Hindawi
Wireless Communications and Mobile Computing
Volume 2023, Article ID 9814723, 1 page
https://doi.org/10.1155/2023/9814723

Retraction

Retracted: Low-Voltage Diagnosis of Energy Distribution Network Based on Improved Particle Swarm Optimization Algorithm

Wireless Communications and Mobile Computing

Received 12 December 2023; Accepted 12 December 2023; Published 13 December 2023

Copyright © 2023 Wireless Communications and Mobile Computing. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] T. Wang, B. Ma, X. Dai, J. Li, and S. Li, "Low-Voltage Diagnosis of Energy Distribution Network Based on Improved Particle Swarm Optimization Algorithm," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 4969410, 7 pages, 2022.

Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 4969410, 7 pages
https://doi.org/10.1155/2022/4969410

Research Article

Low-Voltage Diagnosis of Energy Distribution Network Based on Improved Particle Swarm Optimization Algorithm

Ting Wang, Bingfeng Ma, Xiaohui Dai, Jianfeng Li, and Sheng Li

State Grid Shaanxi Electric Power Co., Ltd., Xi'an, Shaanxi 710048, China

Correspondence should be addressed to Ting Wang; 31115210@njau.edu.cn

Received 7 March 2022; Revised 6 April 2022; Accepted 13 April 2022; Published 5 May 2022

Academic Editor: Aruna K K

Copyright © 2022 Ting Wang et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In order to improve the research on low-voltage fault diagnosis of energy distribution network, a low-voltage multiobjective diagnosis of AC/DC energy distribution network based on ICHPSO is proposed in this paper. Firstly, the types of objective functions are listed, the objective function is transformed into a single-objective function by using the linear weighting method, and the hybrid particle swarm optimization (HPSO) diagnosis algorithm is improved, which can guide the particles to escape from the local optimal solution space, prevent the particles from falling into the local optimal too early, and improve the search accuracy and global search ability of the algorithm. At the same time, the individuals with high fitness are retained, and the convergence performance of the algorithm is improved. Then, the algorithm is coded, and an example of AC/DC energy distribution network with improved ieee33 is adopted. DC side data comes from the first 13 nodes of AC side data, and the voltage level is 10 kV. The diagnostic effects of different schemes were compared. The results show that the expected mean value of node voltage deviation after power compensation diagnosis is 2.26%, which is 61.18% lower than that before diagnosis; the expected average voltage loss is 0.77 kv, which is 52.1% lower than that before diagnosis; the expectation of network loss is 196.45 kw, which is 49.56% lower than that before diagnosis; the minimum voltage of the AC side node (node 18) is expected to be 0.9514 p.u., 2.75% higher than that before diagnosis; and the minimum voltage of DC side node (node 8) is expected to be 0.9918 p.u., 1.11% higher than that before diagnosis. The comprehensive experimental results show that the proposed method can greatly reduce the node voltage deviation, voltage loss, and network loss of AC/DC energy distribution network, improve the node voltage quality, and maintain the stable operation of the whole AC/DC energy distribution network.

RETRACTED

1. Introduction

Voltage is one of the measurement standards of power quality. The low-voltage problem of distribution network not only seriously affects the social and economic development and people's life but also is of great significance to optimize the low-voltage investment scheme, clarify the direction of low-voltage investment, and provide decision support for low-voltage management [1]. Distribution network is one of the important parts of modern power system. Its task is to directly distribute the electric energy obtained from transmission network to users. Compared with transmission network, distribution network has the characteristics of direct connection with users, low voltage level, large number of users, and large number of power equipment [2]. With the development of economy, users' demand for electric energy is increasing. Only through the construction of the power industry itself can we continuously expand the scale of the power system and meet people's demand for electric energy. Power system has the characteristics of long construction cycle and large investment. It is the infrastructure of national economy. Unscientific and unreasonable power grid construction will cause great damage to society, national economy, and power grid operation. Scientific planning of power grid can avoid unreasonable investment and construction to a certain extent [3]. Reasonable power grid planning can save investment to the greatest extent, promote the healthy development of itself and other industries, and improve economic and social benefits. The significance and importance of power grid planning is self-evident. Distribution network planning is not only an important part of the national economic and social development of the planned area but also one of the important foundations of the long-term development planning of power enterprises. The goal of distribution network planning is to make the development of distribution network meet and moderately ahead of the economic development needs of the region and play a leading role in power grid construction, operation, and power supply. Figure 1 shows the structural diagram of traditional distribution network and active distribution network. At present, the distribution network fault diagnosis system generally chooses to install relevant monitoring equipment at the switch or feeder of the distribution network to obtain the information of the distribution network in real time. When the network is in normal working state, it plays the purpose of monitoring and detection and provides convenience for managers to find the source of problems in time, so as to reduce the possibility of failure. When the network is in the fault state, the system can process and diagnose the real-time transmission data information, so as to quickly find the fault point, transmit the relevant information to relevant workers, eliminate it as soon as possible, and quickly restore the power supply [4]. In short, the application of fault diagnosis system can shorten the time of line finding by maintenance personnel, accelerate the speed of fault recovery, and make the power supply system more reliable.

Based on the current research, with the development of smart grid construction, the traditional distribution low-voltage cause diagnosis based on detection technology has become the power big data classification technology based on data mining, while the data classification research focusing on the causes of low-voltage faults is still in its infancy. Therefore, this paper proposes an ICHPSO algorithm to solve the voltage diagnosis problem embedded in stochastic power flow. The results show that the expected mean value of node voltage deviation after power compensation diagnosis is 2.26%, which is 61.18% lower than that before diagnosis; the expected average voltage loss is 0.77 kv, which is 52.1% lower than that before diagnosis; the expectation of network loss is 196.45 kw, which is 49.56% lower than that before diagnosis; the minimum voltage of the AC side node (node 18) is expected to be 0.9514 p.u., 2.75% higher than that before diagnosis; and the minimum voltage of DC side node (node 8) is expected to be 0.9918 p.u., 1.11% higher than that before diagnosis. The comprehensive experimental results show that the proposed method can greatly reduce the node voltage deviation, voltage loss, and network loss of AC/DC distribution network, improve the node voltage quality, and maintain the stable operation of the whole AC/DC distribution network.

2. Literature Review

Aiming at this research problem, Song and others pointed out that the main feature of using matrix algorithm for fault diagnosis is that the principle is simple and easy to understand. There are some differences in the fault location mechanism of radiation networks and networks at both ends with different structures. For the single source radiation network, if there is a section fault, FTU can only detect the fault information on one side [5]. Tang and others analyzed the causes of rural low-voltage problems and pointed out that the main problems are weak distribution network, insufficient reactive power compensation capacity, long power supply radius, insufficient power supply capacity, insufficient power supply capacity of distribution transformer, insufficient power supply capacity of low-voltage lines, and almost no new equipment and technologies have been put into use [6]. Houman and others summarized the causes of short-term continuous low voltage and explained the voltage characteristics of continuous low voltage phenomenon for different reasons [7]. Su and others designed and implemented a big data cloud platform for power quality. The platform can store and analyze high-power quality data [8]. Qi and others introduced data mining and its application in power quality analysis [9]. Sheng and others proposed a steady-state power quality prediction method based on data mining technology [10]. The expert system designed by Pesaran and others is based on years of distribution network operation experience and relevant data, so as to build a fuzzy diagnosis database. When there is a fault in the distribution network, input the obtained information into the database for comparison, and find the fault point according to the judgment rules [11]. On this basis, Lu and others further added the application of fuzzy set and fuzzy reasoning, which greatly improved the accuracy of fault location results, and this research has been applied to practice [12]. Asrari and others divide the distribution network into several subnets for planning, respectively, and express the fixed cost, variable cost, and loss cost as time-related cost items. However, the zoning planning in this model is different from the overall distribution network planning without zoning [13]. El-Ghandour and Elbeltagi studied the planning model and proposed a multistage planning model with voltage drop constraints and radial network constraints [14]. Based on the current research, with the development of smart grid construction, the traditional distribution low-voltage cause diagnosis based on detection technology has become the power big data classification technology based on data mining, while the data classification research focusing on the causes of low-voltage faults is still in its infancy. Therefore, this paper proposes an ICHPSO algorithm to solve the voltage diagnosis problem embedded in stochastic power flow.

3. Multitarget Diagnosis of Low-Voltage AC/DC Distribution Network Based on HP3

3.1. Objective Function

(1) The expected average value of node voltage deviation is

$$\begin{cases} f_{1a} = \dfrac{1}{k}\displaystyle\sum_{k=1}^{K}\left[\left(\sum_{i=1}^{N_a}\left|\dfrac{U_{a,k,i}U_{a\_N}}{U_{a\_N}}\right|\right)/N_a\right], \\ f_{1d} = \dfrac{1}{k}\displaystyle\sum_{k=1}^{K}\left[\left(\sum_{i=1}^{N_d}\left|\dfrac{U_{d,k,i}U_{d\_N}}{U_{d\_N}}\right|\right)/N_d\right], \end{cases} \tag{1}$$

RETRACTED

where K is the total number of times of LHS; K is the number of current LHS; N_a is the number of AC subnet nodes; $U_{a,k,i}$ is the actual voltage value of node i on the AC side during the kth sampling; U_{a_N} is the rated voltage on the AC side; N_d is the number of DC subnet nodes; $U_{d,k,i}$ is the actual voltage of node i on the DC side during the kth sampling; U_{d_N} is the rated voltage at DC side; f_{1a} is the expectation of the average value of node voltage deviation on the AC side; f_{1d} is the expectation of the average value of node voltage deviation at DC side; and f_1 is the expectation of the average value of node voltage deviation of the whole AC/DC energy distribution network.

(2) The expected average value of voltage loss is

$$\begin{cases} f_{2a} = \dfrac{1}{K}\displaystyle\sum_{K=1}^{K}\left[\left(\sum_{i=1}^{N_{al}}\dfrac{P_{al,k,i}R_{al,i} + Q_{al,k,i}X_{al,i}}{U_{al,k,i}}\right)/N_{al}\right], \\ f_{2d} = \dfrac{1}{K}\displaystyle\sum_{K=1}^{K}\left[\left(\sum_{i=1}^{N_{dl}}\dfrac{P_{dl,k,i}R_{dl,i}}{U_{dl,k,i}}\right)/N_{dl}\right], \end{cases} \tag{2}$$

where N_{al} is the number of branches at AC side; $P_{al,k,i}$, $Q_{al,k,i}$ are the active and reactive power passing through the i section of the line at the AC side during the kth sampling; $R_{al,i}$, $X_{al,i}$ are the impedance on the i section line at the AC side; N_{dl} is the number of DC side branches; $P_{dl,k,i}$ is the active power passing through the I-section line on the DC side during the kth sampling; $R_{dl,i}$ is the resistance of section I line at AC side; f_{2a} is the expectation of AC side voltage loss; f_{2d} is the expectation of DC side voltage loss; and f_2 is the expected voltage loss of the whole AC/DC energy distribution network.

(3) The expectation of network loss is

$$\begin{cases} f_{3a} = \dfrac{1}{K}\displaystyle\sum_{K=1}^{K}\sum_{i=1,j=1}^{N_a}\left(U_{a,k,i}^2 + U_{a,k,j}^2 - 2U_{a,k,i}U_{a,k,j}\cos\theta_{a,ij}\right)G_{a,ij}, \\ f_{3d} = \dfrac{1}{K}\displaystyle\sum_{K=1}^{K}\sum_{i=1,j=1}^{N_{dl}} I_{dl,k,i}^2 R_{dl,i}, \\ f_{3c} = \dfrac{1}{K}\displaystyle\sum_{K=1}^{K}\left(aI_{VCS,k}^2 + bI_{a\_VSC,k} + c\right), \\ \min f_3 = \min\left(f_{3a} + f_{3d} + f_{3c}\right), \end{cases} \tag{3}$$

where nodes I and j are adjacent nodes; $U_{a,k,j}$ is the actual voltage value of node j adjacent to node i on the AC side during the kth sampling; $\theta_{a,ij}$ is the phase angle difference of adjacent nodes i and j; $G_{a,ij}$ is the conductance between adjacent nodes i and j on the AC side; $I_{dl,k,i}$ is the current flowing through section i line at the DC side during the kth sampling; $I_{a\_VSC,k}$ is the current flowing through the AC side of voltage source converter VSC (voltage source converter) during the kth sampling; A, B, and C are the loss coefficient of VSC; f_{3a} is the network loss expectation on the AC side; f_{3d} is the network loss expectation of DC side; f_{3c} is the loss expectation of VSC; and f_3 is the network loss expectation of the whole AC/DC energy distribution network.

3.2. Multiobjective Normalization Processing. The subobjective function values adopt the unit value, to realize the unified dimension. The above three objective functions are transformed into single objective functions by linear weighting method, i.e.,

$$\min f = \min\left(w_1 f_1 + w_2 f_2 + w_3 f_3\right), \tag{4}$$

where w_1, w_2, and w_3 are the weight coefficients of the three subobjective functions, respectively, which meet w_1, w_2, and $w_3 \in [0, 1]$, and $w_1 + w_2 + w_3 = 1$. The weight coefficient of subdiagnosis target is generally decided by the operation planner in combination with the specific situation, and different diagnosis results can be obtained by changing the weight coefficient.

3.3. ICHPSO Algorithm Solving Diagnosis Model

3.3.1. Immune Chaotic Hybrid Particle Swarm Optimization. An ICHPSO algorithm is proposed to solve the multiobjective voltage diagnosis problem of AC/DC energy distribution network. The algorithm improves the hybrid particle swarm optimization (HPSO) diagnosis algorithm, which can guide particles to escape from the local optimal solution space, prevent particles from falling into the local optimal solution prematurely, and improve the search accuracy and global search ability of the algorithm. At the same time, individuals with high fitness are retained, which improves the convergence performance of the algorithm [15]. The specific steps are as follows.

Step 1. Initialize the position and velocity of particles in HPSO algorithm by chaotic sequence

Step 2. Use the logistics equation of $z_{n+1} = \mu z_n(1 - z_n)$, $n = 0, 1, 2, \cdots$ to iterate to obtain the chaotic sequence, inverse map the new chaotic sequence from $gb(t+1) = g b(k) + R[Z(t+1) - 0.5]$ to the original solution space, calculate the fitness value of the feasible solution sequence of the chaotic variable, and replace one particle in the original particle swarm with the particle in its optimal position [16]

Step 3. Apply the premature judgment mechanism to hybridize the remaining particles again in addition to the chaotic processing of the optimal particles. In each iteration, a specified number of particles are selected according to the hybridization rate and put into the hybridization pool. The particles in the pool are hybridized randomly in pairs to produce the same number of children, and the offspring particles are used to replace the parent particles. The position of the child is obtained by crossing the position of the parent:

$$\mathrm{child}(x) = p \cdot \mathrm{parent}_1(x) + (1 - p) \cdot \mathrm{parent}_2(x), \tag{5}$$

RETRACTED

where p is a random number between 0 and 1. The speed of offspring can be expressed as:

$$\text{child}(v) = \frac{\text{parent}_1(v) + \text{parent}_2(v)}{|\text{parent}_1(v) + \text{parent}_2(v)|} |\text{parent}_1(v)|. \quad (6)$$

Step 4. In the later stage of the hybridization process, a series of operations such as antigen recognition antibody cloning, immune selection, differentiation, crossover, and mutation in the immune operator are introduced to gradually achieve the highest antibody affinity and increase particle diversity again [17]. The immune selection operation can be obtained by particle concentration probability, which can be expressed as:

$$\begin{cases} D(x_i) = \dfrac{1}{\sum_{j=1}^{N+N_0} \left| f(x_i) - f(x_j) \right|}, \\ P(x_i) = \dfrac{1/D(x_i)}{\sum_{i=1}^{N+N_0} 1/D(x_i)}, \end{cases} \quad (7)$$

where $i = 1, 2, 3, \cdots, N + N_0$; $D(x_i)$ is the concentration of the ith particle; and $P(x_i)$ is the probability that the ith particle is selected.

Step 5. Compare the optimal solution obtained by the immune operator with the optimal solution obtained by the previous chaotic sequence, and keep the two optimal [18]

3.3.2. Algorithm Coding. The variables in this paper are the output of AC side reactive power compensation device and DC side energy storage device. In the ICHPSO algorithm, it is assumed that the dimension D of each particle represents the number of compensation devices connected in the AC/DC energy distribution network, and each component in $x_i = (x_{i,1} x_{i,2}, \cdots, x_{i,N})$ represents the power output of the corresponding compensation device.

3.3.3. Solving Voltage Multiobjective Diagnosis of AC/DC Energy Distribution Network by ICHPSO Algorithm. ICHPSO algorithm is used to solve the voltage diagnosis problem of AC/DC distribution network. The calculation steps are as follows.

Step 1. Enter the original parameter

Step 2. Use LHS technology to generate wind speed, light intensity, and load data

Step 3. Introduce chaotic sequence to initialize the position and velocity of particles within the specified range [19]

Step 4. For each particle in the population, calculate the random power flow and objective function according to the output power of the compensation device at each node; the expected value of particle fitness is evaluated according to the calculation results, and the minimum value is the current optimal solution g_{best} of the population

Step 5. Update the speed and position of particles and modify the inertia weight [20]

Step 6. Calculate the stochastic power flow and objective function again, and reevaluate the expected value of particle fitness. Based on the optimal position searched by the current whole particle swarm, the chaotic sequence is generated by the logistics equation and then inversely mapped to the original solution space. The optimal position particle is taken to replace the position of a particle in the current particle swarm, and the remaining particles are put into the hybridization pool for re hybridization [21]

Step 7. Introduce the immune operator into the hybridization pool, select the particles with strong adaptability by using memory cells, antibody cloning, cell differentiation, and variation, eliminate the particles with poor adaptability, and judge the local extreme point by immunization [22]

Step 8. Compare the optimal solution obtained by the immune operator with the optimal solution obtained by the previous chaotic sequence, and keep the two optimal [23]

Step 9. Check whether the constraint conditions are met. If so, the iteration will terminate and output the optimal solution to jump out of the loop. Otherwise, go to step 5

4. Results and Analysis

4.1. Parameter Setting. In this paper, an example of AC/DC energy distribution network based on improved IEEE33 is adopted. DC side data comes from the first 13 nodes of AC side data, and the voltage level is 10 kV. The AC side substation and DC network node 2 are connected through VSC, and the control mode is constant DC side voltage, $U_{d\_VSC} = 1.0 p.u.$; constant AC side reactive power, $Q_{a\_VSC} = 300k$ var. DC-DC converters adopt constant power control. The number of LHS is 500. The convergence accuracy of power flow calculation is set to 10-6.

The parameters of ICHPSO algorithm are set as follows: the number of particles $N = 4$, the dimension of particles $d = 4$, the learning factor $\text{C1} = 1.5$, $\text{C2} = 1.5$; the maximum number of iterations is 100, and the inertia weight is $w_{\max} = 0.9, w_{\min} = 0.4$; chaos coefficient $u = 4$; the hybridization probability was 0.8, and the size of hybridization pool was 0.1; $w_1 = 0.6, w_2 = 0.2, w_3 = 0.2$ in multiobjective normalization.

4.2. Diagnosis Results and Analysis. Table 1 shows the comparison of diagnostic effects of different schemes. It can be seen from Table 1 that the expected average value of node voltage deviation after power compensation diagnosis is 2.26%, which is 61.18% lower than that before diagnosis; the expected average voltage loss is 0.77 kv, which is 52.1% lower than that before diagnosis; the expectation of network loss is 196.45 kW, which is 49.56% lower than that before diagnosis; the minimum voltage of the AC side node (node 18) is expected to be 0.9514 p.u., 2.75% higher than that before diagnosis; and the minimum voltage of DC side node (node 8) is expected to be 0.9918 p.u., 1.11% higher than that before diagnosis.

Figures 2 and 3 show the expected voltage of each node on the AC and DC sides before and after diagnosis [24]. It can be seen from Table 1 and Figure 2 that the connection of power regulation device can greatly improve the performance of node voltage of AC/DC energy distribution network, especially for the voltage at the end of the line.

RETRACTED

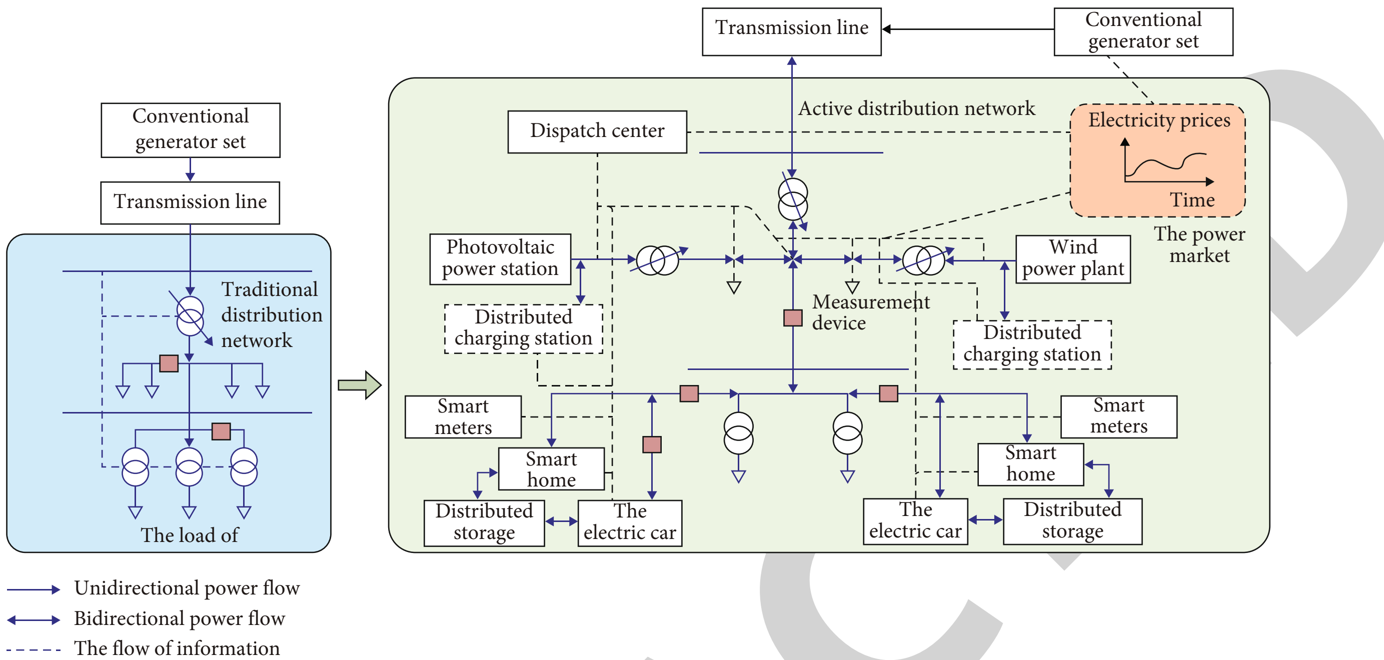

Figure 1: Structural diagram of traditional distribution network and active distribution network.

Table 1: Comparison of diagnostic effects of different schemes.

Diagnostic algorithm	Expected value of network loss/kW	Expected average value of node voltage deviation/%	Expected voltage loss/kV	Expected minimum voltage of AC side node (p.u.)	Minimum expected electric value of DC side node (p.u.)
Not diagnosed	389.67	5.81	1.44	0.9251	0.9806
HPSO	280.23	3.92	1.27	0.9314	0.9895
CPSO	250.76	3.20	1.06	0.9455	0.9900
ICHPSO	196.45	2.25	0.77	0.9514	0.9918

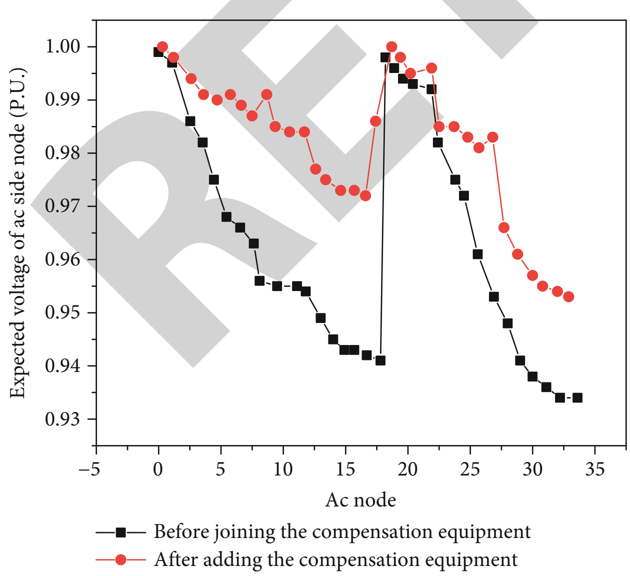

Figure 2: Change of expected value of node voltage before and after AC side is connected to reactive power compensation device.

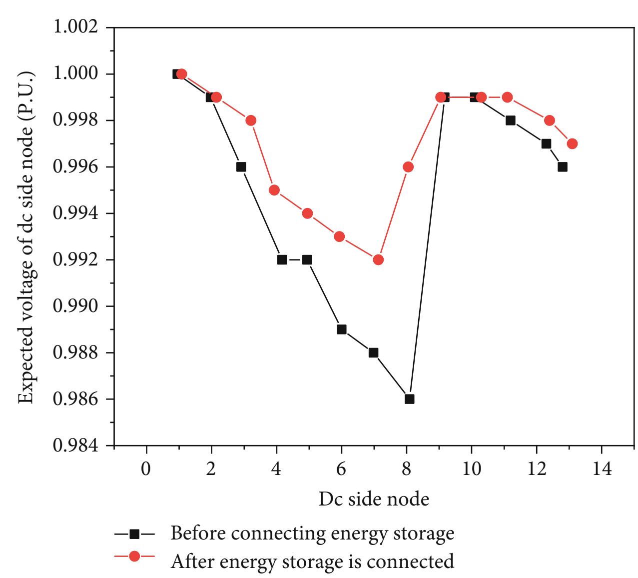

Figure 3: Change of expected node voltage before and after DC side connected to energy storage device.

RETRACTED

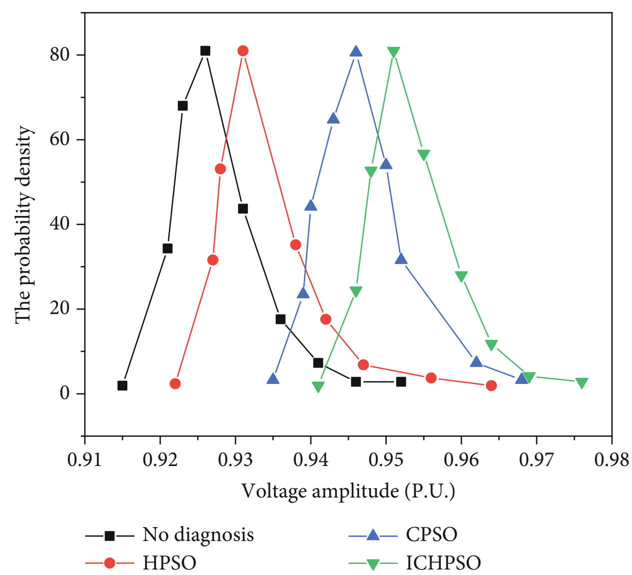

FIGURE 4: Node 18 voltage amplitude probability density.

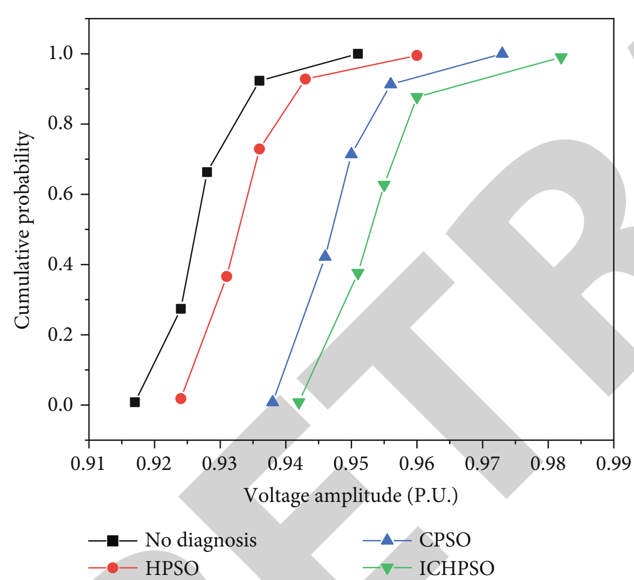

FIGURE 5: Cumulative distribution of voltage amplitude at node 18.

Figures 4 and 5 show the diagnosis results of the proposed algorithm compared with the diagnosis results of CPSO algorithm and HPSO algorithm before diagnosis, taking the AC side node 18 as an example. According to the comprehensive analysis of Table 1 and Figures 4 and 5, the method proposed in this paper can greatly reduce the node voltage deviation, voltage loss, and network loss of AC/DC energy distribution network, improve the node voltage quality, and maintain the stable operation of the whole AC/DC energy distribution network [25]. Figure 6 shows the comparison of algorithm convergence. It can be seen from Figure 6 that the algorithm used in this paper converges to the optimal value after about 20 iterations. Compared with chaotic particle swarm optimization (CPSO) algorithm and HPSO algorithm, the convergence speed is faster, and the final diagnosis result is better [26].

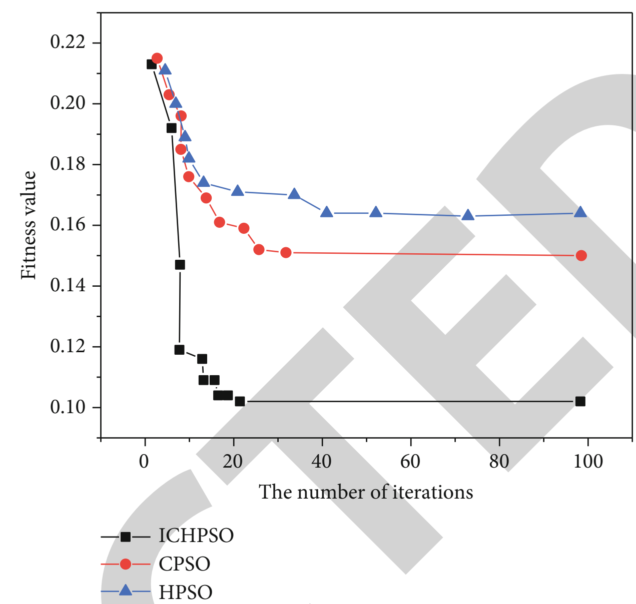

FIGURE 6: Comparison of algorithm convergence curves.

5. Conclusion

In this paper, the research on low voltage diagnosis of energy distribution network based on improved particle swarm optimization algorithm is proposed. Taking AC and DC distribution network as the object, the voltage diagnosis problem considering the randomness of source load is studied. Combining chaos theory and artificial immune theory into hybrid particle swarm diagnosis algorithm, an immune Chaotic Hybrid Particle Swarm diagnosis algorithm is proposed to solve the voltage diagnosis model of AC/DC energy distribution network aiming at the expectation of average node voltage deviation, the expectation of average voltage loss, and the expectation of minimum network loss. Finally, an example shows that the proposed method can effectively improve the voltage level of AC/DC distribution network and improve its ability to deal with source load uncertainty. With the gradual strengthening of power demand, the capacity of distributed generation connected to energy distribution network will gradually increase. The current fault location method has certain requirements for the size of fault current, which limits the capacity of distributed generation. When the capacity of distributed generation is large enough, the applicability of this method will be greatly reduced and still needs to be improved.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

RETRACTED

References

[1] C. Yuan, J. Wang, and G. Yi, "Estimation of key parameters in adaptive neuron model according to firing patterns based on improved particle swarm optimization algorithm," *Modern Physics Letters B*, vol. 31, no. 7, article 1750060, 2017.

[2] N. Kanwar, N. Gupta, K. R. Niazi, A. Swarnkar, and R. C. Bansal, "Simultaneous allocation of distributed energy resource using improved particle swarm optimization," *Applied Energy*, vol. 185, part 2, pp. 1684–1693, 2017.

[3] W. Bai, W. Zhang, N. Zhou, L. Tang, C. Ma, and X. Shi, "Transmission line voltage classes identification based on particle swarm optimization algorithm and pcnn," *Ferroelectrics*, vol. 521, no. 1, pp. 6–17, 2017.

[4] C. Guang, F. Qibo, D. Keqin, and G. Zhan, "Subpixel displacement measurement method based on the combination of particle swarm optimization and gradient algorithm," *Optical Engineering*, vol. 56, no. 10, p. 1, 2017.

[5] X. Song, Y. Gong, D. Jin, and Q. Li, "Nodes deployment optimization algorithm based on improved evidence theory of underwater wireless sensor networks," *Photonic Network Communications*, vol. 37, no. 2, pp. 224–232, 2019.

[6] J. Tang, D. Wang, X. Wang et al., "Study on day-ahead optimal economic operation of active distribution networks based on kriging model assisted particle swarm optimization with constraint handling techniques," *Applied Energy*, vol. 204, pp. 143–162, 2017.

[7] H. Pezeshki, A. Arefi, G. Ledwich, and P. Wolfs, "Probabilistic voltage management using oltc and dstatcom in distribution networks," *IEEE Transactions on Power Delivery*, vol. 33, no. 2, pp. 570–580, 2018.

[8] X. Su, M. Masoum, and P. J. Wolfs, "Multi-objective hierarchical control of unbalanced distribution networks to accommodate more renewable connections in the smart grid era," *IEEE Transactions on Power Systems*, vol. 31, no. 5, pp. 3924–3936, 2016.

[9] Q. Qi, J. Wu, and C. Long, "Multi-objective operation optimization of an electrical distribution network with soft open point," *Applied Energy*, vol. 208, pp. 734–744, 2017.

[10] W. Sheng, K. Y. Liu, Y. Liu, X. Ye, and K. He, "Reactive power coordinated optimisation method with renewable distributed generation based on improved harmony search," *Iet Generation Transmission & Distribution*, vol. 10, no. 13, pp. 3152–3162, 2016.

[11] H. Pesaran, M. Nazari-Heris, B. Mohammadi-Ivatloo, and H. Seyedi, "A hybrid genetic particle swarm optimization for distributed generation allocation in power distribution networks," *Energy*, vol. 209, no. 12, article 118218, 2020.

[12] Z. Lu, T. Wei, J. Liang, P. Cong, and Y. Cai, "Coordinated day-ahead reactive power dispatch in distribution network based on real power forecast errors," *IEEE Transactions on Power Systems*, vol. 31, no. 3, pp. 2472–2480, 2019.

[13] A. Asrari, T. Wu, and S. Lotfifard, "The impacts of distributed energy sources on distribution network reconfiguration," *IEEE Transactions on Energy Conversion*, vol. 31, no. 2, pp. 606–613, 2016.

[14] H. A. El-Ghandour and E. Elbeltagi, "Comparison of five evolutionary algorithms for optimization of water distribution networks," *Journal of Computing in Civil Engineering*, vol. 32, no. 1, article 04017066, 2018.

[15] K. Pereira, B. R. Pereira, J. Contreras, and J. R. S. Mantovani, "A multi-objective optimization technique to develop protection systems of distribution networks with distributed generation," *IEEE Transactions on Power Systems*, vol. 33, no. 6, 2018.

[16] J. Yao, X. Wang, J. Li, R. Liu, and H. Zhang, "Sub-synchronous resonance damping control for series-compensated dfig-based wind farm with improved particle swarm optimization algorithm," *IEEE Transactions on Energy Conversion*, vol. 34, no. 2, pp. 849–859, 2019.

[17] M. Mohammadian, A. Lorestani, and M. M. Ardehali, "Optimization of single and multi-areas economic dispatch problems based on evolutionary particle swarm optimization algorithm," *Energy*, vol. 161, pp. 710–724, 2018.

[18] K. Hu, M. Jiang, H. Zhang, S. Cao, and Z. Guo, "Design of fault diagnosis algorithm for electric fan based on lssvm and kd-tree," *Applied Intelligence*, vol. 51, no. 2, pp. 804–818, 2021.

[19] N. Wang and W. Liu, "Mathematical model of port scheduling problem based on multi-objective particle swarm optimization," *Journal of Coastal Research*, vol. 115, supplement 1, p. 561, 2020.

[20] J. Wong, Y. S. Lim, and E. Morris, "Distributed energy storage systems with an improved fuzzy controller for mitigating voltage unbalance on low-voltage networks," *Journal of Energy Engineering*, vol. 142, no. 1, article 04014058, 2016.

[21] Z. Yin, C. Du, J. Liu, X. Sun, and Y. Zhong, "Research on auto-disturbance-rejection control of induction motors based on ant colony optimization algorithm," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 4, pp. 3077–3094, 2017.

[22] X. Meng and X. Li, "Research on optimization of port logistics distribution path planning based on intelligent group classification algorithm," *Journal of Coastal Research*, vol. 115, supplement 1, p. 205, 2020.

[23] J. Huang, J. Zeng, Y. Bai, Z. Cheng, and D. Liang, "Layout optimization of fiber bragg grating strain sensor network based on modified artificial fish swarm algorithm," *Optical Fiber Technology*, vol. 65, no. 1, article 102583, 2021.

[24] Y. Song, D. Hill, and T. Liu, "Static voltage stability analysis of distribution systems based on network-load admittance ratio," *IEEE Transactions on Power Systems*, vol. 34, no. 3, pp. 2270–2280, 2019.

[25] S. C. Chu, X. W. Xu, S. Y. Yang, and J. S. Pan, "Parallel fish migration optimization with compact technology based on memory principle for wireless sensor networks," *Knowledge-Based Systems*, vol. 241, no. 3, article 108124, 2022.

[26] O. Amjad, E. Bedeer, N. A. Ali, and S. Ikki, "Robust energy efficiency optimization algorithm for health monitoring system with wireless body area networks," *IEEE Communications Letters*, vol. 24, no. 5, pp. 1142–1145, 2020.

RETRACTED