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Capacitors Optimization Placement in Distribution Systems Based on Improved Seeker Optimization Algorithm

*** Hongsheng Su, Jue Yang**
School of Automation and Electrical Engineering, Lanzhou Jiaotong University, 730070, China
* Tel.: 13359492512
E-mail: shsen@163.com

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Abstract: An improved seeker optimization algorithm (SOA) was proposed for capacitors optimization configuration in distribution network in this paper, which was a classical non-linear discrete problem. To aim at the flaws of traditional SOA that it was easy to fall into the local extremum in later stage of optimization process, Simulated Annealing (SA) algorithm was introduced by setting the Boltzmann simulated annealing operator to select a new solution to enhance the global search ability of the algorithm. In addition, search step-length was adjusted using automatic adjustment factor so that non-linear discrete problem can be solved better. Considering the economy as the desired aim function, and power flow, voltage level, and as well as capacitors capacities as the constraints, thus a corresponding mathematical model was established for distribution grid capacitors optimization. Finally, the simulation results for IEEE 33-node distribution system show that the improved SOA is very effective and feasible, and is a quite ideal swarm intelligence algorithm.

Keywords: Distribution grid, Capacitors, Optimization placement, Seeker optimization algorithm (SOA), Simulated annealing (SA).

1. Introduction

In distribution grid, the optimal placement of the capacitors is to determine the best installation location, number, capacity and type of the capacitor so as to minimize the sum of the operating costs and the investment costs of the system [1]. For distribution grids, it is quite essential to perform capacitor optimization configuration to reduce the power loss and to improve the voltage quality. However, the most direct and effective role is to strengthen the safe economic operation of distribution grids. With the complexity of power system loads increasing, and power grids interconnection, and as well as the access of new energy resources, the traditional optimal algorithms show their limitations and shortcomings increasingly. Presently, the traditional methods to allocate the capacitors are relatively backward, which rely mainly on relevant procedures and previous configuration experience. With the development of computer and artificial intelligence technology, artificial intelligence optimization algorithm is getting the attention of more and more scholars, and they have made good application effects in many areas [2, 3]. Based on it, many novel methods to solve the problem have proposed in recent years. In [4], combined with genetic algorithm (GA), fuzzy method for capacitors optimization configuration is expressed as a multi-objective determination problem, where three different targets are considered respectively: the cost of grid loss, the capacitor cost, and the voltage drop, then measuring the satisfaction level of the feasible solutions using these targets, finally, the most satisfactory solution is accepted. In [5], ant colony algorithm is presented to solve the problem, where to take the grid loss as the aim, and to consider the voltage of each node and system power flow as the constraints, and still to consider the distribution network reconfiguration, and thus it better solves the capacitors optimization configuration problem. In [6] an artificial immune algorithm is proposed to solve this problem. Rather than the other methods, the important advantage of immune algorithm lies in its multifunction, i.e., it can investigate many parameters in the target function. In this study, six distinct objectives are considered in all such as the cost of grid loss, voltage profile, power factor, utilities development, and the cost of capacitors including the purchase and installation, and so better optimizing results are acquired. In recent years, some new optimal algorithms are proposed to solve this problem, for instance, plant growth simulation algorithm [7], and shuffled leaping frog algorithm [8]. All of these methods mentioned above have achieved a certain effect, but some deficiencies still are exposed out in process of seeking optimization, for example, it is easy to get into local extremum, and especially in later stage of optimization process, and as well as slow in convergence speed. To change the situation and achieve more satisfactory results, in this paper, the seeker optimization algorithm (SOA) is proposed to solve the puzzle. In process of optimization, to aim at the flaws of SOA, the paper implements the improvements, i.e., the idea of simulated annealing algorithm is introduced into at the late stage of the iteration calculation, and Boltzmann simulated annealing operator is added to strengthen the local search ability of the algorithm so that the seeker will not cluster and fall into stagnation or local extremum. In this algorithm the step-length update formula is improved so as to strengthen its nonlinear optimization ability when the SOA search step-length is very close to zero, but no globally optimal solution is searched at the end of the search under some circumstances. Finally, through applying the improved SOA to optimize the capacitor configuration in IEEE 33-node distribution system, the related simulation results show the method can resolve the puzzle better.

2. Mathematical Model on Capacitors Optimization Configuration

2.1. Aim Function

The aim function to be selected is based on economic considerations in the paper, such as the active grid loss, and the purchasing, installation and maintenance cost of the capacitor. In addition, some constraints are also taken into account, for instance, voltage and power factor constraints. The aim function may be written as

$$\min v = k_{\mathrm{e}} \sum_{i=1}^{n_{\mathrm{t}}} t_i P_{\mathrm{Loss}}(x_i, q_i) + \sum_{k=1}^{n_{\mathrm{c}}} f(q_{k,0}), \quad (1)$$

where k_{e} expresses the cost of unit electric energy consumption, and n_{t} denotes the number of the load level, and t_i means the duration time of the load level i, and $P_{\mathrm{loss}}(x_i,q_i)$ is the active power loss of the system under the load level i, $x_i=[P_i,Q_i,V_i]$, P_i expresses the active power injection vector of each node under the load level i, Q_i expresses the reactive power injection vector of each node under the load level i, V_i expresses the voltage under the load level i, q_i expresses the capacitor configuration state vector under the load level i, and n_{c} denotes the sites number of the installed capacitors, and $f(q_{k,0})$ is the total cost of the installed capacitor at the site k.

Seen from the above equation, the aim function consists of two aspects, one is the active power loss cost of distribution grid, and the other one is the capacitor-related cost.

2.2. Aim Function

There are three constraints to require to be considered, they are respectively defined below.

1) Power flow constraint:

$$P_{\mathrm{fiow}}(x_i, q_i) = 0, \quad (2)$$

where i denotes the load level, and x_i denotes the location information of the seeker, and q_i means the capacitors capacity under the load level i.

2) Voltage constraint:

$$U_{i\min} \le U_i \le U_{i\max}, \quad (3)$$

where $U_{i\max}$ represents the upper limit of the voltage on the bus i, and $U_{i\min}$ presents the allowed lower limit of the voltage.

3) Capacitor capacity constraint:

$$0 \le q_{k,i} \le q_{k,0}, \quad (4)$$

where $q_{k,0}$ denotes the total capacity of the installed capacitors in terms of the site k, and $q_{k,i}$ denotes the installed capacity of the installed capacitors under the load level i for the site k.

3. SOA and its Improvement

SOA was proposed based on intelligent random searching behavior of human beings in recent years

[9]. SOA is an intelligence optimization algorithm with the colony based, and simulates the random search behavior which is described using human natural language, and applies fuzzy reasoning to establish model as its guiding ideology. Different form the existing optimal algorithms, SOA is based on the fuzzy intelligent search behavior of the human beings. Each individual is treated as an independent individual during searching optimum, but the individual has the communication, collaboration, learning, and reasoning abilities. SOA evolution is considered as the locomotion of all the individuals who participate in the searching event. It obtains search experience through cognitive learning between the individuals, and the social learning between the groups when randomly searching, and selects the forward direction, determines the changes of the seeker sites and completes the search of the targets in accordance with human intelligent thought.

3.1. Basic SOA

In SOA, each seeker is seen as an independent individual in the colony, and the teams seeking optimization is enhanced in the algorithm, and the optimal solution for the target problem actually is the best position searched by the seekers. The current location of the seeker i is defined by $x_i=(x_{i1},x_{i2},\ldots,x_{iD})$, where $i\in[1,s]$, s is the size of the populations, and D is the dimensions of the search space. During the seeking optimum, the best position of the individual is expressed using $P_{i,\mathrm{best}}$, and the best position of the adjacent populations is expressed by $G_{i,\mathrm{best}}$, The neighborhood can be defined depending on specific optimization problem, and the search team is divided into three sub-population on average in this paper and each neighborhood comprises of all individuals belonging to the one sub-population. The location update formula of SOA can be simply expressed as:

$$x_{ij}(t+1)=x_{ij}(t)+\alpha_{ij}(t)d_{ij}(t)\,, \tag{5}$$

where $\alpha_{ij}(t)$ express the seeking step-length, $d_{ij}(t)$ express the seeking direction, $x_{ij}(t)$ express the position at time t, i=1,2,…,s, j=1,2,…,D.

3.2. Determination of Seeking Step-Length

As determining the search step-length the reasoning and approximation capability of fuzzy system is adopted [10]. The search rules are described using human natural language instead of computer language to enable SOA to be able to simulate human fuzzy intelligent search behavior. A simple fuzzy rule can be expressed as the forward step being shorter if the fitness value of the function is smaller. In the paper, Gaussian function is selected as the fuzzy membership function of the forward step being shorter as follows.

$$\mu(\alpha)=\mathrm{e}^{-\alpha^2/2\delta^2}\,, \tag{6}$$

where α express the step-length, and δ is the undetermined parameter of the Gaussian function. According to (6), obviously, the probability outside the interval [-3δ, 3δ] is less than 0.0111. Hence, the minimum subjection degree $\mu_{\min}$ is defined as 0.0111. Under normal circumstances, when $\mu_{\max}$=1, the step of the best individual is 0. However, in order to speed up the convergence rate and make the best individual also has a certain step, in this paper $\mu_{\max}$=0.9.

The scope of the aim function value requires setting alone for a variety of optimization problems. In this paper, the values of the aim problems are arranged in descending order, and are converted into a series of natural numbers in sequential order from real numbers, and are severed as the inputs of fuzzy reasoning to establish a general system suitable for commonly-used optimization problems. The following functions are selected as the membership functions of fuzzy variable of the function fitness value being smaller.

$$\mu_i=\mu_{\max}-\frac{s-I_i}{s-1}(\mu_{\max}-\mu_{\min})\,, \tag{7}$$

$$\mu_{ij}=\mathrm{R}(\mu_i,1)\,, \tag{8}$$

where I_i is the series number of the aim function value of the seeker at the current site $x_i(t)$ in descending order, and the function R(μ_i,1) is a value randomly generated belonging to [μ_i, 1]. Seen from (7), it can simulate the randomness of human seeking behavior. The method to obtain the search step-length is described as follows. Firstly, the μ_{ij} is determined in accordance with (7) and (8). Then the j^{th} dimensional step-length is determined according to the following formula.

$$\alpha_{ij}=\delta_i\sqrt{-\ln(\mu_{ij})}\,, \tag{9}$$

where δ_i expresses the Gaussian function parameter which is determined by

$$\vec{\delta}_i=\varphi\,\mathrm{abs}(\vec{x}_{\min}-\vec{x}_{\max})\,, \tag{10}$$

where $\vec{x}_{\min}$ and $\vec{x}_{\max}$ separately represent the two locations with the minimum and the maximum function value that the seeker i searched in its population, and φ is applied to adjust the search precision, with the deepening of the search it linearly decreases from 0.9 to 0.1 to balance local and global exploration and development capabilities, and as well as to achieve the change from rough to fine searching stage, and the signal abs means taking absolute function value.

3.3. Determination on Seeking Direction

The forward direction of the seeker is determined by the so-called experience gradient which is obtained through the evaluation on the locations changes in its own and other seekers searching history [11]. It mainly adopts the three directions, i.e., egocentric direction $d_{i,\text{ego}}$, altruistic direction $d_{i,\text{alt}}$, and pre-action direction $d_{i,\text{pro}}$ [12, 13], which are represented as follows.

$$d_{i,\text{ego}}(t) = p_i - x_i(t), \tag{11}$$

$$d_{i,\text{alt}}(t) = g_i - x_i(t), \tag{12}$$

$$d_{i,\text{pro}}(t) = x_i(t_1) - x_i(t_2), \tag{13}$$

where t_1, $t_2 \in \{t, t\text{-}1, t\text{-}2\}$, $x_i(t_1)$ and $x_i(t_2)$ respectively express the best position and the worst position in terms of $\{x_i(t\text{-}2), x_i(t\text{-}1), x_i(t)\}$, and $p_{i,\text{best}}$ and $g_{i,\text{best}}$ respectively express the best position of the individual and the population so far today. The final search direction of every seeker is determined by the random weighted geometry sum of the above three directions, which can expressed by

$$d_i(t) = \text{sign}(\omega d_{i,\text{pro}} + \phi_1 d_{i,\text{ego}} + \phi_2 d_{i,\text{alt}}), \tag{14}$$

where φ_1 and φ_2 are two unrelated random numbers within the interval [0, 1], and ω is the inertia weight, which decreases linearly from 0.9 to 0.1 with the deepening of the search process.

3.4. Determination on Seeking Direction

Although SOA can solve the discrete nonlinear optimization problem more effectively, but it still explore some deficiencies during applications, such as premature and slow convergence speed at iteration late period. To solve the problem, Boltzmann simulated annealing operator is here applied to select a new solution after the update of the seeker location. To some extent it plays a significant role that we first accept a deterioration solution to get a better solution, similarly, and the requirement of population diversity is also met. In this algorithm, the determination on the initial temperature and the annealing operation are most critical. Too high or too low initial temperature will affect the initial performance of the original algorithm, which will directly lead to ineffective search or take a longer time to search. The initial temperature can be determined based on the relative performance of the initial population. Here the sum of fitness functions is selected as the initial temperature below [14].

$$t_0 = \frac{f_{i\min} - f_{j\max}}{\ln(f_{i\min} / f_{j\max})}, \tag{15}$$

where $f_{i\min}$ and $f_{i\max}$ are the minimum fitness function value and maximum fitness function value in the initial population, respectively. It can minimize the flaws existing in the initial performance of the algorithm if selecting the initial temperature according to (15). The annealing temperature is determined by

$$t_{k+1} = \alpha t_k, k \geq 0, 0 \leq \alpha \leq 1, \tag{16}$$

where γ denotes the selected factor ratio, and k is the iteration times.

The probability for each seeker to be selected is judged using Boltzmann annealing operator after the temperature changes.

$$p_i = \frac{\exp\left(-\dfrac{f(i) - \overline{f}}{t_k}\right)}{\sum_{j=1}^{s} \exp\left(-\dfrac{f(i) - \overline{f}}{t_k}\right)}, \tag{17}$$

where $\overline{f}$ express the average fitness of the population. Seen from (17), that the simulated annealing-based individual searching method enables the populations choose the deterioration solution during the optimization process to prevent the seeker to fall into local extremum.

3.5. Improvement on Search Strategy

A step fitness factor $u(d_i)$ is added to strengthen the nonlinear optimization ability of the algorithm and to improve the step-length, the improved step-length formula is as follows.

$$\alpha_{ij} = \delta_{ij} u(d_i) \sqrt{-\ln(\mu_{ij})}, \tag{18}$$

$$u(d_i) = \begin{cases} 3.55 + \alpha, & d_i \leq R_1 s \\ 3.55, & R_1 s < d_i < R_2 s \\ 3.55 - \beta, & d_i \geq R_2 s \end{cases}, \tag{19}$$

where the α and β are the adaptive adjustment parameters, and defined as α=β=1.05, R_1 and R_2 are the adaptive control parameters, and define as R_1=1/7, and R_2=3/7, and d_i is the corresponding number arranged by each seeker in the group in descending order, and s is the population size, and define as 36.

The search direction $d_{ij}(t)$ and the search step-length $\alpha_{ij}(t)$ of the jth dimension of each step of the seeker i at time t are then calculated based on the above equations, separately, and $\alpha_{ij}(t) \geq 0$, $d_{ij}(t) \in \{-1, 0, 1\}$. From $d_{ij}(t)$, we can know the seeker should keep stationary, or moving along the coordinate j in the positive direction and moving along the coordinate j in the negative direction.

Location updating of the seeker is performed after both the search direction and the step-length are determined, the updating formula is as follows.

$$\Delta x_{ij}(t+1) = \alpha_{ij}(t) d_{ij}(t), \quad (20)$$

$$x_{ij}(t+1) = x_{ij}(t) + \Delta x_{ij}(t+1), \quad (21)$$

We replace the search locations of the two worst seekers in the sub-population with the search locations of the two best seekers in the other two sub-populations after evaluation process each time to share information of the seekers between the diverse populations, which not only avoids premature to some extent, but also achieves the sharing of the social information between the populations.

4. Capacitors Optimization Placement for Distribution Grid

The Fig. 1 is the improved SOA flow chart diagram.

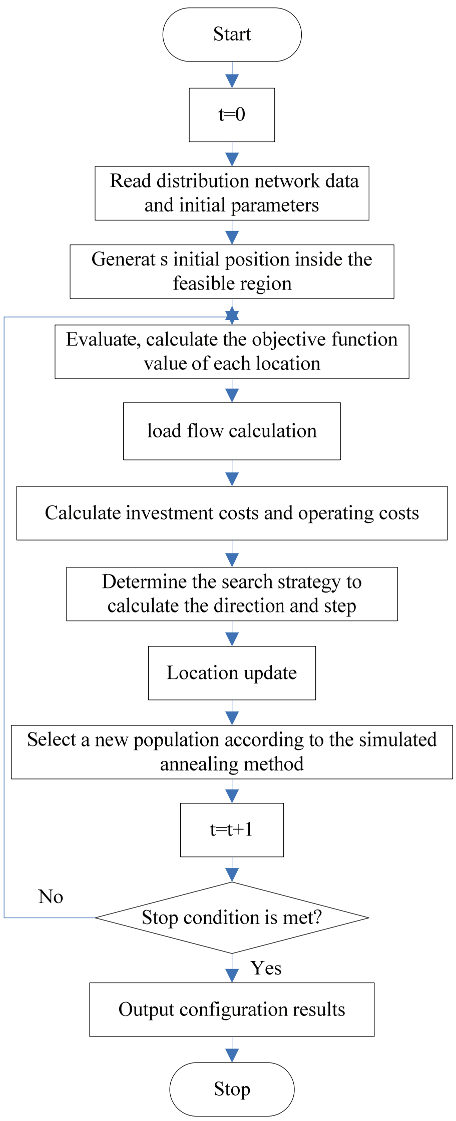

Fig. 1. Improved SOA flow chart diagram.

In this paper an improved power flow calculation method is applied to meet the power flow constraint equations [15], which ensure the speed and accuracy of the power flow calculation. The program adopts integer codes to simplify the calculation process, and the fixed-capacity capacitors are grouped to meet diverse capacity constraints. The range of 0.95 to 1.05 reference voltage of distribution grid is given for the node voltage constraints of distribution grid. The capacitors installed under light loads are used as fixed capacitors, and the number of capacitors installed is not bigger than the number of switching capacitors which are necessary under medium loads and heavy loads. The number of capacitors required under light loads should be firstly calculated in the first configuration, and the required capacitors under light loads are treated as reactive power supply, and on the basis of it the switching capacitors under medium loads and heavy loads are reasonably allocated. Improved SOA flow chart is shown in Fig. 1.

5. Example Analysis

IEEE 33-node standard distribution system is applied to verify the effectiveness of Improved SOA, and whose topology is shown in Fig. 2.

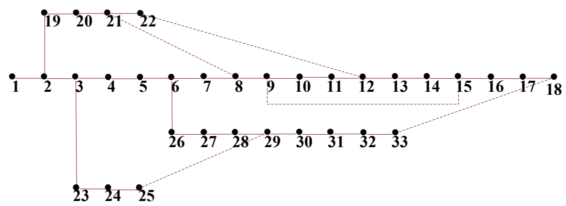

Fig. 2. IEEE33-node distribution system.

In Fig. 2, except that node 1 is the balanced node that cannot be configured with capacitors, the other 32 nodes can be configured with capacitors. The power reference value of the system is defined as 1.0 MVA, and the major parameters are defined as: capacitor capacity with 30 kvar is considered as a unit, the installation cost of the capacitor is expressed by RMB 500 yuan/unit, and a fixed capacitor cost is RMB 650 yuan/unit, and a switching capacitor cost is RMB 1250 yuan/unit, and annual maintenance cost of a capacitor is RMB 150 yuan/unit, and the price of electricity is RMB 0.6 yuan/kW·h. Each node can be installed with 8 capacitors at most which includes the switching and fixed capacitors. The duration time and the proportions of the different load grades are shown in Table 1.

Simulated annealing, SOA and improved SOA are respectively used to calculate the capacitors optimization allocation in IEEE 33-node system. Table 2 shows the details of the optimal configu-ration of the capacitors trough improved SOA, and

Table 3 is the results comparison of grid loss reduction among them, and Table 4 is the results comparison of voltage stabilization, and Table 5 is the results comparison of investment operating costs after optimal configuration.

Table 1. Duration of different loads.

Load level	Duration/h	Proportion
Light load	5260	0.75
Medium load	24520	1
Heavy load	5260	1.25
Four years statistics outcome		

Table 2. Details of the capacitors configuration of each node.

Node number	The number of installed units			Installed capacity (kvar)
	Light load	Medium load	Heavy load	
2	0	0	3	90
3	0	1	7	240
4	0	5	3	240
5	0	0	8	240
6	0	2	4	180
7	0	6	1	210
8	0	6	1	210
9	7	1	0	240
10	0	1	3	120
11	0	4	4	240
12	0	4	2	180
13	0	0	2	60
14	1	3	4	240
15	1	0	2	90
16	0	2	1	90
17	3	0	5	240
18	0	4	4	240
19	0	0	3	90
20	0	1	1	60
21	1	1	2	120
22	0	1	1	60
23	0	1	7	240
24	0	0	3	90
25	0	6	0	180
26	0	1	7	240
27	0	1	7	240
28	0	8	0	240
29	2	4	1	210
30	1	6	1	240
31	3	3	0	180
32	1	5	2	240
33	4	4	0	240
The total number of units	24	81	89	
Total compensation capacity				5820

Table 3. Active power loss comparisons after the configuration.

Load level	Active power loss/kW			
	Before optimization	SA	SOA	Improved SOA
Light load	89.13	65.13	62.88	60.46
Medium load	254.48	188.64	193.75	176.33
Heavy load	433.27	424.89	426.54	421.31

Table 4. Minimum voltage comparison after configuration.

Load level	Minimum voltage/%			
	Before optimization	SA	SOA	Improved SOA
Light load	92.18	95.13	95.11	95.26
Medium load	87.97	95.02	95.07	95.32
Heavy load	83.75	95	95	95.03

Table 5. Total investment and operation cost comparisons after the configuration.

Total costs/Ten thousand yuan in RMB			
Before optimization	SA	SOA	Improved SOA
449.38	429.39	418.21	387.03

Fig. 3 shows the optimization process with three algorithms. We can see from Table 3 that the reduction on the active grid loss of the distribution grid is very significant after the configuration, and it can save RMB 623,500 yuan within 4 years, which accounts for 13.87 % of the total cost before optimal configuration. It also can be seen from the Table 4, the node voltage quality of the distribution network after compensation has been improved, dramatically, and all the node voltages are qualified, but simulated annealing algorithm has a good performance in voltage optimization at the expense of the economy. At the same time, we also can be seen from Fig. 3 that the optimization curve of SOA declines fast in iteration 50 times, this shows the optimization mechanism of SOA is much better than the other two. After iteration 100 times, when other algorithm exhibits cease in converge performance, there are still changes in terms of improved SOA, which shows that the improved SOA is not easy to fall into local optimum compared with the other two algorithms. On the whole, the Improved SOA can get the best solution after 200 times iteration. The comprehensive comparisons indicate that the improved SOA has shown feasibility and superiority in solving this problem.

Taking into account the randomness of the three algorithms, I conducted 20 operations using the three different algorithms, and the result is can be seen from the Table 6. Then I sorted out and calculated the result, and the mean value，standard deviation and variance of three algorithms are got, which can be seen from the Table 7.

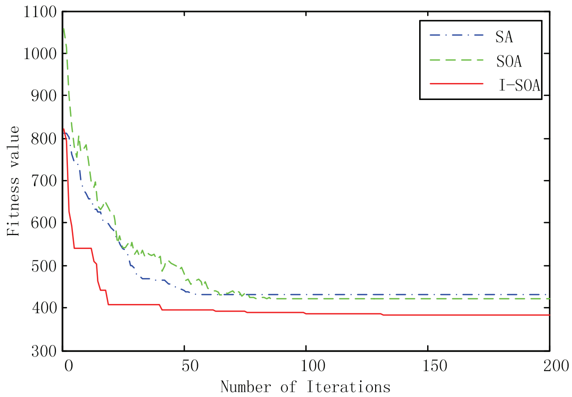

Fig. 3. Optimization procedure with three algorithms.

Table 6. Three algorithms optimal function value of 20 samples.

Number of calculations	SA	SOA	Improved SOA
1	458.5	416.34	397.71
2	426.85	416.75	392.47
3	411.2	401.93	397.71
4	455.29	415.72	384.32
5	441.46	408.47	389.28
6	444.49	434.53	396.99
7	454.75	409.31	397.22
8	421.86	413.6	383.22
9	402.7	408.48	385.04
10	406.4	428.19	392.09
11	447.7	440.23	400.21
12	416.1	409.45	399.4
13	437.46	424.11	392.19
14	437.78	431.05	383.39
15	429.79	427.23	389.32
16	419.53	399.59	396.23
17	405.04	419.49	383.36
18	456.19	432.21	397.26
19	456.82	433.15	386.13
20	424.89	438.38	392.49

Table 7. Mean value, standard deviation and variance of three algorithms 20 samples.

Algorithm	Mean value	Standard deviation	Variance
SA	432.74	18.88	356.53
SOA	420.41	12.25	150.15
Improved SOA	391.80	5.92	35.10

We can see from Table 3 that the mean value of improved SOA is smaller than SOA and SA, which can proof that the improve SOA is suitable for solving such problems, and the standard deviation and variance of it is much lower than the other two algorithm, this result shows that the Stability of improve SOA is better than SOA and SA, the improvement is effective.

6. Conclusions

In this paper, an optimized mathematical model based on economy for the capacitors of the distribution network has been established first, and the seeker optimization algorithm is selected as a solution for the characteristics of discreteness and larger space of the solution of the configuration. Simulated annealing operator is added when improving the algorithm to improve the overall search ability and to avoid the premature in the optimization process and the search strategy has been improved so that it is more suitable for solving nonlinear discreteness. The distribution network is optimized with the improved algorithm, which has an ideal effect both on loss reduction and on voltage optimization and shows the feasibility of the improved algorithm on advancement and technology.

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