Research Article

Memetic Salp Swarm Algorithm-Based Frequency Regulation for Power System with Renewable Energy Integration

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Received 12 November 2020; Revised 25 November 2020; Accepted 29 November 2020; Published 14 December 2020

Academic Editor: Xiao-Shun Zhang

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As the penetration of renewable energy to power grid increases gradually, to ensure the safety and stable operation of power system, it is necessary for renewable energy to participate in the secondary frequency regulation of power system. Therefore, this paper proposes an optimal control model of renewable energy participating in the secondary frequency regulation to solve the dynamic power distribution problem. Besides, memetic salp swarm algorithm (MSSA) is used to solve this complex nonlinear optimization problem, so as to quickly obtain high-quality power distribution schemes under different power perturbations and maximize the dynamic response regulation performance of the entire regional power grid. Finally, based on the improved IEEE standard two-area model, the established model is verified and the performance of the applied algorithm is tested by comparing the traditional engineering allocation method and other intelligent optimization algorithms.

1. Introduction

In recent years, to cope with climate change and sustainable energy development, the penetration of renewable energy connected to power grid has increased rapidly [1–3]. Different from traditional hydrothermal power, wind power and photovoltaic (PV) power with relatively mature technologies are greatly affected by meteorological conditions, so their power fluctuations are highly random [4–6]. As the regional power grid usually cannot fully absorb renewable energy such as wind or solar energy, it is easy to disconnect the wind farm or PV station from the power grid, which also greatly increases the pressure of frequency regulation of the system [7–10]. In this situation, the traditional configuration of hydropower plant and thermal power station as the main frequency regulation resources has been difficult to meet the high quality of the system’s dynamic frequency regulation needs [11–13].

Therefore, the development of new high-quality frequency regulation resources has become one of the main means to relieve the pressure of regional power grid [14–16]. Compared with traditional hydropower plant and thermal power station, wind farm and PV station have faster response speed as well as climbing speed and rapid power fluctuations can be balanced more quickly [17–19]. Therefore, for regional power grids with high renewable energy penetration, especially in low-load areas, and wind farm, PV station can be used on power point control method to control it in below the operation condition of maximum power point, with a certain reserve capacity to participate in the secondary frequency regulation [6, 20, 21], called automatic generation control (AGC) [22–24].

In general, AGC mainly consists of two parts [25–27]: (1) based on the real-time acquisition of frequency and power deviation of the tie line, a centralized controller, such as proportional-integral (PI) controller, is used to acquire the approximate actual power fluctuation of the system, and then the total power instruction of the regional power network is issued; (2) according to the power allocation algorithms, the total power instruction is assigned to each unit participating in the frequency regulation [28–30]. Literature [31] proposes a sliding mode controller for...
math multisource AGC system using teaching and learning-based optimization algorithm. Literature [32] proposes a lifelong learning-based complementary generation control of power grids with renewable energy sources. Literature [33] proposes AGC of a multiarea multisource hydrothermal power system. However, although the abovementioned literature realizes the control of multisource participating in AGC, the modeling is relatively simple, considering only the climbing response characteristics of the units and not other dynamic response characteristics of different frequency regulation resources, which will affect the overall control effect of the system and easily make the system deviate greatly from the optimal operating point. Therefore, this paper proposes a multisource optimal collaborative control method for wind and solar renewable energy based on its dynamic response characteristics to participate in secondary frequency regulation.

In essence, AGC optimal control is a complex non-linear optimization problem [34–36]. In practice, power distribution is often not optimized but arranged according to adjustable capacity ratio and climbing speed, which cannot meet the optimal control requirements of the system [37–40]. On the other hand, traditional mathematical optimization methods (such as interior point method [41]), although fast in solving problems, have poor global searching ability and are prone to fall into local optimal solutions. In comparison, genetic algorithm (GA) [42–44] and other metaheuristic algorithms [45–47] have higher application flexibility and better global search capability, but their solving speed is slow and cannot meet the needs of AGC online control for large-scale regional power grids [48–50]. Therefore, MSSA with a faster convergence speed is used to solve the problem. Compared with the original salp swarm algorithm (SSA), memetic salp swarm algorithm (MSSA) employs multiple independent slap chains to simultaneously implement the exploration and exploitation [51]. Besides, MSSA also has low dependence on the mathematical model. To verify the validity of the proposed method, this paper used the improved IEEE standard two-area model for simulation test and analysis.

The remaining of this paper is organized as follows: Section 2 develops the optimal control model for automatic generation control. In Section 3, MSSA is described. Comprehensive case studies are undertaken in Section 4. Section 5 summarizes the main contributions of the paper.

2. Optimal Control Model for Automatic Generation Control

2.1. Control Framework. Generally, AGC has the following three control modes: (a) flat frequency control, (b) flat tie-line control, and (c) tie-line bias control. Also, tie-line bias control was used in this paper. The two-region interconnection power network is depicted in Figure 1, in which the AGC control process of each region includes two parts: controller control and optimal power distribution. A PI controller is adopted to convert the power deviation and frequency deviation of the real-time receiving tie line into regional control deviation as input and output to the real-time adjusting power of the regional power grid \( \Delta P \). Then, \( \Delta P \) is assigned to each AGC unit through the power allocation algorithm. Different from the traditional power system with hydropower plant and thermal power station as the main reserve capacity, wind farm and PV station no longer need to be disconnected from the grid but participate in the power AGC regulation of the system.

2.2. Dynamic Response Model of Units. The establishment of dynamic response model of the units is mainly in order to more accurately describe the units after the received power adjusts instruction power dynamic response process. For different types of units, the dynamic response model not only regulates the upper and lower limits of capacity, climbing rate, frequency regulation delay, and other common parts [52] but also includes transmission links with their own energy conversion characteristics. Besides, AGC often uses the frequency domain model to describe the dynamic response process of the units, as shown in Figure 2. \( T_d \) represents the secondary frequency regulation delay of the units; \( G(s) \) represents the power transfer function of the units, as shown in Table 1. \( T_0 \sim T_q \) are the known parameters of the transfer function, respectively [53]. Therefore, according to the inverse Laplace transform of the frequency domain transfer function, the real-time output of the regulated power can be calculated through the input power, as follows:

\[
\Delta P_i^\text{in}(t) = L^{-1}\left\{ \frac{G_i(s)}{s(1 + T_d s)} \right\} \sum_{k=1}^{N} \left[ e^{-\Delta T(k-1)/s} \cdot D_i^\text{out}(k) \right] ,
\]

\[
D_i^\text{in}(k) = \Delta P_i^\text{in}(k) - \Delta P_i^\text{in}(k-1),
\]

\[
\Delta P_i^\text{out}(k) = \Delta P_i^\text{out}(t = k \cdot \Delta T),
\]

where \( i \) represents the \( i^{th} \) AGC unit; \( k \) represents the \( k^{th} \) discrete control period; \( \Delta P_i^\text{in} \) and \( \Delta P_i^\text{out} \) represent the input regulation power command and real-time output of regulated power of the \( i^{th} \) AGC unit, respectively; and \( \Delta T \) represents the control period of AGC, with a value of 1 to 16 seconds.

2.3. Optimization Mathematical Model. A performance index is assigned to quantify the total power response deviation, which is defined as the sum of the absolute deviation value of the regulating power command value and the power output value of all units, as follows:

\[
\min f = \sum_{j=1}^{n} \sum_{i=1}^{N} \left| \Delta P_i^\text{in}(j) - \Delta P_i^\text{out}(j) \right| ,
\]

where \( N \) represents the number of control periods and \( n \) represents the number of AGC units.

In addition to considering the dynamic response transfer process of the units, some constraint conditions, such as power balance constraint, units capacity constraint, and
climbing constraint, should also be considered in the power
distribution process, as follows:

\[
\Delta P_{\text{in}}(k) = \sum_{i=1}^{n} \Delta P_{\text{in}}^i(k),
\]

\[
\Delta P_{\text{in}}(k) \cdot \Delta P_{\text{in}}^i(k) \geq 0, \quad i = 1, 2, \ldots, n,
\]

\[
\Delta P_{\text{min}}^i \leq \Delta P_{\text{in}}^i(k) \leq \Delta P_{\text{max}}^i, \quad i = 1, 2, \ldots, n,
\]

\[
\left| \Delta P_{\text{in}}^i(k) - \Delta P_{\text{in}}^i(k-1) \right| \leq \Delta P_{\text{rate}}^i, \quad i = 1, 2, \ldots, n,
\]

where \( \Delta P_{\text{in}} \) represents total power regulation command and
\( \Delta P_{\text{rate}}^i \) represents the maximum climbing speed of the \( i \)th
AGC units.

### 3. Memetic Salp Swarm Algorithm

#### 3.1. Inspiration

Salps are marine creatures that resemble
jellyfish in body structure and movement. They are usually
joined end to end to form a chain, also known as a salp chain.
The leader is located at the first end of the chain and has the
best judgment of environment and food source. The remaining
salps are followers, who follow the previous one
in turn. This movement mode is conducive to the rapid
coordinated movement and feeding of the salps group.

Literature [54] established a mathematical model of salps
chain in 2017 and proposed SSA to solve a series of optimization
problems.

#### 3.2. Optimization Framework

This paper is combined with
cultural genetic algorithm, aiming at the shortcomings
of SSA algorithm to improve, and defined as MSSA. The
optimization process is as follows: the culture of each salp is
defined as a solution to the optimization problem. All salps
in the community are divided into different populations in
the unit of salp chain, and each salp chain has its own culture
and independently searches for food sources. At the same
time, the culture of each salp affects and is influenced by
other individuals and evolves with the evolution of the
population. When the population evolution reaches a certain
stage, the whole community will exchange information to
realize the mixed evolution of the population until the
convergence condition of the optimization problem is
satisfied.

3. Memetic Salp Swarm Algorithm

Figure 1: Illustration of coordinated control of multisource for AGC under two-area framework.
Table 1: Dynamic response transfer functions of different AGC units.

| Type                           | Transfer function       |
|--------------------------------|-------------------------|
| Nonreheat turbine             | $1/1 + T_1s$            |
| Reheat turbine                | $(1 + T_2s)/(1 + T_3s) (1 + T_4s)(1 + T_5s)$ |
| Hydropower                    | $((1 - T_6s)/(1 + T_7s) (1 + 0.5T_8s)(1 + T_9s)$ |
| Wind and solar renewable energy| $1/1 + T_9s$            |

3.3. Local Search in Each Chain. The salp chain can be divided into two roles, i.e., the leader and the follower. It is worth noting that the leader is responsible for directing the entire salp chain to the food source, following each other. For the $m^{th}$ salp chain, the position of the leader can be updated, as follows [55]:

$$x_{m1}^j = \left\{ \begin{array}{l} F_m^j + c_1\left(c_2(ub^j - lb^j) + lb^j\right), \quad c_3 \geq 0, \\ F_m^j - c_1\left(c_2(ub^j - lb^j) + lb^j\right), \quad c_3 < 0, \end{array} \right. \quad (9)$$

where $x_{mi}^j$ is the position vector of the $i^{th}$ salp in the $m^{th}$ chain; $f_{mi}^j$ is the fitness value of the $i^{th}$ salp in the $m^{th}$ chain; $F$ is the fitness value set of all the salps following the descending order; and $X$ is the corresponding position vector set of all the salps, i.e., a position matrix, as follows:

$$X = \begin{bmatrix} x_{11} & x_{21} & \cdots & x_{d1} \\ x_{12} & x_{22} & \cdots & x_{d2} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1nM} & x_{2nM} & \cdots & x_{dnM} \end{bmatrix} \quad (12)$$

where $d$ is the number of dimensions, and each row vector represents the position vector of each salp.

In addition, the overall flowchart of MSSA is given in Figure 5.

3.5. MSSA Design for AGC System. In order to ensure that the initial solution is a feasible solution, this paper forms the initial solution according to an engineering method called PROP method. In other words, the initial solution is obtained by the same adjustable capacities' ratio.

where the superscript $j$ represents the $j^{th}$ dimension of the searching space; $x_{mi}^j$ is the position of the leader in the $m^{th}$ salp chain; $F_m^j$ denotes the position of the food source, i.e., the current best solution obtained by the $m^{th}$ salp chain; and $u^j$ and $b^j$ are the upper and lower bounds of the $j^{th}$ dimension, respectively; $c_1 = 2e^{-\left(\frac{4k}{k}\right)^2}$, where $k$ is the current iteration number and $k_{max}$ is the maximum iteration number, respectively. Besides, $c_2$ and $c_3$ are the random numbers, respectively, and $c_2, c_3 \in [0, 1]$. [56]

In addition, the position of the followers can be updated, as follows [55]:

$$x_{mi}^j = \frac{1}{2}\left(x_{mi}^j + x_{m,j-1}^j\right), \quad i = 2, 3, \ldots, n, m = 1, 2, \ldots, M, \quad (10)$$

where $x_{m}^j$ is the position of the $i^{th}$ salp in the $m^{th}$ salp chain; $n$ is the population size of each salp chain; and $M$ is the number of salp chains, respectively.

3.4. Global Coordination in Virtual Population. To achieve a global coordination, the virtual population will be regrouped into different salp chains according to the salps' fitness values, as shown in Figure 4. Specifically, all salps are sorted according to the order of fitness from large to small. Finally, the salps will be divided into $M$ salp chains, and the distribution rules are as follows: the first salp regroups into the first chain, the $M^{th}$ salps into the $M^{th}$ chain, the $M + 1^{th}$ into the first chain, and so on. The update rules of the $M^{th}$ salp chain are described as follows [57]:

$$Y^m = [x_{mi}, f_{mi}|x_{mi} = X(m + M (i - 1)), f_{mi} = F(m + M (i - 1)), \quad i = 1, 2, \ldots, n, \quad m = 1, 2, \ldots, M, \quad (11)$$

On the other hand, this paper applies the penalty function method to the fitness function $Fit(x)$ to satisfy the constraint conditions (5)–(8), as follows:

$$\text{Fit}(x) = \begin{cases} f(x), & \text{if constraints are satisfied,} \\ f(x) + M\left(Z_u - Z_{lim}^u\right)^2, & \text{otherwise,} \end{cases} \quad (13)$$

where $M$ is the penalty function factor, and its value is usually a relatively large positive number; $Z_u$ is the $u^{th}$ constraint; and $Z_{lim}^u$ is the limit of the $u^{th}$ constraint.

4. Case Studies

The proposed methodology is tested on the IEEE load frequency control model. It is worth noting that 1 AGC unit in region A is increased to 5 units, as shown in Figure 1. Besides, Tables 2 and 3 show the main parameters of response transfer and power regulation of the units, respectively, and the control period of AGC is set to 4 seconds. Also, the response performance is compared to that of PROP, GA, and SSA. To achieve a fair comparison, the population size is set to 10 and the maximum number of
iterations is set to 100. It is worth noting that if the parameters are not chosen properly, the convergence time will be too long or the local optimum will be trapped. Besides, ode23 was selected as the solver, and the sampling rate was set to 0.001 s.

4.1. Convergence Research. Figure 6 shows the convergence curves of MSSA under different power distribution instructions. It can be found that MSSA can solve the optimal solution with high quality after 30 steps of iteration, and the subsequent iteration only makes slight reduction adjustment, which also indicated the fast convergence of the algorithm. In order to better evaluate the quality of the optimal solution of different methods, Table 4 shows the comparison of the convergence results of different methods, in which each indicator unit is MW. It shows that PROP performs power allocation according to the ratio of the adjustable capacity of the unit, so the power output of thermal power units with larger regulating capacity is relatively high, and it will lead to a large power deviation. On the other hand, GA, SSA, and MSSA can significantly reduce power deviation after their respective optimization operation, and MSSA has the best performance.

4.2. Online Optimization. In order to evaluate the online optimization performance of MSSA, in the area of A, a step power perturbation \( \Delta P_L = 80 \text{ MW} \) has occurred. The online optimization results of MSSA and PROP are compared as shown in Figure 7. Compared with previous optimization, the power deviation obtained by MSSA is smaller, and the overshoot of the total power instruction can be avoided. In addition, wind farm and PV station can recover the power system disturbed by high power quickly in the initial stage of power disturbance because of their fast response speed.

To further test the optimization performance of different algorithms, Table 5 presents the online optimization results of different algorithms (the optimal value is marked in bold), in which area control error (ACE), \(|\Delta f_1|\), and CPS1 are the average values in the simulation. Besides, the power deviation is the total deviation in the simulation.
time. Accuracy is used to measure the fitting degree of the actual adjustment output and the adjustment instruction curve in the simulation time. It can be found that, compared with PROP, the other three methods can significantly reduce power deviation, thus significantly improving the system’s dynamic response performance. Compared with GA and SSA, the online optimization results of MSSA are better, which is because memetic computing framework can observably improve the ability of exploration and exploitation.
Table 3: Main parameters of power regulation of AGC units.

| Units | $T_d$ (s) | $\Delta P^{ste}$ (MW/min) | $\Delta P^{max}$ (MW) | $\Delta P^{min}$ (MW) |
|-------|-----------|--------------------------|---------------------|---------------------|
| $G_1$ | 60        | 30                       | 50                  | −50                 |
| $G_2$ | 20        | 18                       | 30                  | −30                 |
| $G_3$ | 5         | 150                      | 20                  | −10                 |
| $G_4$ | 1         | −                        | 15                  | −5                  |
| $G_5$ | 1         | −                        | 10                  | −10                 |

Table 4: Comparison on convergence results obtained by different methods.

| $\Delta P^{in}$ | Method | $\Delta P_{in}^{1}$ | $\Delta P_{in}^{2}$ | $\Delta P_{in}^{3}$ | $\Delta P_{in}^{4}$ | $\Delta P_{in}^{5}$ | Power deviation |
|-----------------|--------|---------------------|---------------------|---------------------|---------------------|---------------------|-----------------|
| 80              | PROP   | 32.00               | 19.20               | 12.80               | 9.60                | 6.40                | 676.95          |
|                 | GA     | 15.52               | 23.18               | 17.92               | 12.7                | 10.68               | 529.86          |
|                 | SSA    | 10.61               | 25.74               | 17.26               | 14.67               | 11.72               | 471.48          |
|                 | MSSA   | 14.26               | 20.84               | 19.52               | 15.12               | 10.26               | 402.451         |
| −50             | PROP   | −23.81              | −14.29              | −4.76               | −2.38               | −4.76               | 479.83          |
|                 | GA     | −4.26               | −23.24              | −10.02              | −3.86               | −8.62               | 274.26          |
|                 | SSA    | −8.65               | −20.62              | −9.85               | −4.29               | −6.59               | 307.48          |
|                 | MSSA   | −4.48               | −20.69              | −9.14               | −5.58               | −10.11              | 234.254         |

Figure 6: Convergence curves of MSSA. (a) $\Delta P^{in} = 80$ MW. (b) $\Delta P^{in} = −50$ MW.

Figure 7: Continued.
5. Conclusions

In this paper, a multisource optimal collaborative control method for power system with renewable energy participation in secondary frequency regulation is proposed. The main contributions can be summarized as follows:

(i) A novel AGC control model is established for the power system with high renewable energy penetration to improve the dynamic response performance of the system;
(ii) The study verified the effectiveness of MSSA for AGC. It can not only meet the online regulation requirements of AGC but also quickly obtain high-quality regulation schemes with high convergence stability, and the dynamic response performance of the entire regional power grid is significantly improved.

Table 5: Result comparison of online optimization obtained by different methods.

| ΔP_L | Algorithms | [ACE] (MW) | Δf_1 (Hz) | CPS1 (%) | Accuracy (%) | Power deviation (MW) |
|------|------------|------------|-----------|----------|--------------|---------------------|
| 80   | PROP       | 7.7678     | 0.0356    | 194.69   | 95.84        | 630.05              |
|      | GA         | 7.4209     | 0.0323    | 195.86   | 98.25        | 261.32              |
|      | SSA        | 7.5095     | 0.0321    | 195.84   | 98.17        | 267.52              |
|      | MSSA       | 7.3995     | 0.0316    | 195.57   | 98.84        | 254.21              |
| −50  | PROP       | 5.0541     | 0.0235    | 197.78   | 94.99        | 477.46              |
|      | GA         | 4.6046     | 0.0203    | 198.25   | 98.21        | 164.26              |
|      | SSA        | 4.6044     | 0.0202    | 198.29   | 98.23        | 161.48              |
|      | MSSA       | 4.6040     | 0.0196    | 198.36   | 98.41        | 149.96              |
Besides, electric vehicles will be considered to participate in AGC in future studies.

**Abbreviations**

- $\Delta P_{in}^i$: Input regulation power command of the $i^{th}$ AGC unit
- $\Delta P_{mat}^i$: Real-time output of regulated power of the $i^{th}$ AGC unit
- $\Delta T$: Control period of AGC
- $N$: Number of control periods
- $n$: Number of AGC units
- $\Delta P_{rate}^i$: Maximum climbing speed of the $i^{th}$ AGC units
- $x_{m}^i$: Position of the leader in the $m^{th}$ salp chain
- $P_{m}^i$: Fitness value of the $i^{th}$ salp chain
- $x_{m}^i$: Fitness value set of all the salps following the descending order
- $X$: Corresponding position vector set of all the salps
- PV: Photovoltaic
- AGC: Automatic generation control
- GA: Genetic algorithm
- SSA: Salp swarm algorithm
- MSSA: Memetic salp swarm algorithm

**Data Availability**

The data that support the findings of this study are available upon request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

**Conflicts of Interest**

The authors declare no conflicts of interest.

**Acknowledgments**

The authors gratefully acknowledge the support of the National Natural Fund of China (52037003) and Key Science and Technology Project of Yunnan Province (202002AF080001).

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