Dynamic reactive power optimization of distribution network based on variable step size beetle antennae search algorithm

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Abstract. To solve the dynamic reactive power optimization problem in the distribution network, a novel optimization algorithm (variable step size beetle antennae search algorithm, VBAS) is introduced. Meanwhile, from the economic point of view, the minimum network loss and capacitor switching cost are taken as the objective functions, and the dynamic reactive power optimization model is established. In contrast with the majority of existing traditional algorithms that are intricate in process, the conducted algorithm is of less calculate and easier achieved. Besides, the variable step size strategy is introduced to improve optimization accuracy. The effectiveness of this algorithm is verified by simulation analysis on the IEEE 33-bus system, and the results show that VBAS obtains the optimum operation point and outperforms traditional algorithms significantly.

1. Introduction
Reactive power optimization (RPO) of distribution network (DN) belongs to a branch of optimal power flow. It refers to the reactive power regulation method when the structural parameters and load conditions of the system are given, and through the optimization of some control variables, under the premise of satisfying the constraint conditions, one or more performance indexes of the system can be optimized [1]. RPO can not only effectively reduce transmission loss, save operation cost, but also improve voltage quality, make DN more reliable and operate safely [2]. With the growth of the size of DN, the economic and security requirements of DN operation are also higher and higher, which makes the RPO problem more significant.

Traditional RPO usually assumes that all loads work stably in a certain state, and equivalent modeling is carried out for each component and node of the system. Because the load change process in a certain period of time is not considered, this kind of RPO process is often called static RPO [3]. However, in the actual DN operation process, the load of each node will change with time, static RPO cannot meet the actual operation needs, correspondingly, the system optimization considering the node load change is called dynamic RPO [4].

After taking into account the time-varying of nodal load, the dynamic RPO of DN is a complex non-convex nonlinear problem with strong time-space coupling. To solve the dynamic RPO problem, a further transformation is usually needed. For example, the dynamic RPO is simplified to the static RPO problem by dividing the time period in [5], then the existing static optimization methods are used to deal with the RPO problem. To solve the static RPO problem, various solutions have been proposed. These methods can be grossly divided into two groups: classical mathematical
optimization methods and heuristic search methods. There are many studies on the former. In [6], from the perspective of voltage regulation, a double loop voltage-current control system is proposed for the RPO problem. The interval RPO problem is solved by employing the linear approximation method based on the first-order interval Taylor expansion in [7]. In [8], an interval sequential quadratic programming is presented to solve the interval dynamic RPO problem, which employs a second-order interval Taylor expansion. The authors in [9] formulate the nonconvex RPO problem as a convex problem using semidefinite relaxation, then the optimum solution is obtained via semidefinite programming-based approach. However, the effectiveness of these methods depends on the specific properties of the objective function. In practice, these conditions are often difficult to satisfy.

Generally, heuristic search algorithms have no property requirements for the objective function, which can effectively solve the difficulties of traditional methods in facing practical problems. In [10], to enhance the global optimization ability, the authors add an immune mechanism to the genetic algorithm. By introducing fractional derivative of velocity term in standard optimization mechanism, a fractional particle swarm optimization gravitational search algorithm is presented for RPO problem [11]. Such methods have good optimization precision in solving various practical problems. Nevertheless, most of these approaches are complex in process and time-consuming, which are not suitable in the actual operation of DN.

In recent years, a new heuristic search algorithm called beetle antennae search algorithm (BAS) has been proposed. This algorithm is inspired by the foraging behaviors of longicorn beetles. Because it requires only one individual to search, i.e. one longicorn beetle, which greatly reduces the amount of computation. To solve the global path planning problem of unmanned aerial vehicles, the authors in [12] proposes a novel obstacle avoidance BAS, which reduces the computational complexity significantly, and can be used for real-time path planning. In [13], the BAS algorithm is introduced to optimize the weights of the neural network classifier, which improves the computational speed effectively. These motivate the current study.

Overall, the main objective of this paper is to introduce a VBAS algorithm to tackle the RPO problem. To do so can simultaneously guarantee the optimum operation point and low computational complexity, which provides an effective method to solve the RPO problem. Specifically, a variable step size strategy is conducted. In this way, the optimization accuracy of the original BAS algorithm is improved significantly. Moreover, to the best of our knowledge, an approach that incorporates VBAS to solve the RPO problem of DN is pioneering.

2. Dynamic reactive power optimization of distribution network

Static RPO is to adjust the reactive power control equipment according to the load size under a certain time section. However, in practical engineering, it is totally unrealistic to use this method to adjust reactive power compensation equipment and transformer tap in each time section, because frequent actions will greatly reduce the service life of the equipment and cause potential accidents. To this end, this paper introduces the concept of dynamic RPO. Now that the dynamic RPO problem contains coupling constraints in various time periods, further simplification is needed. Firstly, the node load is segmented according to the time, then static RPO is carried out for each period, and finally, the dynamic RPO based on real-time load change is completed.

2.1. Objective function

It is inevitable that the existing power consumption in the process of power transmission. If the loss is too large, it will cause power waste. Considering the system economy, the active power loss is selected as the evaluation index of system operation. Although capacitor switching can effectively compensate reactive power, frequent switching will greatly reduce the life of the capacitor, resulting in more adjustment costs. Therefore, the selection of objective function should avoid excessive adjustment of control equipment for the sake of reducing power loss.
Considering the change of node load in one day, the dynamic RPO model is established with the objective function of minimizing active power loss and capacitor switching cost. The objective function expression is:

$$\min f = \sum_{j=1}^{N} \left( \Delta P_{loss} + C_s \sum_{j=1}^{n_Q} \Delta \mu_{ij} \right)$$  \hspace{1cm} (1)$$

where, $\Delta P_{loss}$ is the power loss of each period, $C_s$ is the adjustment cost of switching switch of compensation device, $n_Q$ is the times of reactive power compensation, and $\Delta \mu_{ij}$ is the action times of compensation equipment of in the period, $N_T = 0,1,2,\ldots,23$.

2.2. Constraint condition

1) Node power balance constraints [14].

$$P_i = U_i \sum_{j=1}^{N} U_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij})$$

$$Q_i = U_i \sum_{j=1}^{N} U_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij})$$  \hspace{1cm} (2)$$

where, $N$ is the total number of DN nodes, $P_i$ and $Q_i$ are respectively the active and reactive power of the injected node in each period, $U_i$ and $U_j$ respectively indicate the node voltages of nodes $i$ and $j$ in each period, $G_{ij}$ and $B_{ij}$ are branch conductance and admittance, respectively, and $\delta_{ij}$ is the voltage phase differences between nodes $i$ and $j$.

2) Node voltage constraints.

$$U_{i_{\min}} \leq U_i \leq U_{i_{\max}}, t \in N_T$$  \hspace{1cm} (3)$$

where $U_{i_{\max}}$ and $U_{i_{\min}}$ are the upper and lower limits of voltage amplitude fluctuation allowed by node $i$ in each period, respectively.

3) Reactive power compensation constraints.

$$Q_{g_{\max}} \leq Q_{g_{it}} \leq Q_{g_{\min}}, t \in N_T$$  \hspace{1cm} (4)$$

where $Q_{g_{\max}}$ and $Q_{g_{\min}}$ are the upper and lower limits of reactive power generated by reactive power compensation equipment in each period, respectively.

2.3. Solution method

Most stochastic intelligent optimization algorithms need huge computational power, however, in practical application scenarios such as factory workshop, most of the existing equipment is weak computational power equipment, which cannot provide enough computing power. Furthermore, most of the stochastic intelligent optimization algorithms have complex calculation process, long iteration time and long convergence time, which cannot be applied to scenes with high real-time requirements such as manipulators, robots, automated guided vehicles, etc. During the operation of DN, to reduce the power loss and loss in time, timely optimization results are needed, which can ensure that the compensation equipment for reactive power compensation quickly. As a consequence, this paper introduces a kind of VBAS to solve the dynamic RPO problem of DN.

BAS is an algorithm inspired by the longicorn foraging principle. Longicorn beetles forage according to the smell of food. Longicorn beetles have two long antennae. If the odor intensity received by the left antenna is higher than that on the right, it will search for food on the left, and vice versa. The purpose of longicorn is to find the point with the largest global odor value. BAS is similar to intelligent optimization algorithms such as PSO and GA, which can achieve efficient optimization and solution without the specific form of gradient information and objective function. However, compared with traditional algorithms such as PSO, BAS only needs one individual, namely one
longicorn, to search, which greatly reduces the computational load of the algorithm. The original BAS step size is a fixed value, and in the process of global search and local search, the search efficiency and accuracy of the algorithm are relatively general.

In view of the above problems, this paper introduces the VBAS. In the beginning, it uses a large step size, roughly searches to determine the approximate range, and then uses a small step length fine search after reaching the target location. The combination of the two strategies ensures the balance between the accuracy and the global convergence speed of the algorithm. The basic process of VBAS is as follows:

1) Establish a simplified mathematical model of longicorn beetles. The whole longicorn can be transformed into a simplified model as shown in Figure 1. The centroid of the longicorn beetle is \( x \), the position of left antennae is \( x_l \), the position of right antennae is \( x_r \), and the distance between two antennae is \( d_0 \).

![Figure 1. Simplified model of beetle antennae search.](image)

2) Establish search direction and position.

\[
\bar{b} = \frac{\text{rand}(k,1)}{\|\text{rand}(k,1)\|}
\]

\[
x_r = x + d_0 \bar{b}
\]

\[
x_l = x - d_0 \bar{b}
\]

where \( \bar{b} \) is the search direction, \( \text{rand} \) is a random function and \( k \) is the dimension to solve the problem.

3) Update location.

\[
x = x + \text{step} \times \text{sign}(f(x_r) - f(x_l))
\]

where, \( \text{step} \) is the step size, \( \text{sign} \) is the symbolic function, and \( f(\cdot) \) is the objective function.

4) Variable step size strategy.

Because longicorn may be far away from the target at the beginning, a larger initial step is usually chosen, and the closer the beetle approaches the target, the step size should gradually decrease. As a result, the variable step size strategy is obtained as follow:

\[
\text{step} = \text{step} \times \text{eta}
\]

where \( \text{eta} \) is usually between 0 and 1, approach to 1.
Obviously, VBAS has the advantages of simple process and easy implementation. Indeed, the key point of the algorithm to solve the optimization problem is the step size strategy. When the appropriate step size strategy is adopted, it can have the ability of global optimization. To sum up, the dynamic RPO solution flow based on variable step size beetle antennae search algorithm is shown in Figure 2.

![Figure 2. Dynamic RPO solution process based on variable step size longicorn antennae algorithm.](image)

3. Example analysis

3.1. Example parameters

This paper chooses the IEEE 33-bus system [15] as an example of dynamic RPO. The IEEE test system is usually a simplified model of an actual power system, equivalent to a standard test system, and used to test the performance of different algorithms in different research directions. The IEEE 33-bus system is shown in Figure 3. The six nodes (7, 8, 24, 25, 30, 32) with higher load levels and lower voltage levels are selected as reactive power compensation points. The capacity of reactive power compensation equipment is 0.2Mvar × 5.

![Figure 3. Improved the IEEE 33-bus system.](image)
The typical daily curve is shown in Figure 4, where the total network load is 3715kW + j2300kvar. The rated voltage of the system and the allowable range of node voltage are 12.66kV, 0.95 ~ 1.05p.u. respectively, and the adjustment cost is chosen as 8 kW / time.

3.2. Optimization results
In order to verify the feasibility and effectiveness of VBAS in dynamic RPO, a comparative analysis is made between VBAS and traditional PSO and GA. The number of iterations of the algorithm is unified to 200. The variable step size parameter $\eta$ of VBAS is set to 0.95; The population number, crossover rate, and mutation rate of GA are 100, 0.003, and 0.8, respectively; the population size and inertia weight of PSO are 25 and 0.95, respectively.

| Algorithm | Solution time(s) |
|-----------|------------------|
| VBAS      | 184.8513         |
| PSO       | 1445.2275        |
| GA        | 3323.1581        |
The optimization results of network loss and voltage are shown in Figure 5 and 6, respectively. The operation points are obtained by the optimization algorithm, which significantly reduce the system network loss and raise the node voltage in each period. Moreover, the improved node voltage is guaranteed to be within the constraint range (0.95–1.05p.u.). It is clear that VBAS has better optimization precision compared with other algorithms. The Comparison of the computing time under different algorithms is shown in Table 1. It can be seen that the computation time of VBAS is much less compared to that of traditional algorithms. This is because compared with the traditional group search algorithm, the VBAS algorithm requires only one individual to search, i.e. one longicorn.

4. Conclusions

This paper introduces a VBAS algorithm to solve the dynamic RPO problem of DN. The dynamic RPO problem is formulated as a static RPO problem by dividing the time period. The optimum operation point is then obtained via a VBAS algorithm. Numerical experiments demonstrate that the RPO problem can be solved efficiently by the VBAS algorithm. The comparison with the traditional algorithm through the IEEE 33-bus system is established. The results show that the VBAS algorithm can achieve better optimal solutions and computational performance than traditional algorithms. For example, in the IEEE 33-bus test system, the VBAS significantly reduces the network loss and raises node voltage, and the results are better than the traditional algorithms in each period. In addition, the computational complexity in terms of computation time is established, it can be seen that the computation time of VBAS is much less compared to that of other algorithms. Overall, the VBAS is easy to implement and applicable to the actual operation of DN.

As mentioned above, the key point of VBAS is the step size strategy. Therefore, in order to ensure the algorithm convergence to the global optimum, designing an appropriate step size strategy is a potential future direction.

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