table 2 – Best power outputs of generation units and optimal objective function values for 10-unit EELD problems

Unit power output	Best solutions			
	MDF	IDF	CO	BBO/Complex
P_1 (MW)	139.55	248.70	174.23	159.62
P_2 (MW)	96.32	211.34	82.36	102.17
P_3 (MW)	150.16	260.17	141.37	161.87
P_4 (MW)	207.23	149.35	185.44	165.32
P_5 (MW)	165.42	155.19	180.23	168.73
P_6 (MW)	215.14	151.63	206.77	219.42
P_7 (MW)	160.78	157.84	159.64	155.61
P_8 (MW)	228.47	312.85	236.15	246.50
P_9 (MW)	352.16	270.11	338.62	329.62
P_{10} (MW)	342.89	328.42	327.46	336.71
Generation cost ($/h)	38455.1	40327.8	38465.6	37655.2
Emission cost (Kg/h)	863.54	903.62	883.19	803.70
Network loss (MW)	31.25	36.74	32.15	27.32

V. CONCLUSION

In this paper an economic emission load dispatch is formulated as a complex system, which is more complicated than the ordinary multi-objective system. Then we introduce BBO/complex, which uses the original framework of standard BBO but extends it to a multi-archipelago environment to suit the structure of complex systems. Finally, we apply BBO/complex to economic emission load dispatch under new circumstances, and the simulation results indicate that BBO/complex can successfully solve the EELD problems we study, and it is a competitive complex system optimization algorithm.

This paper shows that BBO/complex has good results for solving the EELD problems, but still opens the door for additional development and empirical investigation. First, a real-world EELD problems integrated with renewable power sources and other flexible charging load demand is formulated in a way that is amenable to dynamic complex system optimization algorithms. Second, the framework of algorithm presented here could be extended for other types of heuristic algorithms to solve complex system problems.

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