An improved differential evolution algorithm-based optimal series compensation voltage control strategy for an active distribution network

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An Improved Differential-Evolution-Algorithm-Based Optimal Series Compensation Voltage Control Strategy for an Active Distribution Network

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SUMMARY

A distribution network with distributed generation (DG) is usually called an active distribution network. The voltage quality in an active distribution network tends to degrade because of the bidirectional power flow in the network and the random output characteristic of DG. Existing voltage control methods cannot effectively address this issue. In this article, an improved differential evolution (DE)-algorithm-based optimal series compensation voltage control method for an active distribution network is presented. It is assumed that the series compensating voltage is produced flexibly by modern power electronics equipment. The quantitative relationship connecting the node voltage deviation, network power loss and compensating voltage is analysed. The optimal control model, including the power loss and load node voltage, is constructed. Then, an improved DE algorithm is proposed to solve the optimal model, which combines the standard DE approach with the simulated annealing and adaptive mutation operator method. The optimal control model can be solved effectively by the improved algorithm. A simulation model is developed based on the IEEE 33 standard distribution network with DG. Simulation results confirm the validity of the optimal control model and the advantages of the improved DE algorithm.

KEYWORDS
active distribution network, series compensation, optimal voltage control, improved differential evolution algorithm.

1. Introduction

Voltage quality is an important parameter to describe a power system [1][2]. Distributed generation (DG) has been developing rapidly because of the energy crisis and environmental problems. DG is commonly injected into the distribution network, which is usually described as an active distribution network [3][4]. DG and loads work with both random and intermittent characteristics; the power flow in an active distribution network is bidirectional. The voltage quality tends to be worse than that of a radial network [5]-[7]. There are certain voltage regulation measurements, such as the on-load tap changer and shunt capacitor, that can regulate the stable voltage for the conventional distribution network, but they cannot meet the voltage control demands of an active distribution network, particularly in adjustments of speed and continuity [8]-[15]. This limitation is the primary factor governing the amount of DG that can be injected into the distribution system.

Series capacitor compensation technology has been widely used in transmission systems to regulate system parameters to enhance transmission capability and operational stability [16]. In a distribution network, the equivalent resistance is usually greater than the equivalent reactance; in some cases, their ratio is over 5. The series capacitor can compensate for the voltage drop across the equivalent resistance along the distribution line, but it cannot

accommodate the voltage drop of the equivalent resistance [17]. In contrast, a series capacitor can automatically change the compensating voltage according to the current flowing through it. When amounts of DG are injected by the feeder or customer side, the power flow in the distribution network will be bidirectional. In this case, the voltage will degrade under the control of the series capacitor. An interline dynamic voltage restorer method is presented, and the compensation range is analysed for different voltage sag types [18]. The unified power flow controller (UPFC) as a flexible alternative current transmission system (FACTS) apparatus has a powerful capability to adjust the power flow [19]. This method has been used successfully in transmission systems to enhance transmission capability; it can control the compensation voltage amplitude and phase continuously and rapidly. A UPFC-based optimal power flow control model for a closed-loop distribution network has been presented that incorporates the power loss and node voltage [20]-[22]. In those reports, the UPFC-based optimal control model including load node voltage and power loss was constructed, but the solution algorithm for the optimal control model was not addressed.

The power flow control model is a multi-objective nonlinear optimization problem, which is challenging to solve by conventional algebraic analysis. Artificial intelligence (AI) is well suited to solve such nonlinear optimization problems [23]. In 1995, Rainer Storn and Kenneth Price presented a differential evolution (DE) algorithm [24]. Distinct from other evolutionary algorithms, mutation in DE is completed by the difference of multiple sectors selected at random. This approach can solve complicated nonlinear problems with high efficiency and satisfactory robustness [25][26]. It is challenging for standard DE algorithms to produce appropriate initial populations because the mutation is highly random and because the calculation process is greatly influenced by the algorithm parameters. To obtain an optional initial population

for the genetic algorithm, one initial individual is produced randomly that can meet the constraint condition. Then, the remaining individuals are gradually regulated similar to the first individual until the entire population meets the constraint condition [27]. The initial population production process can be effectively optimized by this method, but the distribution breadth is insufficient in the feasible solution region. The method for adaptive mutation operator is presented elsewhere [28][29]. In this method, the zooming coefficient is much larger in the initial period to increase the breadth of the population distribution. The zooming coefficient becomes smaller over subsequent periods to speed up the convergence rate. Simulated annealing strategy is also used to improve the DE algorithm [30]. The variation is adjusted by changing annealing factors to escape the local minimum solution in the beginning stage. The best parent individual will lead the variation to enhance the local searching ability in the late stage. This method can effectively improve the convergence rate. An adaptive DE algorithm has been proposed [31]. Its mutation and crossover operators continue to change during the evolution process, and unsuitable parameters can be avoided to a certain extent. A DE algorithm incorporating the improved method has been used to solve the optimal dispatch problem for hydroelectric power [32]. It can effectively enhance calculation efficiency, but the convergence rate of this algorithm is random because the parameter selection is not deterministically controlled.

This article presents an optimal series compensation voltage control method for an active distribution network and an improved DE algorithm to solve this optimal model. Simulation results based on the IEEE 33 bus distribution network confirm that the optimal voltage control method can improve the voltage quality and lower the active power loss. The improved DE algorithm can solve the optimization problem universally with high efficiency.

2. Relationship between the compensation voltage and operating parameters of an active distribution network

2.1. Relationship between series compensation voltage and power loss

A radial distribution feeder with n load branches and DG is shown in Fig. 1. DG is injected at the feeder end. It is assumed to act as a voltage source. $\dot{I}_{DG}$ is the current injected by DG, $\dot{I}_i$ is the current of feeder section i, and $\dot{I}_{Li}$ is the current of load i. All loads are assumed to behave as constant-current models. $\dot{U}_i$ is the voltage of load i. Z_i is the equivalent impedance of feeder section i, and $Z_i = R_i + j\omega L_i$.
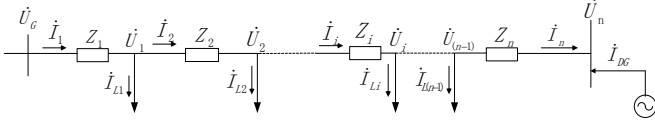

FIGURE 1 Equivalent circuit of one feeder with DG and n load branches

When there is no series compensation, the loop current $\dot{I}_{loop}$ can be expressed as

$$\dot{I}_{loop} = \frac{\Delta\dot{U} - \sum_{i=1}^{n} j\omega L_i \dot{I}_i}{R_\Sigma} \qquad (1)$$

where $\Delta\dot{U} = \dot{U}_G - \dot{U}_n$ and $R_\Sigma = \sum_{i=1}^{n} R_i$. When $\Delta\dot{U}$ is equal to $\sum_{i=1}^{n} j\omega L_i \dot{I}_i$, the circle current $\dot{I}_{loop}$ is 0. In this case, the power loss is minimal and can be expressed as $P_{loss-\min}$.

The UPFC has powerful power flow control capability, which is used here to produce the series compensation voltage $\dot{U}_{SC}$. As discussed above, when $\Delta\dot{U} + \dot{U}_{SC} = \sum_{i=1}^{3} j\omega L_i \dot{I}_i$, the power loss is minimal; thus, it is necessary to adjust the compensation voltage further to improve the load

voltage. Consequently, the loop current will change, and the power loss will increase. $\Delta\dot{I}'_{loop}$ is the loop current increment based on the condition of minimal power loss, and P'_{loss} is the power loss after further adjustment.

$$P'_{loss} = P_{loss-\min} + 3 \times \sum_{i=1}^{n} R_i \left| \Delta\dot{I}'_{loop} \right|^2$$

The power loss increment is related only to the amplitude of the loop current increment and is unrelated to its phase. The new loop current $\dot{I}'_{loop}$ can be described simply as

$$\dot{I}'_{loop} = \dot{I}_{loop} + \frac{\dot{U}_{SC}}{Z_\Sigma}$$

Therefore, the relationship between the series compensation voltage and active power loss for the network in Fig. 1 can be expressed as

$$P'_{loss} = P_{loss-\min} + 3 \times R_\Sigma \left| \dot{I}_{loop} + \frac{\dot{U}_{SC}}{Z_\Sigma} \right|^2 \qquad (2)$$

2.2. Relationship between compensation voltage and load node voltage

Suppose that the UPFC is inserted between node i-1 and i. The UPFC produces the compensation voltage $\dot{U}_{SC}$, as shown in Fig. 2, where $\dot{U}_{1i}$ is the voltage of load i after compensation and $\dot{I}_{1i}$ is the current of feeder section i.

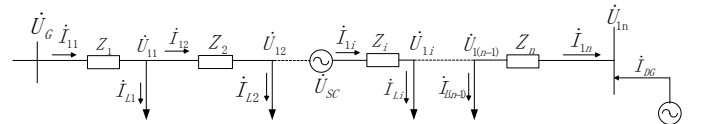**FIGURE 2** Equivalent network after series compensation

Based on the superposition theorem, the network in Fig. 2 can be divided into two parts. The first one is the original network without compensation, as shown in Fig. 1. The other is the network powered only by $\dot{U}_{SC}$, as shown in Fig. 3. where $\Delta\dot{U}_i$ is the voltage difference and $\Delta\dot{I}_i$ is the current difference led by $\dot{U}_{SC}$.
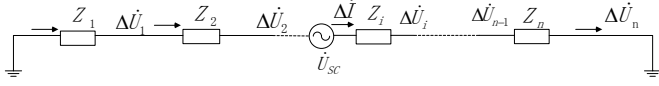
FIGURE 3 Network powered by compensation voltage

The node voltage difference between Z_1 and Z_{i-1} in Fig. 3 can be expressed as

$$\Delta\dot{U}_j = -\frac{\dot{U}_{SC}\cdot\sum_{i=1}^{j}Z_i}{\sum_{i=1}^{n}Z_i} \qquad (j=1,2,\cdots,i-1) \qquad (3)$$

The voltage difference of the nodes between Z_i and Z_n in Fig. 3 can be expressed as

$$\Delta\dot{U}_j = \frac{\dot{U}_{SC}\cdot\sum_{i=j+1}^{n}Z_i}{\sum_{i=1}^{n}Z_i} \qquad (j=i,i+1,\cdots,n) \qquad (4)$$

The node voltage after compensation in Fig. 2 is

$$\dot{U}_{1j} = \dot{U}_j + \Delta\dot{U}_j \qquad (j=1,2,\cdots,n) \qquad (5)$$

The conclusion in 2.1 shows that the power loss is related only to the compensation voltage amplitude, but the node voltage is related to both the amplitude and phase of the compensation voltage. Therefore, the node voltage and power loss can be controlled separately.

3. Optimal power flow control model for an active distribution network

Considering the power loss and node voltage deviation, an optimal control model is constructed. The associated multiple-objective optimization problem can be simplified into a single-objective optimal model by designing the membership function.

3.1. Membership function of power loss

Suppose that the original power loss before control is $P_{loss-ori}$ and that the minimal power loss in theory is $P_{loss-\min}$. P'_{loss} is the actual power of the network. The membership function of power loss is designed as

$$\mu_{P_{loss}} = \begin{cases} 1 & P'_{loss} \leq P_{loss-\min} \\ \dfrac{P'_{loss} - P_{loss-ori}}{P_{loss-\min} - P_{loss-ori}} & P_{loss-\min} < P'_{loss} < P_{loss-ori} \\ 0 & P_{loss-ori} \leq P'_{loss} \end{cases} \qquad (6)$$

3.2. Membership function of load node voltage deviation

Suppose that voltage varies from $-7\%U_N$ to $+7\%U_N$. The membership function $\mu_{\Delta Ui}$ for the voltage of the load node i is designed as

$$\mu_{\Delta Ui} = \begin{cases} 0 & U_i < 0.93U_N \\ \dfrac{U_i - 0.93U_N}{0.07U_N} & 0.93U_N \leq U_i \leq U_N \\ \dfrac{1.07U_N - U_i}{0.07U_N} & U_N < U_i \leq 1.07U_N \\ 0 & U_i > 1.07U_N \end{cases} \qquad (7)$$

where U_N is the rate voltage, U_i is the actual voltage of load node i, which is $\dot{U}_{1j}$ as shown in equation (5), and n is the total quantity of load node $1 \leq i \leq n$.

3.3. Optimal control model for power loss and voltage

The single objective optimal control model is constructed as shown in equation (8). It is based on the membership functions defined in (6) and (7).

$$\max(\alpha\sum_{i=1}^{n}\frac{\mu_{\Delta Ui}}{n} + \beta\mu_{loss}) \qquad (8)$$

$$\text{s.t} \begin{cases} S_G \leq S_{G\max} \\ U_{\min} \leq U_i \leq U_{\max} \end{cases}$$

where α, β is the weight coefficient for the power loss and load node voltage $\alpha + \beta = 1$, n is the total quantity of load node $1 \leq i \leq n$, S_G is the actual power of the feeder, $S_{G\max}$ is the maximum power capacity of the feeder, $U_{\max}$ and $U_{\min}$ are the upper and lower limits of the load node voltage, respectively, and U_i

is the actual voltage of load node i.

4. Improved DE algorithm

To solve the nonlinear optimal control model as shown in (8), an improved DE algorithm is studied.

4.1 Optimal production of initial population

Suppose that the population size is NP and X_i is the individual vector i. Then, $X_i = (x_{i,1}, x_{i,2}, \cdots, x_{i,n}), X_i \in R^n$, where n is the resolution space dimension. In the standard DE algorithm, the individual vector is selected at random but must meet the given bounded constraint. The vector can be expressed as

$$x_{i,j} = x_{i,j\min} + rand()(x_{i,j\max} - x_{i,j\min}) \qquad (9)$$

where $x_{i,j}$ is the component j of the individual sector X_i and $x_{i,j\max}$ and $x_{i,j\min}$ are the upper and lower bounds of $x_{i,j}$, respectively. Rand() signified a random number distributed uniformly from 0 to 1.

An optimal method for producing the initial generation was previously reported [27]. First, based on (9), one initial generation continues producing randomly until it meets the demand of the given bounded constraint. Then, it is adopted as the first feasible individual and is expressed as $X_1^0 = (x_{11}^0, x_{12}^0, \cdots, x_{1n}^0)$. Second, other individuals are produced randomly based on (9). If they cannot meet the demand of the given bounded constraint, they will be regulated to approach X_1^0 according to (10):

$$X_2^0 = X_1^0 + \mu(X_2^0 - X_1^0) \qquad (10)$$

where μ is the contraction coefficient and $\mu \in [0,1)$. If a new individual cannot meet the demand of the given bounded constraint after regulation, μ will be divided by two automatically until the feasible individual is obtained. In the end, the entire initial population can be obtained successfully. In this paper, the optimal production of the initial population based on (10) is adopted.

4.2 Improved strategy for the mutation operator

The adaptive mutation operator is introduced [28], which can broaden the initial population distribution in the feasible region. The adaptive zoom factor F is expressed as

$$F = F_0 * 2e^{(1-G)/(G_{\max} + 1 - G)} \qquad (11)$$

where F_0 is the initial zoom factor, $G_{\max}$ is the maximum evolution generation number, G is the present evolution generation number, and $G \in [0, G_{\max}]$. During the initial period, the zoom factor F is relatively large to retain population diversity. Subsequently, the zoom factor F automatically decreases to retain qualified information and provide fast convergence.

There are many variations of the DE algorithm. Among them, the method shown in (12) and (13) performs well and has been used successfully in practical applications [29]:

$$v_i^{t+1} = x_{r3}^t + F * (x_{r1}^t - x_{r2}^t) \qquad (12)$$

$$v_i^{t+1} = x_{\text{gbest}}^t + F * [(x_{r1}^t - x_{r2}^t) + (x_{r3}^t - x_{r4}^t)] \qquad (13)$$

where v is the new individual, which may be out of the given bounded constraint. x is the basic individual for the mutation operator and can be selected randomly, in which case it is expressed as x_{ri}^t. It can also be obtained by selecting the optimal individual among the present population, which is expressed as x_{gbest}^t. t is the generation number, and F is the zoom factor. As shown in (12), a new individual is produced by the last three different individuals, which is unrelated to the goal function. It is beneficial to maintain population diversity to enhance the universal searching capability, but this method will influence the DE algorithm

convergent rate. As shown in (13), the new individual is produced with the guidance of the last optimal individual. It has strong searching capability with a fast convergence rate, but it may not escape from a local optimum, particularly at the initial stage.

A simulated annealing algorithm can change the focus of the mutation operator by the annealing factor λ, which is expressed as [30]

$$\lambda = (G_{\max} - G) / G_{\max} \qquad (14)$$

where $G_{\max}$ is the maximum evolution generation number and G is the present evolution generation number.

Based on (12)-(14), an improved mutation operator algorithm is presented that combines the simulated annealing strategy and adaptive mutation operator. The new mutation operator algorithm can be expressed as

$$\begin{aligned} \mathrm{v}_i^{G+1} = {}& \lambda x_{r1}^G + (1-\lambda)x_{best}^G + \mathrm{F}\lambda*(x_{r2}^G - x_{r3}^G) + \\ & F(1-\lambda)*(x_{r2}^G - x_{r3}^G + x_{r4}^G - x_{r5}^G) \end{aligned} \qquad (15)$$

where $\lambda \in [0,1]$. When $\lambda = 1$, formula (15) is the same as (12), and when $\lambda = 0$, formula (15) is the same as (13). During the searching process, λ will increase automatically to reduce the weight of (12) and increase the weight of (13). The mutation operator method in (15) can balance the universal searching capability and convergence rate.

Based on the above analysis, the improved DE algorithm is presented based on (10) and (15). It has strong universal searching capability over the initial period and satisfactory local searching capability over subsequent periods. The flow chart of the improved DE algorithm is shown in Fig. 4.
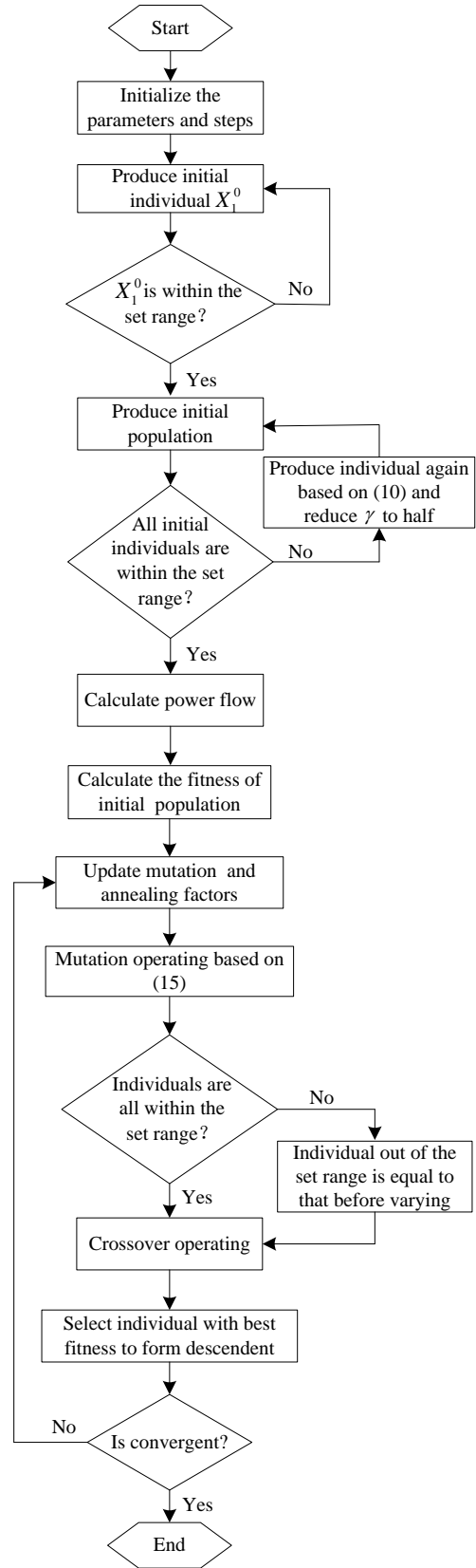

FIGURE 4 Flow chart of improved DE algorithm

6

5. Simulation and analysis

The simulation model is constructed using PSCAD software. The structure is based on the IEEE 33 standard distribution system as shown in Fig. 5. The load in some nodes is changed, and all the simulating parameters are shown in Tab. 1. U_N=12.66kV. All the branches, including 18-21, 22-24 and 25-32, are simplified into a central load. Then, the main feeder 0-17 is analysed. All loads are described by a constant-current model. DG is connected by node 17 and is simulated as motor type DG, which can be regarded as a voltage source. The improved DE algorithm discussed above is used to solve the optimal control model, where the weight coefficient $\alpha = \beta = 0.5$. The size of the population is 20, and the maximum iteration time is 80. The crossover factor is 0.5, and the initial mutation factor is 0.6. The improved DE algorithm is implemented by programming in Matlab.
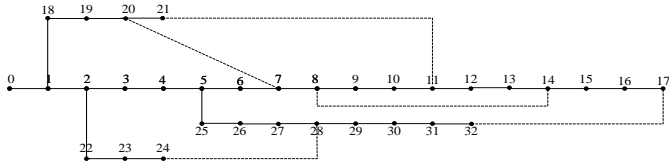

FIGURE 5 IEEE 33 distribution system

TABLE 1 Simulated model parameters

Node i	Node j	Impedance （Ω）	Load j (kVA)
0	1	0.0922+j0.047	100+j60
1	2	0.4930+j0.2511	90+j40
2	3	0.3660+j0.1864	120+j80
3	4	0.3811+j0.1941	60+j30
4	5	0.8190+j0.7070	60+j20
5	6	0.1872+j0.6188	200+j100
6	7	0.7114+j0.2351	396+j198
7	8	1.0300+j0.7400	590+j296
8	9	1.0440+j0.7400	396+j198
9	10	0.1966+j0.0650	590+j296
10	11	0.3744+j0.1238	60+j35
11	12	1.4680+j1.1550	60+j35
12	13	0.5416+j0.7129	120+j80
13	14	0.5910+j0.5260	60+j10
14	15	0.7463+j0.5450	60+j20
15	16	1.2890+j1.7211	396+j198
16	17	0.3720+j0.5740	0
1	18	0.1640+j0.1565	90+j40
18	19	1.5042+j1.3554	90+j40
19	20	0.4095+j0.4784	90+j40
20	21	1.7089+j0.9373	90+j40
2	22	0.4512+j0.3083	90+j50
22	23	0.8980+j0.7091	420+j200
23	24	0.8960+j0.7011	420+j200
5	25	0.2030+j0.1034	60+j25
25	26	0.2842+j0.1447	60+j25
26	27	1.0590+j0.9337	60+j20
27	28	0.8042+j0.7006	120+j70
28	29	0.5075+j0.2585	200+j600
29	30	0.9744+j0.9630	150+j70
30	31	0.3105+j0.3619	210+j100
31	32	0.3410+j0.5362	60+j40
7	20	2+j2	Inter connection switch
8	14	2+j2	
11	21	2+j2	
17	32	0.5+j0.5	
24	28	0.5+j0.5	

5.1. Simulation result of optimal voltage control

5.1.1 Voltage control effectivity: The simulation results for the load node voltage are shown in Tab. 2, which includes three states to compare the voltage control effect. In State 1, there is no series compensation voltage or DG. In State 2, DG is injected, but there is no series compensation voltage. In State 3, DG is injected and a series compensation voltage is applied, and the optimal control model includes the node voltage and power loss. The compensating apparatus is set at node 8. Based on equation (8) and the improved DE algorithm in Fig. 4, the compensating voltage $\dot{U}_{SC}$ can be obtained as $0.512\angle 81.58°$. In State 1, the voltage of node 5-17 is below the lower voltage limit. In State 2, the overall voltage level is improved, but the voltage of node 8-10 is still below the lower voltage limit. DG can improve the voltage distribution, but it cannot entirely resolve this issue. After performing series compensation as shown in State 3, the voltage of all nodes can meet the constraint of the voltage

7

variation range. The simulation results establish the effectiveness of the optimal voltage control strategy.

TABLE 2 Comparison of load node voltages

Load No	Node voltage as State 1	Node voltage as State 2	Node voltage as State 3
1	0.9957	0.9968	0.9967
2	0.9746	0.9819	0.9807
3	0.9623	0.9742	0.9722
4	0.9499	0.9665	0.9637
5	0.9191	0.9461	0.9425
6	0.9101	0.9397	0.9373
7	0.8959	0.9344	0.9300
8	0.8755	0.9269	0.9338
9	0.8601	0.9248	0.9300
10	0.8582	0.9253	0.9300
11	0.8560	0.9279	0.9315
12	0.8473	0.9379	0.9395
13	0.8438	0.9417	0.9434
14	0.8412	0.9468	0.9478
15	0.8383	0.9536	0.9534
16	0.8330	0.9662	0.9660
17	0.8330	0.9716	0.9716

5.1.2 Power loss control effectivity: Simulation results for power loss in different conditions are shown in Fig. 6, in which State 1, State 2 and State 3 are the same as defined in 5.1.1. In State 4, DG is injected and a series compensation voltage is applied, but the optimal control model consists only of power loss. The power loss in State 1 is 0.4942 MW. In State 2, it is 0.2724 MW. Therefore, the injected DG can decrease the power loss. The power loss of the active distribution network in State 4 is the minimum in theory, and it is 0.2149 MW. In State 3, it is 0.2378 MW. The power loss in State 3 is larger than that in State 4 because the series compensating control strategy in State 3 includes simultaneous voltage and power loss. In State 4, the power loss is minimized. The difference between State 3 and State 4 is the weight coefficients α and β, which are set according to the actual demand [20]. A comparison of State 2 and State 3 confirms that the optimal voltage control method can decrease the power loss.
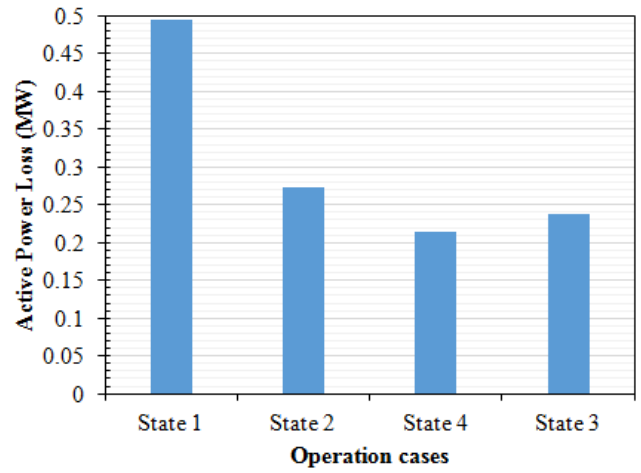

FIGURE 6 Power loss at different conditions

5.2. Simulation for improved DE algorithm

5.2.1 Speed of producing the initial population: The speed of producing the initial population can affect the time to solve the optimization object. The results for different DE algorithms are shown in Tab. 3. The improved DE algorithm is faster than the standard DE algorithm when the population scale is known. Increasing the population requires more time to produce the initial population, but the improved DE algorithm offers absolute advantages in producing the initial population.

TABLE 3 Time contrast for producing different scale populations with varying DE algorithm

Scale population	Time with standard DE (s)	Time with improved DE (s)
10	0.087263	0.013623
20	0.204181	0.018638
30	0.270601	0.021246
40	0.339764	0.023020
50	0.408676	0.025390
60	0.556561	0.032148

5.2.2 Convergence speed contrast: Suppose that the population scale is 20, the maximum iteration time is 80, the crossover factor is 0.5, the initial mutation factor F0 is 0.6, the normal mutation factor F is 1, and α = β = 0.5. The simulated satisfaction value of different DE algorithms is shown in Fig. 7. The results of the standard DE, adaptive DE [30][31] and improved DE algorithm are compared. The improved DE algorithm has a

8

clear advantage in the convergence rate based on universal optimization. Because the beginning mutation factor is improved and the variation probability is much larger, the improved algorithm is slower than the standard DE in the initial period, but the mutation factor is adjusted to decrease with the calculation process, and the global optimal solution can be obtained with fewer steps by the improved DE algorithm.
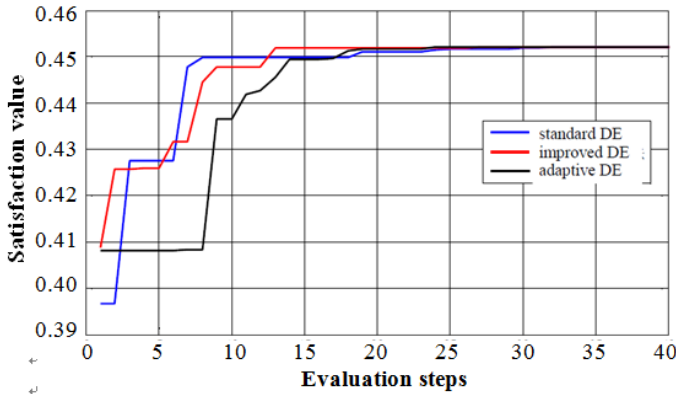

FIGURE 7 Satisfaction value curve with three DE algorithms

To confirm the reliability of the DE algorithm, 100 testing experiments were conducted to solve the same optimal object with the three different DE algorithms. The static probability of convergence steps with the different algorithms is shown in Fig. 8. In most cases, the standard DE algorithm requires approximately 30 to 40 steps, and the improved DE and adaptive DE algorithm can complete optimization in 20 to 30 steps. The probability of the improved DE in this zone is greater than that of the adaptive DE algorithm.
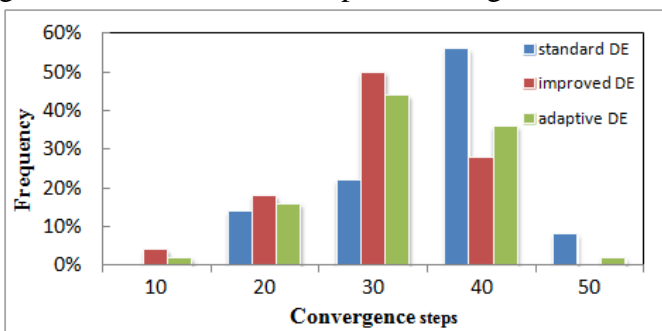

FIGURE 8 Static convergence step distribution for three DE algorithms

6. Conclusions

When DG is connected into a distribution network, the voltage tends to become degraded. To resolve the voltage issue in an active distribution network, the optimal voltage control method, which analyses the power loss in terms of series compensating theory, is studied. An optimal control model is developed that incorporates the power loss and node voltage. An improved DE algorithm is introduced to effectively solve the optimal voltage control model. Simulations based on the IEEE 33 distribution network confirm that the voltage control method can decrease the power loss and improve the load node voltage. The improved DE algorithm can solve the optimal model universally with higher efficiency and convergence speed than the standard DE and adaptive DE algorithms. The method presented is also suitable for optimal power flow control in normally looped distribution systems with dual sources.

With the development of modern power electronics technology and advanced control theory, active control measures based on FACTS are expected to be applied widely in future distribution networks. Increasingly more DG will be injected into distribution networks. The optimal voltage control method presented in this paper provides a theoretical foundation for the further development of active distribution networks.

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