A Novel Multi-information Fusion Algorithm Based on Population for Wind Power System

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Abstract. Reserve capacity optimization of power system plays an important role in large-scale Wind Power System. In this paper, a novel multi-information fusion algorithm based on population (MIFA-P) is proposed, which can balance the problem of reserve capacity optimization. MIFA-P determines the type of optimization problem by counting the maximum number of projections on the principal characteristic axis of the optimal individuals of the current population. Therefore, the corresponding class of evolutionary algorithm is chosen to solve the problem. In the process of evolution, each evolutionary algorithm achieves the organic integration through sharing population information. Finally, the validity and applicability of MIFA-P algorithm for large-scale decision variable black box optimization problem are verified by solving a practical scenario optimization problem of reserve capacity distribution in power system after wind power integration.

1. Introduction

Wind energy is a clean and renewable energy source. It plays an important role in energy saving and emission reduction and improving economic benefits of power grid. However, the scale of wind power generation is uncontrollable, because the wind power of wind farm is affected by natural climate [1]. When wind power is integrated into the power grid, it will directly lead to the uncontrollability of the entire power grid system.

In order to ensure the stability of the whole power grid system, conventional energy reserve capacity is put into use at multiple nodes of the whole power grid [2]. Therefore, how the reserve capacity of conventional energy is distributed in each node has a great influence on the stability of the whole power system. Inspired by nature, a variety of meta-heuristic algorithms have been proposed recently to deal with optimization problems, such as Evolution-based Algorithms [3], Swarm Intelligence-based Algorithms [4] and Cooperative coevolution-based Algorithms [5]. These have been successfully deal with different types of optimization problems. However, these meta-heuristic algorithms have failed to make full use of valuable information available from the individuals in previous iterations to guide their current and later search in the black-box real world optimization problems.

In this paper, we propose a novel multi-information fusion algorithm based on population, called MIFA-P. MIFA-P uses mathematical statistics to approximate classify optimization problems. Then, by sharing population information, it chooses a better algorithm to solve the corresponding type optimization problems, so as to improve the performance of the whole algorithm for solving unknown
type optimization problems. In the process of evolutionary algorithm solving, the problem type is checked every $k$ generations, and then the better algorithm is chosen to solve the problem. Because MIFA-P can learn the historical evolution information of the population in the whole process of solving, and automatically select the corresponding algorithm by calculating the projection relationship of each decision variable on the principal feature axis.

2. Probabilistic Principal Component Analysis

Probabilistic Principal Component Analysis (PPCA) model is a Bayesian treatment of Principal Component Analysis (PCA), and can be run generatively to provide samples from its distribution [6].

PPCA firstly introduces latent variables explicitly and corresponds to the principal component subspace of the original data. Then, the observed variables are sampled under the condition of this latent variable [7]. That is, the $d$-dimensional decision variable is added a Gaussian noise by a linear transformation of the $m$-dimensional implicit variable.

$$x = Wz + \mu + \varepsilon$$

Where $W$ is a rotation matrix, the size of which is $D \times M$ dimension, $z$ is the latent variable vector, $z = (z_1, z_2, \cdots, z_M)$, $\mu$ is the mean value of the current population, and $\varepsilon$ is the additional Gauss noise vector, $\varepsilon = (\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_D)$.

$$p(z) = N(z \mid 0, I)$$

$$p(x \mid z) = N(x \mid Wz + \mu, \sigma^2 I)$$

$$p(\varepsilon) = N(\varepsilon \mid 0, \sigma^2 I)$$

We can see that the linear Gaussian latent subspace model is fully determined by its parameters: $W$, $\mu$ and $\sigma$. In high-dimensional space, the calculation cost of solving model parameters directly and accurately is high. Therefore, the expectation maximization algorithm is used to estimate its parameters. Specific methods are as follows: In step $E$, the distribution parameters are initialized, the old parameters are used as fixed observation points, the distribution of hidden variables in the current algorithm is calculated, and the expected values are calculated. Then, the latent variable distribution is substituted into the logarithmic likelihood function of the complete data to calculate the maximum likelihood estimate. In $M$-step, the likelihood estimates calculated in $E$-step are maximized. Repeat steps $E$ and $M$ until the termination conditions are met. The logarithmic likelihood function of $X$ is:

$$\ln p(X, Z \mid \mu, W, \sigma^2) = \sum_{n=1}^{N} \{ \ln p(x_n \mid z_n) + \ln p(z_n) \}$$

Where $X$ is the latent space corresponding to the original space, and the exact maximum likelihood solution of the mean $\mu$ is:

$$\mu = \bar{x} = \frac{1}{N} \sum_{n=1}^{N} x_n$$

In step $E$, the old parameters are used to calculate the expected values.

$$\mathbb{E}[z_n] = \mathbf{M}^{-1} \mathbf{W}^T (x_n - \bar{x})$$

$$\mathbb{E}[z_n z_n^T] = \sigma^2 \mathbf{M}^{-1} + \mathbb{E}[z_n] \mathbb{E}[z_n]^T$$

In step $M$, the new parameter values are estimated.

$$W_{new} = \left[ \sum_{n=1}^{N} (x_n - \bar{x}) \mathbb{E}[z_n]^T \right] \left[ \sum_{n=1}^{N} \mathbb{E}[z_n z_n^T] \right]^{-1}$$
\[
\sigma_{\text{new}}^2 = \frac{1}{Nd} \sum_{n=1}^{N} \{ \| x_n - \bar{x} \|^2 - 2E[z_{ni}]^T W_{\text{new}}^T (x_n - \bar{x}) + Tr(E[z_{ni}z_{ni}^T]W_{\text{new}}^T W_{\text{new}}) \} 
\]

(10)

3. Proposed Approach

3.1. Basic Ideas

Each optimization algorithm can effectively solve some specified types of optimization problems. In the black box optimization problem, the hybrid algorithm can significantly improve the efficiency of solving the black box optimization problem by detecting the type of the problem and choosing the optimal algorithm with better effect in solving the specified type of optimization problem. The basic framework diagram of MIFA-P is shown in Figure 1.

MIFA-P is divided into five steps: initialization population, evaluation population, selection of dominant population, problem type detection and selection algorithm. Among them, the problem type detection step is to classify the problems by projecting historical information of each decision variable on the principal feature axis in the statistical dominant individuals. The selection algorithm step is to automatically select the better algorithm to solve the type of problem according to the information detected by the detection step of the problem type. There are three kinds of algorithms in the candidate pool: swarm intelligence-based algorithms, cooperative coevolution-based algorithms and estimation of distribution algorithm.

\[
P^u_v = |u| \cos \theta = \frac{|u| \times |v| \cos \theta}{|v|} = \frac{u \cdot v}{|v|}
\]

(11)

Where \( \theta \) is the angle between vectors \( u \) and vectors \( v \), \( v \) is the principal eigenvector, that is, the eigenvector corresponding to the maximum eigenvalue, \( u \) is the normalized value of the current optimal individual.

\[
\phi = \frac{\sum_{n=1}^{D} \max p^u_n}{D!}
\]

(12)
Where $\phi$ is algorithm selection coefficient. If $\phi = [0.75, 1]$ , MIFA-P select cooperative coevolution-based algorithms as based algorithm. If $\phi = [0.5, 0.75]$ , MIFA-P select swarm intelligence-based algorithms as based algorithm. If $\phi = [0, 0.5]$ , MIFA-P select estimation of distribution algorithm.

3.2. The flowchart of MIFA-P

Algorithms 1 show the pseudocode of MIFA-P. The algorithm consists of four parts: initialization, constraint checking, problem type checking and selection. Among them, code 1 is population initialization; code 3-6 are system reliability constraints detection part punishes individuals who do not meet the constraints; code 7-13 are problem detection part, according to the type of problem, chooses PSO, DECC and EDA algorithm to generate new population; code 14-18 are population selection part, the current generation population and the previous generation population. The best individuals of the group are combined.

Algorithm 1 General Framework of an MIFA-P

Input: Population Size $N$; Mixing rate $\omega$;

Output: Optimal Population $Pop_g$;

1. random initialization population
2. While the termination condition is not met do
3. Non-sequential Monte-Carlo simulation is used to test whether each individual in a new population satisfies the system reliability constraints
4. If Individual dissatisfaction constraint then
5. Punishment of individuals
6. End If
7. Calculate and rank all individual fitness functions satisfying system reliability constraints;
8. Problem characteristics of detection based on $Pop^e_g$
9. Select the corresponding algorithm to cross-mutate the population and generate a new population
10. Non-sequential Monte-Carlo simulation is used to test whether each individual in a new population satisfies the system reliability constraints.
11. If Individual dissatisfaction constraint then
12. GOTO Step 10
13. End If
14. If $g > 0$ then
15. $Pop_g = Top_{\omega N}(Pop_{g-1}) \cap Top_{(1-\omega)N}(Pop_g)$
16. Else
17. $Pop_g = Pop^e_g$
18. End If
19. $g = g + 1$;
20. End While

3.3. Problem Mapping

According to the requirements of Technical Specification for Power System Design (DL/T5429-2009), the maximum reserve capacity of the system is 15%~20% of the total rated load of the system. Therefore, the decision variables range from zero to 20% of the total system load. The fitness function is:

$$F(x) = \sum_{i=1}^{D} x_i$$

(13)
Where \( x \) is an individual in the population, \( x = (x_1, x_2, \ldots, x_D) \). \( D \) is the dimension of the problem, which represents the number of nodes that can add spare capacity. Each decision variable ranges from zero to 20% of the total system load.

4. Experimental Results

4.1. Parameter setting

In order to fully verify the performance of MIFA-P algorithm in solving practical optimization problems, this section uses the IEEE-RTS79 system for reliability testing. Assuming that all the equipment in the system is in normal operation and no overload occurs, the transmission power of the transmission line takes the maximum load value of the system. In this section, the reliability evaluation module is simulated by non-sequential Monte Carlo method, and the probability sampling of wind speed and output power are determined by Weibull distribution model. The capacity of each wind turbine in the wind turbine is 1500 kW, and the forced outage rate of the wind turbine is 0.05. Among them, the starting wind speed of the fan is 3 m/s, the rated wind speed is 10.5 m/s, and the cut-out wind speed is 25 m/s, respectively.

4.2. Analysis of Standby Capacity of Power System with Fixed Wind Capacitance Connected to Grid

In order to test the effectiveness of MIFA-P algorithm in the optimization of reserve capacity distribution of power system, this section analyses the optimization of reserve capacity distribution of power system after the fixed wind capacity is connected to the grid. By adding 60 MW wind turbines and reducing the reserve capacity of 60 MW conventional units, the distribution of additional reserve capacity in power system is calculated on the premise that the two indicators of the probability of load loss and the expected value of insufficient energy are not lower than the index value of the system before the wind power is connected to the grid. The experimental results are shown in Table 1 and Figure 2.

| Algorithm | 1  | 2  | 7  | 13 | 15 | 16 | 18 | 21 | 22 | 23 | Sum   |
|-----------|----|----|----|----|----|----|----|----|----|----|-------|
| GA        | 8.42 | 14.88 | 5.57 | 4.06 | 3.03 | 1.99 | 1.48 | 3.92 | 0.65 | 2.83 | 46.83 |
| PSO       | 8.91 | 14.53 | 6.32 | 4.13 | 2.95 | 1.81 | 1.67 | 4.12 | 0.63 | 2.92 | 47.99 |
| MIFA-P    | 7.22 | 14.57 | 6.01 | 3.36 | 2.37 | 1.35 | 1.50 | 4.64 | 0.33 | 2.78 | 42.63 |

Table 1 and Figure 2 shows that when 60 MW wind turbines are integrated into the grid system, under the premise that the two indicators of load loss probability and power shortage expectation are lower than those before wind power grid connection, GA algorithm needs to increase 46.83 MW of conventional energy reserve capacity, PSO algorithm needs to increase 47.99 MW of reserve capacity, MIFA-P algorithm needs to increase 42.63 MW of reserve capacity. The capacity allocation scheme increased by MIFA-P algorithm is 4.2 MW less than that of GA algorithm, accounting for 7% of the grid-connected capacity of wind power. The capacity allocation scheme increased by MIFA-P algorithm is 5.36 MW less than that of PSO algorithm, accounting for 9% of the wind power grid-connected capacity. When the nodes of power system continue to increase, the economic benefits will be more obvious. The convergence curves of the three contrast algorithms are shown in Figure 2. Figure 2 shows that the convergence speed of MIFA-P algorithm is faster than that of GA and PSO algorithm when the 60 MW fixed-capacity wind turbines are connected to the grid and the three algorithms of GA, PSO and MIFA-P are used to optimize the reserve capacity distribution.
5. Conclusions
In this paper, a new multi-agent intelligent algorithm MIFA-P based on population sharing is proposed. The algorithm judges the type of the optimization problem by counting the occurrence times of the maximum projection value of the current optimal individual on the principal feature axis. Thus, the evolutionary algorithm of corresponding classes is chosen to solve the problem. In the process of evolution, each evolutionary algorithm achieves organic fusion by sharing population information. Finally, the effectiveness and applicability of MIFA-P algorithm in solving large-scale decision variables black box optimization problems are verified by solving a practical scenario optimization problem of reserve capacity distribution after wind power grid connection.

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